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Review Paper

Progress in Food Security Risk Sensing and Early Warning Studies Incorporating Intelligent Algorithms

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Abstract. Food security risk perception and early warning are of great significance to guarantee global food security. This paper provides a systematic review of the research in this field, covering core technologies such as multi-source data fusion and intelligent algorithms, analyzing the application and effectiveness of single Baidu intelligent algorithm and multi-algorithm fusion model, exploring the practice in the fields of food production prediction and quality and safety risk assessment, analyzing the existing challenges and looking forward to the future trends, so as to provide comprehensive and in-depth references for the related research. This study compiles a large amount of literature and combines practical cases and data analysis to help understand the mechanism, application potential and development direction of intelligent algorithms in food security risk perception and early warning.

Keywords: *food security risk, intelligent algorithms, sensing and early warning, data fusion, modeling applications*

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Introduction

With the intensification of global climate change, population growth, and geopolitical conflicts, the issue of food security is increasingly receiving great attention from the international community [1]. In such a context, food security risk perception and early warning technology has become a key tool to ensure stable food supply, reduce food loss and waste, and maintain social and economic stability [2-3]. Traditional food security risk assessment methods mainly rely on statistical data and expert experience, which can provide valuable information to a certain extent, but often suffer from poor timeliness, low precision, and difficulty in realizing early warning when coping with complex and changing modern food security risks [4-6]. Some statistical models based on historical yield data and meteorological data, although they can predict food production to a certain extent, are less sensitive to risk factors such as sudden natural disasters, pests and diseases, or market fluctuations, and it is difficult to issue timely and accurate early warning signals [7].

The rapid development of intelligent algorithms provides new ideas and methods to solve these problems [8]. Intelligent algorithms, such as machine learning and deep learning, have powerful data processing and pattern recognition capabilities, and can mine valuable information from massive and complex data, thus realizing accurate perception and early warning of food security risks [9-11]. In recent years, more and more studies have begun to explore the application of intelligent algorithms to the field of food security risk perception and early warning, and have achieved remarkable results [12]. Literature [13] used deep learning algorithms to analyze remote sensing images to achieve real-time monitoring of crop growth conditions and early warning of pests and diseases; literature [14] studied accurate prediction of price fluctuations and supply and demand balance in the grain market by constructing a prediction model based on machine learning.

However, there are still some problems and challenges in the current research. First, the multi-source data fusion technology needs to be further improved. Food security risk perception and early warning require the integration of data from multiple sources, including remote sensing data, meteorological data, soil data, market data and other literature [15]. These data may differ in format, accuracy, temporal resolution, etc., and how to effectively fuse these heterogeneous data so that they can provide high-quality inputs for intelligent algorithms is an urgent problem literature [16]. Second, the interpretability of intelligent algorithms is insufficient. Some complex intelligent algorithms, such as deep learning models, are usually regarded as “black box” models, whose decision-making process and results are difficult to be understood and explained by humans [17]. This limits the practical application of intelligent algorithms in the field of food security risk perception and early warning to a certain extent, because the relevant decision makers and managers need to clearly understand the basis and reasons for risk warning in order to make reasonable decisions. Again, the cost of technology application is high literature [18]. The application of intelligent algorithms usually requires a large amount of computational resources and professional technical talents, which may be a greater obstacle for some developing countries or regions with limited resources, thus affecting the popularization and promotion of related technologies. Finally, interdisciplinary research is difficult literature [19-20]. Food security risk perception and early warning involves knowledge and technology from multiple disciplinary fields, such as agronomy, computer science, mathematics, statistics, economics, and so on. Conducting interdisciplinary research requires close cooperation and communication between researchers with different professional backgrounds, but in actual research, such cooperation often faces many difficulties and challenges due to the differences and barriers between disciplines [21].

The purpose of this paper is to provide a systematic review and analysis of the research on food security risk perception and early warning by integrating intelligent algorithms, with a view to providing reference and reference for the further development of this field. The main contributions of this paper are: first, it comprehensively compiles the current research status in this field, including the research progress in data acquisition and fusion technology, the application of intelligent algorithms, model construction and evaluation; second, it analyzes in depth the main problems and challenges in the current research, and puts forward the corresponding ideas and suggestions for solving them; and third, it provides an outlook on the future research direction, which provides researchers with valuable information and inspiration for researchers.

Key approaches to food security risk perception and early warning

Data Acquisition and Fusion Technologies

Data collection and fusion technology is the basis for food security risk perception and early warning, and its main purpose is to obtain comprehensive, accurate and real-time data information to provide data support for subsequent risk assessment and early warning [22].

Data acquisition technology

The data collected are mainly from satellite or aerial sensors [23], farmland deployment of sensor networks [24], and other data sources, as described below:

Remote sensing technology acquires images and data of the Earth's surface through satellite or airborne sensors, which can monitor crop acreage, growth conditions, damage, and so on [25]. For example, crop types can be identified and crop growth stages and health conditions can be assessed using high-resolution remote sensing imagery [26]. Table 1 shows different remote sensing satellites and their main parameters.

Table 1. Parameter settings of MOEA/D optimization algorithm

Type of remote sensing satellite	Resolution (m)	Bandwidth	Revisit cycle (days)	Major application
Landsat	15-30	Visible light, near infrared, thermal infrared, etc.	16	Crop monitoring, land use change, etc.
MODIS	250-1000	Visible light, near-infrared, mid-infrared, etc.	1-2	Vegetation indices, climate monitoring, etc.
Sentinel-2	10-60	Visible light, near infrared, short-wave infrared, etc.	5	High-precision crop growth monitoring, disaster assessment, etc.

IoT technology deploys a sensor network in the farmland to collect soil moisture, temperature, nutrients, and meteorological data such as rainfall, light intensity, wind speed and direction in real time [27] and also to monitor crop growth indicators such as plant height and leaf area [28]. The sensor types and functions are shown in Table 2.

Table 2. Parameter settings of MOEA/D optimization algorithm

Sensor type	Measured parameter	Accurate	Application scenario
Soil Moisture Sensor	Soil volumetric moisture content	±5%	Irrigation management, drought monitoring
Weather station	Temperature, humidity, precipitation, wind speed, wind direction, etc	Temperature ±0.5℃, Humidity ±5%	Microclimate monitoring, disaster early warning
Crop growth monitor	Plant height, leaf area index, etc.	Height ± 1cm, Leaf Area Index ± 0.5	Assessment of growth conditions, production forecasts

Other sources of data include market data (food prices, supply and demand information, trade data, etc.), socio-economic data (demographics, income levels, consumption habits, etc.) and historical data (food production, disaster records, etc.). These data can be obtained through government statistical departments, market research institutions, international organizations and other sources [29].

Data fusion technology

Data fusion techniques need to address two issues such as multi-source data fusion and data preprocessing as follows:

Multi-source data fusion methods include statistical-based methods [30] (e.g., principal component analysis, factor analysis, etc.) for downscaling and extracting the main features of the data; model-based methods [31] (e.g., Bayesian networks, Markov chains, etc.) for establishing probabilistic relationships between the data; and artificial intelligence-based methods [32] (e.g., neural networks, support vector machines, etc.) for learning the patterns and rules of data fusion. The comparative analysis of multi-source data fusion methods is shown in Table 3.

Table 3. Comparison of data fusion methods

fusion algorithm	Dominance	Limitations	Applicable Scenarios
Principal Component Analysis (PCA)	Dimensionality reduction and extraction of main features	Weakness in dealing with nonlinear relationships	Multi-source data feature extraction, data compression
Bayesian network	Dealing with Uncertainty, Causality Modeling	High computational complexity and reliance on a priori knowledge	Risk assessment, prediction
Neural network fusion	Strong nonlinear mapping capability, adaptive learning	Strong nonlinear mapping capability, adaptive learning	Image recognition, time series prediction

Data preprocessing technology cleans, standardizes, normalizes, etc. the collected data in order to eliminate noise and outliers in the data and improve the quality and consistency of the data [33]. Atmospheric correction, geometric correction, etc. are performed on remote sensing data, and filtering is performed on IoT sensor data [34]. The following table shows the common data fusion algorithms and their characteristics:

Intelligent *Algorithms*

Intelligent algorithms are the core of food security risk perception and early warning, which are used to mine valuable information from massive data to realize accurate perception and prediction of risks [35]. This subsection analyzes the problem of food security risk perception and early warning from three approaches, including machine learning algorithms, deep learning algorithms, and integrated learning algorithms.

Machine learning algorithms

Machine learning algorithms are mainly divided into supervised learning algorithms [36], unsupervised learning algorithms [37], which are analyzed as follows:

In supervised learning algorithms, the support vector [38] machine realizes the classification of different categories of data by finding the optimal classification hyperplane; the decision tree generates decision rules top-down based on information gain and other indicators [39], which is suitable for dealing with nonlinear relational data; and the neural network consists of a large number of neurons, and adjusts the connection weights between the neurons through training to achieve the tasks of fitting complex functions and data classification and regression [40]. Table 4 demonstrates the comparison of common supervised learning algorithms.

Table 4. Comparison of common supervised learning algorithms

Arithmetic	Dominance	Limitations	Application scenario
Support Vector Machines (SVM)	Good classification performance and generalization ability in high dimensional space	Inefficient processing of large-scale data	Small sample classification problems, risk assessment
Decision tree(DT)	Strong interpretability, good handling of nonlinear relationships	Easily overfitted, sensitive to noise	Decision support, feature selection
Artificial Neural Networks (ANN)	Strong nonlinear fitting ability, adapting to complex patterns	The training process is complex and prone to overfitting	Image recognition, predictive modeling

In unsupervised learning algorithms, cluster analysis clusters similar data points into one class and is used to discover potential patterns and structures in the data [41]; principal component analysis is used for data dimensionality reduction, extracting the main feature information of the data and simplifying the model input [42]. Cluster analysis can be used to categorize the food security risk status of different regions and identify high-risk areas.

Deep learning algorithms

Convolutional Neural Networks (CNNs) have excelled in the field of image recognition and can be used to analyze remotely sensed images to identify crop growth conditions and pests and diseases [43]. CNNs are used to extract the features of an image and perform classification and prediction through convolution, pooling, and other operations on the remotely sensed image.Typical architectures of CNNs are shown in Table 5.

Table 5. CNN architecture analysis

Layer type	Functionality	Parameters
Convolutional layer	Extract image features	Filter size, step size, padding
Ponding layer	Downsampling to reduce parameter and computational complexity	Pooling window size, step size
Full connectivity layer	Classification or regression	Number of neurons, activation function

In the analysis of Recurrent Neural Network (RNN) and its variants applications, Long Short-Term Memory Network (LSTM) [44] and Gated Recurrent Unit (GRU) [45] are good at dealing with sequential data and have advantages in time series prediction, which can be used for food production prediction, price fluctuation prediction and so on. Table 6 demonstrates the characteristics of RNN and its variants.

Table 6. Characterization of RNN and its variants

Arithmetic	Dominance	Limitations	Application scenario
RNN	Capable of processing sequential data and capturing temporal dependencies	Long-term dependency issues, disappearance of gradients	Time series prediction, natural language processing
LSTM	Effective in solving long-term dependency problems, strong memory skills	Complex structure and high computational effort	Serial data with long term dependencies need to be handled
GRU	Simple structure and high computational efficiency	Slightly weaker than LSTM for some complex long-term dependencies	Sequence modeling tasks with high computational efficiency requirements

Integrated Learning Algorithm

The integrated learning algorithms mainly include Random Forest [46], Adaboost [47], XGBoost [48] and other algorithms, the specific comparison is shown in Table 7.

Table 7. Comparative analysis of integrated learning algorithms

Arithmetic	Dominance	Limitations	Application scenario
Random forest	Reduced overfitting, high accuracy, good stability	Inefficient processing of high dimensional data	Classification issues, characterization importance assessment
Adaboost	Adapts to different weak learners, can handle uneven data	Inefficient processing of high dimensional data	Classification and regression tasks
XGBoost is efficient, accurate and supports large-scale data	XGBoost is efficient, accurate and supports large-scale data	Complex hyperparameter tuning	Classification and regression tasks requiring efficient modeling

As can be seen from Table 7, Random Forest reduces the overfitting risk of a single decision tree and improves the accuracy and stability of the model by constructing multiple decision trees and synthesizing their predictions [49]. Random forest has a wide range of application prospects in food security risk assessment and early warning, for example, it can be used to assess the impact of different factors on food production. Adaboost iteratively trains multiple weak learners (e.g., decision tree stumps) by giving different weights to different training samples and combines them into a strong learner [50]. Adaboost can improve the model's classification performance of complex data, and it is suitable for handling imbalanced datasets, can enhance the model's ability to recognize a few categories, and is useful in identifying early signs of risk. XGBoost is based on the gradient boosting framework, which optimizes the training process and performance of the model, and has efficient computational efficiency and good prediction accuracy [51]. XGBoost can handle large-scale food security data, improve the efficiency of model training, and is suitable for complex model training, which can improve the risk The timeliness and accuracy of the early warning system can be improved.

A Food Security Risk Perception and Early Warning Model Incorporating Intelligent Algorithms

Single Intelligence Algorithm Model

Single Intelligent Algorithm models are widely used in food security risk perception and early warning, which are characterized by simplicity and directness by constructing the model through one intelligent algorithm. The following are six common single intelligent algorithm models:

Support Vector Machines (SVMs) Modeling

Support Vector Machines (SVMs) are used to separate different categories of data by finding the optimal classification hyperplane, and are used for food security risk classification prediction, such as predicting whether the grain yield reaches the safe level based on multiple indicators [52]. Based on statistical learning theory, SVM maps the data to high dimensional space through kernel function, and searches for the optimal classification hyperplane in high dimensional space to maximize the spacing between different categories, so as to effectively deal with nonlinear data [53]. SVM is mainly composed of kernel function and classification hyperplane. Common kernel functions include linear kernel function, polynomial kernel function, radial basis kernel function and so on. Choosing the appropriate kernel function and parameters is crucial to the model performance. Using the training dataset, the parameters of the optimal classification hyperplane are solved by an optimization algorithm (Sequential Minimum Optimization Algorithm) to maximize the interval and minimize the classification error [54]. After the model training is completed, it is used to predict the class of new samples.

Artificial Neural Network (ANN) models

Artificial neural network consists of a large number of neurons, which are trained to adjust the connection weights between neurons, fit complex nonlinear relationships, and improve the accuracy of food security risk assessment [55]. ANN consists of an input layer, a hidden layer, and an output layer, which receives the data, the hidden layer performs the nonlinear transformation through the activation function, and the output layer outputs the prediction results. The neurons in the input layer correspond to the input features, the number of neurons in the hidden layer and the activation function (ReLU, Sigmoid, etc.) affect the model expression ability, and the neurons in the output layer correspond to the output variables. Using training datasets and optimization algorithms (stochastic gradient descent), the output is computed by forward propagation, and back propagation adjusts the weights and biases to minimize the prediction error, which usually requires a large amount of data and computational resources [56].

Decision Tree (DT) Modeling

The decision tree generates top-down decision rules based on information gain, Gini coefficient and other indicators for food security risk assessment and early warning, which can visualize the impact of each indicator and decision path [57]. It divides the data into different subsets by dividing the feature space, and each subset corresponds to a decision rule. The structure of the decision tree model consists of nodes and directed edges, with internal nodes representing feature tests and leaf nodes representing decision results. The structure of the tree such as depth and number of branches affects the model complexity and generalization ability. Using the training dataset, the decision tree is constructed by dividing the feature space [58]. At each internal node, the optimal features and split points are selected to maximize the purity of the subset; at the leaf nodes, the decision results, such as the food security risk level, are determined. The tree usually needs to be pruned to prevent overfitting.

Long- and short-term memory network (LSTM) models

LSTM is a special kind of recurrent neural network (RNN) that can effectively deal with long-term dependencies in sequential data, and performs well in time-series problems such as food production forecasting and price fluctuation prediction [59]. LSTM controls the flow of information by introducing gating mechanisms, including input gates, forgetting gates, and output gates, so as to solve the gradient vanishing problem of the traditional RNN when dealing with long-term dependencies [60].

In food security risk perception and early warning, LSTM models can be trained using historical time-series data (such as grain production, price, weather data, etc.) to learn the time-dependent patterns in the data, and then predict future food security-related indicators [61]. Based on the past years' food production data and the corresponding meteorological conditions data, the LSTM model can predict the next year's food production, providing an important basis for food security early warning.

Random Forest (RF) Modeling

RF constructs multiple decision trees by bootstrap clustering and feature random selection to combine most decisions for prediction. Each tree is trained with bootstrap clustering samples and a random subset of features to reduce overfitting and variance [62]. For prediction, samples are entered into each decision tree and the results are either voted or averaged.

In food security risk assessment, RF can assess the impact of multiple factors and provide the importance of characteristics to help identify key risk factors and develop prevention and control strategies [63]. For example, it analyzes the impact of weather, soil and market factors on food production, and builds RF models to identify key factors and decision-making paths [64]. The characteristics of the single intelligent algorithm model application are summarized in Table 8.

Table 8. Characteristics of Single Intelligent Algorithm Model Applications

Model Type	Dominance	Limitations	Applicable Scenarios
SVM	Good classification performance and generalization ability in high dimensional space	Inefficient processing of large-scale data	Small sample classification problems, risk assessment
ANN	Strong nonlinear fitting ability, adapting to complex patterns	The training process is complex and prone to overfitting	Image recognition, predictive modeling

DT	Strong interpretability, good handling of nonlinear relationships	Easily overfitted, sensitive to noise	Decision support, feature selection
LSTM	Strong ability to handle sequential data, capture long-term dependencies	Complex structure and high computational resource requirements	Time series prediction, natural language processing
RF	Reduced overfitting, high accuracy, good stability	Inefficient processing of high dimensional data	Classification issues, characterization importance assessment

Multi-intelligent algorithm fusion model

Multi-intelligent algorithm fusion models combine the advantages of multiple intelligent algorithms to improve the effectiveness of food security risk perception and early warning [65]. Common fusion modeling methods are introduced as shown in Table 9.

Table 9. Characteristics of common fusion model applications

Fusion model	Vantage	Drawbacks
Weighted average fusion model	Simple and easy to use, effectively improving prediction stability and robustness	Weight settings are highly subjective and difficult to adjust dynamically
Fusion modeling based on integrated learning	High prediction accuracy and generalization ability to handle large-scale data	Complex hyperparameter tuning and poor model interpretation
Deep Learning and Traditional Machine Learning Fusion Models	Combining the strengths of both to improve model performance	Complex model structure, high training and optimization requirements
Multi-Algorithm Co-Fusion Model	Dynamic adaptation and co-optimization to improve model adaptability and generalization capabilities	Dependent on reinforcement learning hyperparameters and reward function design with high training computational cost

The weighted average fusion model is a weighted summation of the predictions of multiple intelligent algorithms [66]. The weights are determined by equalization, weighting based on historical performance, etc., and the fusion effect is optimized by adjusting the weights [67]. The weighted average fusion model is suitable for all kinds of food security risk perception and early warning scenarios, especially when the performance of a single algorithm is close to each other, it can reduce fluctuations and improve stability and robustness.

Integration learning-based fusion models utilize integration learning algorithms to fuse multiple base learners [68]. Taking XGBoost as an example, it is based on the gradient boosting framework, which iteratively trains decision trees and combines them by optimizing the objective function and regularization terms to improve model accuracy and generalization ability. The fusion model based on integrated learning handles large-scale food security data, such as grain yield-related data containing millions of samples, and XGBoost can efficiently train prediction models to improve the timeliness and accuracy of the risk warning system [69].

Deep learning and traditional machine learning fusion model combines the features of deep learning (such as LSTM) to extract sequence data features and traditional machine learning (such as SVM) with strong classification ability. After LSTM extracts the features of grain yield data, SVM carries out classification prediction, and the process of fusion is as follows: data preprocessing → LSTM feature extraction → SVM classification prediction [70]. The fusion model of deep learning and traditional machine learning is suitable for time series prediction and classification problems, such as the prediction of grain yield and price fluctuation. LSTM captures the time-dependent relationship, and SVM accurately classifies and improves the prediction accuracy.

The multi-algorithm collaborative fusion model fuses different algorithms through a collaborative training mechanism. It combines the global optimal classification ability of SVM and the local decision-making advantage of DT, and uses reinforcement learning to dynamically adjust the data distribution and sample weights, so that the algorithms collaborate with each other in the training process and jointly optimize the model performance [71]. The multi-algorithm synergistic fusion model solves the problem of food security risk assessment and early warning under complex factors such as global climate change and market fluctuations, and can effectively deal with uncertainty and dynamic changes [72].

Application analysis

Deep learning-based grain yield prediction

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture for processing sequential data, which is good at capturing long-term dependencies of time series. The LSTM memory unit and the gating mechanism (input gate, forgetting gate, and output gate) enable the network to selectively memorize or forget the information, solving the gradient vanishing problem of the traditional RNN, which is suitable for the prediction of food production and this kind of time series.

During the data collection and preprocessing phase, grain yield data along with relevant meteorological and soil data from a specific region were gathered. After cleaning and normalization, the data were divided into training, validation, and test sets [73]. An LSTM model comprising two LSTM layers, a Dropout layer, and a fully connected output layer was constructed. Hyperparameters were configured, using mean squared error as the loss function and the Adam optimizer for model training. By comparing the loss on the validation set, model performance was evaluated on the test set. Finally, the trained model was utilized to forecast future grain yields.

By learning the long-term dependencies in the time series data, the LSTM model can more accurately capture the trend of grain yield, and has higher prediction accuracy compared with the traditional time series prediction methods [74]. The LSTM model is able to automatically learn the complex nonlinear relationships in the data without manually extracting the features, which is suitable for such complex nonlinear problems as grain yield prediction. By adjusting the model structure and hyperparameters, LSTM can be adapted to the needs of grain yield prediction in different regions and crops.

Machine learning-based risk assessment for food quality and safety

Support Vector Machine (SVM) is suitable for dealing with high-dimensional data and nonlinear problems by finding the optimal classification hyperplane to maximize the interval between different classes [75]. Random Forest (RF) reduces the risk of overfitting and improves the accuracy and stability of the model by constructing multiple decision trees and synthesizing their predictions [76].

Grain sample data, including quality and safety indicators and relevant background information, were collected, cleaned and normalized, and then divided into training and testing sets. SVM and RF models were used for training, and the parameters were tuned by grid search and cross-validation. The test set evaluates the model performance, compares the accuracy, recall, F1 value and AUC value, and is practically applied to grain purchasing enterprises to verify its effectiveness [77].

Through optimized feature selection and model parameter tuning, the RF model demonstrates outstanding performance in accuracy and recall, effectively identifying samples posing security risks [78]. The SVM model provides an intuitive risk decision boundary through support vectors and classification hyperplanes, while the RF model can assess feature importance, aiding in the understanding of key risk factors [79]. Both SVM and RF models can adapt to different types of grain samples and variations in quality and safety indicators. By updating training data and adjusting model parameters, they can be extended for application in other grain quality and safety risk assessment scenarios.

Challenges

In the research on food security risk perception and early warning by integrating intelligent algorithms, although significant progress has been made, there are still many challenges, which are mainly in the areas of data quality problems, insufficient model interpretability, high cost of technology application, and the difficulty of interdisciplinary research.

Data quality problems

In the process of multi-source data fusion, the data may have problems such as incompleteness, inaccuracy, and non-uniformity of data format, which affect the effect of data fusion and analysis. Remote sensing data may be missing due to cloud cover and other factors, and observation errors in meteorological data may lead to inaccurate data, etc [80]. These low-quality data can reduce the accuracy of risk perception and early warning.

Insufficient model interpretability

Complex intelligent algorithms such as deep learning models have a complex structure, and the decision-making process and results are difficult to explain. Deep neural networks have numerous neurons and complex connections, making it difficult to clearly articulate their decision-making logic, which is not conducive to professional understanding, trust and application, limiting their practical promotion.

High cost of technology application

Food security risk perception and early warning technologies that integrate intelligent algorithms involve a large number of high-performance hardware and specialized software tools. The deployment of IoT sensor networks requires the purchase of a large number of sensors and communication equipment, and the construction and maintenance of data centers is costly. This makes it difficult for some economically underdeveloped regions to bear the related costs, limiting the widespread application of the technology.

Difficult in interdisciplinary research

Research in this field requires multidisciplinary collaboration, but researchers from different disciplinary backgrounds often face difficulties in cooperation due to professional barriers and communication barriers. Computer science personnel and agronomy experts differ greatly in their knowledge backgrounds and research methods, which can easily lead to a disconnect between needs and solutions, hindering research progress and application effects.

Conclusion

Research on food security risk perception and early warning by integrating intelligent algorithms provides powerful technical support for guaranteeing global food security. Through the application of data collection and fusion technology, intelligent algorithms and multi-algorithm fusion models, real-time and accurate perception and early warning of food security risks can be realized, and the level of food security guarantee can be improved. However, the field is still facing many challenges such as data quality, model interpretability, technical cost, and interdisciplinary research. In the future, it is necessary to strengthen technological research and development and innovation, improve the data governance system to enhance data quality, reduce the cost of technology to promote widespread application, and promote interdisciplinary collaboration to enhance the depth and breadth of research, so as to promote the in-depth application of related technologies in the field of food security, and provide a more solid guarantee for global food security.

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