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Original scientific paper

Formation Mechanism and Implementation Path of a Digital Agriculture Innovation Ecosystem

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Abstract: Digital agricultural innovation ecosystems defined the notion of agricultural innovation ecosystems in regional areas. Developing a data economy for agriculture based on digital spaces necessitates an awareness of and proficiency with digital innovation ecosystems. The digital formation of agriculture has played a great role in enhancing agrarian production, encouraging the ecological development of the agricultural economy, and accomplishing sustainable economic goals. The profound integration of the digital economy and the agriculture industry has become a major concern. A multifaceted technology expansion across the agricultural economy, a Remote Sensing Assisted Digital Agriculture Innovation Ecosystem (RS-DAIE) has been developed to enhance country-level digital agriculture requirements. Therefore, simple guidelines for building an efficient marketing strategy are crucial for expanding access to healthy food options and fostering the growth of organic farmers locally and internationally. The trial findings show that RS-DAIE has the finest accuracy by 98.9%, reliability rate by 99.3%, data transmission by 97.3%, and moisture content ratios, which are better than other technologies.

Keywords: artificial intelligence; digital agriculture; innovation ecosystems; machine learning; remote sensing

1 INTRODUCTION

Technological innovations have been crucial to the development of modern agri-digital advances. Multifaceted interaction and company ecosystems with several role-specific participants characterize the present stage of technology development. New economic drivers must be encouraged, and the rural vitalization approach must be implemented. With a new definition of creativity at its center, the 14th Five-Year Plan makes creation its top priority and the driving force behind its transformation push. Biological grain business and digital agriculture are two of the projected key development avenues that place a premium on the growth of agricultural and rural communities. There is a large disparity between urban and rural regions regarding inventive ability, even though total technical growth has reached an internationally advanced level. As a foundation for economic growth, countries still fall behind large and medium-sized cities in their capacity for innovation. The General Office of the State Council published several recommendations on innovation-driven development in county regions to address these deficiencies. These stress the importance of creating inventive counties and towns as a springboard for fostering widespread innovation and entrepreneurship, which are establishing a complex and varied framework for these activities at the county level. Countries should take advantage of the shift from innovation systems to the innovation ecosystem age as it becomes prevalent in the community. Creating and growing innovative agricultural ecosystems in county areas must be encouraged by increasing collaboration between agricultural companies, universities, government departments, investigation organizations, financial organizations, and intermediary organizations.

There are notable geographical and economic differences in agriculture. Studying innovations in agriculture at the regional level provided the first concrete example of this approach. Multiple actors coordinate with one another in what is known as a heterogeneous network in the context of an innovative agricultural system. The theory of innovation ecosystems is grounded in the study of the system of innovation and the innovation network. There are gaps between academic study and actual policy implementation concerning the innovation ecosystem. This is particularly relevant when considering how the innovation is affected by and interacts with its environments. The qualities of an innovation ecosystem are integrity, hierarchy, dissipation, dynamism, stability, complexities, and governance, and it is a system in which multiple actors engage in joint development to create value through invention. One of the biggest problems in modern farming is that there is not enough information about agricultural circumstances, limiting the number of new ideas that can be implemented. Less expensive methods for producers to recoup productivity have benefited greatly from the evolution of remote sensing in the agriculture setting. A digital agricultural building uses artificial lighting to control the environment, provide adequate humidity, and maximize light absorption for plant growth.

Overall, the focus of innovative research in agriculture has moved from innovative agricultural systems to the environmental system theory of sustainable growth. There is a shortage of case studies and empirical data on innovation in industry environments, and much of the current research on innovative ecosystems is still theoretical. High-tech, strategically emergent, cultural, and creative sectors are frequently included in the research conducted at provincial and municipal levels and on a regional and industrial scale in the middle. Counties are often overlooked in studies of breakthroughs in agricultural ecosystems. The article builds a conceptual framework of the innovative agricultural ecological systems in county areas using ecological concepts and then examines its evolution law using a life-cycle perspective. This research has essential practical and theoretical implications.

The advancements in integrated sensors used in agricultural production include the master and the worker to boost environmentally friendly output. Several humidity, ammonium, and moisture sensors are used in the service for ongoing monitoring. Farmers can use cell phones to track food production. Furthermore, several sensors are used by intelligent systems for agricultural production there to track crop development. It allows for measuring greenhouse conditions such as CO_2 concentration, soil moisture, temperature, and light intensity. Unpredictable conditions in greenhouses can stunt plant growth and diminish harvest yields. The Internet of Things (IoT) and artificial intelligence (AI) technologies can help with the problem by regulating the temperature, water flow, and light radiation in a greenhouse. Equipment and innovation based on AI have truly taken the agricultural industry to a new level. This innovative innovation has increased agricultural output by allowing for continuous tracking, interpreting, and gathering. New computerized systems with remote sensing and robots have contributed significantly to the agri-based industry. By providing periodic information regarding yield quality during investigated times at varying degrees and for different reasons, remote sensing can encourage the development of agricultural technologies to overcome this major barrier.

The method has been involved in AI's ongoing development and can potentially exacerbate agriculture instability. Commercial crop prediction using machine learning requires high-resolution remote sensing data and continuous sampling of crop yields from agricultural output.

The main contributions article includes:

- A Remote Sensing Assisted Digital Agriculture Innovation Ecosystem (RS-DAIE) has been created to meet county digital agriculture needs. AI and ML can improve economic resource management and agricultural product innovation in a digital agriculture innovation ecosystem.
- Thus, basic marketing strategies are essential for increasing healthy food options and organic farmer growth locally and globally. RS-DAIE employs AI to maximize environmentally friendly manufacturing, manage scarce financial assets, and speed up the spread of innovative food production techniques.
- The trial results demonstrate that RS-DAIE has the best accuracy ratio, reliability ratio, data transmission ratio, agricultural output ratio, irrigated control ratio, moisture content ratio, and carbon dioxide emission ratio compared to other technologies.

The rest of this research follows. Section 2 presents a county region model with a digital agricultural innovation ecosystem. Section 3 discusses innovative agricultural ecosystems and county evaluations. Sections 4 and 5 cover study techniques and information analysis. Section 6 summarizes and concludes. Section 7 discusses the findings and effects.

2 LITERATURE SURVEY

Sridhar et al. [16] examine the effects of COVID-19 on the agri-food system and its economy, with a special focus on the most crucial aspects, such as food manufacturing, request, price increases, security, and the adaptability of the supply chain. The potential for technological advances such as implementing AI, ML, DL, and blockchain technology in the agri-food industry has been proposed to foster the growth of a more self-sufficient society. Understanding the expanding effects of the pandemic and promoting affordable options for an ecological ecosystem would benefit greatly from the work.

Shaikh et al. [17] discuss the advantages and disadvantages of using Information and Communication Technology (ICT) in conventional farming. The roles of robotics, IoT, AI, and sensors in farming are discussed in depth, as are those of machine learning and AI. Drones are also being studied for agricultural monitoring and production improvement. When relevant, highlight international and state-of-the-art agricultural platforms and IoT systems. Based on this extensive analysis, we conclude the present and potential directions of AI and draw attention to the on-going and developing academic difficulties in AI application in agriculture.

Akhter et al. [18] proposed the efficacy and ability of computer approaches such as IoT, WSN(Wireless Sensor Networks), data analytics, and ML in farming. Combining statistical analysis and Machine learning in an IoT system (SA-ML-IoT), the authors of this research suggest a model for predicting Apple disease in the apple orchards of the Kashmir valley. The results of a local survey on the effects of new technologies on precision farming were also analysed. The paper addresses some difficulties of combining these technologies with more conventional farming methods.

Abioye et al. [19] introduce the best control irrigation systems by integrating many predictive models. The article discusses the current state of research into machine learning, its practical applications, and the dissemination of created artificial intelligence models to farmers for use in responsible irrigation management. It explains that digital farming technologies like mobile and web frameworks can allow remote monitoring and control smart irrigation operations, relieving pressure on farmers and researchers. Both the problems that need to be solved and how research should go in the future are covered.

Treiber et al. [20] proposed that Digital agri-ecosystems have emerged because multiple technologies and platforms are often necessary to run Farm Equipment effectively. Digital agri-ecosystems provide multi-layer digital services and dismantle conventional categories due to the increasing use of IoT technologies. The experiences and needs of developers are discussed in depth through expert interviews (n = 21). In conclusion, IoT-Ecosystems are helpful for the creation of multi-layer digital services; nevertheless, changes in platform functions and enhanced testing chances on real farms are needed to satisfy programmers and content providers completely.

Vaillant et al. [21] proposed a Product-Service Innovation (PSI) ecosystems have emerged in response to the rising popularity of products enhanced by additional services. Therefore, this work aims to empirically address a neglected area of PSI ecosystems research by answering whether PSI ecosystems in territories develop more effectively when they emerge from an already established industrial foundation in terms of manufacturing employment growth. The ramifications of our approach and findings for researchers, business leaders, and public policymakers are multifaceted.

Guo et al. [22] offer economic, social, and physical geographic information from China's Ministry of Agriculture and Rural Affairs (MARA) 2021 and 2022 national-level environmental farms listings for GIS spatial analysis and Geo-detector. The outcomes are as follows:

(1) China's sustainable farms are concentrated in select areas. It consistently has great in the east and low in the west with concentrated cores' topography. Ecological farms depend on environmental conditions, social and economic development, and financial help. China's substantial industrial foundation influences the size of its environmental farms, while its excellent science and technology help overcome other variables. This research can help China improve its ecological farming and infrastructure.

Smania et al. [23] proposed the abilities' driving power and reliance power were then defined using Interpretive Structural Modelling and fuzzy MICMAC analysis. Conceptual frameworks that unify these two sets of skills by combining these analyses consist of three macro-levels: linkage, driving, and dependant. This result was accomplished through several different approaches. A rigorous literature assessment first defined key digitization and ecosystem-related competencies. This article adds to the knowledge by illuminating the connections between digitization and the capacities connected to ecosystems. Furthermore, a conceptual framework is proposed for those classes' abilities according to their roles in the growth of digital service innovation.

3 SYSTEM METHODOLOGY

3.1 Digital Agriculture Development

The variables contributing to the growth of digital agriculture are shown in Fig. 1. Most of the crop production worldwide is produced through managed agricultural innovation ecosystem. The unsustainable vicious loop can be traced back to the large quantities of waste that leak into the soil and disappear into the atmosphere due to ammonium evaporation and oxidizing nitrogen-fixing. As a result, progress toward better environmental safeguards has slowed. Establishing digitally innovative farming ecosystem operations as a solution to the difficulties of preserving plant safety and protecting the environment. As shown in Fig. 1, environmental input and sustainable operation on farmland necessitate an agriculture production system. Changing and combining crop systems and developing new crop plants, vegetables, and green herbicides for a combined soil culture control unit are all part of this strategy for increasing agricultural production while maintaining excellent effectiveness, high utilization of resources, and sustainability for the environment; the radical shift from a resource-based type of farming to one with higher environmental type. The transition from intense agricultural activity to environmentally friendly cultivation is a major shift in the history of agriculture since it translates into increased efficiency, high effective resource usage, and poor ecological impact.

Control of inputs and outputs, source monitoring and control of green commodities are integral to green crop cultivation, providing a better ecosystem. Land quality and agricultural production, which are crucial if excellent food is to be given on a large scale, may be considerably improved via the planning of the farming system. Animal foods like meat, eggs, and milk are simpler to digest than many plant foods, making livestock production an important part of the food supply. The data processing system produces a predetermined output set for each input level. Inputs and outputs are analyzed to conclude the data, facts, information, etc. The common misconception is that information systems are the same as storage or data processing management systems. Consequently, I now understand that farming must adapt to changing conditions if it is to continue feeding the world. To maintain fertile soil, Digital Agriculture innovation ecosystem maintains soil fertility through wise water management.

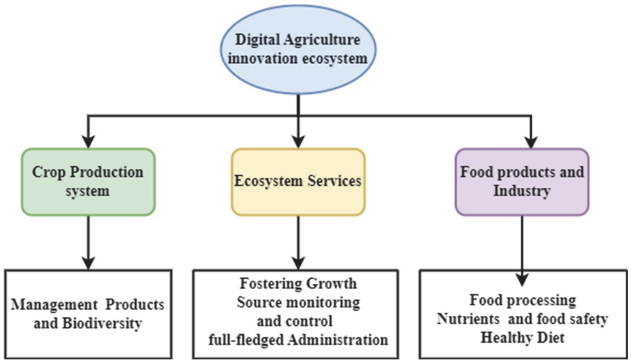

Figure 1 Digital agriculture innovation ecosystem

In addition, these structures are considered essential to the longevity and expansion of the industry's primary raw material suppliers. Connecting the plans so that farming receives nearly all the assets needed to feed the cattle is possible. Collecting the waste and using it as a plant nutrient source is important. Non-connected and interconnected animal mass farming would increase the contamination hazards from leakage of livestock toxins from the livestock system, which can be utilized as useful nutrients for crop production. Performance in the agricultural sector ought to optimize during the period of transformation from a monoculture to a more diverse integrative system of animal crop production. The effectiveness of the food system in terms of the consumption of nutrients can be improved by integrating farming and animal production.

AI and ML systems have allowed for developing a digital innovative agriculture ecosystem, frequently called precise agriculture. These techniques help improve the general precision and quality of harvesting. Farms can better detect plant diseases, pests, and nutrient deficiencies with the help of AI technology. AI sensors can determine which weeds require herbicide treatments and select the most appropriate herbicide for that area. During harvest, ML is utilized for forecasting the weather, diagnosing plant diseases, identifying crops, and controlling soil nutrients. ML is employed in the post-processing phase to forecast demand and manufacturing scheduling. Asset administration and customer profiling are the distribution's primary ML applications. A Remote Sensing Assisted Digital Agriculture Innovation Ecosystem (RS-DAIE) has been developed as a multidimensional technological expansion across the farming sector to improve digital agriculture necessities in county regions. It is suggested that AI and ML should be incorporated into the structure and execution path of a digital farm innovation ecosystem to improve economic resource administration and agricultural goods creation. The AI-powered solutions help farmers maximize their profits through strategic resource allocation and crop selection.

3.2 Structure of RS-DAIE

Recent years have seen a rise in the number of studies examining the innovation ecosystem, with researchers primarily interested in its constituent parts, network framework, and the rapid change between the creativity subject and the creativity ecosystem. The Smart agricultural innovation mission aimed to create use-case scenarios built on this shared infrastructure. With this as a starting point, Smart Agri set out to increase smart farming, logistics, and food awareness in the digital agriculture sector by future Internet technologies. Modern agricultural produce innovations are largely due to the contributions of digital technologies. Multifaceted convergence and company ecosystems with several role-specific participants characterize the current stage of technology evolution. Fig. 2 illustrates the structure of RS-DAIE. With this novel complexity, a new paradigm for technological advancement is required. Innovation technique (i), creative structure (AI and ML technique) (ii), Digital structure organization (iii), Innovative ecosystem model (iv), and inspiration infrastructure that make up the theoretical structure. Design principles are derived along these four ideas from examining the projects serving as a foundation for the structure. The framework is built around cross-disciplinary activities, including creating a shared technical team infrastructure, determining value streams through user participation, and coordinating with the appropriate parties at the appropriate times through strategic project planning and agile management. The most significant takeaway is that actors should not analyse in isolation from their technological and commercial environment if they are to make efficient, successful, and speedy use of suitable IT in the agri-food sector.

3.3 Digital Agriculture Organization

Several challenges must be overcome by the digital agricultural organization, particularly the creative growth of agriculture on the county level. A more robust innovation platform is required because of the instability of the mechanisms underlying agricultural innovation. Interface's contribution to encouraging and achieving wider and deeper integration of innovative resources can only be achieved this way.

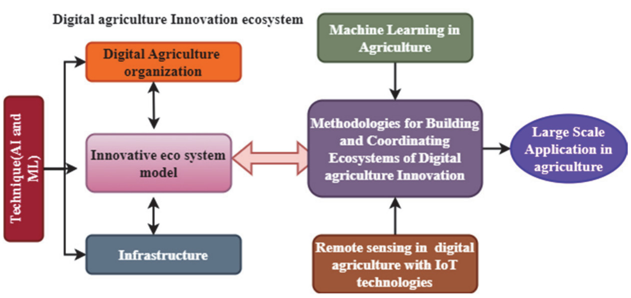

Figure 2 Structure of RS-DAIE

The revolutionary platform provides a wealth of advertising, distribution methods, acceptable, and other expert assistance in addition to its technological, informational, and monetary assets for innovation. Connecting the central layer to the application layers and development is the responsibility of the platform's infrastructure layer. The connection between the two ecologies is formed through integrating the development platform into the agricultural technology environment at the county level.

3.4 Innovative Ecosystem Model

Under the supervision of value co-creation, the subjects of digital innovation in agricultural innovation ecosystems in county regions have a tight association of mutual dependency, constructive collaboration and together produce value. As a result, hierarchical digital agricultural innovation ecosystems have designed in county regions, with the topics of innovation competing and cooperating. As shown in Fig. 3 below, the system comprises three distinct layers: the small-scale subjective layer, the medium-scale interaction layer, and the large-scale ecosystems layer.

Innovation subjects, such as agriculture-related businesses, governments, higher education and academic structures, monetary and intermediary institutions, and the public, comprise the small-scale businesses' subjective ecological layer, which supports agricultural innovation on the county level. Topics of innovation influence the ecosystem for digital agricultural innovation connects. The system's potential to sustainably innovate is being steadily enhanced through the innovation network developed via the collaboration of all the primary entities. They build a strong innovation community through their interactions with one another. The technological R&D group is the backbone of the county's innovative agricultural ecosystem, comprising agricultural companies, colleges and universities, and scientific research facilities. Strategy demands an ecosystem comprised of government agencies and the general people. Auxiliary service providers include banks, brokers, and other financial and business intermediaries. Distinct communities serve distinct functions within an intricate, interconnected structure at the size of a local ecosphere.

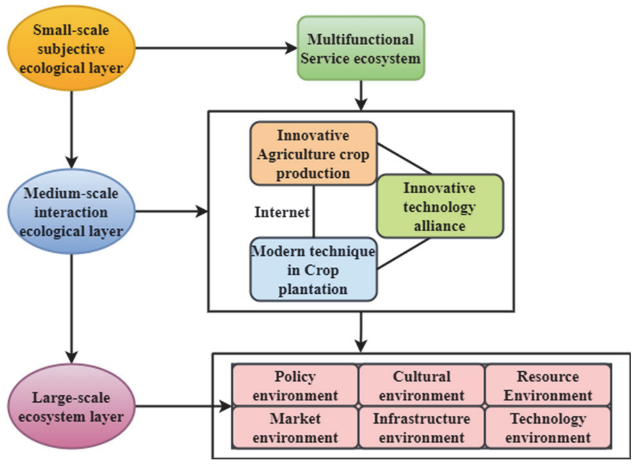

Figure 3 Conceptual model of digital agriculture innovative ecosystem

The agricultural technological and scientific recreational areas, modern techniques in crop plantation, agriculture crop production, and agricultural-related creative thinking alliances are all examples of organizations that comprise the medium-scale interaction ecological layer. They all serve as interfaces and avenues for exchanging materials, energy, knowledge, and technology amongst innovation subjects and the innovation ecology. These platform organizations reflect the regional agricultural development system's innovative prowess, and they can link together diverse themes of innovation to facilitate collaborative invention.

The regulatory circumstances, asset surroundings, marketplace environment, scientific environment, social environment, facilities environment, etc., that comprise the large-scale ecosystems layer are essential external situations for the micro-main environmental layer and the medium-scale interaction ecological layer, which are essential for county agricultural innovations. The surrounding innovation environments influence local agricultural innovation environment efficiency and the evolution route of innovative activities. Each small-scale-subjective ecological layer and medium-scale interaction layer in the ecosystem self-adjusts and co-evolves under the influence of the creative thinking environment, achieving equilibrium and long-term stability in the system thanks to the microenvironment's promotion or restriction of the inventiveness subjects and creativity platforms. Each of these three tiers is essential to the success of the digitized agricultural technology environment.

3.5 Innovative Infrastructure

An innovation platform can serve as the large-scale environment's innovation topic while providing a wealth of resources (financial, technological, cultural, etc.) to micro-innovation persons. Because of the innovation platform's dual role and function in county agricultural innovation ecosystems, this paper treats it as an embedded environmental layer. It builds a sophisticated and multi-level innovation ecosystems framework with a more comprehensive approach.

3.5.1 Techniques for Developing Digital Agriculture Innovation Ecosystems

The analytical findings are presented in Fig. 4, which depicts the foundational conditions for ML in agriculture. The preparatory phase is the first step in an agricultural distribution system. Crop yield forecasting, soil quality forecasting, and watering schedule planning all fall within the stage's purview. The ability to predict soil quality is crucial for effective land management. Research shows that soil prediction can improve our knowledge of soil ecosystem processes. The success of agriculture and the environment depends on good cultivation methods. At this stage, ML is used to improve intelligent digital crop production and create a decision support system for use in semi-arid and dry areas to predict product quality. Improved crop administration and advertising strategies rely heavily on agricultural product output. Therefore, further agricultural inputs, such as vitamins and minerals, agricultural inputs, and production times, can be arranged following the environment and crop needs if crop output in a specific site is projected.

The application of machine learning and signal processing techniques enhances decisions about the forecasting of crop production. Prices were estimated and evaluated to help with harvesting and boost field efficiency. The research indicates that the ML method can handle non-linear problems and provide more accurate forecasts for all three soil characteristics.

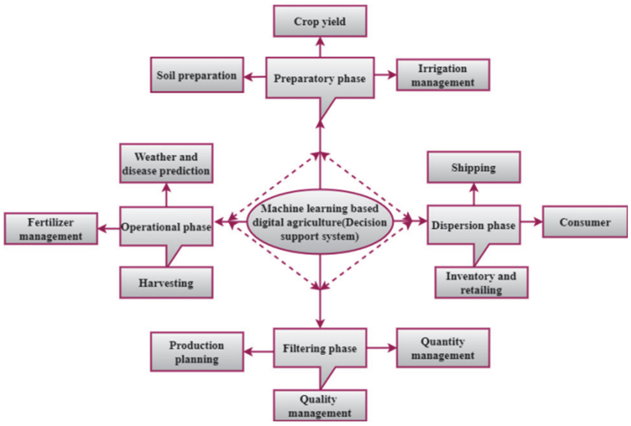

Figure 4 Machine learning-based digital agriculture innovations

Weather forecasting, plant identification, disease diagnosis, livestock management, fertilizer management by location, harvest timing, and crop quality are all significantly aided by ML's operational phase during harvesting time. Sunlight, precipitation, moisture, and humidity are all factored into the weather forecast to help you decide how much water to use for irrigation. Early detection, a biotic and biotic stress, biotic stress factor nutritional diagnostics, and crop catastrophes are all addressed by effective crop protection strategies. Careful monitoring of crop quality is essential for achieving a fair market price, and it was only through location-specific administration and innovative agricultural technologies that scientists could identify insect diseases. Fertilizer control and other methods of crop quality control are great for producing homogenous crops or field regions that can be processed similarly.

The Filtering phase alters the commodities physically and can positively and negatively affect the final product, depending on the methods used. After processing agricultural products, they are packaged and prepared for dispersal and retail. The research centered on how garbage may be handled better to lessen its carbon footprint. It is possible to avoid stress, waste, and excessive use of resources through careful inventory management based on forecasts of future food demand. The final step in the farm-to-fork cycle, distribution and retail, combines food production and its ultimate consumption.

The packaged agricultural product is transferred to storage and distribution centres during the dispersion phase. Most products go through some transportation system before reaching their intended audience. A cloud-based problem with a distribution and storage site is identified using rule-based association mining in the combined production and delivery scheduling challenge. Also, ML algorithms are used to assess the effectiveness of logistics, inventory control, and late payments. ML's local food chain systems guarantee safe food and promote long-term growth in the logistics sector. Shipping, managing inventory, and late payments are also evaluated using ML algorithms. ML has created local food chain systems to guarantee food safety and sustainable transportation growth. The most popular ML methods for managing nutrients are forecasting and classification. Farmers can use the estimated production of crops to better allocate resources before, during, and after harvest. Predicting crop yield from RS data is the primary emphasis of the ML algorithms at this tier. During the harvest, a set learning model was used to analyse the soil's attributes and predict yield using a combination of random forest modelling and regression estimation.

3.5.2 Remote Sensing in Digital Agriculture with IoT Technologies

The current move toward development expects agriculture to recognize the organization of this issue by utilizing IoT agriculture and innovation. These difficulties include handling water shortfalls associated with agriculture and productivity problems. IoT's problems have uncovered these concerns and revealed low-cost solutions. Thanks to remote network monitoring based on innovation, gather sensor data, and send it to an online server. The detectors' data provides a comprehensive system assessment for information on various environmental conditions. The crop's performance is evaluated by observing environmental factors and yield productivity. When information gathered by artificial sensors in agriculture is readily available, remote sensing serves as a compass for developing smart farming practices.

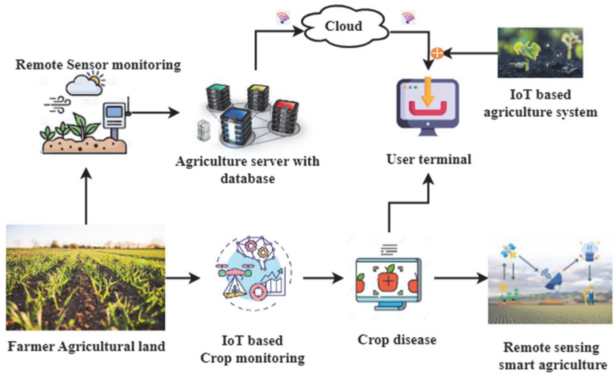

Figure 5 Remote sensing in digital agriculture with IoT technologies

Remote sensing architecture for innovative digital farming is depicted in Fig. 5. This technology exemplifies recent advancements in agriculture by facilitating secure, hassle-free connections between separate greenhouses, livestock, and farmers. The IoT-based agriculture system employs IoT gadgets to streamline livestock production and real-time monitoring. With its increasing benefits of growing connectedness of end devices, systems, and services, the IoT is now recognized as the next-generation technological megatrend with the potential to touch every business area. Smart farming is one area where the Internet of Things can be used effectively. The IoT has significantly altered the agricultural landscape by addressing various problems and obstacles. IoT is expected to be used by farmers and technicians shortly to help farmers overcome issues including water scarcity, cost management concerns, and low productivity. Data gathered by remote sensing provides insight into various environmental factors, allowing for precise system monitoring. A remote sensing monitoring system has become invaluable for precise farming and environmental surveillance. Its close-range, excellent-quality data collection is a boon to our understanding of plant growth, soil quality, and ecological processes. The data must be handled, examined, and evaluated after it has been acquired. Assessment and monitoring of land cover changes in India using GIS-integrated remote sensing data to support environmental policy decisions. Measuring environmental conditions or crop production is an issue in crop evaluation, but that is far from the only factor affecting farming output. IoT also provides a streamlined scheduling mechanism for scarce assets, ensuring that its optimal deployment will boost productivity.

Digital farming requires the technology to recognize important IoT-supporting elements. The procedures, topologies, and linked devices used in agriculture are all part of the IoT communications network, which has been the subject of a thorough investigation. Several domains have been discussed, along with the mobility and sensors applications that are relevant to them. The major manufacturing areas that are actively studying IoT-based agriculture are analysed in this article. Different countries' efforts to create uniform standards for the use of IoT in farming are discussed. Finally, the problems and opportunities in IoT applications in agriculture have been discussed. Remote sensing can identify and monitor an area's physical properties by monitoring reflected and radiation released at distant locations. Production from agriculture processes for irrigation must keep the earth healthy. The goal of the irrigated controller is to maintain an optimal range of soil humidity between dry and wet. Soil with higher limits has more ability to hold water, while a lower limit serves as a limit on how much water the ground retains.

$$G = \nabla \left\{ e\left(\operatorname{avg} x(t)\, r(t) \right) \right\} \tag{1}$$

The soil moisture, G, is determined by solving Eq. (1). The typical average soil moisture level is denoted here by [avg($x(t)$, $r(t)$)], where $x(t)$ is the time variable and $r(t)$ is the spreading of rain levels. Agriculture is irrigated by watering systems (e), where $r(t)$ and $x(t)$ are soil capabilities and soil wetness.

$$z_{\max} = \partial\left(G, \operatorname{avg} x(t) \right) \tag{2}$$

Eq. (2) and Fig. 5 define optimal soil water retention. Soil reservoir capacity ($z_{\max}$) is determined when a soil type has been recognized. The relationship between plant varieties and soil moisture is represented by.

$$z_t = 1000 \times x(t)\, p_r \tag{3}$$

The moisture percentage at a given depth is calculated using Eq. (3). The quantity of groundwater maintained at the base of the plant at time instant t reflects the amount of the moisture level millimetres water. It is calculated throughout the irrigation procedure as z_t where p_r is the plant's bottom diameter in meters.

$$z_{ws} = z_{\max} - z_t \tag{4}$$

The maximum allowable water stress is computed using Eq. (4). When the soil's water retention capacity, z_t, reaches its upper boundary, the water stress, z_{ws}, can be zero, and further watering is unnecessary. If maximum soil retention is reached, then no need for irrigation.

$$\Delta m = \frac{p_{\text{in}} - p_{\text{out}}}{\Delta_t m} \tag{5}$$

The long-term preservation moisture is accumulated as shown in Eq. (5). It refers to the difference in humidity between the soil and the plant's terminal roots. The quantity of water used for cultivation, denoted by p_{in} and p_{out}, is water usage. This amount of water lost through evaporation is known as the crop's transpiration. The simulated controlled atmosphere approach is used to determine the transpiration baseline.

$$CE = IWQ - W - WA - \Delta m \tag{6}$$

The evapotranspiration of the crop is estimated using Eq. (6). CE is crop transpiration, IWQ is the amount of water used for irrigation, W is the amount of waste, and WA is the amount of water absorbed. High precision, lower moisture content, lower CO_2 emission level, enhanced efficiency, substantial information transfer, hydro management, and greater agricultural output are all attainable through the suggested RS-DAIE's monitoring of agricultural products.

4 RESULTS AND DISCUSSION

Nations and worldwide organizations have set a target date of 2030 to end world hunger as part of their 2030 Agenda for Sustainable Development. According to the World Health Organization, over 800 million individuals worldwide are struggling to get enough to eat. As the world's population rises, so will the demand for nutritious food; consequently, diversifying crop output to include food and agricultural products is essential. The dataset for the Statistical Analysis of Satellite Images (RSI-CB256) is used in the proposed work (RS-DAIE). https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification. The dataset combines sensor information and a Google Maps image to form four categories. Now more than ever, there is a need for images taken with an RS camera to automatically interprete. Benchmark datasets are crucial in developing and accessing smart interpretation algorithms. After reviewing existing benchmark database in the RS image interpretation research community, this work delves into the difficulty of quickly creating a high-quality benchmark dataset for RS image interpretation. Bibliometric studies should initially be used to evaluate the existing challenges of developing sophisticated algorithms for RS photo comprehension.

4.1 Accuracy Ratio (%)

Correlation to on-the-ground observations or estimations is common to evaluate the accuracy of remote sensing, as shown in Fig. 6. Accuracy agriculture is a technical approach to farming that aims to increase yields and quality by optimizing how conventional products react to agricultural inputs, including fuel, water, fertilizer, and pesticides. The accuracy ratio in digital agriculture can significantly elevate the industry's prominence. Technology advancements have led to improvements in farming by encouraging new approaches, such as smart, data-centred, and multi-storage agricultural processes. Full crop requirements, error prevention, and environmental impact in agriculture and associated water management depend on the successful execution of manufacture, accuracy, and sufficient irrigation control. To choose seed kinds that will thrive in each region's environment, ML is applied in agriculture to foresee the most productive genes. Articles in high demand and those out of stock are uncovered by ML algorithm. According to ML and data analysis advances, farmers can now accurately classify their crops before processing and delivering them to consumers. Compared to existing models such as SA-ML-IoT, Digital agri-ecosystems, PSI, and Fuzzy MICMAC, the proposed RS-DAIE achieve a greater accuracy ratio by 98.8%. The ratio of accuracy is determined using the confusion matrix.

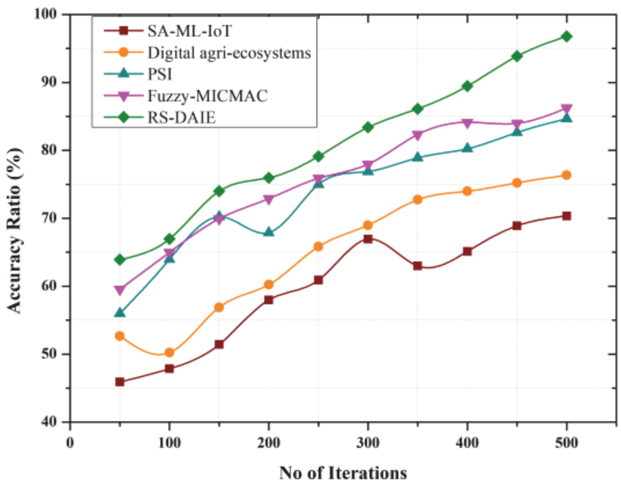

Figure 6 Accuracy ratio

4.2 Reliability Ratio (%)

The reliability ratio of the ML-based digital agriculture innovation is depicted in Fig. 7. The quantitative and qualitative goals of assessing the technology's effectiveness, advance time, and a suitable approach to eliminate the signs and analyze insightful data to alter crop production efficiency are standardized. With technological advancements, sensors now understand their solution from the perspective of data processing through contact with their external atmosphere. Predictive data analysis and improved technology for solving basic problems in decision-making. Development maximizes efficiency in the use of resources and fosters a personalized, productive environment to raise agricultural output through pre-processing technological advances. The suggested

RS-DAIE model outperforms state-of-the-art models such as SA-ML-IoT, digital agri-ecosystems, PSI, and fuzzy MICMAC regarding reliability ratio. RS-DAIE reliability ratio reaches at 99.2%, which is higher than others.

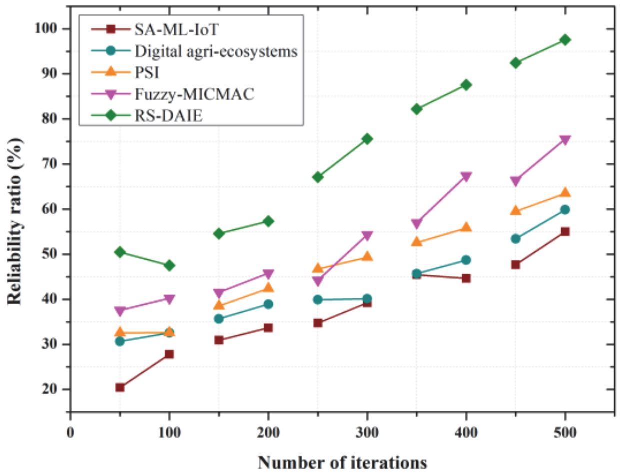

Figure 7 Reliability ratio (%)

4.3 Data transmission Ratio (%)

The rate at which network components can exchange data is the data transfer rate shown in Fig. 8. Data bits per second are the units used to measure it. Recent research has shown that low-cost IoT can boost the effectiveness of manufacturing facilities in terms of polluting substances control. Carbon emissions cause most industrial air pollutants and all industrial wastewater emissions. High efficacy, low prices, energy conservation, and low emissions are all necessary outcomes of an IoT-based expansion mode in the agricultural sector. Capital and labor were incorporated into the production process by using energy utilization modes of processing and releasing carbon dioxide from the degradation of the environment. Environmental protection was de-emphasized by agricultural organizations, leading to increasing emissions control waste and higher carbon emissions indices. Farming harmful emissions has been decreased, and new restrictions and goals for energy saving and mitigation have been proposed. The amount of data created and the time it takes for each step of the verification process to transmit are referred to as overlapping interactions.

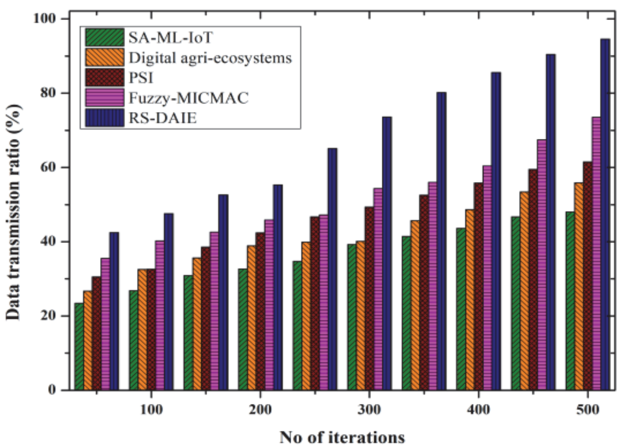

Figure 8 Data transmission ratio

The lightning-fast data transmission rate for data transfer precedes an approach at which the platform's prevent characteristics are determined to evaluate vibrations. The ML algorithm then immediately changes the buffering knowledge stored in the data being transmitted sensor by collection to identify the accurate conjunction delay acceptance levels. The features of the method used to transmit data are assessed. In contrast, it is being transmitted to make reduced changes and adaptations if the transmission's eventual application is needed for the primary power output signalling. Compared to other, more advanced models, the RS-DAIE proposal for predicting data transmission rate is at 97.3%, which performs better than SA-ML-IoT, Digital agri-ecosystems, PSI, and fuzzy MICMAC.

4.4 Moisture Content ratio (%)

Adequate moisture is necessary for continued plant growth and fruitful harvests. The crop needs a temperature controller because irrigation does not replenish the lost moisture. Therefore, it is not hard to see the crop has different moisture needs at different times and places. Consequently, a farmer's primary problem is enhancing moisture content production, storage, and efficient usage. The typical moisture ratio (%) in Fig. 9 reflects plant and soil moisture potentials, which are good indicators of actual moisture levels. The moisture content of the ground has impacted the results of several ML methods applied to wet soil samples. An effective agricultural field's ecosystem is evaluated and managed with the help of moisture level metrics, soil moisture, and evaporation data. Predicted weather conditions such as sunshine, rain, evaporation, and humidity affect agricultural water allocation. The moisture content of the soil can be varied for one set of data points to compare predictor variables and AI efficiency.

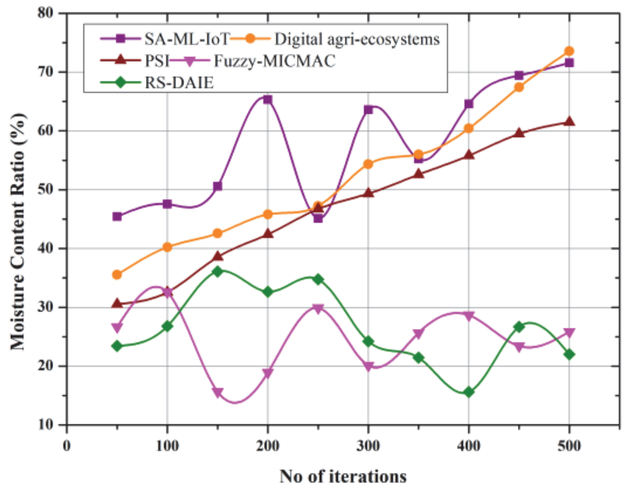

Figure 9 Moisture Content ratio

5 CONCLUSION

Digital Agricultural innovation ecosystems were previously undefined, but the concept of digital agricultural innovation ecosystems has helped. Controlling irrigation systems work prioritizes needs important to agriculture, like preserving groundwater purity and crop production. The highest possible energy usage of the nodes that transmit sensors is the primary determinant of the longevity of an IoT platform. The advantages of the used method in the agriculture and food production industries have been filled by this analysis. This article argues that by emphasizing farm production and employing green management techniques, a company can expand its core business and reap the advantages of agriculture to make its manufacturing sector more dynamic and competitive. An understanding of and facility within digital innovation ecosystems is crucial to the growth of a data economy for agriculture in digital environments. The limitation is the lack of this paper on the differences in the central and western regions. There has been significant progress toward achieving long-term economic goals in the agricultural sector, thanks largely to the digital transformation of farming. Concerns have been raised about the growing interdependence of the digital economy and agricultural sectors growing interdependence. Remote Sensing Assisted Digital Agriculture Innovation Ecosystem (RS-DAIE) has been created to improve digital agriculture needs in county regions through the growth of technology across the agricultural business. Incorporating AI and ML into the mechanism and establishment route of a digital agriculture innovation ecosystem is recommended to manage economic resources better and create novel agricultural products. Therefore, easy-to-follow instructions for establishing an efficient marketing policy are essential for increasing access to nutritious food options and encouraging the development of organic farmers on a local and global scale. The results of the trials demonstrate that RS-DAIE has the best accuracy ratio, reliability ratio, data transmission ratio, and moisture content ratio compared to the other technologies.

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6 REFERENCES

[1] Singh, P. K. & Sharma, A. (2022). An intelligent WSN-UAV-based IoT framework for precision agriculture application. *Computers and Electrical Engineering*, *100*, 107912. https://doi.org/10.1016/j.compeleceng.2022.107912

[2] Singh, D. K., Sobti, R., Jain, A., Malik, P. K., & Le, D. N. (2022). LoRa based intelligent soil and weather condition monitoring with internet of things for precision agriculture in smart cities. *IET Communications*, *16*(5), 604-618. https://doi.org/10.1049/cmu2.12352

[3] Triantafyllou, A., Sarigiannidis, P., & Bibi, S. (2019). Precision agriculture: A remote sensing monitoring system architecture. *Information*, *10*(11), 348. https://doi.org/10.3390/info10110348

[4] Ullo, S. L. & Sinha, G. R. (2021). Advances in IoT and smart sensors for remote sensing and agriculture applications. *Remote Sensing*, *13*(13), 2585. https://doi.org/10.3390/rs13132585

[5] Yang, C. (2020). Remote sensing and precision agriculture technologies for crop disease detection and management with a practical application example. *Engineering*, *6*(5), 528-532. https://doi.org/10.1016/j.eng.2019.10.015

[6] Liu, J., Xiang, J., Jin, Y., Liu, R., Yan, J., & Wang, L. (2021). Boost precision agriculture with unmanned aerial vehicle remote sensing and edge intelligence: A survey. *Remote Sensing*, *13*(21), 4387. https://doi.org/10.3390/rs13214387

[7] Rehman, A., Saba, T., Kashif, M., Fati, S. M., Bahaj, S. A., & Chaudhry, H. (2022). A revisit of internet of things technologies for monitoring and control strategies in smart agriculture. *Agronomy*, *12*(1), 127. https://doi.org/10.3390/agronomy12010127

[8] Whig, P., Kouser, S., Velu, A., & Nadikattu, R. R. (2022). Fog-IoT-Assisted-Based Smart Agriculture Application. *Demystifying Federated Learning for Blockchain and Industrial Internet of Things*, 74-93. https://doi.org/10.4018/978-1-6684-3733-9.ch005

[9] Gupta, A. & Nahar, P. (2022). Classification and yield prediction in smart agriculture system using IoT. *Journal of Ambient Intelligence and Humanized Computing*, 1-10. https://doi.org/10.1007/s12652-021-03685

[10] Arrubla-Hoyos, W., Ojeda-Beltrán, A., Solano-Barliza, A., Rambauth-Ibarra, G., Barrios-Ulloa, A., Cama-Pinto, D., & Manzano-Agugliaro, F. (2022). Precision Agriculture and Sensor Systems Applications in Colombia through 5G Networks. *Sensors*, *22*(19), 7295. https://doi.org/10.3390/s22197295

[11] Ouafiq, E. M., Saadane, R., & Chehri, A. (2022). Data management and integration of low power consumption embedded devices IoT for transforming smart agriculture into actionable knowledge. *Agriculture*, *12*(3), 329. https://doi.org/10.3390/agriculture12030329

[12] Hrynevych, O., Blanco Canto, M., & Jiménez García, M. (2022). Tendencies of precision agriculture in Ukraine: Disruptive smart farming tools as cooperation drivers. *Agriculture*, *12*(5), 698. https://doi.org/10.3390/agriculture12050698

[13] Chaganti, R., Varadarajan, V., Gorantla, V. S., Gadekallu, T. R., & Ravi, V. (2022). Blockchain-based cloud-enabled security monitoring using internet of things in smart agriculture. *Future Internet*, *14*(9), 250. https://doi.org/10.3390/fi14090250

[14] Fakhar, M. & Khalid, M. (2023). Satellites to Agricultural Fields: The Role of Remote Sensing in Precision Agriculture. *Biological and Agricultural Sciences Research Journal*, *2023*(1), 14-14. https://doi.org/10.54112/basrj.v2023i1.14

[15] Samreen, T., Ahmad, M., Baig, M. T., Kanwal, S., & Nazir, M. Z. (2023). Remote Sensing in Precision Agriculture for Irrigation Management. *Environmental Sciences Proceedings*, *23*(1), 31. https://doi.org/10.3390/environsciproc2022023031

[16] Sridhar, A., Balakrishnan, A., Jacob, M. M., Sillanpää, M., & Dayanandan, N. (2023). Global impact of COVID-19 on agriculture: role of sustainable agriculture and digital farming. *Environmental Science and Pollution Research*, *30*(15), 42509-42525. https://doi.org/10.1007/s11356-022-19358-w

[17] Shaikh, T. A., Rasool, T., & Lone, F. R. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, *198*, 107119. https://doi.org/10.1016/j.compag.2022.107119

[18] Akhter, R. & Sofi, S. A. (2022). Precision agriculture using IoT data analytics and machine learning. *Journal of King Saud University-Computer and Information Sciences*, *34*(8), 5602-5618. https://doi.org/10.1016/j.jksuci.2021.05.013

[19] Abioye, E. A., Hensel, O., Esau, T. J., Elijah, O., Abidin, M. S. Z., Ayobami, A. S., &Nasirahmadi, A. (2022). Precision irrigation management using machine learning and digital farming solutions. *Agri Engineering*, *4*(1), 70-103. https://doi.org/10.3390/agriengineering4010006

[20] Treiber, M., Grebner, S., Spierer, S., & Bernhardt, H. (2023). On the current state of software development for agricultural equipment in the dawn of IoT-Ecosystems. *2023 ASABE Annual International Meeting*, 1. American Society of Agricultural and Biological Engineers. https://doi.org/10.13031/aim.202300299

[21] Vaillant, Y., Lafuente, E., & Vendrell-Herrero, F. (2023). Assessment of industrial pre-determinants for territories with active product-service innovation ecosystems. *Technovation*, *119*, 102658. https://doi.org/10.1016/j.technovation.2022.102658

[22] Guo, D., Lin, Y., Wang, M., & Huang, Z. (2023). Spatial Distribution Pattern, Evolution and Influencing Mechanism of Ecological Farms in China. *Land*, *12*(7), 1395. https://doi.org/10.3390/land12071395

[23] Smania, G. S., de Sousa Mendes, G. H., Godinho Filho, M., Osiro, L., Cauchick-Miguel, P. A., & Coreynen, W. (2022). The relationships between digitalization and ecosystem-related capabilities for service innovation in agricultural machinery manufacturers. *Journal of Cleaner Production*, *343*, 130982. https://doi.org/10.1016/j.jclepro.2022.130982

[24] https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification.

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