Current Status and Future Prospects of Agricultural Intelligent Knowledge Services: Postprint

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Abstract

The extensive application of modern information technologies such as big data, the Internet of Things (IoT), and artificial intelligence in agriculture has propelled the modernization of agriculture and rural areas and the development of smart agriculture, thereby stimulating robust demand for technology and knowledge among agricultural business entities. Agricultural knowledge services have become a crucial engine for agricultural transformation, upgrading, and high-quality development. To address existing challenges including scattered and disordered agricultural knowledge, untimely updates, imbalanced knowledge services oriented toward business entities, and supply-demand disconnects, this paper systematically reviews and analyzes the current state of research and practice in agricultural knowledge services both domestically and internationally, and proposes a comprehensive framework for an agricultural intelligent knowledge service system that is based on the entire agricultural industry chain, follows the full lifecycle of agricultural data, and is oriented toward agricultural business entities. The framework comprises three hierarchical layers: agricultural situation perception and big data aggregation and governance based on Artificial Intelligence & Internet of Things (AIoT), agricultural knowledge organization and computational mining based on knowledge graphs, and multi-scenario agricultural intelligent knowledge services. This paper further synthesizes the key technologies involved in agricultural intelligent knowledge services, encompassing space-air-ground all-dimensional AIoT agricultural situation perception, multi-source heterogeneous agricultural big data aggregation and governance, knowledge modeling, knowledge extraction, knowledge fusion, knowledge reasoning, cross-media retrieval, intelligent question answering, personalized recommendation technology, and decision support, with illustrative examples of their research applications. Finally, future development trends and strategic recommendations for agricultural intelligent knowledge services are discussed from the perspectives of agricultural data acquisition, model construction, knowledge organization, intelligent knowledge service technologies, and application promotion. The findings conclude that agricultural intelligent knowledge services are pivotal for resolving current supply-demand contradictions in agricultural knowledge services, bridging the gap from cross-media agricultural data to knowledge, and advancing the evolution of agricultural knowledge services toward personalization, precision, and intelligence, thereby serving as a vital underpinning for achieving self-reliance and strength in agricultural science and technology and for enhancing quality and efficiency in modern agriculture.

Full Text

Preamble

Agricultural Intelligent Knowledge Service: Overview and Future Perspectives

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Abstract: The widespread application of modern information technologies such as big data, Internet of Things, and artificial intelligence in agriculture has accelerated the modernization of agriculture and rural areas while driving the development of smart agriculture. This technological transformation has generated strong demand for scientific knowledge and technological support among agricultural business entities. Agricultural knowledge services have become a critical engine for agricultural transformation, upgrading, and high-quality development. To address existing challenges—including fragmented and disorganized agricultural knowledge, outdated information, unbalanced knowledge services for business entities, and disconnected supply-demand relationships—this paper systematically reviews the current state of agricultural knowledge service research and practice both domestically and internationally. We propose a comprehensive framework for agricultural intelligent knowledge service systems based on the entire agricultural industry chain and the full lifecycle of agricultural data, designed specifically for agricultural business entities. The framework comprises three hierarchical layers: (1) AIoT-based agricultural situation perception and big data aggregation/governance, (2) knowledge graph-based agricultural knowledge organization and computational mining, and (3) multi-scenario agricultural intelligent knowledge services. We summarize key technologies involved in agricultural intelligent knowledge services, including aerial-ground integrated AIoT full-dimensional agricultural situation perception, multi-source heterogeneous agricultural big data aggregation/governance, knowledge modeling, knowledge extraction, knowledge fusion, knowledge reasoning, cross-media retrieval, intelligent question answering, personalized recommendation, and decision support, with examples of their research applications. Finally, we discuss future development trends and countermeasures from the perspectives of agricultural data acquisition, model construction, knowledge organization, intelligent knowledge service technology, and application promotion. Our analysis reveals that agricultural intelligent knowledge service is crucial for resolving current supply-demand contradictions in agricultural knowledge services, achieving the leap from cross-media agricultural data to knowledge, and promoting the upgrade of agricultural knowledge services toward personalization, precision, and intelligence. It also serves as an important support for achieving self-reliance and strength in agricultural science and technology, and for enhancing the quality and efficiency of modern agriculture.

Keywords: intelligent knowledge service; artificial intelligence; Internet of Things; agricultural situation perception; knowledge management; knowledge reasoning; knowledge search & QA; personalized recommendation; decision support

2. Current Status of Agricultural Knowledge Service Research and Practice

Based on the Web of Science Core Collection database, we conducted a fuzzy search using TS = ((agricultur*) and (“knowledge service” or “knowledge discovery” or “intelligent knowledge service” or “intelligent knowledge discovery” or “intelligent knowledge service platform” or “intelligent knowledge service system” or “intelligent knowledge discovery platform” or “knowledge discovery system” or “knowledge service platform” or “knowledge service system” or “knowledge service cloud platform” or “knowledge service cloud system” or “knowledge association” or “knowledge graph” or “multi-modal knowledge graph” or “cross-media knowledge graph” or “artificial intelligence” or “cloud service platform” or “cloud computing” or “knowledge computing” or “precise knowledge matching” or “intelligent recommendation” or “adaptive intelligent recommendation” or “personalized customization” or “big data” or “big data platform” or “big data system” or “data fusion” or “multimedia data fusion” or “multi-scenario knowledge services” or “consulting services” or “agricultural conditions inversion” or “inversion prediction of agricultural situation” or “analysis of agricultural situation data content” or “cross-domain knowledge acquisition” or “agricultural information service” or “agricultural information service platform” or “agricultural information service system” or “intelligent information service” or “intelligent information service platform” or “intelligent information service system”) as the search terms. We performed bibliometric analysis on global literature in the field of agricultural knowledge services indexed by SCI (Science Citation Index) from 2012 to 2021, examining publication trends, country distribution, and topic distribution.

As shown in [Figure 1: see original paper], global publications in agricultural knowledge services have shown a growth trend over the past decade, with a particularly rapid increase since 2018, yielding numerous scientific achievements. In terms of country distribution, the top ten countries in terms of publication volume are China, the United States, India, Australia, Spain, Italy, Germany, the United Kingdom, Brazil, and Canada, as illustrated in [Figure 2: see original paper]. China and the United States have significantly higher publication volumes than other countries, ranking first and second respectively, with China surpassing the United States.

Using VOSviewer to conduct keyword co-occurrence-based thematic clustering analysis on the global agricultural knowledge service literature, the top 20 keywords and their co-occurrence frequencies are presented in . Based on keyword co-occurrence frequency and clustering, agricultural knowledge service research primarily focuses on precision agriculture, smart agriculture (smart farming), management, adaptation, prediction, irrigation, soil, productivity, and yield, based on big data, Internet of Things (IoT), artificial intelligence, machine learning, deep learning, cloud computing, internet systems, and data fusion. These keywords all appear more than 300 times, reflecting the main research focus in the global agricultural knowledge service field over the past decade.

2.1 International Status of Agricultural Intelligent Knowledge Services

In terms of practice and application, international agricultural knowledge services have integrated advanced information technologies such as big data and artificial intelligence, primarily manifesting as full lifecycle data services for agricultural products, visual diagnosis, intelligent decision-making, and precision services for agricultural production and management.

United States: The U.S. has applied remote sensing (RS), geographical information systems (GIS), global positioning systems (GPS), artificial intelligence, IoT, big data technologies, and various sensors to all aspects of agricultural production, providing knowledge services for agricultural meteorological monitoring, crop growth monitoring, soil observation and analysis, plant pest and disease management, and livestock production guidance. The Farmers Business Network platform utilizes IoT sensors for air temperature/humidity, light, and soil moisture content to obtain precise agricultural data covering over 647,497 km^2, offering farmers comprehensive product performance, predictive analysis, and personalized consulting services. Gro Intelligence has established multiple model frameworks and analysis index systems for pests and diseases, yield prediction, and crop price markets, integrating over 40,000 datasets and 650 trillion data points to provide decision-making tools, solutions, and analysis for agricultural and climate economies and their participants.

European Union: With the implementation of strategies such as "Horizon Europe," EU countries have accelerated the application of digital, sensing, and geospatial technologies throughout the entire process of agricultural production, operation, and management, and encourage relevant institutions and platforms to provide diversified knowledge services for different agricultural operators. The University of Sheffield has applied remote sensing, GIS, computer technology, communication, and network technologies to precision planting in agriculture, collecting farm data from approximately 12 million hectares across Belgium, Brazil, Ireland, and other countries through iFarms, B2B websites, technology centers, and demonstration farms. They have developed a data warehouse covering five facts—Field Fact, Sale, Order, Testing, and Management Action—including weather datasets with meteorological station locations, air and soil temperature, rainfall, humidity, and wind speed/direction over time. This system integrates crop data, knowledge extraction, and management decision-making to provide solutions that help farmers optimize farm management and decision-making, such as optimizing fertilizer, pesticide, and irrigation amounts. The French SMAG platform applies information and communication technologies to the entire process of agricultural production, operation, and management, providing farmers with planting plans, agricultural production information, product quality monitoring, and agricultural operation knowledge services. It has served approximately 30,000 farmers and ranked third in market share in France by 2022. Bayer' s Climate FieldView platform integrates remote sensing, big data, IoT, and cloud computing throughout agricultural production, processing, and sales, offering farmers regional planting plans, field production recommendations, farm operation management, agricultural machinery management, optimal production condition configuration, input-output estimation, product traceability management, sales management, and quality control services, covering over 600,000 km^2 of land across more than 20 countries. BASF' s digital crop optimization tool xarvio FIELD MANAGER provides growers with full-cycle protection from sowing to harvest, integrating climate data and real-time disease warnings to provide data-driven pesticide usage recommendations on when, where, and how much to apply, now deployed globally. The Maglis platform effectively monitors and collects crop data, providing planting and sales decisions and personalized field and crop management plans based on operator needs. By combining crop information with solutions and professional expertise, it helps farmers reduce operational risks and optimize investment returns. Launched in 2016, Maglis currently has 37,000 users across 15 countries, covering 20,000 km^2 of land. The Cropio platform (acquired by Syngenta in 2019) provides remote sensing images, IoT records, production analysis reports, and operation planning services, managing approximately 10 million hectares of crops.

Japan: Under relevant policy guidance, numerous research institutions and service entities in Japan have combined big data, artificial intelligence, computer networks, and wired devices to provide agricultural knowledge services based on big data analysis through the aggregation and sharing of agricultural meteorological, soil, terrain, and crop growth monitoring data. They have built a series of service platforms providing information retrieval, statistical charts, and trend analysis, achieving good social and economic benefits. For example, the Akisai cloud service comprehensively supports agriculture and food sales, covering crop production, livestock, horticulture, equipment machinery, and management, transforming Japanese agriculture from a yield-based profit model to an intelligent industry pursuing high operational efficiency and high profits.

In summary, with the cross-integration of information technology and modern agriculture, the intelligence level of various agricultural production links has greatly improved. International research and practice in agricultural knowledge services have progressed rapidly, fully utilizing key technologies such as data science, visual analysis, and artificial intelligence to integrate, correlate, and analyze full-chain agricultural production data, achieving the "data-knowledge-solution" value chain. Agricultural knowledge service platforms in some developed countries and international agricultural organizations have transformed toward specialization, personalization, precision, and intelligence, providing full lifecycle data services, visual diagnosis, intelligent decision-making, and precision implementation services for agricultural production and management based on massive multi-domain agricultural big data.

2.2 Domestic Status of Agricultural Intelligent Knowledge Services

Driven by government promotion and domestic demand, China' s agricultural information service industry has developed rapidly and achieved remarkable results. A nationwide agricultural information service institutional network has been established, comprising national and provincial agricultural research institutes, higher agricultural and forestry institutions, municipal agricultural information agencies, county-level agricultural technology extension stations, and township information service stations. Comprehensive information service platforms integrating television, telephone, and computer ("three-in-one") have been built, effectively expanding agricultural information service coverage by leveraging the advantages of various information carriers. In terms of talent development, approximately 150,000 agricultural science and technology commissioners are active at the grassroots level in rural areas. More than 40 agricultural information service network channels have been established, led by "China Agricultural Information Network."

Currently, multiple large-scale networked knowledge service platforms have been built in China to collect, transmit, and preserve digital research achievements in agriculture, disseminate agricultural knowledge to production operators, and provide agricultural information services and value-added services. For example, the "Nongsou" professional search engine has 6 million agricultural cooperative websites, enabling full-text and semantic retrieval. The "Sounong" search engine provides information retrieval on supply and demand, prices, market dynamics, agricultural technology, videos, news, and pests/diseases. Wanfang Data has built an agricultural knowledge service platform based on Chinese literature data. Under the guidance of the Science and Education Department of the Ministry of Agriculture and Rural Affairs, the Agricultural Science and Technology

Network Bookstore provides personalized customized push services for modern agricultural technology promotion. The "National Agricultural Science and Education Cloud Platform" enhances the efficiency of agricultural technology extension services and professional farmer training. The "Comprehensive Agricultural Education Service Platform" (Yunshang Zhinong) provides the latest and most popular agricultural knowledge articles, market trends, and relevant policies, creating an all-weather, full-process, and full-function service center integrating education, industry, and life for farmers.

The Agricultural Information Institute of the Chinese Academy of Agricultural Sciences has developed the "Agricultural Professional Knowledge Service System," pioneering scenario-based intelligent knowledge services based on agricultural science and technology big data under Internet conditions. It provides agricultural science and technology knowledge supply services to 33 provinces, 875 research institutions, and over 30,000 university users nationwide. The system has created an "Internet + Agricultural Technology Extension" cloud platform portal achieving full coverage of 37 provincial units and over 2,600 agricultural counties, serving more than 500,000 grassroots agricultural technicians, over 3 million technology demonstration households, and over 30 million radiating farmers. The Beijing Academy of Agriculture and Forestry Sciences has developed the "Jingke Huinong" agricultural information AI consulting service platform, creating scenario-based intelligent knowledge services including "intelligent search + knowledge topics + intelligent Q&A + personalized recommendation," covering 31 provinces and 2,845 counties with 7 million users. The College of Information Science and Technology of Hunan Agricultural University has created a comprehensive service platform for rural agricultural informatization based on cloud computing, which has been fully promoted and applied in 14 cities and prefectures in Hunan, training over 5,000 agricultural information officers and addressing more than 370,000 farmer requests. The C-life Smart Agriculture company has built an agricultural big data service platform applied to multiple agricultural enterprises such as Shenzhen Pengcheng Farmer Guangming Grape Garden, Henan Linying Chili Pepper, and Guangdong Xuwen Pineapple.

Domestic research and practice on agricultural information service platforms have progressed rapidly, propelling China' s agricultural information services into a new stage of intelligent knowledge services. However, overall, China' s agricultural knowledge services still face issues such as imbalanced knowledge supply and demand, significant regional disparities, inadequate information service channels, and insufficient application of modern information service technologies. These manifest as poor timeliness and continuity of real-time agricultural data collection, untimely information services, insufficient data mining and analysis, limited coverage of business entity types and scope, and scarcity of effective data for production management and decision-making. There is an urgent need to build multi-scenario, professional, and personalized intelligent knowledge service platforms to comprehensively serve the knowledge needs of China' s agricultural business entities and support the improvement of quality and efficiency in modern agriculture.

3. Framework and Key Technologies for Agricultural Intelligent Knowledge Services

Under new circumstances, the demand for knowledge services from agricultural business entities exhibits new characteristics of personalization, precision, and intelligence. Traditional information services focused primarily on information search can no longer meet the complex needs of different industrial stages, regions, varieties, users, and scenarios. Utilizing new technologies such as IoT, big data, and artificial intelligence to provide full-chain knowledge and technology empowerment for agricultural business entities before, during, and after production—enabling agricultural situation data perception, intelligent agricultural production early warning, precise agricultural knowledge recommendation, and smart agricultural management decision-making—represents the development goal of current and future agricultural knowledge services.

3.1 Framework for Agricultural Intelligent Knowledge Services

Based on the entire agricultural industry chain and following the full lifecycle of agricultural data, this paper proposes a systematic framework for agricultural intelligent knowledge service systems that integrates data acquisition, knowledge organization, and intelligent services. The framework includes three hierarchical layers: multi-source heterogeneous agricultural big data aggregation/governance, agricultural knowledge organization and computational mining, and multi-scenario agricultural intelligent knowledge services. This provides new ideas and implementation pathways to address emerging contradictions in agricultural knowledge supply and demand, as illustrated in [Figure 3: see original paper].

The **data acquisition layer** primarily implements AIoT-based agricultural situation perception and aggregation/governance of agricultural prior knowledge, forming the data foundation for knowledge services. According to the intelligent knowledge service requirements of agricultural business entities, we construct a real-time agricultural situation data perception system with aerial-ground integrated AIoT as key elements. This system effectively leverages the combined advantages of satellite remote sensing (wide coverage, spatial continuity), UAV ultra-low-altitude multi-angle observation (high precision, temporal continuity), and ground intelligent IoT real-time observation (authentic information) to overcome the limitations of single sensors and single observation pathways. It enables comprehensive, three-dimensional, real-time, and accurate acquisition of agricultural situation data including meteorology, hydrology, area, and information on animal/plant environments and life activities. Combined with agricultural prior knowledge accumulated through scientific literature (journals, books, reference books, conference proceedings, technical reports, dissertations, standards, patents, etc.), scientific data (agricultural scientific achievement data obtained by universities, research teams, and research institutions through large-scale observation, detection, investigation, and experimentation), historical statistics (statistical yearbooks collected by governments and third-party organizations, government reports, and guidelines and alerts from public institutions), and domain experts (expert knowledge accumulated and compiled over the long term by academicians, researchers, and innovative talents with scientific research achievements and teaching influence in the agricultural field), as well as massive multimedia agricultural data (text, audio, images, video) obtained from internet consulting (science and technology policies, news, academic websites, forums, etc.) and crowdsourcing technologies (data on transportation, plants, crops, yield, weather conditions, etc.), this layer achieves data support for all agricultural fields, all elements, and the entire industry chain.

The **knowledge organization layer** primarily uses agricultural scientific thesauri, scientific corpora, and classification systems as reference tools. Through operations such as determining core concepts and hierarchical structures, constructing inter-concept relationships, and establishing concept attributes and constraints, it guides the construction of a complete and shared cross-domain agricultural situation ontology model to better characterize agricultural domain entities, attributes, relationships, and processes. Furthermore, it implements cross-media agricultural knowledge representation and knowledge association/fusion based on knowledge graphs, connecting massive, discrete, and structurally complex agricultural data to provide unified, standardized conceptual terminology in structured form. Finally, through collaborative knowledge annotation, mining, reasoning, and natural language processing by industry experts and AI experts, it tightly integrates knowledge graphs with agricultural content resources, supporting the generation of new agricultural knowledge objects through computation, reorganization, fusion, and recreation. This achieves the transformation from data to knowledge and forms the foundation for intelligent services.

The **intelligent service layer** builds multi-scenario agricultural intelligent knowledge service applications for end users. Only by constructing a self-growth model in the form of agricultural knowledge organization and knowledge computation, and automatically utilizing real-time agricultural situation data and prior knowledge to support decision-making applications, can it be applied to more complex full-process agricultural production scenarios. This layer helps agricultural business entities formulate more effective pre-production planning, in-production management, and post-production guidance strategies, providing full-process cross-media knowledge retrieval, intelligent Q&A, service customization, personalized intelligent recommendation, and decision support services for agricultural production before, during, and after production, including pre-production planting planning decision support, in-production planting technology recommendations, pest/disease diagnosis, monitoring and early warning, agricultural situation prediction, and post-production processing and sales decision support.

3.2 Agricultural Data Acquisition

Data acquisition forms the foundation of knowledge service data sources. Based on data source channels and structural characteristics, diversified directional monitoring and dynamic collection strategies can be formulated. The main technologies include aerial-ground integrated AIoT-based agricultural situation perception and multi-source heterogeneous agricultural big data aggregation/governance.

3.2.1 AIoT-Based Agricultural Situation Perception AIoT refers to the integration of artificial intelligence technology and Internet of Things applications, widely used in national defense, smart industry, public utilities, and other fields. With the development of smart agriculture, AIoT technology has gradually become active in all aspects of agricultural production, transaction, finance, and management. As an important approach for data acquisition in agricultural intelligent knowledge services, constructing a full-dimensional agricultural data monitoring system with aerial-ground integrated AIoT as key elements can collect weather and climate data to guide farming, obtain livestock monitoring, field research and observation, inventory and budget monitoring, and vehicle/transportation management data to provide smart planting and breeding guidance services.

In practice, Liao et al. designed a smart agricultural AIoT system data processing platform based on a front-end and back-end separation architecture, enabling real-time multi-dimensional data monitoring, historical data query, data visualization, and abnormal data alarm for crops, providing effective data support for soil environment monitoring systems and intelligent pest monitoring systems. Chen et al. utilized UAV high-definition cameras and above-ground/underground sensors to obtain pest damage and soil condition data, constructing an agricultural pest detection system that effectively provides pest locations and damage levels to help farmers apply pesticides precisely at the right time and place. Liao obtained multi-spectral image data based on remote sensing for meteorology, hydrology, and crop growth conditions, imaging spectrometer data based on UAV for farmland vegetation health status, and IoT-based monitoring data on animal/plant physiological behavior and growth to build a smart agricultural information system oriented toward agricultural situation perception at different spatial scales, effectively guiding agricultural production planning.

Aerial-ground integrated AIoT agricultural situation perception technology can effectively leverage the joint advantages of satellite remote sensing (wide coverage, spatial continuity), UAV observation (high precision, temporal continuity), and ground intelligent IoT real-time observation (authentic information). This overcomes the limitations of single sensors and single pathways, ensuring comprehensive, three-dimensional, real-time, continuous, and accurate agricultural situation data acquisition, providing a reliable data foundation for agricultural intelligent knowledge services. Additionally, agricultural data obtained through

AIoT technology can analyze and predict the needs of agricultural business entities in a more dynamic and systematic manner in real time. Based on analysis results, services can be automatically optimized and adjusted, and even adapt to environments and make autonomous decisions. In summary, aerial-ground integrated AIoT-based agricultural situation perception organically integrates various physical, process, and knowledge links in agricultural production through intelligent technology, enabling automatic, autonomous, adaptive, and self-optimizing operations, gradually transforming from a production model centered on human physical and intellectual labor with agricultural equipment as auxiliary facilities to one centered on human-machine collaborative intelligence with automated, intelligent, and knowledge-based agricultural production.

3.2.2 Multi-Source Heterogeneous Agricultural Big Data Aggregation/Governance Agricultural big data encompasses AIoT-based agricultural situation perception data, agricultural scientific literature data, agricultural scientific data, internet open data, and domain expert knowledge. With diverse sources, massive scale, varied types, and complex structures, it requires cleaning, processing, aggregation, fusion, storage management, and other treatments to improve digital resource utilization efficiency and fully realize data value. Common big data integration/governance is typically based on the full data lifecycle, focusing on solving issues such as data collection, conversion, aggregation, management, privacy, quality, evaluation, and interface services. This involves key technologies including data resource registration, unified management, multi-point transmission, multi-modal storage, visual monitoring analysis, high-performance parallel computing, and multi-channel data incremental update and distribution.

In practice, Kamilaris et al. introduced the acquisition of multi-source heterogeneous agricultural big data through continuous monitoring of agricultural animal/plant growth physical environments, government/third-party organizations, networks, and crowdsourcing channels, covering data properties, dimensions, usage scales, aggregation/governance solutions, and tools. Cravero et al. used PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) methods to review agricultural big data aggregation/governance methods, processing unstructured agricultural data at maximum capacity through machine learning methods such as neural networks, support vector machines, decision trees, and Bayesian methods to generate effective relationships and reconstruct knowledge patterns. Newton et al. designed a big data aggregation/governance framework for Australian dairy herd records, using thematic analysis, content analysis, bag-of-words models, and natural language processing to analyze data from multiple dairy farms including environmental and biological data, farm business and financial data, and farm infrastructure investment data. Roukh et al. proposed a cloud-based Wallesmart intelligent agricultural big data processing platform that introduces Lambda, Kappa, and hybrid architectures to solve problems of real-time collection, processing, storage, and visualization of data.

Agricultural big data aggregation/governance is key to improving data quality and ensuring sustainable data utilization, providing high-quality basic data guarantees for subsequent agricultural knowledge organization and computational mining.

3.3 Agricultural Knowledge Organization and Computational Mining

The standardized organization, management, and computational mining of multi-source agricultural knowledge are important foundations for achieving intelligent knowledge services. The essence is to establish relationships between isolated knowledge units, mine implicit or potential knowledge, form systematic knowledge, and solve knowledge fragmentation problems. Knowledge Graph, as a new data infrastructure and knowledge organization form in the big data era, can gradually refine originally unstructured, unassociated rough data into structured, strongly associated high-quality knowledge through its semantic standardization and linking ideas. It has powerful advantages in achieving semantic association and evolutionary updates of multi-source multi-modal data, scenario-based intelligent search, precise recommendation, and knowledge inversion reasoning. Examples include Knowledge Vault, Freebase, DBpedia, Wikidata, and Yago. [Figure 4: see original paper] summarizes knowledge graph construction methods and basic processes; for more application examples and creation tools, please refer to the literature.

Agricultural knowledge graphs have attracted widespread international attention, such as the FOODIE agricultural knowledge graph from the Poznan Supercomputing and Networking Center (PSNC) laboratory in Poland, the multi-source knowledge graph from Bayer Corporation in the United States, the holographic knowledge graph database developed by the Beijing Agricultural Information Technology Research Center, and the crop pest/disease and rice knowledge graphs from the Agricultural Information Institute of the Chinese Academy of Agricultural Sciences. Knowledge graphs are important methods for agricultural knowledge organization and computational mining, involving key technologies such as knowledge modeling, knowledge extraction, knowledge fusion, and knowledge reasoning.

3.3.1 Agricultural Knowledge Modeling Ontology knowledge modeling is the semantic foundation for entity connectivity in knowledge graphs. It requires designing concept sets and frameworks to reasonably organize knowledge and accurately describe relevant classes and attributes—namely, entities and their relationships. The construction of agricultural situation ontology models is based on agricultural scientific thesauri (Chinese Agricultural Thesaurus, CAT), scientific corpora, and classification systems to determine core concepts and their attributes/constraints, hierarchical structures, and inter-concept relationships. This is typically done through manual construction using ontology editing software or through automatic extraction based on rules and conditional random fields. For example, the Levy method effectively overcomes the problems of uncertain dimensions and insufficient semantic data in traditional vector space-based ontology extraction. To fully consider factors such as meteorology, pests, and soil in agricultural production, Deepa and Vigneshwari used a term relationship identification method combining text similarity and Naïve Bayes algorithms to achieve cross-domain agricultural situation ontology extraction based on rule-based formal concept analysis and mapping. Goldstein et al. designed a method for evaluating the effectiveness of agricultural ontology extraction, fully considering the value of agricultural ontologies for research and practical applications.

Currently, research on agricultural situation ontology model construction has yielded abundant results with relatively mature technical methods. In practice, factors such as the rationality of concept division, attribute definition methods, and the extensibility of conceptual systems must be considered to ensure the scientific and systematic nature of knowledge modeling.

3.3.2 Agricultural Knowledge Extraction Knowledge extraction refers to extracting elements such as entities, relationships, and attributes from large amounts of different sources and data types. It is an important technology for automatically constructing large-scale knowledge graphs, and the completeness and accuracy of knowledge extraction directly affect knowledge graph quality. Agricultural knowledge extraction mainly includes two tasks: entity extraction and relationship extraction. Agricultural entities are the core units of agricultural knowledge graphs, and the completeness, accuracy, and recall rate of entity extraction directly affect knowledge graph quality. Traditional entity extraction methods such as Hidden Markov Models, Maximum Entropy, and Support Vector Machines are mostly applied to single text modalities and require large amounts of annotated corpora. Agricultural data is widely distributed, diverse in type, and varied in structure, with multimedia characteristics including text, audio, images, and video. Deep learning-based entity extraction methods are typically used.

Relationship extraction refers to automatically detecting and identifying semantic relationships between entities from text/images/videos. Widely used methods include Feature engineering, kernel, graph models, and deep learning-based Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks. For multi-modal mixed agricultural data, knowledge extraction research mainly uses deep learning methods such as Convolutional Neural Networks (CNN) and attention mechanisms combined with LSTM. Examples include a self-training framework embedding multiple semantic heterogeneous elements in recurrent neural networks, extended graph convolutional neural networks that can effectively process arbitrary dependency structures in parallel, and methods based on natural language generation of graph neural network parameters that enable neural networks to perform relational reasoning on unstructured text inputs. Additionally, the BERT (Bidirectional Encoder Representation from Transformers) model can be used for relationship extraction and semantic role labeling, extracting relationships between people while reducing the impact of noisy data on relationship extraction models.

Agricultural data often contains large amounts of text descriptions and image/video materials. For multi-modal mixed agricultural data, knowledge extraction research mainly uses deep learning methods such as CNN and attention mechanisms combined with LSTM. To address the problem that traditional named entity recognition methods for agricultural pest information extraction rely on manual dictionaries and insufficient feature extraction, Lun and Hui proposed an agricultural knowledge extraction method based on pre-trained BERT, combining the particularity of agricultural entity texts and scene image features for relationship prediction using multi-modal semantic and structural representation to achieve rapid and accurate agricultural knowledge extraction. Qiao et al. introduced the BERT pre-trained language model, combining agricultural text and image features to build a joint knowledge extraction method for extracting agricultural multi-modal entities and discovering intra-modal and cross-modal entity relationships. Zhao Pengfei et al. proposed a named entity recognition method fusing BERT character-level features and external dictionary features. Multi-modal data entity relationships in agriculture are primarily extracted by obtaining semantic and structural representations of cross-media information to extract text corpora containing entities and scene image features for relationship prediction. Deep learning-based entity relationship extraction methods are currently the mainstream direction, effectively combining multi-modal data features to ensure maximum extraction of semantic information from different agricultural data modalities.

3.3.3 Agricultural Knowledge Fusion Knowledge fusion refers to aligning and merging knowledge from different sources to solve the heterogeneity problem of knowledge graphs and make knowledge connections denser. It includes two aspects: schema layer fusion and data layer fusion. Schema layer knowledge fusion aligns multiple knowledge bases, mainly including entity alignment and cross-language fusion technology. Entity alignment performs concept mapping between ontologies, discovering hidden relationships between heterogeneous ontologies based on similarity of attribute names, types, and values. Cross-language fusion technology facilitates worldwide knowledge sharing and improves machines' automatic integration capabilities for different languages, thereby constructing large-scale cross-language knowledge bases covering important knowledge bases. Data layer knowledge fusion primarily focuses on entity linking and entity resolution. Entity linking connects entities extracted from text with corresponding entity objects in knowledge bases, with the key being entity identification, including identifying ambiguity of similar entities and co-occurring entities.

Common knowledge fusion methods include: enriching the neighborhood of equivalent entities through ontology entity labels and subgraph matching of external ontologies; achieving knowledge graph embedding through simple constraints; and measuring the correlation between questions and entities using cosine similarity between corresponding vectors. For massive data processing, Tai et al. proposed the HykOffice (Hybrid Knowledge Fusion and Inference on Cloud Environment) system, which can perform parallel computing in the cloud and control the execution time of hybrid knowledge fusion and reasoning. Considering the heterogeneity between agricultural multi-modal data, knowledge fusion of either text or image single modality alone makes the alignment mapping between text feature vectors and image entity feature vectors extremely difficult. Current mainstream agricultural knowledge fusion methods primarily use deep learning. For example, Qin and Yao used deep learning to obtain complementary features between text and image from massive datasets acquired through remote sensing, UAV, and near-ground sensors at different spatiotemporal scales and combined them to achieve comprehensive agricultural data fusion. Moshou and Pantazi proposed a multi-modal agricultural knowledge fusion method based on word vectors and semantic cosine distance similarity calculation, which can effectively fuse different attributes of the same agricultural entity from different data sources.

As agricultural knowledge graphs expand in scale and entity numbers, large amounts of data and knowledge from different sources need to be fused, often using knowledge base alignment methods. For agricultural (text, image, and video) multi-modal data, due to heterogeneity between image knowledge and text knowledge, separate embedding makes entity alignment extremely difficult. Therefore, based on joint embedding results, agricultural entity alignment is achieved according to distances in low-dimensional semantic spaces. Two challenges encountered in this process include synonyms and polysemous words. For example, leaf spot disease is a general term for different crop leaf spot diseases, including black spot, red spot, paint spot, etc., while corn leaf spot disease is also known as stripe disease, coal sheath disease, leaf blight, or leaf spot disease. In summary, how to accurately and efficiently align entities is one of the future research focuses of agricultural knowledge fusion and a key task in agricultural knowledge graph construction.

3.3.4 Agricultural Knowledge Reasoning Knowledge reasoning refers to inferring new facts, relationships, axioms, and rules based on existing facts or relationships in knowledge graphs. Main technical methods include description logic-based reasoning, graph structure-based reasoning, distributed representation learning-based reasoning, neural network-based reasoning, and hybrid reasoning. With the development of intelligent technologies such as deep learning in recent years, relevant research results have continuously emerged, such as joint reasoning methods based on rules and neural networks, and automatic knowledge reasoning methods combining concept graphs with semantic webs.

In agricultural knowledge graphs, there are three data storage methods: nodes, relationships, and attributes. Data with uniqueness is stored as nodes (e.g., wheat, corn, soybeans); data with high repetition is stored as attributes (e.g., agricultural animal physiological indicators such as heart rate and body temperature, individual behavior indicators such as feeding and activity, production indicators such as weight and yield, and agricultural plant indicators such as plant height and color); and data with important semantic information is stored as relationships (e.g., remote sensing, UAV, and monitoring equipment). By setting reasonable data storage methods, redundant nodes with less semantic information can be reduced on one hand, and isolated nodes with too few adjacent nodes can be reduced on the other, thereby improving the density of effective knowledge in the graph.

Currently, many applications of knowledge graphs in agriculture have been reported, including knowledge graphs for optimizing agricultural production structures, ontology-based agricultural knowledge management systems, agricultural ontology construction frameworks for smart agriculture, China meteorology and agriculture knowledge graphs based on semi-structured data, automatic integration of massive agricultural data from the internet, and variable-speed irrigation and fertilization control systems for crop irrigation. Zhang et al. introduced the research and application status of knowledge graphs in agriculture both domestically and internationally, and proposed systematic solutions and approaches for the construction and application of knowledge graphs in China' s agricultural domain. Agricultural knowledge reasoning mainly uses knowledge graph completion methods to predict relationships between entities and attributes in agricultural knowledge graphs. Common application scenarios include agricultural animal/plant pest/disease diagnosis and management, with corresponding research practices. For example, Guan et al. used pest/disease text and image features to build a fruit tree pest/disease knowledge graph associated with symptoms, encoded agricultural domain knowledge through knowledge representation models, and performed knowledge reasoning using joint representation vectors of pest/disease text and images to achieve accurate prediction of fruit tree pests/diseases. Fajri et al. proposed a framework and rule-based knowledge graph construction and reasoning method to determine whether peanut plants are infected with certain diseases. Nascimento et al. developed a handheld pest/disease diagnosis tool using expert knowledge to assist in diagnosing important pests in commercial teak. Damos developed a pest expert system using ontology and semantic knowledge representation technology to simulate the impact of pests/diseases on crops. Babalola et al. combined pest/disease models with crop models to design a modular method for pest diagnosis modeling based on knowledge reasoning. Zhang Shanwen et al. used Bi-directional Long Short-Term Memory (Bi-LSTM) networks based on knowledge graphs to predict wheat stripe rust, providing a scientific basis for wheat stripe rust prediction and early warning. Knowledge reasoning can automatically complete auxiliary decision-making and quality assessment, ensure data quality, and improve the reliability and accuracy of agricultural knowledge.

Due to the diverse types and hierarchies of relationships between different modal entities in agriculture, although the agricultural knowledge graph generated through multi-source heterogeneous agricultural big data aggregation/governance contains massive data, basic relationships may be missing during construction for various reasons, resulting in incomplete agricultural knowledge graphs. The completeness of knowledge graphs directly affects the application of knowledge graph reasoning. Therefore, to effectively adapt to the dynamic evolution of agricultural content, it is necessary to combine the agricultural information needs of business entities and use human-machine collaborative knowledge annotation methods to construct agricultural multi-modal knowledge graphs. Based on agricultural ontology annotation, human intelligence is introduced to regularly correct and update annotation results, and the corrected agricultural semantic concept information is used to further update and optimize semantic annotation models for animal/plant environment and life feature extraction and state recognition, improving the accuracy of semantic annotation algorithms in subsequent annotations. Shi et al. used agricultural Q&A data and popular science data obtained through text crawlers as raw data, selected tags to establish crop portraits including three major categories—crops, pesticides, and pests/diseases—and used graph databases to store and display these portrait data. Dung et al. proposed a set of methods, computational frameworks, and practical application systems for vertical knowledge graph construction in the agricultural domain, using agricultural knowledge reasoning to adjust planting plans for small agricultural-related enterprises.

3.4 Agricultural Intelligent Knowledge Services

The goal of agricultural knowledge services is to achieve dynamic matching between knowledge and application scenarios, providing agricultural production and business entities with full-process knowledge retrieval, Q&A, personalized recommendation, and decision support services for pre-production planning, in-production management, and post-production guidance.

3.4.1 Agricultural Cross-Media Retrieval With the rapid growth of agricultural knowledge and the increasing complexity of agricultural knowledge types and structures, different modalities such as text, images, video, and audio coexist. Traditional single-media search based on content feature similarity can no longer meet the retrieval needs for multi-modal agricultural knowledge. How to break through the expression boundaries of multimedia resources and obtain potential associative knowledge between different types and structures of multimedia data to achieve cross-media retrieval based on semantic correlation has become a hotspot in current agricultural knowledge services. The difficulty of cross-media retrieval technology lies in eliminating the heterogeneous gap between different media. Early methods relied heavily on manual annotation, while later methods adopted machine learning, conditional random models, topic models, and deep learning.

Chen et al. proposed an agricultural cross-media knowledge retrieval method that can automatically identify agricultural entities from unstructured text and simultaneously present attribute information including text, images, video, and audio, as well as other relevant information when retrieving agricultural animal/plant names. Wang Dandan et al. developed a cross-media rice knowledge search platform that uses differences in text and image modal rice field data for knowledge extraction, completing retrieval tasks using a rice knowledge graph. Zhang Haiyu et al. built a cross-media knowledge retrieval system for grain crops, collecting a large number of proprietary terms in semantic knowledge graph construction, performing word segmentation and part-of-speech annotation to help farmers solve retrieval problems more accurately and timely, improving efficiency in actual production processes. Compared with traditional information search, agricultural cross-media knowledge search is more user-friendly for agricultural business entities, improves the dissemination efficiency of agricultural knowledge, and suits different users' reading habits.

3.4.2 Agricultural Intelligent Q&A In 2011, Etzioni from the University of Washington published an article in *Nature* stating: "Automatic question-answering systems that answer user questions in natural language directly and accurately will constitute the basic form of next-generation search engines."Intelligent Q&A technology has become a research hotspot in information intelligent services due to its support for natural language input, precise capture of user intent, and accurate feedback of answers. Early Q&A systems were mostly based on similarity matching and required pre-prepared large Q&A databases. Knowledge graph technology, with its powerful knowledge representation and reasoning capabilities, has further improved the performance and scalability of intelligent Q&A systems. Especially by constructing domain-oriented knowledge graphs, more complex Q&A applications can be achieved.

For example, Chen et al. built an agricultural technology knowledge Q&A system where users can ask questions in text or image form, and the system provides relevant agricultural knowledge and links based on the knowledge graph. Kalita et al. developed a rice Q&A system that can answer questions about problems or diseases occurring throughout the entire rice lifecycle. Xue Huifang designed an agricultural information intelligent Q&A system that builds interest trees according to user preferences and predicts user interests to recommend a series of related agricultural information. In summary, with the advent of the big data and intelligent era, the demand for knowledge search and acquisition based on intelligent Q&A will become increasingly strong, becoming an important driving force for the upgrade of information services to intelligent knowledge services.

3.4.3 Personalized Recommendation Technology Agricultural production has obvious dynamic variability, regional diversity, and cyclical changes. General information service systems often struggle to meet the personalized and professional needs of agricultural production and management, leading to mismatches between knowledge supply and demand. Personalized recommendation technology can provide more targeted and precise services by incorporating contextual factors and user characteristics.

Qiu Jin and Li Qiuxia designed an agricultural information personalized recommendation service platform that incorporates agricultural context characteristics, user search/browse behavior, features, and preferences to recommend agricultural information that better meets the real needs of agriculture-related users. Hui Yinfan proposed an agricultural planting technology personalized recommendation system that ensures the accuracy and timeliness of recommended planting technologies by obtaining and analyzing users' current behavioral characteristics. Jia Weiyang developed a personalized recommendation system that obtains group user portraits through clustering of basic information and content preferences, uses a collaborative filtering algorithm based on user interest proximity to weight and fuse recommendation results, and pushes them to users, improving the quality and personalization of system recommendation services. In recent years, with the development of knowledge graph technology, research on knowledge graph-based personalized recommendation systems has gradually deepened. Knowledge graphs can describe user characteristics at a finer granularity, improve similarity calculation accuracy, enrich recommendation results, and enhance personalized recommendation system performance.

Guo Shuai built an agricultural information service personalized recommendation system that constructs an agricultural domain ontology for comprehensive agricultural information service applications, combines user demands, user emotions, and user interest levels to build user portraits, and comprehensively considers the structural characteristics of agricultural comprehensive information service platforms as well as constructed user models and graph information to provide precise personalized recommendations for users. Wang Mengyao developed an agricultural product e-commerce personalized recommendation system that constructs group dynamic user portraits based on agricultural product domain knowledge graphs, uses a hybrid recommendation algorithm combining dynamic portraits and collaborative filtering within groups to achieve personalized recommendations, and predicts agricultural product supply and demand to achieve precise matching of production, supply, and sales, as well as intelligent recommendations for production-supply-sales knowledge services and industry experience.

3.4.4 Agricultural Decision Support With the widespread application of agricultural information technology, using agricultural decision support systems to guide agricultural production and assist decision-making has become very common. Typical application scenarios include agricultural situation monitoring, production guidance, market analysis, and predictive decision-making.

The DSSAT (Decision Support System for Agrotechnology Transfer) launched by the University of Hawaii is a crop simulation model-based decision support system that provides decision support for users through computation and Q&A. Paredes et al. built a vegetable price prediction system that applies historical price data analysis to construct price prediction models, providing better decision support information for Mexican farmers. Ballot et al. used case matching to propose an agricultural intelligent decision support simulating continuous crop yields, taking winter wheat and broad beans as examples, combining farmland soil, meteorological, economic, and social data to provide the most valuable agricultural guidance for farmers and evaluate the system’ s long-term sustainable operation.

In China, although research and application of agricultural decision support systems started later than abroad, they have developed rapidly. Classic agricultural decision support systems such as agricultural product monitoring and early warning systems, rice fertilization expert systems, and wheat-corn intelligent decision systems have been launched, strongly supporting China’ s agricultural modernization. For example, Zhuang Jiayu et al. built a supply and demand prediction model for multiple agricultural products based on deep learning LSTM, achieving analysis and prediction of supply and demand for nine major agricultural products including rice, wheat, and corn, providing intelligent technical support for multi-regional, cross-period agricultural outlook work. Li Zhibo et al. launched a rice canopy variable nitrogen application decision system that diagnoses rice canopy nitrogen content by detecting soil nitrogen content and constructing variable nitrogen application models, proposing decision plans for variable nitrogen application for precise fertilization, effectively increasing rice yield while avoiding excessive growth and lodging. Wang Hongxi et al. developed a precision irrigation decision support system for winter wheat and summer corn that meets both government needs for regional groundwater exploitation regulation and water management needs of farmers with different operation scales. Huazhong Agricultural University proposed a farmer decision-making behavior simulation model under changing economic environments, and the Chinese Academy of Sciences proposed an intelligent production scheduling calculation method based on crop models to meet planting needs.

In summary, driven by new information technologies and artificial intelligence, especially the in-depth application of knowledge graphs, agricultural decision support systems exhibit trends of intelligence, integration, and distribution. By using deep learning, knowledge graph concepts and methods to store and analyze expert knowledge from different fields and intelligently select among various possible solutions, they achieve decision support for highly complex tasks and promote the integration of agricultural intelligent decision support into agricultural production and operation environments.

4. Challenges and Future Perspectives

Although research and practice in agricultural intelligent knowledge services have made progress, they still face the following challenges.

4.1 Challenges

1. **Agricultural Data Acquisition:** Multi-source cross-domain agricultural situation data has become an important resource element and strate-

gic resource for modern agriculture. As an important approach for data acquisition in agricultural intelligent knowledge services, the difficulty of aerial-ground integrated AIoT full-dimensional agricultural situation perception lies in the high cost of deploying agricultural IoT and the lack of technical standards for data collection, transmission, platform interfaces, and sensors. Particularly in terms of low-cost sustainable acquisition of long-cycle, long-sequence agricultural situation data, the integration of real-time agricultural knowledge mining and discovery is relatively low. Although the development of big data, cloud computing, and IoT technologies has promoted the continuous improvement of multi-dimensional agricultural knowledge acquisition task accuracy, there is still a large gap from achieving large-scale, multi-domain agricultural knowledge services. Additionally, "single-source" agricultural situation data, "untimely" knowledge updates, insufficient precision management, "disconnected" service supply and demand, and lack of high-precision, large-scale crop production intelligent monitoring means make it difficult to achieve spatiotemporal fusion of multi-source, multi-scale, multi-dimensional, and multi-media key parameters for intelligent agricultural situation monitoring.

2. **Agricultural Model Performance:** The processing accuracy of agricultural models is relatively low. Although developments in machine learning, computer vision, natural language processing, and speech recognition have promoted continuous improvement in agricultural intelligent service task accuracy, multi-modal collaborative agricultural situation inversion, prediction, and intelligent computing are insufficient to support scientific decision-making across the upstream, midstream, and downstream agricultural industry chain. There is still a large gap from achieving high-level artificial intelligence.

3. **Knowledge Organization:** Current agricultural knowledge is fragmented and decentralized, making it difficult to effectively discover high-economic-value multi-domain cross-media agricultural situation knowledge and rules. Constructing cross-domain agricultural situation ontologies combining agronomy, meteorology, hydrology, economics, sociology, and other theories and case studies is extremely difficult, making it challenging to establish a unified global view of multi-domain, multi-media, multi-scenario agricultural situation feature data in high-level semantic space.

4. **Knowledge Graph Engineering:** The professionalism of agricultural knowledge graphs is relatively low. Currently, agricultural knowledge graphs generally have problems of small scale, single modality, and single domain, with very limited accessible knowledge. There is an urgent need to develop and establish large-scale, multi-modal, cross-media agricultural knowledge graphs.

5. **Intelligence and Precision:** The intelligence level of agricultural knowledge mining and the precision of agricultural knowledge services are rel-

atively low. Faced with problems such as insufficient traditional agricultural information services and prominent knowledge supply-demand contradictions, intelligent service scenarios based on operator needs—such as online-offline interaction, adaptive collaboration, seamless cloud-network-end coupling, and personalized information recommendation—are increasing daily. Although knowledge mining analysis, precise matching, and intelligent recommendation based on machine learning and artificial intelligence are widely applied, the imbalance between massive agricultural data and valuable agricultural knowledge supply and demand is a difficult problem to solve, also limiting the robustness, credibility, and performance accuracy of downstream tasks.

4.2 Future Perspectives and Recommendations

With the cross-integration development of emerging technologies such as edge computing, big data, artificial intelligence, IoT, and the metaverse with modern agriculture, agricultural intelligent knowledge services will be strengthened in the following aspects:

1. **Agricultural Data Acquisition:** Emphasize the construction of low-cost sustainable agricultural and rural informatization infrastructure, strengthen independent research and development of key data collection equipment and technologies such as agricultural sensors, enhance precise perception, monitoring, collection, fusion, and analysis of multi-domain, multi-terminal, multi-modal agricultural situation information such as crop breeding and growth, agricultural resources and environment, animal epidemics, and plant pests/diseases. Accelerate the improvement of the aerial-ground integrated agricultural situation holographic perception technology system based on AIoT technology, establish multi-source multi-scale agricultural big data knowledge fusion strategies, create "data + knowledge" collaborative agricultural real-time knowledge mining and discovery models, and build a national grid-based full-chain agricultural situation data monitoring and sharing system.
2. **Agricultural Model Construction:** Strengthen the combination of agricultural models and perception technologies, attempt to add or replace modules in key technologies such as multi-source cross-domain agricultural knowledge acquisition, association discovery, iterative evolution, inversion prediction, retrieval, and Q&A. Construct a multi-modal collaborative agricultural situation inversion, prediction, and intelligent computing system, research technologies and models for plant growth monitoring, public opinion prediction, agricultural situation inversion, and yield/price prediction. Accelerate independent research and development of full-industry-chain agricultural models oriented toward agricultural situation information needs throughout the entire process from breeding, planting to rough processing, deep processing, assembly, transportation/storage, sales, and consumption. Promote the application of agricultural models, artificial

intelligence, and data analysis technologies in smart agriculture.

3. **Agricultural Knowledge Organization:** Emphasize the construction of foundational agricultural knowledge corpora, strengthen the research and development and engineering application of agricultural domain knowledge graph construction tools, and accelerate the construction of practical agricultural knowledge graphs. Technically, establish large-scale, multi-modal, cross-media agricultural knowledge graphs, focusing on improving the accuracy of agricultural knowledge extraction and semantic association. Refer to cutting-edge methods of cross-media knowledge graph construction to improve the performance of dynamic generation, semantic association, and evolutionary update tasks of agricultural knowledge. Leverage the complementarity of knowledge contained in different modal data to enhance and supplement each other, using multi-modal data to further complete knowledge graphs and improve the efficiency of multi-modal agricultural knowledge service tasks.

4. **Agricultural Intelligent Knowledge Service Technology:** Establish an intelligent knowledge service model integrating knowledge organization and machine learning, construct a "knowledge + scenario" dual-driven agricultural knowledge service system, accelerate the research and development of key technologies such as cognitive search, knowledge matching, intelligent Q&A, and personalized services. Based on intelligent service scenarios such as online-offline interaction, adaptive collaboration, seamless cloud-network-end coupling, and personalized information recommendation according to operator needs, achieve the upgrade of agricultural knowledge services to personalization, precision, and intelligence.

5. **Application Promotion:** Increase the integration of efficient agricultural technology with the market, continuously improve the national agricultural information service system, and form a socialized service pattern with government coordination, departmental collaboration, and social participation. Accelerate the cultivation of new agricultural business entities, enhance their ability to acquire and apply agricultural knowledge, and promote the transformation of agricultural knowledge into agricultural productivity.

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