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## Review of Intelligent Service Technologies for Agricultural Knowledge (Postprint)

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### Abstract

[Purpose/Significance] The agricultural environment is characterized by dynamic variability, with numerous influencing factors on animal and plant growth and complex interactions among them. How to comprehend dispersed and disordered information to generate production knowledge or decision cases represents a worldwide challenge. Agricultural knowledge intelligent service technology is the core key to addressing current situations such as the low-rank nature of agricultural data, low rule correlation, and poor inference interpretability, and to enhancing comprehensive prediction and decision analysis capabilities throughout the entire agricultural production process. [Progress] This paper comprehensively analyzes agricultural knowledge intelligent service technologies such as perception and recognition, knowledge coupling, and inference decision-making, constructs an agricultural knowledge intelligent service platform composed of a cloud computing support environment, big data processing framework, knowledge organization and management tools, and knowledge service application scenarios, proposes a method for agricultural condition analysis and production inference decision-making based on the combination of knowledge rules and factual cases, and constructs full-chain knowledge intelligent application scenarios including pre-production planning, in-production management, harvesting operations, and post-production management. [Conclusion/Outlook] This paper summarizes the development trends of agricultural knowledge intelligent service technology from aspects such as multi-scale agricultural condition sparse feature discovery and spatiotemporal situation recognition, agricultural cross-media knowledge graph construction and self-evolutionary updating, multi-granularity association and multi-mode collaborative inversion prediction of agricultural conditions with complex causes, design of large language models for the agricultural domain based on generative artificial intelligence, and construction of knowledge intelligent service platforms and new paradigms, which provides technical support for realizing the transformation of agricultural production from “farming by

observing the weather” to “farming with weather knowledge” .

## Full Text

### Preamble

#### Agricultural Knowledge Intelligent Service Technology: A Review

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#### Abstract:

[Significance] Agricultural environments are dynamic and variable, with numerous factors affecting the growth of animals and plants and complex interactions among them. How to understand and generate production knowledge or decision-making cases from scattered and disordered information is a worldwide challenge. Agricultural knowledge intelligent service technology addresses the current situation of low-rank agricultural data, low rule correlation, and poor reasoning interpretability, representing the core key to enhancing comprehensive prediction and decision-making capabilities throughout the entire agricultural production process. [Progress] This paper comprehensively analyzes agricultural knowledge intelligent service technologies such as perception recognition, knowledge coupling, and reasoning decision-making. It constructs an agricultural knowledge intelligent service platform comprising a cloud computing support environment, big data processing framework, knowledge organization management tools, and knowledge service application scenarios. The paper proposes a method for agricultural situation analysis and production reasoning decision-making based on the combination of knowledge rules and factual cases, constructing full-chain intelligent knowledge application scenarios for pre-production planning, in-production management, harvest operations, and post-production operations. [Conclusions and Prospects] The development trends of agricultural knowledge intelligent service technology are summarized from the perspectives of multi-scale agricultural situation sparse feature discovery and spatiotemporal situation recognition, agricultural cross-media knowledge graph construction and self-evolutionary updating, multi-granularity correlation and multi-mode collaborative inversion prediction of complex agricultural situations, agricultural domain large language model design based on generative artificial intelligence, and knowledge intelligent service platform and new paradigm construction. This provides technical support for achieving the transformation of

agricultural production from “working by observing the sky” to “working by understanding the sky.”

**Keywords:** agricultural knowledge intelligent services; knowledge coupling; reasoning decisions; multimodal knowledge graph; agricultural condition early warning

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China’s agricultural production is widely distributed, with enormous differences in planting regions, climate, varieties, and agronomy. The correlation mechanisms between environmental factors (light, temperature, water, soil, and air) and crop growth or pest occurrence are extremely complex. Additionally, uncertainties in agricultural habitats, hydrology, meteorology, and other external conditions make scientific and precise production decisions very difficult [1]. There is an urgent need to deeply integrate new-generation artificial intelligence technologies such as deep learning, machine vision, knowledge engineering, and reasoning decision-making with agricultural scenarios to enhance comprehensive prediction and knowledge service capabilities throughout the entire life cycle of agricultural products, including agricultural situation assessment, early warning and prevention, environmental regulation, and standardized management. This will enable the transformation from “working by observing the sky” to “working by understanding the sky.”

Currently, agricultural production and management still heavily rely on manual experience. From the perspective of replacing manual decisions with intelligent ones, this paper fully considers the current challenges in agricultural knowledge services, including data low-ranking, knowledge fragmentation, and high correlation complexity. Research breakthroughs are made from three levels: “perception recognition,” “knowledge coupling,” and “reasoning decision-making,” focusing on solving key problems such as animal and plant state recognition in complex and uncertain environments, multimodal data association knowledge extraction, and collaborative reasoning in multiple agricultural application scenarios. Through the joint drive of data, knowledge, and cases, full-chain intelligent knowledge services are provided for agricultural producers, including soil improvement, variety selection, seedling regulation, production management, water-fertilizer-pesticide reduction, harvest decision-making, production-marketing docking, and quality control traceability.

## 2 Overview of Agricultural Knowledge Intelligent Services

As agricultural production methods transform, agricultural knowledge has become a key element for quantified decision-making and precision operations in modern agriculture. The demand for knowledge from farmers and other production and management entities has surged, but current channels and means for

farmers to access agricultural knowledge are limited, constraining agricultural production transformation and upgrading. Agricultural knowledge intelligent service refers to the use of new artificial intelligence technologies to collect, store, process, analyze, and utilize agricultural knowledge, establishing an agricultural knowledge intelligent service system that integrates and optimizes various agricultural knowledge information to provide intelligent agricultural knowledge services for farmers. This service can greatly improve farmers' awareness and understanding of agricultural production, enhancing the scientific, precise, and efficient nature of agricultural production. Simultaneously, platform-based agricultural knowledge intelligent services can help farmers solve difficult problems in agricultural production anytime and anywhere, timely optimize agricultural production plans, and improve production efficiency.

In terms of agricultural habitat information acquisition, accurate identification of animal and plant states and appropriate intervention are key to improving agricultural product yield and quality [4]. With the development of artificial intelligence technologies such as image recognition, agricultural production process information acquisition has shifted from traditional sensor-based perception to multimodal information perception dominated by image perception with participation from multiple sensors. From the perspective of industrial problem objects, agricultural plant perception research mainly focuses on classification and identification of weeds, diseases, pests, nutritional status, and water deficiency [5-7]. Purdue University in the United States has proposed crop target detection methods based on deep learning and image segmentation for accurate acquisition and identification of different crop plant shapes and physiological information in farmland scenes. The National Engineering Research Center for Information Technology in Agriculture in China has proposed crop growth and disease identification methods based on remote sensing images [8]. Agricultural animal research mainly concentrates on discrimination and identification of health status, breeding status, and abnormal behavior [9].

In agricultural knowledge engineering, Google released the knowledge graph in 2012. Through "entity-relationship-entity" triples and corresponding "attribute-value pairs," it changed the traditional organization form of knowledge, providing excellent support for efficient searching in massive knowledge and precise knowledge reasoning [10, 11]. With the continuous development of artificial intelligence technology, agricultural knowledge graphs have entered the stage of automated construction with entity recognition and relationship extraction as core technologies. From the perspective of data objects for knowledge extraction, early knowledge graph construction mainly relied on single text analysis, particularly using structured data to quickly build triples [12]. However, with the rapid development of mobile internet in recent years, massive knowledge is presented in unstructured forms, with multimodal data such as images, voice, and unstructured text becoming important carriers of information and knowledge. The introduction of massive multimodal data has made multimodal semantic understanding and knowledge graph representation a research hotspot in this field [13]. The first multimodal knowledge graph (MMKG), Richpedia, was for-

mally proposed in 2019 [14], with its construction method based on Wikipedia text entities, adding images corresponding to entities to form a multimodal knowledge graph.

In terms of agricultural knowledge service applications, the EU's "Horizon 2020" Demeter smart agriculture project has built an agricultural food knowledge graph that has been practically applied in 18 countries. In the United States, Google and Farmers Business Network (FBN) use spatial image feature extraction and deep learning technology to identify and characterize agricultural product quality and yield. IBM launched the Watson Decision digital platform, containing more than 60 crop models and domain knowledge bases for crops such as corn, wheat, and soybeans, which can help farm owners formulate planting plans, production scheduling plans, and water-fertilizer application schemes [15]. In China, the Chinese Agricultural Technology Extension Information Platform developed by the National Engineering Research Center for Information Technology in Agriculture has formed a massive knowledge base with broad domain coverage and complete knowledge classification, possessing hundreds of millions of agricultural Q&A pairs [16]. Recently, generative large models such as ChatGPT (Chat Generative Pre-trained Transformer), GPT-4.0, Bard, and Baidu Wenxin have gradually entered the field of knowledge services. Through high computing power, massive data, and ultra-large-scale parameters, they achieve a leap in intelligent service capabilities, characterized by comprehensive and cross-media multimodal knowledge representation and expression, representing the future trend of knowledge services. For example, text input and image or video output during Q&A interactions, automatic generation of video-form agricultural production plans, and companion dialogue robots with agricultural experience derived from multi-round feedback and context fusion will to some extent change future knowledge service models and farmers' production methods.

### 3 Agricultural Knowledge Intelligent Service Technology

#### 3.1 Technical Architecture

The technical architecture of agricultural knowledge intelligent services (Figure 1 [Figure 1: see original paper]) mainly includes data perception recognition, knowledge coupling, and reasoning decision-making levels. In perception recognition, "satellite-air-ground" multi-channel perception devices and internet data mining tools are used to comprehensively acquire multi-source data including agricultural conditions, disasters, crop site conditions, animal and plant growth status, and agricultural knowledge, providing a dynamic and accurate foundation for agricultural knowledge services. In knowledge coupling, research is conducted on multimodal data semantic alignment, model construction, knowledge transfer, knowledge graph autonomous evolution and updating, and natural language pre-training models—Artificial Intelligence (AI) large models—to achieve dynamic updating of multimodal agricultural knowledge bases, construct agricultural knowledge service datasets, and provide knowledge-driven intelligent services. In reasoning decision-making, focusing on difficulties such

as the lack of agricultural domain decision support models and long traditional model construction times, the agricultural knowledge intelligent service platform integrates multimodal AI models and dimensionality-reduced optimized agricultural mechanism models to provide timely and accurate intelligent services for the agricultural industry.

### 3.2 Intelligent Perception and Analysis Technology

Through intelligent perception and analysis of crop growth status and environmental characteristics, scientific agricultural production management can be achieved, optimizing inputs in various production stages. Technologies such as intelligent sensors, remote wide-area networks, 4G/5G networks, and wireless sensor networks have been widely applied in agricultural production [17], monitoring parameters such as air temperature and humidity, illumination, and soil moisture [18, 19], enabling early prevention and control through disease prediction [20] to improve crop yield.

In recent years, due to the powerful adaptive feature extraction and nonlinear mapping capabilities of convolutional neural networks, deep learning models have been widely applied in agricultural visual target detection and scene semantic recognition for precise extraction, identification, and localization of complex features in agricultural environments. Typical deep learning models include AlexNet, VGGNet, GoogLeNet, ResNet, Region Convolutional Neural Networks (R-CNN), YOLO (You Only Look Once), etc. [21].

**3.2.1 Machine Vision-Based Target Detection** Machine vision-based target detection refers to the technology of detecting agricultural target objects in complex environments based on collected data, such as fruit quality detection [19], picking robot target localization [20], livestock individual monitoring and identification [21], disease-pest-weed detection [22], and crop counting [23]. Due to dense crop growth with mutual occlusion of branches, leaves, and fruits, and high similarity between foreground targets and background structures, these characteristics of agricultural scenes pose new challenges to target detection technology.

Agricultural visual target detection can currently be divided into two-stage detection networks represented by Faster R-CNN and one-stage detection networks represented by SSD (Single Shot Multibox Detector) and YOLO. The difference between the two types of networks is that two-stage networks require generating candidate boxes that may contain anomalies first, followed by classification, while one-stage networks directly predict the location and category of anomalies using features extracted by the backbone. Table 1 shows that crop disease detection based on target detection is currently a relatively active research field, so this paper details the development status of the two detection methods using crop disease detection as an example.

Table 1 summarizes the current status of visual target detection in agriculture.

Most studies train specialized target detection models for different agricultural needs, with model validation mostly based on self-built datasets, resulting in limited generalization and universality. How to conduct transfer learning for growth characteristics of different crops at different growth stages, including disease characteristics, growth parameter extraction, and contour detection localization, to train general detection models for the agricultural domain is an urgent problem to be solved.

**(1) Two-stage detection network-based disease detection.** Faster R-CNN integrates feature extraction, bounding box regression, and classification into a single network, significantly improving detection speed and accuracy, making it a typical representative of two-stage detection networks. The two-stage disease detection network structure is shown in Figure 2 [Figure 2: see original paper], usually consisting of four parts: convolutional layers, region proposal network, region of interest pooling layer, and classification and regression layers. This network uses selective search methods to generate sparse candidate boxes, maps candidate boxes to agricultural visual features, and performs feature detection and recognition through a region classifier. Fuentes et al. [24] first used Faster R-CNN for tomato disease and pest localization detection, combining VGG with a dataset of 5,000 types of tomato diseases and pests to achieve an average recognition accuracy of 85.98%. Since Faster R-CNN performs well on disease detection tasks with complex backgrounds, multi-scale, and small targets, subsequent improvements based on Faster R-CNN have achieved some results. Typical improvements mainly include: improving feature extraction networks to enable models to achieve better detection accuracy and robustness [32, 33]; appropriately increasing network width or depth to enhance feature extraction capabilities [34, 35]; and adding attention mechanisms to suppress useless noise to improve disease feature detection capabilities in complex backgrounds [36].

**(2) One-stage detection network-based disease detection.** One-stage target detection networks eliminate the region proposal stage, directly performing category prediction for objects at each position on the feature map, greatly improving the inference speed of detection networks. One-stage detection networks use the entire image as network input and directly return the location of bounding boxes and their categories at the output layer. The YOLO series model was first proposed by Redmon et al. [37] in 2016. Compared with Faster R-CNN, the YOLO model removes the candidate box extraction stage and can simultaneously achieve target region prediction and classification regression, thus being considered a one-stage detection algorithm. YOLO divides the image into grids, determining target boundaries and categories centered on grids, improving detection speed while maintaining high accuracy. Bhatt et al. [38] proposed a YOLOv3-based disease and pest detection method, achieving a mean Average Precision (mAP) of 86% for tea plantation disease and pest detection under natural conditions. Sun Fenggang et al. [31] improved model accuracy by adding convolutional block attention modules and weighted bidirectional feature pyramid networks, proposing a fruit disease recognition model

GHTR2-YOLOv5s based on YOLOv5s, achieving mAP@0.5 of 0.909 for rapid and accurate identification of apple fruit diseases.

**3.2.2 Agricultural Multimodal Data Semantic Recognition** Unlike agricultural target detection, scene semantic recognition not only needs to identify and extract the categories of agricultural-related objects but also accurately calculate the position and area of different agricultural production element regions. Through pixel-by-pixel assignment of different semantic category labels such as leaves, fruits, stems, land, agricultural machinery, and other agricultural backgrounds, image segmentation divides agricultural images into several specific regions containing different production elements and calculates the region of interest, enabling applications such as crop coverage and type analysis [39], forest tree species marking [40], and disease and pest development degree identification [41]. Image segmentation technology is replacing traditional manual observation and measurement of phenotypic data, playing an extremely important role in modern agriculture. For example, image segmentation technology is often used to monitor crop growth trends, predict canopy area and biomass, and extract key points from fruit surfaces to determine fruit geometric dimensions and maturity [42].

Agricultural images have similar features among different production elements. For instance, plant leaves and stems have similar colors, field plastic film and ridge paths interfere with each other, and phenotypic features of different diseases on the same crop are not obvious, increasing the difficulty of segmenting key agricultural regions. Traditional threshold segmentation techniques struggle to accurately extract agricultural regions of interest. Fully Convolutional Networks (FCN) [43], U-Net [44], and other segmentation models are favored by researchers due to their efficient learning performance and good application effects. Huang et al. [45] built an FCN segmentation of tomato leaf images based on the VGG-16 model. To improve model feature extraction capability, they introduced a dual-path network model and adaptively optimized the parameters of the dual-path neural network through switchable normalization layers, improving model universality and training speed with a recognition accuracy of 97.59%. For Lingwu long jujubes at different maturity stages, Li et al. [46] improved the convolutional modules in FCN-8s using multi-scale feature fusion, achieving pixel accuracy of 98.44%, an improvement of 1.51% over the original network, enabling accurate segmentation of Lingwu long jujubes. Liu et al. [47] used a multi-scale global attention module to improve the U-Net bottleneck layer, forming enhanced features by aggregating multi-scale global context information and using improved attention mechanisms, achieving a dice coefficient of 93.88% for farmland segmentation.

To improve segmentation accuracy and efficiency of detection targets in agricultural images, researchers have attempted to integrate clustering, threshold segmentation, region growing, and other methods with deep semantic models to form new segmentation architectures. Narushin et al. [48] proposed an egg

geometric feature detection method, improving detection accuracy through 2D image recognition and geometric transformation. Zhang et al. [49] proposed an IoT-based plant diseased leaf segmentation and recognition method, extracting histogram pyramid features from segmented disease images and grayscale images with different color components, and using superpixel clustering and K-means clustering fusion methods to achieve 92.15% disease classification and recognition accuracy. Yue et al. [50] proposed a segmentation method combining conditional random fields with SegNet networks, which improved segmentation precision P, recall R, and comprehensive evaluation index F compared with Otsu threshold and Grabcut segmentation methods.

For the differential feature information between foreground elements and complex backgrounds in agricultural images, KHAN et al. [51] and TASSIS et al. [52] proposed a two-stage image segmentation method fusing DeepLabV3+ and U-Net. The two-stage complex background image segmentation network structure is shown in Figure 3 [Figure 3: see original paper]. In the first stage, DeepLabV3+ is used to mine shallow and deep features of cucumber leaves under different complex backgrounds for coarse segmentation of diseased leaves in complex backgrounds. In the second stage, U-Net is used for further precise localization of disease spots, using smaller downsampling multiples to retain more detailed disease spot shape, color, and other image features, which helps target region localization.

### 3.3 Agricultural Knowledge Coupling and Knowledge Graph Technology

Based on perceiving agricultural environmental images, videos, and other multimedia data, visual analysis and processing technology can extract features of agricultural production elements such as operating equipment, agricultural personnel, and crops. According to global information, intelligent services such as disease and pest feature classification, crop canopy key point recognition, crop growth parameter extraction, and quality grading can be achieved. However, the agricultural environment has complex interference factors such as complex illumination changes, high crop growth density, and similar crop growth characteristics, making it difficult to distinguish different agricultural production elements. In recent years, various agricultural decision-making models have been trained using deep learning's powerful adaptive feature extraction and nonlinear mapping capabilities. However, as agricultural transformation and upgrading progress toward high-density planting and large-scale production, the scale and diversity of agricultural datasets in actual production grow exponentially with the number of objects and their interactions. The cost reduction of hardware devices such as multispectral cameras and improved computing capabilities have provided more means for agricultural complex environment perception, posing new challenges to the generalization ability and robustness of visual models. Further exploration is still needed in large-scale agricultural unstructured environment perception and recognition.

### 3.3.1 Agricultural Text Classification and Feature Representation

Agricultural text classification and feature representation are fundamental technologies for agricultural knowledge coupling and graph construction. Natural language-based agricultural text representation methods mainly include Bag of Words, Term Frequency-Inverse Document Frequency (TF-IDF), Word2Vec and Doc2Vec word vector models, and BERT (Bidirectional Encoder Representation from Transformers) models. Pre-trained models use large-scale unlabeled text data to learn general language representations through neural networks or statistical methods, which are then applied to downstream processing tasks, reducing data annotation requirements. ELMo and GPT are second-generation pre-trained models that learn dynamic word vectors, where each word's vector representation changes according to different contexts, capable of handling polysemy problems. Their advantages are strong generalization and transfer capabilities, while their disadvantages are high computational complexity and the need for fine-tuning. BERT and XLNet are third-generation pre-trained models that learn bidirectional language models, simultaneously considering left and right context information, capable of capturing richer semantic relationships and improving task processing performance, but their disadvantages are the need for large computational resources and training time. Overall, pre-trained models can improve the accuracy and efficiency of agricultural domain named entity recognition, enhance the performance of agricultural domain text classification and clustering, and are fundamental technologies in tasks such as agricultural text generation, text summarization, and question-answering systems.

Agricultural text classification methods mainly include Support Vector Machine (SVM) classification based on statistical learning theory, Naive Bayes classification based on Bayes' theorem, decision tree classification based on tree structures, and deep learning classification based on neural networks. Among them, deep learning methods based on neural networks are widely used in recent years due to their strong ability to extract features from complex raw data and their good performance in solving nonlinear problems. Zhang Mingyue et al. [53] proposed a convolutional neural network-based agricultural question-answering sentiment polarity feature extraction and analysis model, using the Skip-gram model to convert to 256-dimensional word vectors and obtaining classification models through convolutional neural networks. Luo and Zhang [54] constructed a Word2Vec and LSTM-based classification model, achieving text information classification based on sentiment understanding. Wang Haoriqin et al. [55] used a CNN model as the foundation, adopted densely linked networks to connect upstream and downstream convolutional blocks, and combined attention mechanisms to mine text keyword features, achieving good results.

The agricultural text classification model flowchart is shown in Figure 4 [Figure 4: see original paper], mainly including three parts: corpus construction, text feature representation, and model training. The specific implementation methods are as follows: (1) Construct agricultural corpus. The corpus can provide strong support for the accuracy and scalability of agricultural knowledge anal-

ysis. The agricultural domain can build domain-specific agricultural corpora through knowledge bases of crop cultivation, crop varieties, crop diseases and pests, etc. (2) Text feature representation. Currently, mainstream text feature representation is word embedding, including co-occurrence matrices, word2vec, ELMO, and BERT. BERT uses pre-trained models as word vector conversion tools, simultaneously obtaining text syntactic and semantic features, solving the problem that traditional word embedding models struggle to distinguish word polysemy. (3) Model training. Taking the pre-trained BERT model as an example, after obtaining vectorized representation of question features, bidirectional neural network layers such as BiGRU or BiLSTM are used for text feature information extraction, combined with collaborative attention mechanisms to enhance the capture ability of inter-word semantic relationships, achieving local feature extraction at different granularities, and outputting the final obtained feature vectors to the interactive classification layer.

**3.3.2 Multimodal Knowledge Graph Construction** Agricultural domains involve diverse data forms, including text, expert knowledge, images, videos, and other information modalities. Multimodal data fusion is an important link in the agricultural knowledge graph construction process, aiming to integrate and align different modal data through technologies such as data cleaning, integration, alignment, and fusion, mining correlations and potential knowledge between data to provide more comprehensive and accurate information foundations for agricultural knowledge graph construction.

Multimodal data fusion brings many advantages and applications to agricultural graph construction. First, the increase in modality numbers makes semantic expression of image and text data more sufficient. For example, through correspondence between disease names and images, or agricultural product images and names, more complete knowledge can be presented. Fusion between different modalities can mutually enhance information accuracy and richness. Second, significant achievements have been made in disambiguation. For example, it is difficult to accurately express which crop is affected by powdery mildew using only text information, while image modality allows farmers to intuitively understand the specific situation of disease occurrence. Additionally, multimodal data fusion can enable convenient retrieval methods such as searching text by image, searching images by voice, and searching videos by voice in production sites. In recent years, deep learning-based multimodal data fusion methods have made significant progress in agricultural knowledge graph construction. Deep learning models can automatically learn complex relationships between data and correlations between modalities, achieving more precise data fusion. Patil and Kumar [56] proposed a multimodal data fusion framework called Rice-Fusion, considering agricultural meteorological attributes and rice crop images, using a convolutional neural network architecture with two dense layers to extract features from images, while using multilayer perceptrons to extract features from agricultural meteorological data, providing new solutions for rice disease problems. Kiryo et al. [57] based on multimodal data fusion from

drones, used RGB, multispectral, and thermal sensors within a Deep Neural Networks (DNN) framework to estimate soybean crop growth status.

Multimodal knowledge graph construction is based on multimodal data fusion, performing structural and semantic representation of fused multimodal data, integrating and linking fragmented knowledge to form a comprehensive and three-dimensional knowledge system, providing precise and efficient support for agricultural production and decision-making. Agricultural multimodal knowledge graph construction involves multiple aspects including multi-source data acquisition, multimodal feature extraction, alignment, feature concatenation and relationship prediction, and multimodal knowledge fusion, as shown in Figure 5 [Figure 5: see original paper]. Multimodal knowledge graphs include not only basic knowledge such as crop growth cycles and variety characteristics but also knowledge in multiple aspects including soil improvement, variety selection, seedling regulation, production management, water-fertilizer-pesticide reduction, harvest decision-making, production-marketing docking, and quality control traceability, providing scientific basis for agricultural decision-making and management.

Multimodal knowledge graphs integrate three elements: entity structured attributes, numerical features, and corresponding images. Currently, there are some representative multimodal knowledge graphs, such as IMGpedia, which fuses semantic knowledge graphs with multimodal data, containing 450 million visual similarity relationships. ImageGraph organizes a large number of images into image graphs and establishes associations between image entities, containing a large number of entities, triples, and relationship types. Richpedia is a large-scale, comprehensive multimodal knowledge graph containing graph entities, text entities, image entities, and their relationships. In recent years, agricultural domain knowledge graphs have received attention and research. Chen Jiayun et al. [10] explained agricultural multimodal knowledge graph construction methods and introduced their important role in disambiguation and visual information supplementation. Zhou et al. [11] established a knowledge graph including 6 types of tomato and cucumber diseases, proposed a multimodal semantic embedding method based on “image-text,” achieving joint representation learning of disease characteristics with an identification accuracy of 99.63%. Zhao Pengfei et al. [12] proposed a BERT multi-feature fusion recognition method to address problems of missing local context features, single sub-vector representation, and low recognition rate of rare entities during the recognition process, achieving 94.84% accuracy in 5,295 annotated corpora combined with domain expert knowledge and agricultural domain dictionaries. Yuan Peisen et al. [13] proposed a rice phenotype knowledge graph entity relationship classification method integrating rice genes, environment, and phenomics for rice phenotype knowledge graph entity relationship extraction, achieving 95.11% precision through BERT-based relationship extraction of three types. Alahadh et al. [58] proposed a pest feature detection and extraction method, using extended cross-stage partial networks and improved attention mechanisms to achieve multimedia information association extraction, providing support for

knowledge graph construction.

Agricultural multimodal knowledge graphs are being built from bottom to top, including disease dual-modal knowledge graphs, rice knowledge graphs, etc. Knowledge from different modalities has different representation forms and semantic structures, making unified representation and integration a key issue. Additionally, knowledge graph updating and maintenance are continuous tasks requiring solutions for dynamic knowledge extraction and graph evolution.

**3.3.3 Knowledge Graph Collaborative Completion** The incompleteness of knowledge graphs limits their application effects in real agricultural scenarios. To solve this problem, knowledge graph completion technology has become a key technical means. Among them, knowledge graph collaborative completion refers to improving the content and structure of agricultural knowledge graphs through the mutual complementation and collaborative action between multiple knowledge graphs. Different knowledge graphs may come from different domains or data sources, having certain redundancy and complementarity. Through collaborative completion, gaps and missing parts in knowledge graphs can be filled, improving knowledge completeness and accuracy, and further enhancing the application effects and value of agricultural knowledge graphs.

In research on collaborative completion of agricultural knowledge graphs, there are some representative works. For example, Wang Wenjun and Yu Yinfeng [59] proposed an automatic completion algorithm for missing connections in knowledge graphs, building a graph embedding representation model based on data sparse neighborhood structures, using Long Short-Term Memory (LSTM) models to automatically complete missing data, thereby improving data sparsity problems in knowledge graphs. Zhang Ningyu et al. [60] proposed a low-resource knowledge graph completion method based on knowledge collaborative fine-tuning, learning optimal templates, labels, and model parameters through collaborative fine-tuning algorithms, applicable to scenarios with different numbers of annotated samples.

Agricultural knowledge graph collaborative completion still faces some challenges and problems. First, semantic and structural differences between different knowledge graphs need to be aligned and mapped to ensure that completed knowledge can be seamlessly integrated. Second, consistency and credibility between knowledge graphs need to be guaranteed to avoid introducing inaccurate or inconsistent knowledge during the completion process.

**3.3.4 Agricultural Knowledge Retrieval and Matching** In the agricultural domain, users may face various problems such as crop planting techniques, disease and pest diagnosis, and fertilizer usage methods. Traditional search engines mainly rely on keyword matching, cannot deeply understand question semantics and context, and struggle to accurately answer agriculture-specific questions. Therefore, agricultural knowledge retrieval and matching technology is particularly important. Agricultural knowledge retrieval and matching can

automatically extract relationships between questions and answers by learning and training on large amounts of agricultural domain data, providing timely and accurate agricultural problem answers and decision support for farmers, agricultural experts, and decision-makers, improving agricultural production efficiency and quality.

### **3.4 Agricultural Knowledge Reasoning and Decision-Making Technology**

Agricultural knowledge reasoning and decision-making is based on agricultural knowledge and experience, analyzing and reasoning about agricultural problems through logical reasoning, association analysis, and model building to provide scientific and accurate agricultural decision support for crop planting management, disease and pest prevention and control, agricultural disaster early warning, and agricultural product market analysis. In agricultural knowledge reasoning and decision-making, multiple key technologies and methods are involved, which can be divided into knowledge graph-based reasoning decision-making and reinforcement learning-based reasoning decision-making.

**3.4.1 Knowledge Graph-Based Reasoning Decision-Making** Knowledge graph-based reasoning decision-making uses relationships and rules in agricultural knowledge graphs for logical reasoning, discovering potential agricultural laws, associations, and solutions, thereby providing agricultural decision support. The structured representation of knowledge graphs makes the reasoning process more interpretable and understandable, allowing decision-makers to intuitively understand the logic and basis of reasoning results. In knowledge graphs, various forms of reasoning such as deductive, inductive, abductive, and analogical reasoning can be achieved. Here, we mainly introduce knowledge graph reasoning based on symbolic logic and knowledge graph reasoning based on representation learning. Symbolic logic-based methods include Datalog reasoning and production rule reasoning. Datalog reasoning derives path facts based on the first rule and first fact, and uses the second rule and newly generated facts to derive new paths. The fact set in this scenario is usually large, and the overall reasoning computational complexity increases with the rule set. Production rule reasoning mainly appears in the expert system era, controlling system execution through an inference engine to complete pattern matching, conflict resolution, and action execution operations, with rule matching at its core. The biggest advantage of symbolic logic-based knowledge graph reasoning is interpretability, but it has high requirements for knowledge representation and description. When the knowledge base is large, reasoning robustness and efficiency decrease. With the development of deep learning, representation learning and knowledge graph embedding reasoning methods have received increasing attention. Many real-world problems can be reduced to inferring relationships between two entities or new facts based on known facts and relationships in knowledge bases. Better knowledge reasoning can be achieved through complex relationship processing, multi-hop processing,

and sparsity problem processing. Knowledge graph reasoning based on rule learning mainly uses rules to complete reasoning, utilizing graph structure characteristics to learn rules. For example, the Path Ranking Algorithm (PRA) uses paths between two entities as features to predict relationships between them, judging whether relationships exist between nodes based on a directed graph with edges, and calculating a set of paths from head nodes to tail nodes through weighted supervised learning methods. Association Rule Mining Under Incomplete Evidence (AMIE) is an inductive method that sequentially predicts rules for each relationship through support, head coverage, and confidence. Additionally, knowledge graph reasoning has certain long-tail effects.

**3.4.2 Reinforcement Learning-Based Reasoning Decision-Making** Reinforcement learning-based reasoning decision-making methods learn optimal decision-making strategies through interaction with the environment based on agricultural environment and feedback information, dynamically adjusting decision strategies to adapt to different agricultural scenarios and needs. In agricultural decision-making, agricultural problems can be modeled as reinforcement learning tasks, learning optimal decision strategies through continuous interaction and trial with the agricultural environment. Elavarasan and Vincent [63] proposed an enhanced random forest algorithm that performs reinforcement learning each time a splitting attribute is selected to effectively utilize available samples, improving accuracy by 92.2%. Based on reinforcement learning and fuzzy logic methods, a method for robots to autonomously acquire navigation control strategies was designed, enabling robots to automatically obtain optimal navigation strategies in actual navigation environments. Liu Huidan et al. [64] built a prediction model based on deep reinforcement learning methods, weighted and combined LSTM, gated recurrent units, and Bi-LSTM to achieve precise prediction of moisture and temperature in tillage layer soil. Song Haonan et al. [65] proposed a method combining knowledge representation and deep reinforcement learning, training models through single-step optimization strategy networks and multi-step reasoning strategy networks to effectively solve problems of poor interpretability and low accuracy in knowledge reasoning.

Knowledge graph-based reasoning decision-making can use existing agricultural knowledge for reasoning and problem-solving, while reinforcement learning-based reasoning decision-making learns optimal decision strategies through environmental interaction. Agricultural domain knowledge reasoning decision-making has complexity in several aspects: crop physiology and environment representation usually requires multimodal and cross-media expression methods, including structured data, text, images, videos, and sound patterns. Their semantic expression needs to couple multiple features including region, season, and reference objects. The same problem has differences in knowledge representation, reasoning, and feedback across different regions, times, and varieties, making reasoning more complex and requiring consideration of more types of information. Additionally, full-chain information and knowledge such as agricultural cultivation, agricultural conditions, fertilization,

plant protection, and market prices have long chains and strong contextual correlations. Therefore, in the reasoning process, based on factual cases, it is also necessary to consider as many associated factual data as possible. More detailed information acquisition enables more accurate judgment or feedback, such as real-time monitoring data, public opinion information, physiological basic information, and agricultural interaction information.

## 4 Construction of Agricultural Knowledge Intelligent Service Application Scenarios

Data and knowledge dual-driven agricultural intelligent services involve multiple links such as pre-production planning, in-production management, and post-production guidance, facing multiple types of agricultural users, connecting multi-dimensional data. With the improvement of intelligent computing capabilities, popularization of agricultural IoT technology, and advancement of machine learning algorithms, constructing multi-type agricultural knowledge intelligent service application scenarios promotes the deep application and development of knowledge intelligent technology in the agricultural field.

### 4.1 Agricultural Pre-Production Planning Knowledge Intelligent Service

Accurate and timely pre-production knowledge intelligent services can provide valuable information for farmers as references for agricultural production plans. Through direct supply of important theme information in different periods, the suitability of crop environments can be ensured, thereby saving agricultural production costs. With the development of generative knowledge models, recommended prescriptions are gradually being upgraded from traditional graphic and text forms to video forms, which are more understandable and operable, representing an important form of future knowledge services.

The main aspects of agricultural pre-production include high-quality variety selection, planting and breeding environment evaluation, planting and breeding plans, agricultural equipment maintenance, and agricultural input preparation, requiring high extensiveness, timeliness, and accuracy of knowledge services. These are usually provided through agricultural information platforms and mobile mini-programs, combined with knowledge recommendation and direct supply, big data mining, and other technologies.

In variety selection, factors such as yield, disease resistance, planting environment adaptability, and commercial quality are typically considered. The China Agricultural Information Network (<http://ncpscxx.moa.gov.cn/>) provides reference data for eight types of agricultural products including grain, cotton, oil, sugar, vegetables, fruits, livestock products, and aquatic products, including production, cost-benefit, and public opinion information. Combined with spatiotemporal information, experience, and public opinion, various trend statistical charts are analyzed and drawn, providing relatively comprehensive

variety selection information references. Syngenta MAP Smart Agriculture (<https://www.syngentagroup.cn/>) provides services such as plot division, remote sensing viewing, meteorological viewing, and accumulated temperature and rainfall, fully integrating agricultural meteorology, water temperature, habitat, and crop knowledge to provide flexible plot-level pre-production evaluation information.

In planting scheme formulation, through the massive data of the China Agricultural Technology Extension Information Service Platform (<http://njtg.nercita.org.cn/>), resource portraits are constructed to match users with suitable planting varieties, practical technologies, guidance experts, and knowledge service resources based on their region, variety, and time, solving the current problem of farmers' over-reliance on long-term planting habits and providing planting prescriptions based on agricultural prior knowledge. Bai Jingbo [66] based on standardized planting schemes, precisely delivered key points of the planting process through the "Nong Baomu" App, guiding farmers in planting through online and offline integration, realizing an agricultural knowledge-empowered socialized service system.

In planting environment evaluation, Jiang Yun et al. [67] analyzed and inverted physical and chemical indicators of black soil cultivated land through remote sensing technology, indirectly monitoring cultivated land quality based on vegetation indices. Qian Fengkui et al. [68] constructed a Land Evaluation and Site Assessment (LESA) system, building a minimum dataset for cultivated land evaluation by analyzing sand particles, organic matter, total potassium, available phosphorus, pH values, and comprehensive pollution indices in cultivated land, dividing cultivated land into five grades to simplify the county-level cultivated land quality index system. Jiang Shaohuai et al. [69] based on Geographic Information System (GIS) technology, used spatial structure analysis, hierarchical structure analysis, and comprehensive index methods to achieve cultivated land quality and fertility evaluation in Shandan County, providing references for farmland quality detection.

#### **4.2 Agricultural Production Management Knowledge Intelligent Service**

With the accelerated integration of 5G, big data, artificial intelligence, IoT, and other technologies with agricultural production, agricultural digital transformation continues to accelerate, giving rise to a series of agricultural production knowledge service application scenarios. These include precise prevention and control of diseases, pests, and weeds; intelligent regulation of light, temperature, water, air, and heat in solar greenhouses; precise application of water-fertilizer integration; livestock individual behavior and shape recognition; and precise feeding management. Key factors in agricultural production knowledge service scenarios cover four aspects: information perception, intelligent analysis, decision guidance, and feedback control [70].

#### 4.2.1 Agricultural Condition Monitoring and Early Warning Service

Agricultural condition monitoring and early warning refers to using satellite imagery, low-altitude UAV spectra, and ground field survey data to identify crop growth and nutritional status, analyze disease and pest occurrence degree and development trends, predict drought and flood occurrence, and integrate agricultural meteorology and hydrology data combined with agricultural expert knowledge models for knowledge intelligent early warning services to guide production management personnel to take timely measures.

Large-scale crop growth monitoring uses remote sensing technology, utilizing crop spectral features and vegetation indices to calculate and reflect spatial information of crop growth, playing an important role in water-fertilizer input, yield estimation, and food policy formulation. In small-scale crop production scenarios, Michael and Lee [71] developed the nitrogen fertilizer management system CropManage, which reduced nitrogen fertilizer application by 30% in field experiments. Santos et al. [72] predicted potential crop functional abnormalities, increasing crop leaf area by 17.94% and weight by 14.29% in vegetable cultivation. By integrating crop physiological perception data, crop growth image data, and growth description knowledge graphs, parameters such as crop leaf area, plant height, leaf angle, and daily dry matter production are automatically obtained, and comprehensive analysis of crop growth functions is performed using prediction models.

The occurrence of crop diseases and pests often causes irreversible losses to agricultural production, adversely affecting crop yield and quality. Therefore, timely disease detection and precise prevention are of great significance [73, 74]. For large-scale monitoring, timely and rapid acquisition of information such as crop disease and pest types, locations, severity, and area is needed. Currently, domestic and foreign scholars have applied hyperspectral remote sensing technology to medium- and small-scale crop disease monitoring and early warning, with main applications focusing on effective identification when multiple diseases and pests occur simultaneously, quantitative analysis of disease and pest severity, and early detection of diseases and pests [75, 76]. In fixed-point monitoring of crop disease identification and early warning, due to complex annotation of disease characteristics and difficult image background noise processing, deep learning methods based on large-scale disease image data have become a hotspot [77, 78], especially crop disease image diagnosis methods that integrate environmental factors, disease text understanding, and multispectral images, which have obvious application advantages in real-time and predictive disease detection [79, 80].

Agricultural drought and flood are the main meteorological disaster types affecting crop yield. The agricultural drought and flood monitoring and early warning application is shown in Figure 7 [Figure 7: see original paper]. Relying on remote sensing, UAV, and video technology equipment, combined ground monitoring and spatial monitoring are adopted. Based on crop type, variety, planting region, and growth stage, historical precipitation, rainfall, and crop wa-

ter demand data are integrated to parse knowledge rules for agricultural drought assessment. Irrigation districts, meteorological stations, watershed zones, and other entities and related data are graphized. According to agricultural drought and flood assessment indicator systems, drought and flood meteorological disaster monitoring and early warning services are implemented, helping meteorological departments strengthen agricultural disaster prevention and enhancing agricultural production personnel's awareness and preventive handling of meteorological disasters.

**4.2.2 Agricultural Production Management Decision-Making** Currently, breakthroughs have been made in agricultural production decision-making application models. The application of artificial intelligence technologies such as big data and machine learning has solved the problem of difficult database and knowledge base updates in traditional knowledge service systems. Based on real-time acquisition of multimodal agricultural data such as environment, soil, and crop physiology, agricultural spatiotemporal knowledge graphs are used to semantically link multimodal data, providing users with decision-making services such as standardized production management, water-fertilizer decisions, plant protection operations, and business management, which is a current research hotspot [81].

As shown in Figure 8 [Figure 8: see original paper], the agricultural production decision-making process covers three important aspects: First, constructing knowledge ontology based on multimodal agricultural data resources, and building knowledge graphs based on multimodal knowledge rules and agricultural models, where the applicability of agricultural models determines the accuracy of knowledge decisions [82, 83]; second, establishing appropriate knowledge deep learning methods based on multimodal knowledge graphs to effectively mine implicit semantic information in knowledge graphs; third, knowledge reasoning based on multimodal knowledge graphs, determining tasks according to decision-making objectives in agricultural production management, and selecting knowledge graph reasoning methods based on symbolic logic or representation learning to achieve knowledge decisions such as production management and water-fertilizer-pesticide decisions.

Taking facility cultivation as an example, intelligent management is reflected not only in quantitative monitoring of crop growth environments but more importantly in analyzing crop needs based on monitoring data to take targeted production measures. To achieve these goals, mathematical models linking observation data with crop needs for water, fertilizer, light, trace elements, and other factors need to be established, integrating long-term monitoring data and real-time perception data. Long-term monitoring data includes soil testing and formula data, water evaporation and infiltration, precipitation, etc. Real-time perception data includes real-time measurement of water-fertilizer application using high-precision flow meters, and monitoring of soil moisture, soil pH, and soil electrical conductivity. Based on water-fertilizer models, expert knowledge,

and graph decision models, the control system is driven to achieve intelligent water-fertilizer irrigation, as shown in Figure 9 [Figure 9: see original paper].

### 4.3 Agricultural Post-Production Operation Knowledge Intelligent Service

Agricultural post-production knowledge services involve aspects such as agricultural product grading and processing, warehousing and logistics, and market marketing. Addressing current problems of low efficiency and lack of objectivity in manual agricultural product grading, research on intelligent grading and sorting technology based on machine vision is of important practical value for improving agricultural product grading quality and reducing labor costs and losses. Currently, machine vision technology has been widely applied in agricultural product detection and grading research. Zhang Yiping et al. [84] designed a rapid non-destructive detection and intelligent grading system for *Hericium erinaceus* quality based on machine vision, with speed reaching more than 5 times that of manual non-destructive detection. Lü Zhengchao [85] designed a non-destructive detection model for chicken wing surface quality, using lightweight Netv2-YOLOv4 as the core algorithm, capable of grading 14,400 chicken wings per hour. Additionally, Fitri, Mesa, and others have applied image processing and machine learning technologies to intelligent grading of red dragon fruit and bananas, significantly improving post-production grading efficiency [86, 87]. Furthermore, Ropelewska et al. [88] studied intelligent monitoring technology for cucumber pickling processing, achieving intelligent distinction and identification of spontaneous lactic acid fermentation, vinegar solution pickling, and fresh cucumber slices by comparing image features of cucumber slices under different pickling methods.

In agricultural product warehousing and logistics, multi-source data such as agricultural product inventory, product cycles, and consumption are integrated. Based on knowledge service models, agricultural product inventory capacity is analyzed, shelf life is predicted and arranged, and methods such as clustering, decision trees, and association analysis are used to achieve optimal regulation in warehousing and logistics. In agricultural product quality traceability [89], blockchain technology has technical advantages in ensuring traceability system credibility, enhancing the reliability of full-process agricultural product quality traceability.

In agricultural product market marketing, based on multi-dimensional data such as agricultural product consumer data, consumer portraits, and consumption orders, online analysis statistics and deep mining are performed through consumer data mining algorithms to form multi-dimensional mining indicators for guiding agricultural product marketing. Agricultural product market marketing big data analysis covers product sales analysis, online consumption preference analysis, etc. Among them, online consumption preference analysis is based on statistical analysis of user behavior characteristic tags to build precise user portraits, such as basic attributes including user gender, city, and age, as well as

user consumption characteristics and consumption viscosity, thereby analyzing consumption preferences of different consumer groups.

In agricultural product price forecasting, sharp price fluctuations not only affect agricultural development and interest distribution among various links but also increase market operation risks. Currently, BP neural networks, SVM, Elman neural networks, and wavelet neural networks have been applied in agricultural product price forecasting for soybeans, cotton, and aquatic products [90]. However, the neural network theoretical system is not perfect enough, and there are some problems in specific applications: for example, learning time is generally long for training data with large samples; complex neural network models have poor interpretability, making it impossible to intuitively explain models and results from an economic perspective, limiting guidance for agricultural operations. Currently, some scholars have used AI models to learn basic price laws and spatiotemporal variation characteristics, dividing complex neural networks into sub-networks according to economic principles to ensure overall model interpretability, fully utilizing neural networks' strong ability to discover detailed feature laws, achieving a two-way balance between prediction accuracy and result interpretability [91].

#### 4.4 Knowledge-Driven Agricultural Unmanned Operations

Addressing the problems of land fragmentation in China's smallholder-dominated production model and rising labor costs, the knowledge-driven unmanned production system is an important means to promote green, ecological, and efficient industrial development. Due to the complex systems engineering characteristics of unmanned operations, knowledge about crop physiological characteristics, agricultural machinery operator experience, and full-growth-period cultivation technology is fully applied in environmental monitoring and early warning, precise water-fertilizer irrigation, and unmanned driving operations. As shown in Figure 10 [Figure 10: see original paper], unmanned operations usually take the intelligent knowledge service brain as the core, can real-time perceive satellite positioning, working conditions, operating environment, and other data. Related data is transmitted to the agricultural production big data center, and after cleaning and processing, is stored in various databases. Through fusion with knowledge about crop varieties, physiology, diseases and pests, and cultivation, operation instructions are formed and sent to the execution system, and decision models are matured through feedback.

In terms of field unmanned farms, Luo Xiwen et al. [92] used artificial intelligence technology to learn full-process operation knowledge for rice transplanting, plant protection, and harvesting. By integrating intelligent agricultural machinery and equipment, experienced operators' knowledge was adapted to machine operations to achieve unmanned driving. In Zengcheng District, Guangzhou City, Guangdong Province, full-process automatic operation and full-scenario unmanned intelligent decision-making for rice industry were achieved, with early

rice yield increasing by 32.58% compared with local average yield. In terms of open-field vegetable unmanned farms, Wu Huarui [93] applied perception recognition, machine vision, unmanned driving, intelligent decision-making, safety control, and flexible operation technologies. By building an agricultural intelligent display service brain, multidisciplinary knowledge such as vegetable characteristic breeding, cultivation, and agricultural machinery was comprehensively applied to achieve full-process unmanned operation of cabbage. Applications were conducted in Xiaotangshan Base, Changping District, Beijing, Zhao County and Cangzhou in Hebei Province, and Ulanqab in Inner Mongolia, with related technical models and knowledge migrated to radish, pepper, and other varieties, achieving knowledge-driven full-process unmanned operation of vegetables.

In terms of facility greenhouse unmanned management and control, scholars from the Beijing Agricultural Intelligent Equipment Technology Research Center and Shanghai Ocean University used artificial intelligence technology to effectively integrate crop physiological characteristics, full-life-cycle planting experience, knowledge graph construction and reasoning application, and IoT device monitoring and control technology. In the largest single greenhouse for seedling cultivation in Shouguang City, Weifang City, Shandong Province, applications such as tomato flowering stage recognition [94], maturity recognition [95], and flower localization [96] were implemented. Through knowledge coupling of more than 2,000 sensors and crop models and planting knowledge in greenhouse environments, full-process intelligent management of more than 200,000 tomato plants was achieved. Chu [97] studied agricultural robot operation processes based on intelligent scheduling methods, designing agricultural robots capable of mobile operation in complex greenhouse environments to accurately control fertilization, spraying, and other actions in response to uncontrollable natural factors and changes in crop growth conditions.

#### 4.5 Agricultural Knowledge Intelligent Q&A

Agricultural knowledge intelligent Q&A systems are AI-based agricultural information service tools that can provide fast and accurate agricultural information query and answer services for users through natural language processing technology. They can solve problems of low timeliness and accuracy in agricultural technology knowledge acquisition and shortage of agricultural technology experts. With continuous development and application of AI technology, agricultural intelligent Q&A systems are increasingly applied in agricultural production, scientific research, education, and other fields.

In agricultural production, agricultural intelligent Q&A systems can provide technical guidance and consulting services for farmers in planting, breeding, fertilization, disease and pest prevention and control, etc. Farmers can obtain local weather forecasts, rainfall, temperature, and other meteorological information through the system to better arrange agricultural production plans; they can upload photos of crop leaves, fruits, etc., and the system automatically

identifies disease and pest types and provides corresponding prevention and control measures; they can obtain professional consultation on fertilizers, planting techniques, irrigation, etc., to improve agricultural production efficiency and quality; they can obtain local agricultural product market information including prices and sales channels to better sell their products; and they can obtain interpretation and guidance on national and local policies to better understand policy implementation and impacts. Yang Guofeng and Yang Yong [98] built a BERT-based common crop disease Q&A system question classification model, constructing Bi-LSTM self-attention network classification models, Transformer classification models, and BERT-based fine-tuning classification models, achieving efficient and accurate classification of common crop disease questions through training of the three classification models. Zhang Bokai and Li Xiang [99] developed an Android agricultural technology Q&A system based on knowledge graphs to address limitations of telephone consultation, centralized training, and on-site expert guidance in terms of time, space, and manpower. They used Conditional Random Fields (CRF) models to identify entities, built “crop-disease-pesticide” triple knowledge bases, imported them into Neo4j graph databases, and provided question query and recommendation services. Zhang Caili et al. [100] built an intelligent Q&A system for crop scientific fertilization management and soil fertility queries, achieving Q&A functions through pattern matching to construct question type templates, keywords, and rules, effectively answering common crop scientific fertilization management questions in Anhui Province.

In agricultural scientific research, agricultural intelligent Q&A systems can provide scientific and technical information query and research support for researchers, helping them obtain agricultural scientific and technical information faster and improving research efficiency and result quality. In agricultural education, agricultural intelligent Q&A systems can provide agricultural knowledge query and learning support for students and teachers, helping students better master agricultural knowledge and improving teaching quality and effectiveness. Academic social network platforms such as ResearchGate (RG), Mendeley, and Academia.edu [101, 102] all provide intelligent Q&A services, offering intelligent scientific research information acquisition and communication for researchers.

In terms of service forms, in addition to traditional web pages and mobile Apps, agricultural intelligent robots are becoming increasingly widespread applications, aiming to achieve convenient agricultural knowledge human-computer interaction through voice recognition, natural language processing, responsive architecture frameworks, and large-scale knowledge base processing technologies. The agricultural intelligent Q&A robot developed by the Beijing Academy of Agriculture and Forestry Sciences Information Center provides a knowledge base covering more than 240 crop varieties and involving 20 million Q&A pairs for pre-production, in-production, and post-production stages, used in application scenarios such as agricultural technology services, exhibition hall guidance, and agricultural park tour guidance.

## 5 Agricultural Knowledge Intelligent Service Platform

Currently, agricultural knowledge services still generally have problems such as high technology application thresholds, difficulty in meeting user personalized needs, and weak knowledge continuous updating capabilities. There is an urgent need to build a new type of agricultural intelligent knowledge service platform with self-evolutionary learning capabilities. The platform architecture (Figure 11 [Figure 11: see original paper]) uses cloud-native development and operation integration, microservices for modular assembly, where businesses do not affect each other, while enabling AI model scheduling and crowdsourced online annotation functions, providing all-weather, all-region agricultural knowledge services through platform and mobile App interfaces.

The platform provides a distributed cloud storage environment from the architecture perspective, supporting scheduling of intelligent equipment and software systems. The data knowledge resource pool implements distributed storage management of resources, providing basic data services for upper-layer applications and supporting integrated management of agricultural big data. Immersive scene interaction tools and intelligent online decision-making modules integrate graph services, shared knowledge tools, and component customization and encapsulation tools, providing online and offline full-chain knowledge services. At the service application layer, personalized services such as production decision-making, knowledge recommendation, and agricultural situation cognitive reasoning are provided based on subject background portraits.

The core business application services of the agricultural knowledge intelligent service cloud platform include: (1) Agricultural production knowledge services, providing online knowledge services such as planting planning, soil evaluation, agricultural situation early warning, water-fertilizer decisions, and disease and pest diagnosis. Planting planning includes recommendations for row spacing, plant spacing, planting time, agricultural operations, and management plans for each stage. Standardized planting schemes are formulated by agricultural technicians and put online, precisely matched based on farmer portraits, and pushed to farmers according to phenological period nodes to guide agricultural production and management, promoting standardized agricultural production management and improving agricultural product quality and yield. (2) Agricultural cross-media knowledge services. Building an agricultural scene cross-media knowledge service technology system driven by knowledge and data with structural and functional negative feedback mechanisms. Based on voice dialogue, text recommendation, image recognition, video retrieval, and other methods, precise delivery of industrial technology and immersive learning experience services are provided for different user groups, including functions such as agricultural technology Q&A, agricultural situation monitoring, technical guidance, live streaming services, and video push. (3) Agricultural product market forecasting services. Building market price analysis and mining tools based on internet data, field reporting data, and platform Q&A service interaction data. Through data aggregation, cleaning, and standardization processing, integrat-

ing variety, location, and time information, an agricultural product market price system covering field prices, wholesale prices, and retail prices is formed, providing reference basis for agricultural product sales timing selection. Meanwhile, the intrinsic correlation between market prices and public opinion is analyzed and predicted to achieve guidance for agricultural product marketing.

## 6 Summary and Prospects

The “14th Five-Year Plan for National Economic and Social Development of the People’s Republic of China” and the “2035 Long-Range Objectives Outline” propose “to accelerate the development of smart agriculture, build industry artificial intelligence datasets, and construct industry artificial intelligence platforms.” As a typical application of artificial intelligence technology in the agricultural field, agricultural knowledge intelligent service has achieved a series of results in data perception recognition, knowledge fusion, and knowledge services, playing an increasingly prominent role in promoting and driving agricultural industry development. However, due to the complex and variable agricultural production environment, climate, and crop varieties, agricultural data exhibits characteristics of multi-source heterogeneity, distributed low rank, and weak coupling connections, leading to difficulties in agricultural knowledge intelligent services such as multi-layer spatiotemporal variation of ontology, interlaced context relationships, difficult noise classification, dynamic application changes, and diverse behavioral performance.

With the rapid development of new-generation artificial intelligence technology, breakthroughs are expected in agricultural artificial intelligence service technology in the following aspects: (1) Multi-scale agricultural situation holographic perception, sparse feature discovery, and spatiotemporal situation recognition. Focus on establishing small-sample transfer discovery and spatiotemporal target detection and tracking models for sudden and variable agricultural situations, solving problems such as difficult acquisition of uncertain agricultural situation information and spatiotemporal situation recognition, achieving transformation from data to features, promoting the accelerated formation of more and higher-quality datasets in the agricultural field, and supporting industry development needs. (2) Agricultural cross-media knowledge graph construction and self-evolutionary updating. Focus on constructing robust knowledge bases and knowledge graphs based on multi-task learning to achieve high-level semantic information correlation analysis and data connectivity across media content. Through knowledge mining and fusion contained in various agricultural data, build a complete and rich agricultural knowledge graph to meet knowledge needs of different users and scenarios. (3) Multi-granularity correlation and multi-mode collaborative inversion prediction of complex agricultural situations. Focus on breakthroughs in cross-domain and cross-media reasoning mechanisms and visualizable and interpretable presentation methods to address challenges such as difficult origin tracing and low comprehensive prediction accuracy for complex agricultural situations including agricultural meteorological

disasters, drought and flood, animal and plant diseases, soil eutrophication, and growth inhibition. (4) Large language model design in the agricultural field based on generative artificial intelligence. ChatGPT and other large language models based on generative AI can accurately mine agricultural domain data and automatically generate questions through ultra-large-scale computing power, solving problems of user intention understanding and precise service under conditions of dispersed agricultural data, multi-source heterogeneity, high noise, low information density, and strong uncertainty. Additionally, agricultural domain large language models can significantly improve the accuracy of intelligent algorithms such as identification, prediction, and decision-making through the combination of strong algorithms, big data, and ultra-large-scale computing power, bringing important opportunities for large-scale smart agricultural production applications. (5) Construction of agricultural multi-scenario, large-scale knowledge intelligent service platforms and new paradigms. Integrate and innovate key technologies such as human-machine-thing fusion cloud computing architecture, software-defined and converged cloud-network-edge resources, and human-machine hybrid knowledge recommendation and service matching to build an agricultural knowledge intelligent service cloud platform with self-evolutionary learning capabilities, achieving large-scale collaboration and open sharing of knowledge resources, supporting the quality upgrading of agricultural industry forms from “small specialties” to “large industries,” and promoting the modernization transformation of agricultural production through the combination of “knowledge + cases + services.”

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