Postprint: A Survey of Artificial Intelligence Applications in Agricultural Risk Management

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Abstract

Agriculture is a foundational industry that concerns national economy and people's livelihood, yet it is also a vulnerable industry. Traditional research methods for agricultural risk management suffer from insufficient mining of nonlinear information, low precision, and poor robustness. Artificial Intelligence (AI), with its powerful capabilities including strong nonlinear fitting based on big data, end-to-end modeling, and automatic feature learning, can effectively address these issues. This paper first analyzes the research progress of AI in three major areas: agricultural vulnerability assessment, agricultural risk prediction, and agricultural damage assessment, and draws the following conclusions: 1. In agricultural vulnerability assessment, the evaluation of feature importance by AI lacks scientifically effective validation metrics, and the application approach prevents comparison of the relative merits of multiple models; it is recommended to adopt subjective-objective methods for evaluation; 2. In risk prediction, it is found that as the prediction horizon increases, the predictive capability of machine learning models tends to decline; overfitting is a common issue in risk prediction, and current research has rarely explored the spatial information of graph data; 3. The complex agricultural production environment and variable application scenarios are important factors affecting the accuracy of damage assessment; enhancing the feature extraction capability and robustness of deep learning models represents a key and challenging problem for future technological development. Subsequently, corresponding solutions are proposed for the performance improvement issues and small-sample problems that exist in the application of AI. For performance improvement issues, depending on users' familiarity with artificial intelligence, multiple methods can be employed respectively, including multi-model comparison, model ensemble, and neural network structure optimization to enhance model performance; for small-sample problems, data augmentation, generative adversarial networks, and transfer learning can often be combined to enhance model robustness and improve model recognition accuracy. Finally, prospects for the application of AI in agricultural risk management are discussed. In the future, AI could be introduced into the construction of agricultural vulnerability curves; regarding the upstream-downstream relationships in agricultural industry chains and relationships with agriculture-related industries, graph neural networks could be more extensively applied to conduct in-depth research on agricultural price risk prediction; in the damage assessment modeling process, professional knowledge from domains related to the assessment targets could be more extensively introduced to enhance feature learning for the targets; augmenting small-sample data is also a key focus for future research.

Full Text

Research Application of Artificial Intelligence in Agricultural Risk Management: A Review

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Abstract: Agriculture is a foundational industry critical to national welfare and people' s livelihoods, yet it remains a vulnerable sector. Traditional agricultural risk management research methods suffer from insufficient mining of nonlinear information, low accuracy, and poor robustness. Artificial Intelligence (AI), with its powerful capabilities in strong nonlinear fitting based on big data, end-to-end modeling, and automatic feature learning, can effectively address these issues. This paper first analyzes research progress in three major areas: agricultural vulnerability assessment, agricultural risk prediction, and agricultural damage assessment. The analysis reveals that: (1) Feature importance assessment in agricultural vulnerability evaluation lacks scientifically valid verification metrics, and the current application approach prevents comparison of multiple models, suggesting the adoption of subjective-objective evaluation methods; (2) In risk prediction, the predictive capability of machine learning models tends to decline with increasing forecast horizons, overfitting is a common problem, and current research has rarely explored spatial information mining from graph data; (3) Complex agricultural production environments and variable application scenarios are key factors affecting damage assessment accuracy, and improving the feature extraction capability and robustness of deep learning models represents a critical challenge for future technological development. The paper then proposes solutions for performance improvement and small sample problems encountered in AI applications. For performance enhancement, users with varying levels of AI familiarity can employ multiple model comparison, model combination, or neural network structure optimization methods. For small sample problems, data augmentation, generative adversarial networks, and transfer learning can be combined to enhance model robustness and recognition accuracy. Finally, the paper prospects future AI applications in agricultural risk management, suggesting: AI could be introduced for constructing agricultural vulnerability curves; graph neural networks could be more extensively applied to agricultural price risk prediction by leveraging upstream-downstream relationships in agricultural industry chains and connections with related sectors; and domain-specific knowledge should be incorporated into damage assessment modeling to enhance target feature learning, with data augmentation for small samples being a key research priority.

Keywords: agricultural risk management; artificial intelligence; vulnerability assessment; risk prediction; damage assessment

1. Introduction

China is a major agricultural nation where agriculture constitutes a basic industry essential for national food security, yet it remains a vulnerable sector. Compared to other industries, agriculture is more susceptible to various risks due to the uncontrollability of natural environments, uncertainties in animal and plant growth processes, and price volatility of costs and selling prices under market economic systems. Agricultural production loss appears particularly urgent and important. The essence of agricultural industry is a process intertwining economic reproduction with natural reproduction, which determines both its vulnerability and the diversity of risk categories. Agricultural risks are broadly classified into four categories: natural production risk, market risk, personal risk, and policy/regulatory risk. From a severity perspective, agricultural risks primarily originate from natural risk factors, making agriculture a high-risk industry. Therefore, implementing risk management for agricultural production and market risks to reduce food security risks and minimize farmer losses is crucial.

Based on the timing relative to risk events, the agricultural risk management cycle can be divided into three stages: pre-event preparation, during-event response, and post-event recovery [Figure 1: see original paper]. In each stage, traditional approaches often employed quantitative indicator weighting and scoring, simple linear regression, and manual feature extraction, which not only failed to mine nonlinear information but also suffered from insufficient accuracy and poor robustness. Artificial Intelligence (AI), represented by machine learning and deep learning, has conducted extensive research in three major aspects of the agricultural risk management cycle—vulnerability assessment, risk prediction, and damage assessment—effectively addressing limitations of previous technical methods.

This paper analyzes current AI applications in agricultural risk management from these three perspectives, summarizes the development status, identifies existing problems and solutions, and prospects future technical research and development directions, aiming to provide references for better AI service to agricultural risk management.

2. AI Applications in Agricultural Vulnerability Assessment

Vulnerability, in its narrow sense, measures the capacity of disaster-bearing bodies to withstand hazard impacts, comprising only adaptability. In its broad sense, vulnerability is a comprehensive concept encompassing risk, adaptability, and resilience. This paper discusses vulnerability in its broad sense.

Current domestic and international AI-based agricultural vulnerability assessment primarily involves constructing quantitative indicator evaluation systems that reflect agricultural vulnerability, then employing AI for weighting and scoring to obtain final vulnerability scores or grades [Figure 2: see original paper]. Vulnerability assessment provides policy basis for enhancing agricultural risk management capabilities and targeted governance.

In multi-dimensional vulnerability assessment systems, input variable selection is crucial. Agricultural vulnerability possesses both natural attributes and socio-economic characteristics—it relates not only to local temperature, precipitation, and topography but also to GDP per capita, population density, and technological factors. However, no universally effective evaluation standards exist for weighting different quantitative indicators. This section introduces three AI methods for variable feature importance weighting in agricultural vulnerability assessment: model output method, correlation coefficient method, and neural network method.

2.1 Model Output Method and Applications

Ensemble learning algorithms based on decision trees, such as Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), can directly score feature importance by learning relationships between input vulnerability indicators and target values. Li et al. [16] created a rainstorm disaster vulnerability indicator system based on the Exposure-Sensitivity-Adaptive capacity (ESA) framework, using precipitation, economic, and social development data as inputs with RF to evaluate spatiotemporal features and feature importance. Deng et al. [17] employed RF to quantify impacts of major factors on agricultural drought, identifying total crop sown area, precipitation, effective irrigation area, domestic patent applications granted, and regional GDP as the top five dominant factors—where patent grants reflect local scientific-technological levels, an important drought resistance indicator. Kinnunen et al. [18] used XGBoost to measure anthropogenic impacts on crop yield loss risk, finding human factors explained 40%-60% of yield loss variation. Sun et al. [19] selected 16 indicators correlating positively and negatively with drought vulnerability, using vulnerability indicators as inputs and disaster rate as targets, applying RF to assess indicator importance for objective weighting before determining drought vulnerability through weighted comprehensive scoring.

The model output method is easy to implement with mature engineering practices, directly outputting indicator importance bar charts post-modeling. However, it cannot measure positive/negative impacts of input indicators on target values, which require further logical relationship analysis.

2.2 Correlation Coefficient Method and Applications

Machine learning models like linear regression and Logistic Regression (LR) can use correlation coefficients between input variables and target values post-modeling to measure agricultural vulnerability indicator impacts. Samuel et al. [20] employed differential models and stepwise multiple linear regression to quantify climate adaptation technology impacts on farmer income during drought, identifying farm size, livestock ownership, climate adaptation technology, and agricultural investment as decisive factors. Liu et al. [21] used multiple linear regression to analyze factors influencing household exposure, sensitivity, adaptability, and livelihood vulnerability. Melketo et al. [22] applied principal component analysis and general linear models to determine food insecurity resilience factors for pastoral households, finding household size, age, wealth, irrigation conditions, and soil-water conservation technology utilization significantly explained resilience variations. He and Zhou [23] used entropy method to evaluate household livelihood vulnerability, then applied multiple linear regression for empirical analysis of influencing factors. Saha and Pal [24] used logistic regression and fuzzy logic for wetland physical vulnerability assessment based on seven parameters.

The correlation coefficient method models relationships between inputs and targets, with linear regression weights clearly measuring input feature impacts and correlation sign indicating positive/negative relationships. However, linear models are relatively simple, only mining linear relationships, and perform poorly when modeling objects are complex or nonlinear.

2.3 Neural Network Method and Applications

Artificial Neural Networks (ANN), represented by Back Propagation Neural Networks (BPNN), establish relationships between input variables and evaluation object vulnerability to provide quantitative weights. Roy et al. [25] used ANN and maximum entropy models to assess drought vulnerability impacts on Indian food security based on 18 drought vulnerability factors. Xie et al. [12] constructed 30 basic indicators from natural, economic, social, and technological dimensions, analyzing neuron weights to obtain decision weights for comprehensive drought vulnerability evaluation. Zhang et al. [26] used BPNN for comprehensive land ecosystem vulnerability evaluation and spatiotemporal evolution analysis based on sensitivity and coping capacity indices. Saha et al. [27] employed 50 drought vulnerability variables, categorized drought into hydrological, agricultural, meteorological, and socio-economic types, then used deep learning neural networks, ANN, and multi-task Gaussian processes to map drought vulnerability. Su et al. [28] used BPNN to quantify farmer livelihood risks from health, environmental, financial, social, and information dimensions.

Neural network weighting leverages powerful nonlinear fitting capabilities, particularly suitable for high-dimensional complex nonlinear modeling tasks, but suffers from "black box" problems with weak interpretability.

2.4 Evaluation of Vulnerability Assessment Methods

Current multi-dimensional agricultural vulnerability assessments lack quantitative scientific indicators to prove one AI algorithm' s superiority over others, determined by AI's application method in vulnerability evaluation. While AI applications in other domains primarily involve regression/classification (supervised learning) with clear evaluation standards like RMSE, MSE, and AUC, vulnerability assessment only requires obtaining input-output mapping relationships (variable weights) without corresponding metrics to evaluate the weights themselves, preventing model comparison. However, literature comparisons show RF performs significantly better due to its relative insensitivity to noise, introduced randomness preventing overfitting, and effective mining of nonlinear relationships between inputs and outputs.

Future research should use RF as a baseline model for comparison with other weighting methods, then incorporate expert knowledge for secondary subjective screening or weight adjustment to achieve comprehensive subjective-objective evaluation and improve assessment accuracy.

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3. AI Applications in Agricultural Risk Prediction

Agricultural risks primarily originate from natural production and market risks. Risk prediction helps people take appropriate actions and preparation plans in advance to reduce losses. Current AI applications in risk prediction mainly use regression and classification algorithms, with clustering and dimensionality reduction often serving as data preprocessing methods. Input agricultural risk variable data types significantly impact AI-based risk prediction. This section introduces applicable AI algorithms and their applications for three input data types—common data, time-series correlated data, and graph data [Figure 3: see original paper].

3.1 Common Data and Applicable Algorithms

Common data types include continuous data (quantitative with infinite possible values) and discrete data (qualitative with finite values). Risk prediction using common data constitutes the main component of agricultural risk prediction, with diverse applicable algorithms including RF, neural networks, Support Vector Machine (SVM), linear regression, and gradient boosting trees. Most studies compare multiple machine learning models to select the best-performing one, with applications covering crop yield prediction, natural risk prediction, and agricultural product market risk prediction.

3.1.1 Natural Risk Prediction Natural risks, primarily water and drought risks, are major factors damaging crops and livestock. Hydrological systems are complex, with dynamic processes depending on interconnections between direct factors (meteorology, environment) and indirect factors (human activities). Natural risk prediction helps protect farmer income and national food security.

Drought Risk Prediction: Remote sensing data aids agricultural drought characterization and prediction across large geographic areas. Prodhan et al. [41] used MODIS vegetation indices (500m resolution) and land surface temperature (1km resolution) with deep learning to monitor drought, achieving soil moisture deficit index estimates similar to standardized precipitation evapotranspiration indices. However, short-term drought prediction remains challenging and can be improved by introducing real-time data. Park et al. [42] used MODIS data (5km resolution) with real-time multivariate Madden-Julian Oscillation (MJO) indices in RF models, demonstrating that MJO-enhanced RF (average R^2=0.7) outperformed original RF (average R^2=0.4). Besides remote sensing, constructing precipitation indices describing drought enhances data mining capabilities. Zhang et al. [43] found precipitation and soil moisture contributed significantly to drought, with normalized difference water index importance reaching 50%. Integrating new prediction methods into machine learning models improves learning capacity. Li et al. [44] combined sea surface temperature fluctuation patterns with machine learning to effectively predict drought spatiotemporal evolution. Zhang et al. [45] combined ARIMA and LSTM models, achieving lower RMSE than ARIMA alone.

Flood Risk Prediction: Floods cause enormous economic, social, and environmental damage globally. Comparing multiple AI models and using hybrid models improves prediction performance. Venkatesan and Mahindrakar [47] compared machine learning models for short-term flood prediction using Nash-Sutcliffe efficiency, percent bias, RMSE, and R^2, verifying XGBoost' s superiority over RF and SVM. Mirzaei et al. [48] compared XGBoost and RF for flood susceptibility assessment, achieving AUC values of 0.985 and 0.980 respectively, with RF identifying distance to rivers as a critical factor. Tabbussum and Dar [49] optimized ANN, fuzzy logic, and adaptive neuro-fuzzy inference system algorithms, developing nine flood prediction models, with the hybrid adaptive neuro-fuzzy system achieving best performance (R^2=97.066%, MSE=0.00034, RMSE=0.018). However, machine learning predictive capability generally declines with increasing forecast horizons. Zhang et al. [50] compared decision trees, MLP, RF, and SVM for hourly flood forecasting in three watersheds, finding SVM most stable with clear advantages, while RF and decision tree performance declined slowly, and MLP performance dropped rapidly.

3.1.2 Production Risk Prediction In agricultural operations, livestock are vulnerable to internal and external factors causing disease. Timely assessment of livestock health conditions and production environments is crucial for sustainable development. With IoT and sensor technology, production risk prediction often integrates multi-source data for more accurate state prediction. Ebrahimi et al. [51] input physiological indicators like lactose concentration and protein levels from online monitoring systems into multiple machine learning models for sub-clinical mastitis prediction in dairy cows, with gradient boosting trees achieving 84.9% accuracy. Teixeira et al. [52] used LSTM models on wearable sensor data for cattle disease prediction, reaching 98% accuracy. Casella et al. [53] combined machine-automated and manually collected data using cost-optimized value methods for feature selection before predicting dairy calf respiratory diseases, achieving 97% correct classification five days before diagnosis. For small sample problems during data collection, generative adversarial networks can expand datasets. Ahmed et al. [54] used IoT wearable devices for poultry disease detection, employing GANs for data augmentation before machine learning classification, achieving 97% accuracy.

Dimensionality reduction and clustering algorithms enhance model robustness and learning capacity. Chen et al. [55] combined principal component analysis with LSTM for aquaculture dissolved oxygen prediction, outperforming traditional methods. Hao et al. [56] developed RF-LSTM for surface water quality prediction, demonstrating superior performance to LSTM, RF-BPNN, and other algorithms.

3.1.3 Market Risk Prediction Market economy price volatility causes farmer losses. Market risk prediction includes price and future market state forecasting. Jha and Sinha [57] used ANN for soybean and rapeseed monthly wholesale price prediction, proving superior to linear models. Paul et al. [58] compared generalized neural networks, SVM regression, RF, and ARIMA for vegetable price prediction, finding generalized neural networks most accurate. Zhang et al. [59] used 29 variables to characterize agricultural product price features, employing RF and SVM to learn relationships between features and candidate models, using minimum redundancy maximum relevance to reduce feature redundancy, with their proposed model outperforming all candidates. Lyu and Lin [60] used SVM, BPNN, and XGBoost for pork price classification, with BPNN-XGBoost achieving 94.59% accuracy. Xu et al. [61] improved LSTM with attention mechanisms for corn and soybean futures price prediction, demonstrating superior performance to ARIMA and SVR, with RMSE improvements of 0.6% and 1.8% respectively.

3.2 Time-Series Correlated Data and Applicable Algorithms

Time-series data records uniform indicators in chronological order, where consecutive data points are correlated. For such data, Recurrent Neural Networks (RNN) and LSTM are suitable, with RNN for short sequences and LSTM addressing long-term dependency problems.

Xing et al. [63] compared multiple models including multivariate linear regression, Deep Belief Network, and LSTM-RNN for apple tree transpiration prediction, finding LSTM-RNN most accurate. Venkatachalam et al. [64] used LSTM and Transductive LSTM for weather prediction based on 14 features, demonstrating superior generalization and learning capacity. Wang et al. [65] used LSTM with MODIS LAI products for winter wheat yield prediction. Zhang et al. [66] employed CNN-LSTM combining CNN-extracted spatial features and LSTM-extracted temporal features for soil organic carbon prediction, proving effective against RF baselines.

Model improvements enhance data mining capacity. Liu et al. [67] proposed four RNN methods with spatial, temporal, and spatiotemporal attention mechanisms for dissolved oxygen prediction, validating superiority in both short- and long-term forecasting. Attention mechanisms mine more temporal and spatial information, increasing accuracy. Celik et al. [68] combined satellite imagery with static soil/terrain data and dynamic climate data for multidimensional soil moisture prediction using LSTM, achieving RMSE of 0.046. Zhuang et al. [69] integrated key supply-demand factors like yield, consumption, and prices with natural, social, and economic factors for LSTM-based analysis tools.

3.3 Graph Data and Applicable Algorithms

Graph data describes relational data through objects (nodes) and their relationships (edges), representing complex unstructured data unlike structured voice, image, or text data. Graph Neural Networks (GNN), Graph Convolutional Networks (GCN), Graph Attention Networks (GAN), and Graph Recurrent Networks (GRN) learn rich relational information between nodes, offering advantages over traditional methods in complex systems with non-independent factors.

Li et al. [74] used GNN to predict rice heavy metal concentrations, significantly outperforming baseline models. Zeng et al. [75] proposed an environment-consistency-constrained GNN for landslide susceptibility evaluation, maintaining high precision even with small training sets. Kim et al. [76] used hierarchical graph attention networks on multi-category graph data for market index trend prediction.

Current agricultural risk prediction research on graph-structured data remains limited. Future work should leverage upstream-downstream agricultural industry chain relationships and sector connections for deeper agricultural price risk prediction using GNNs.

3.4 Evaluation of Risk Prediction Methods

Different input data types have suitable AI algorithms, though AI' s powerful learning capacity often causes overfitting. Generally, selected algorithm complexity should match learned model complexity; otherwise, overfitting occurs where known data predictions are excellent but unknown data predictions are poor. Model selection can avoid overfitting and improve prediction capability.

Since learned model complexity is often unknown or difficult to evaluate, researchers commonly compare multiple models for the same task using metrics like MSE, RMSE, MAE, and R-squared for model selection. Regularization, parameter reduction, network layer reduction, data augmentation, and random perturbation can address overfitting.

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4. AI Applications in Agricultural Damage Assessment

Natural disasters and pests pose enormous threats to agricultural production. Accurate and comprehensive damage assessment is crucial for reducing farmer losses and restoring production. Deep learning in AI enables target object image feature recognition for category or state determination, representing the mainstream damage assessment approach. Convolutional Neural Networks (CNN), typical in image recognition, consist of convolutional layers (local feature extraction), pooling layers (dimensionality reduction), and fully connected layers (output). Improved models like AlexNet, VGG, ResNet, GoogLeNet, YOLO, SSD, and FCN have been applied to agricultural damage assessment through damaged object image detection, recognition, and segmentation to output damage degree, quantity, and disease type [Figure 4: see original paper].

4.1 Image Detection and Recognition

Image detection and recognition in agricultural damage assessment first identifies damaged product states to distinguish normal from damaged products, then counts damaged products. Deep learning' s powerful feature self-learning capability excels at image object feature extraction. Khattak et al. [83] used CNN to identify healthy and diseased fruits/leaves with 94.55% test accuracy. Singh et al. [84] proposed a 19-layer CNN for apple leaf disease recognition with 99.2% accuracy. Mirzazadeh et al. [85] used VGG16 and ResNet50 for rapeseed damage assessment, achieving 93.7% and 98.2% overall classification accuracy respectively. Yang et al. [86] used CNN to extract visible-near-infrared spectral features for corn seedling freeze damage estimation, with CNN results correlating 0.8219 with chemical detection methods.

Enhancing feature extraction capability and comparing multiple models improves performance. Jiao et al. [87] integrated adaptive feature fusion pyramid networks into two-stage region-based CNN for agricultural pest detection, significantly outperforming other models on the AgriPest21 dataset. Bi et al. [88] improved Swin Transformer with feature attention and multi-scale fusion for maize seed recognition, achieving highest classification precision with 96.53% average precision, 96.46% recall, and 96.47% F1-score. Lyu et al. [89] combined dilated and multi-scale convolutions in DMS-Robust AlexNet for maize leaf disease classification, reaching 98.62% accuracy. Sahu and J [90] optimized DenseNet121, achieving 99.35% accuracy with only 7.21 million parameters—fewer than CNN and ResNet50. Gehlot and Saini [91] found DenseNet-121 achieved highest tomato leaf disease classification accuracy (99.694%) with smallest size (89.6 MB). Hamidisepehr et al. [92] compared Faster R-CNN, YOLOv2, and RetinaNet for post-disaster corn damage detection, with RetinaNet and YOLOv2 achieving 98.43% and 88.19% average precision respectively.

Transfer learning effectively alleviates small sample problems and accelerates training. Wan et al. [94] combined transfer learning with GoogLeNet, achieving 99.35% pest recognition accuracy and 92.78% damage grading precision—2.38%-11.44% higher verification accuracy than common models with fastest convergence. Chen et al. [95] used ImageNet-pretrained VGGNet weights for initialization, achieving 77.0% on public datasets and 92% average accuracy for rice disease classification in complex environments. Zhou et al. [96] replaced YOLOv4' s backbone with GhostNet for optimized feature extraction, combining transfer learning with YOLOv4 training techniques to create YOLOv4-GhostNet for rice pest recognition, achieving 79.38% average precision.

Improving feature extraction capability and robustness is the mainstream direction. Designing lighter models also reduces usage barriers for AI promotion.

4.2 Image Semantic Segmentation

Image semantic segmentation shares similar processes with detection/recognition but requires higher segmentation precision, training volume, and data preprocessing workload. Reddy and Neeraja [97] used DenseNet for leaf damage classification followed by 1D-CNN segmentation, achieving 97% segmentation accuracy. Yumang et al. [98] used Mask R-CNN for damaged coffee bean segmentation with 87.5% accuracy. Kumar and Kukreja [99] used ResNet-50 as Mask-RCNN backbone for wheat mosaic virus segmentation, reaching 97.0% accuracy.

Confusion between segmented objects and backgrounds is a key challenge. Das and Bais [100] proposed DeepVeg to address confusion between small circular crop leaf damage and white stones in backgrounds, achieving >0.97 accuracy for rapeseed damage segmentation. Loyani et al. [101] developed U-Net and Mask R-CNN models for pixel-level pest impact segmentation on tomatoes, with Mask R-CNN achieving 85.67% average precision and U-Net achieving 78.60% intersection over union and 82.86% Dice coefficient. Zhang et al. [102] fused multispectral, vegetation index, and RGB information using ResNeSt with attention mechanisms in RSPR-UNet++ for bark beetle and aspen leaf miner infection segmentation in remote sensing images, achieving 85.11% accuracy. Nasiri et al. [103] used U-Net architecture for pixel-level semantic segmentation of sugar beet, weeds, and soil, finding appropriate data distribution and custom loss functions improved segmentation precision to 0.9606 accuracy and 0.8423

IoU. Memon et al. [104] proposed a meta-deep learning corn leaf disease recognition model achieving 98.53% accuracy, outperforming CNN, VGG16 transfer learning, and ResNet50.

Pixel-level segmentation precision makes objects prone to background confusion. Beyond model structure optimization, incorporating domain-specific knowledge enhances target feature learning. Pixel-level annotation is labor-intensive; reducing data preprocessing costs is crucial for AI promotion.

4.3 Evaluation of Agricultural Damage Assessment Methods

Image detection/recognition has lower precision than pixel-level semantic segmentation but requires less training data generation workload. Selection should be based on application scenarios and cost budgets. Complex agricultural production environments and variable application conditions—lighting, growth stages, occlusion, livestock overlap—reduce recognition precision. Improving deep learning feature extraction capability and robustness remains a key future challenge.

Current deep learning models still employ end-to-end modeling. While model optimization improves learning capacity, future work should incorporate external knowledge such as professional features of recognition objects to enhance feature extraction.

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5. Main Problems and Recommendations

AI demonstrates excellent performance and advantages in agricultural risk management research, particularly in accuracy and robustness. However, defects and deficiencies exist. Technical issues requiring further discussion for deep AI application and promotion include model performance improvement and small sample problems.

5.1 Model Performance Improvement

Model performance enhancement in agricultural risk management includes improving feature extraction, prediction/recognition accuracy, and robustness. While parameter adjustment provides limited improvement, three methods can better enhance performance:

Multiple Model Comparison Method: Without modifying existing models, exhaustively apply all candidate models and possible parameters, selecting the best-performing model and parameters based on prediction results. For regression or classification tasks, apply all possible algorithms and select the optimal based on evaluation metrics.

Model Combination Method: Different models have varying mining capabilities and applicable scopes. By combining different models and selecting the best combination based on evaluation metrics, significant optimization can be achieved. Practical combinations include linear and nonlinear models, time-series and spatial structure models, or dimensionality reduction/clustering with regression/classification models.

Neural Network Structure Optimization [Figure 5: see original paper]: Modifying network structures—layers, activation functions, convolution kernel sizes, pooling types—improves automatic feature extraction, recognition precision, robustness against overfitting, training efficiency, and reduces parameters for lightweight applications. LeNet was originally proposed for handwritten digit recognition; as task complexity increased, LeNet became inadequate, leading to AlexNet, which won the 2012 ImageNet competition and demonstrated powerful image recognition capabilities. Customized structures can be constructed based on task requirements, such as using different convolution kernel sizes to extract multi-scale features.

These three methods can be selectively adopted based on user familiarity with AI. Multiple model comparison is easiest to implement. Model combination requires understanding various models' application domains and advantages, often requiring time for model selection and parameter training using grid search. Neural network structure optimization demands high theoretical foundation and coding ability, representing the most difficult approach.

5.2 Small Sample Problem

Data is AI' s "fuel." Machine learning requires large datasets to learn information and features for pattern recognition. However, agricultural risk management research often faces limited training samples, especially for multi-indicator modeling where data collection is difficult, creating small sample problems that prevent AI from full utility. Additionally, specific sample data preparation (e.g., pest/disease photo labeling) is labor-intensive and time-consuming, often resulting in low-quality, small-sample data.

To solve small sample problems without increasing labor/time costs, data augmentation, transfer learning, and generative adversarial networks can be employed. Data augmentation suits image-based deep learning tasks, using mirroring, rotation, scaling, cropping, translation, color jittering, contrast adjustment, random erasing, and Gaussian noise to increase data volume. Transfer learning has proven effective for small sample problems in computer vision. Generative adversarial networks, an unsupervised generative model using minimax game between generator and discriminator networks, have been widely applied for small dataset expansion.

In practice, these three techniques can be combined. Data augmentation and GANs emphasize increasing data volume from the source to enhance robustness, while transfer learning focuses on leveraging existing network structures and parameters for model initialization under similar recognition patterns, typically achieving faster training and higher recognition precision.

6. Summary and Outlook

This paper elaborates AI application research progress in agricultural vulnerability assessment, risk prediction, and damage assessment, concluding that AI agricultural risk management should develop as follows:

1. **Vulnerability Assessment:** Feature importance evaluation lacks scientific verification metrics, preventing model comparison. Subjective-objective evaluation methods are recommended. Future work should consider AI for agricultural vulnerability curve construction.
2. **Risk Prediction:** Machine learning predictive capability declines with forecast horizon extension; overfitting is common. Graph data spatial information mining remains limited. Graph neural networks should be more extensively applied to agricultural price risk prediction by leveraging agricultural industry chain relationships and sector connections.
3. **Damage Assessment:** Improving feature extraction capability and robustness is mainstream. Future work should incorporate more domain-specific knowledge to enhance target feature learning. Data augmentation for small samples is also a research priority.

While AI's powerful self-learning capability enables wide applications, its "black box" nature, high data annotation costs, and computational requirements limit further development. Enhancing AI interpretability, improving training efficiency, boosting learning capacity, and reducing manual annotation costs require deeper research. As China' s agriculture transforms toward smart agriculture, with advancing AI, IoT, big data, and cloud computing technologies, future agricultural risk management will become increasingly efficient, precise, and intelligent.

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