

BIG DATA BASED SMART SENSING FOR PRECISION AGRICULTURE USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

By boosting production, efficiency, and sustainability, precision farming has revolutionized modern agricultural practices. Advances in big data and artificial intelligence (AI) make this feasible. This paper explores potential applications of AI and big data in conjunction with smart sensing technologies to enhance precision agriculture. In addition to outlining the fundamental components of smart sensing systems—data collection, processing, analysis, and decision-making—the article also demonstrates how these systems work to maximize resource usage, agricultural management, and environmental sustainability. Numerous AI approaches, such as machine learning and deep learning, are described in the context of their applications in the analysis of agricultural data collected from sensors. The paper also discusses the challenges and possible routes for developing and deploying big data-driven intelligent sensing systems for precision farming. This essay's main goals are to help readers understand the most current applications of big data in smart agriculture and the pertinent social and economic challenges that need to be addressed. This article covers big data applications that make sense for precision agriculture as well as data generating strategies, technology accessibility, device accessibility, software tool accessibility, and data analysis approaches. Furthermore, the widespread use of big data technologies in agriculture still faces several challenges.

Keywords: Smart farming, sensing, bigdata analytics, precision agriculture, AI.

1.INTRODUCTION

In an attempt to maximize agricultural operations, precision agriculture makes data-driven judgments appropriate for specific field conditions using technology. Large-scale approaches are often used in conventional agriculture, which leads to resource waste and decreased yields. However, farmers can now acquire and analyze huge amounts of data to make fast, precise choices that increase productivity while decreasing resource waste and environmental impact, all owing to big data and artificial intelligence (AI) technologies.

The harsh weather conditions of traditional agriculture significantly restrict crop growth and yield [1]. Due to the growing population, the resources in the region where crops are cultivated are also experiencing previously unheard-of strain [2]. As a response to the negative impacts of the

environment and the scarcity of available resources, facility agricultural production technology has grown in popularity.

territory [3]. In this new historical stage of social evolution, people's need for sustenance is being matched by an ever-growing longing for a better existence, which has caused the basic contradiction in our society to change [4]. The need for facility agriculture is growing yearly, as is consumer demand for off-season fruits, vegetables, flowers, and other agricultural products [5]. Consequently, facility agriculture must expand notwithstanding any obstacles imposed by outside forces or individual needs [6]. In the greenhouse production process, temperature is one of the most important parameters affecting the growth of indoor crops [7]. The temperature of the greenhouse is mostly managed by adjusting the actuators based on the data obtained from the sensors. As a result, the greenhouse may adjust its atmosphere to meet the growing needs of the crops [8]. But because of the complex interior environment of the greenhouse, getting accurate and efficient sensor data is a crucial problem that must be fixed immediately to ensure the greenhouse management system operates as planned [9].

In order to continually monitor a variety of parameters, such as temperature, humidity, crop health, and environmental factors, precision agricultural systems rely on smart sensing. These sensors may be used to gather data at high temporal and geographical resolutions in fields, greenhouses, and livestock ranches. Intelligent sensing systems consist of sensor nodes, which are frequently equipped with an assortment of sensors, data collection modules, communication interfaces, and power sources. Independently obtaining data, these nodes forward it to a central processing unit for analysis.

Big data is the phrase used to characterize the enormous amounts of data produced by the extensive usage of agricultural sensors. This data is challenging to manage, handle, and analyze because of its volume, speed, diversity, and validity. Big data technologies like cloud, edge, and distributed computing are critical for effectively managing agricultural data. Cloud-based systems provide scalable infrastructure for processing and storage, while edge computing enables real-time analysis and decision-making closer to the data source.

Artificial intelligence (AI) methods, particularly machine learning (ML) and deep learning (DL), which can provide significant insights, are crucial to the study of agronomic data. Machine learning (ML) algorithms, which examine historical data to identify patterns, correlations, and anomalies, provide predictive analytics for crop growth, insect infestation, and disease outbreak. DL models perform exceptionally well in image recognition and time-series analysis, making them ideally suited for applications like yield prediction, weed detection, and crop categorization. These models include recurrent neural networks (RNNs) and convolutional neural networks (CNNs).

According to UN estimates, the world's population will reach 7.8 billion by November 2020. By 2030 and 2050, this number is expected to climb to 8.5 billion and 9.9 billion, respectively. Alongside the rapid population growth comes a rapid increase in global food consumption. Only the previous three decades have seen a rise in agricultural productivity of over 17%. 821 million people globally, however, lack access to enough food. Achieving a rapid growth in agricultural or food production to meet the growing need for food supply is no small feat. This problem is caused by a number of factors, including markets, political turmoil, poor storage, agricultural practices that date back 10 years, and others. By 2050, food and agriculture groups predict that the growing global population would require a 70% increase in agricultural production to feed the world's growing population. Not only must we feed them, but we must also provide them very nutritional food that doesn't harm the

ecosystem. Since groundwater levels are dropping, the amount of arable land is not increasing, and the quality of the soil is not improving, we must appropriately increase agricultural production.

2.RELATED WORKS

In "Big Data Analytics for Smart Farming: Case Studies in Precision Agriculture" (2019), S. B. S. Sreeja et al. In this article, we provide case studies of big data analytics used to precision agriculture, with a focus on soil health assessment, yield prediction, insect detection, and crop monitoring. The statement highlights the significance of utilizing several data sources, including weather, sensors, and satellite imagery, in order to enable data-driven agricultural decision-making.

The 2020 publication "A Review of Big Data Applications in Agriculture" by A. K. M. Nazmul Haque et al.: This paper provides an overview of the latest advancements in big data applications, namely in precision agriculture. It describes the integration of several technologies, including artificial intelligence (AI), remote sensing, and the Internet of Things, for data collection, analysis, and decision support in agricultural operations.

The paper "Deep Learning for Agriculture: A Survey" by S. K. Sharma and colleagues (2021): The application of deep learning techniques in agriculture is the main topic of this thorough research, which also covers the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other models for tasks including yield prediction, weed identification, and crop disease detection. Deep learning in precision agriculture is also examined, along with its challenges and future directions.

As to the publication "IoT-Based Smart Agriculture: Recent Advances, Taxonomy, and Open Challenges" by D. P. Mago et al. (2021): In this paper, an overview of Internet of Things (IoT)-based smart agricultural systems and its applications to precision farming is presented. The integration of sensor networks, cloud computing, and Internet of Things devices for real-time data monitoring, analysis, and decision-making for agricultural operations is discussed.

The publication "Machine Learning in Agriculture: A Comprehensive Review" (2019) by A. B. Hemalatha and associates: This extensive study looks at the application of machine learning techniques in precision agriculture and other agricultural domains. Crop classification, yield prediction, and pest control are just a few of the issues it tackles using algorithms for supervised, unsupervised, and reinforcement learning.

In 2020, R. K. Mishra and associates published "Precision Agriculture Techniques Using Big Data Analytics: A Review": With an emphasis on big data analytics-enabled precision agriculture techniques, this review article clarifies the role that cloud computing, artificial intelligence, and data analytics play in optimizing agricultural practices. Crop monitoring, irrigation control, and farmer decision support are all covered through case studies and big data analytics applications.

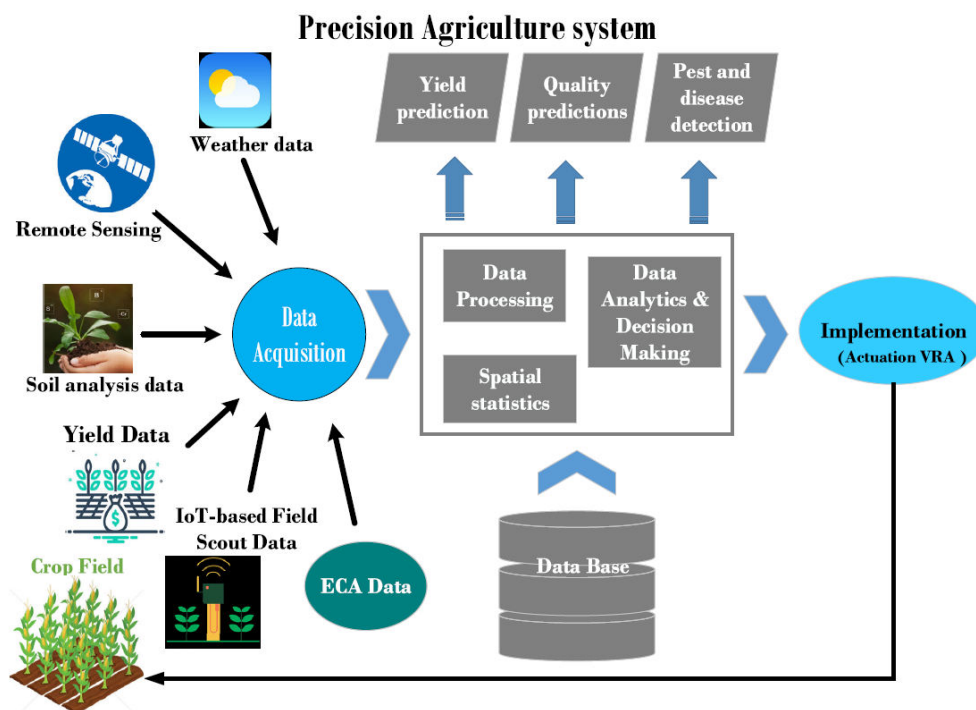


Figure 1. Big data-based precision agriculture system representation.

These related works add to the growing body of research and practical applications aimed at leveraging big data and artificial intelligence to elevate agriculture to the status of a more efficient, sustainable, and productive economic sector.

The paper "Precision Agriculture: A Worldwide Overview" by Pierre Robert et al. (2018) This extensive review provides a global overview of precision agriculture techniques, including technology, methodology, and applications. Precision agricultural data management, variable rate technology, remote sensing, and GPS navigation systems are some of the topics covered.

In 2019 Gerrit Hoogenboom and colleagues published "Precision Agriculture: Challenges and Future Directions": In addition to issues regarding data administration and sensor technology, this research covers the challenges and future directions of precision agriculture.

acceptability among farmers, agronomic modeling, and technology. Perceptions of recent advancements and potential strategies to enhance precision farming techniques are provided.

The publication "Advancements in Precision Agriculture Technologies for Horticultural Crops" (2020) by Umezuruike Linus Opara et al.: With a focus on precision agriculture technologies for horticultural crops, this research examines recent advancements in sensor technology, automation, data analytics, and decision support systems. It emphasizes how resource usage efficiency, productivity, and quality may all be improved by precision agriculture in horticultural production systems.

The publication "Precision Agriculture Techniques for Crop Management: A Review" by Arun K. Senthil and associates (2021): This review research presents an overview of precision agriculture crop

management techniques, including soil mapping, crop monitoring, irrigation management, and pest control. It discusses how precision agriculture applications may use technology like GPS, GIS, IoT, and remote sensing.

In "Recent Advances in Precision Agriculture: A Review" (2020), Shiyu Zhang et al. Current advancements in precision agricultural technology are the main topic of this review article, which covers innovations in robotics, automation, machine learning, and data analytics for applications in precision farming. It examines recent advancements in precision agriculture as well as case studies.

In 2019 Abdullah M. Al-Showiman and colleagues published "Precision Agriculture: An Overview and Future Perspectives": This paper presents an overview of precision agricultural techniques, including as irrigation, precise fertilization, and site-specific management. Precision agriculture's benefits, challenges, and possible uses to improve agricultural output and sustainability are discussed.

These related articles offer valuable information regarding the current state of precision agriculture, recent advancements in the field, and prospective directions for further research and development.

3.FRAMEWORK FOR BIGDATA BASED PRECISION AGRICULTURE

Every level of agricultural production and supply chains, including data on soil moisture, weather, and environment, crop yield and harvest, supply and demand data from the supply chain, food processing data from the food processing industries, and farmer-used pesticide data, are preserved by the recommended system architecture. Figure 2, displays a summary of the recommended system's crop selection decision support system. Cloud storage and other local databases are the sources of the pertinent data on soil quality, including pH and nutrient levels. By tying biotic or abiotic data to the evolution and probable existence of infections, pests, and toxicants, it is possible to investigate seed qualities, food sorting, weather patterns, marketing and trade management, and the presence of food risks. Big data analytics suggests to agriculture practitioners which crop would be most in demand. Farmers are prevented from harvesting more crops than expected by the technology, which maps and tracks the crops with the corresponding demand.

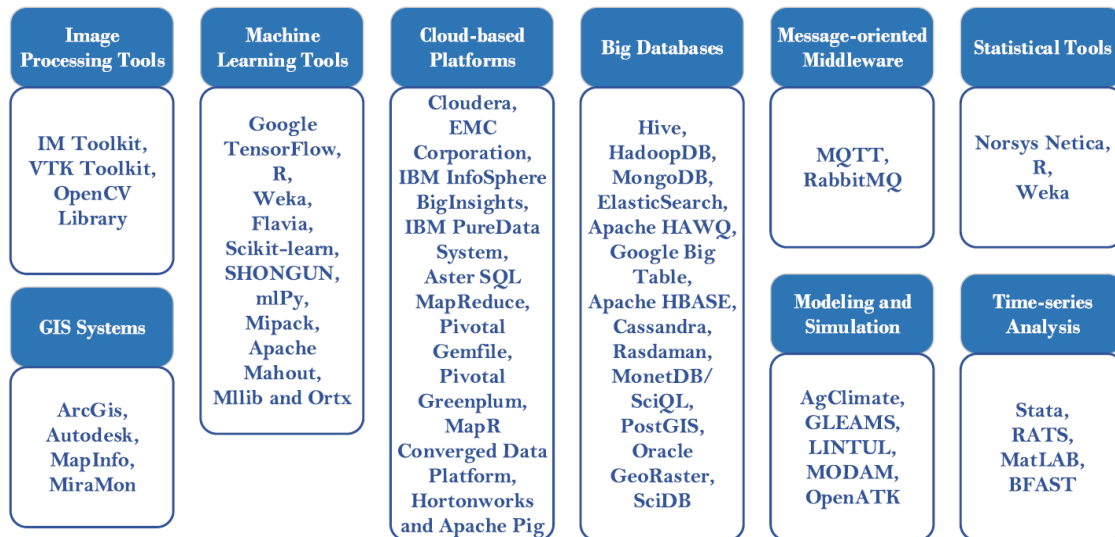


Figure 2. Software tools employed in agriculture big data analysis.

To convert statistics and pictures into information that is helpful, the unprocessed assessment of crucial elements from the agricultural data has to be thoroughly processed. The growth and quality of the crops may be monitored using the photo data collected from the farm; other Python image processing packages, such as Scikit-image, Matplotlib, and OpenCV, can then be employed. Through the process of deriving distinct crop attributes from the photographs, such as crop quality and height and width, we are able to infer information about the color of the leaves and crops. Other Internet of Things sensors are used to collect and store in the cloud all other environmental parameters in the interim. Information gathered by IoT networks used in the food processing industries includes, but is not limited to, the quality of the raw materials utilized and other components needed to make the finished food product. Any type of file format, including CSV files, may be used to store these values on the network. After a quick analysis and evaluation of the importance of the traits that were recovered, machine learning or deep learning models can be trained using some of the abstracted data. Then, these trained deep learning models and algorithms are used to extract the required features from large data sets collected from the field.

The extensive usage of machine learning algorithms in many real-time application scenarios can be attributed to their capacity to produce reliable answers for complex problems. Large-scale data processing becomes less challenging when features and contexts are categorized and then structured using training sets [10]. The many iteration validations generated by this type of processing help to ensure accurate and reliable analysis. This intelligence is integrated into data processing and decision-making systems connected to smart farms in order to boost the definiteness of the offered solutions [11]. Machine learning applied to sensor data analysis satisfies criteria pertinent to each application scenario, including complexity-free and tardiness-less methods. The immediate judgments required to enhance automation efficiency are mostly derived from the farm information's time- and instance-dependent solutions [12]. Given these many limitations, a number of artificial intelligence and machine learning approaches have been applied recently to preempt data processing and decision-making in the backend of smart farming. These connections aim to deliver accurate results and well-coordinated decisions that are advantageous in real-time situations [13].

This paper addresses the uncertainties in sensor data processing caused by various aggregation times. This idea also lessens the uncertainty in data processing since it takes accuracy and timing into account. Consequently, this article's contributions are summed up in the following.

One way to identify the uncertainties in sensor data management at several levels is to develop an information evaluation approach.

- 2) Developing an analysis of sensor data to create a control distribution procedure that allows the devices to function selectively against uncertainties.
- 3) Information handling uncertainties are identified and reduced by the use of SSA, which combines BM with efficient, limited layered processing.
- 4) Proposing changes to the BM output so that the devices are more accurate by distributing controls based on training sets and BM restrictions.
- 5) Analyzing the proposed SSA in comparison to make sure it is consistent.

4. SAMRT SENSING AGRICULTURE

The use of smart sensing technology to agricultural operations to enhance management and control procedures is referred to as "smart sense farming control". This concept optimizes crop quality,

maximizes resource use, and increases overall farming operations efficiency by combining automation, data analytics, and state-of-the-art sensor technologies.

Sensational agricultural control employs a variety of sensor technologies to collect data on crop health, soil properties, weather, and other relevant variables. In addition to GPS tracking and location monitoring, these sensors may also contain soil moisture sensors, temperature and humidity sensors, cameras for visual monitoring, and spectrum sensors for assessing crop health.

Collecting and Tracking Data: Continuous data collection is facilitated by sensors positioned across fields, providing real-time information on various aspects of agricultural activities. To assist in decision-making, this data is sent to a central monitoring system for analysis and processing.

Automation & Control Systems: Smart sense farming control systems often interface with automation & control systems to provide remote monitoring and management of agricultural activities. An automated irrigation system, robotic harvesters, accurate planting tools, and unmanned aerial vehicles (UAVs) for crop observation are a few examples of this.

Decision Support and Data Analytics: Advanced data analytics methods like as artificial intelligence and machine learning are used to identify patterns, trends, and anomalies in the collected data. With the help of decision support technology, farmers may make wise decisions instantly by obtaining relevant information and guidance.

The most efficient use of resources is achieved through the continuous monitoring of crop health and environmental factors by smart sense agricultural management systems. This entails managing the soil's moisture content while applying fertilizers and pesticides, carefully scheduling irrigations, and utilizing energy-saving tools and machinery.

Increased Crop Quality and production: The ability to closely monitor crops and adjust management tactics as needed may lead to increased crop quality and production. With the use of control systems, smart sense farmers may detect disease, stress, or nutrient deficiencies early on. Quick action to reduce potential losses and boost productivity is made feasible by this.

Advantages for Environmental Protection and Sustainability: Sustainability and environmental stewardship are upheld when prudent farming techniques minimize inputs such as water, fertilizer, and pesticides. Precise resource management minimizes waste and the negative environmental impact of agricultural operations.

In conclusion, smart sense farming control is a comprehensive approach to modern agriculture that maximizes agricultural operations, increases production, and advances sustainability via the use of automation, data analytics, and state-of-the-art sensing technologies. With data-driven decision-making, farmers can minimize resource use and environmental harm while addressing the challenges of feeding a growing world population.

An electronic surveillance system for agricultural machinery is established through the use of intelligent sensor data processing. An information management strategy called an SSA is intended to minimize and clarify ambiguity. With minimal effort and efficient layering, BM equipment handles information processing unpredictability. BM performance criteria dictate how system controls are

distributed. The gadgets in a smart farm setup are controlled by access points, device controllers, and a centralised control unit. Wireless communications together with electric pulses power the devices. SSA operates between control units and smart farms. Turning the devices on or off is controlled by the control unit, which makes intelligent decisions and computations. Intelligent decision making is done to turn the devices ON or OFF based on the sensor data (S). Temperature/humidity, air movement, water level, and other sorts of sensors might be used. Function controls are sent out appropriately once the control unit has evaluated the S's inputs. The two components of SSA that result are information assessment and control distribution.

$$\left. \begin{aligned} I &= s \frac{\times (S_{\max} - S_{\min})}{S} + S_{\min} \\ \text{and} \\ \Xi &= 1/\sqrt{2\pi} \left[\frac{\left(\frac{S_{\min}}{S_{\max}} - \frac{s}{S} \right)}{2(I-I^*)} \right] \end{aligned} \right\}$$

The active sensor in this case is denoted by $s \in S$, and the $S_{\max}$, $S_{\min}$, and observed sensor data in various cases are represented by S , $S_{\max}$, and $S_{\min}$, respectively. The felt prior knowledge and degree of uncertainty are represented by the variables E and I^* .

The number of mismatched cases seen at various S observations is used to determine the uncertainty. There are instances where errors in I arise as a result of s 's operational and physical problems. As a result, these problems affect the I at all times, and normalisation is carried out as

$$\left. \begin{aligned} \mathcal{N}(I) &= \frac{\Delta^2}{\Delta^2 \left(\frac{S_{\min}}{S_{\max}} - \sigma \right)^2} \\ \text{and} \\ \sigma &= \frac{1}{S} \sqrt{\frac{1}{s-1} \sum_{i=1}^S \left(\frac{I-I^*}{I} \right)^2} \end{aligned} \right\}.$$

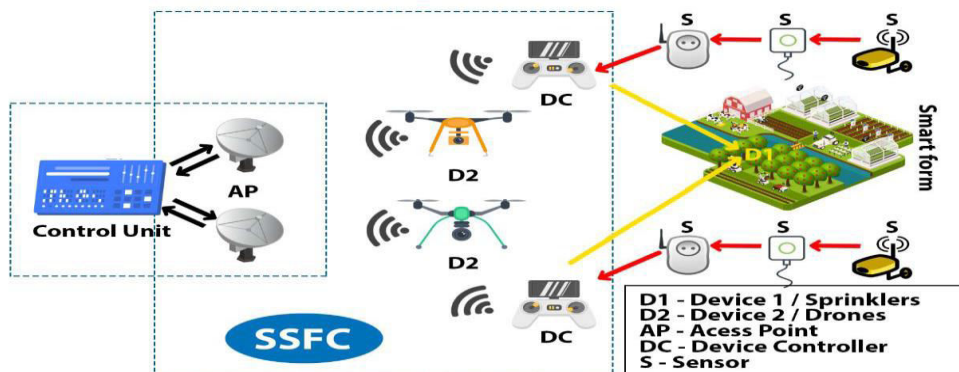


Figure 3. SSA for smart agricultural farm data analysis.

This section examines the recommended SSA approach's performance evaluation. Performance is assessed on a 0.4-hectare corn field using a data set of 20 drones and 60 sprinklers. Before corn is

planted, 80 sensors are randomly placed on the farm to control the drone and sprinkler operations. A drone has a six-kilometer operational range in a single session. Fertilize the farm by applying fertilizer sporadically for fifteen minutes and evenly for forty minutes. The sprinklers are activated by sixteen sensing incidences that occur during the day. A farm has eight to twenty days between each successive operation. Four local access points are utilized to control the drones, and two electrical circuits oversee eleven sensors. This section examines the recommended SSA approach's performance evaluation. Performance is assessed on a 0.4-hectare corn field using a data set of 20 drones and 60 sprinklers. Before corn is planted, 80 sensors are randomly placed on the farm to control the drone and sprinkler operations. A drone has a six-kilometer operational range in a single session. Fertilize the farm by applying fertilizer sporadically for fifteen minutes and evenly for forty minutes. The sprinklers are activated by sixteen sensing incidences that occur during the day. A farm has eight to twenty days between each successive operation. Four local access points are utilized to control the drones, and two electrical circuits oversee eleven sensors.

Name	Simulation results	Experimental results	Percent
D1	2.660805252	1.134926777	134.4473058
D2	5.340829801	1.761145317	203.2588934
D3	9.263162618	8.547389901	8.374167153
D4	1.838614743	5.158892888	64.3602846

Table 1. The simulation results are compared with the existing experimental results.

Then, analysis time, analyzed rate (for various sensors), dissemination delay, accuracy (for various devices), and uncertain controls (for various devices) are used to gauge how successful SSA is. This assessment is conducted against various existing approaches, such as ANM-SFS [21], SAIS [17], and MOTT-IoT [26]. The comparative study takes into account the computation and analysis rather than the application scenario from each of these approaches. Early on in the development of a software application, the kind and exact name of user data storage must be determined and validated. Potential avenues for program development might be opened by a more standardized database design. A large amount of data will be generated when the system is utilized to monitor environmental data and gather ginseng experimentation data. The various data types will be categorized and stored in the relevant data table to complete the basic data storage function. The system's update and data collecting procedures are closely tied to the system's routine contacts with the database, which is an essential component of data storage. Effective database architecture affects function utilization, system performance, and interface presentation effect. The validity and correctness of the data have a significant impact on the application system's viability. The basis for collecting data on environmental parameters and storing data from ginseng experiments is a significant amount of data. To meet the challenge of logically storing the enormous volume of data, the system needs a database as the cornerstone for data storage that has a condensed and clear structure.

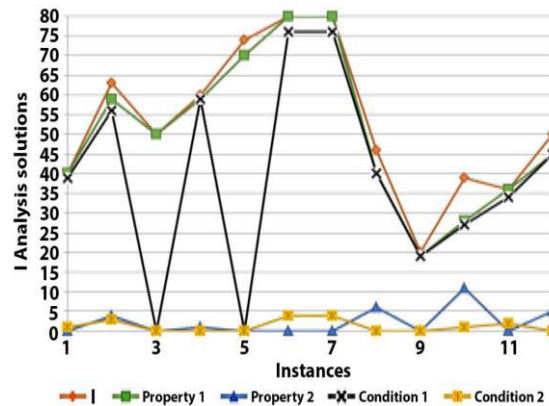


Figure 4. Variation of I based on different conditions

Certain crops have a timing module inserted during planting based on historical data analysis and the expertise of relevant agronomic professionals. The fans and the additional illumination are controlled by this module to open and close at regular times throughout the day. The timing control setting's initial conditions are determined by the administrator using the crop-growing environment's experience during this period, but there may be noticeable changes in the external environment during this time. For this reason, it is crucial to pay attention to setting the priority value when using timing control. If it is still using the preset timed mode, the greenhouse environment management system may not be suitable for the demands of the present crop development. The gateway periodically polls each information collecting and control module to get environmental data, and each module sets its own address information. This stops data blocks from being created when several nodes give the gateway environmental data simultaneously.

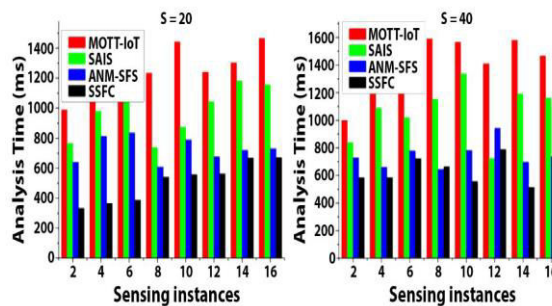


Figure 5. Analysis time verses sensing instances with and other existing methods.

Acquire the first traffic data, which has been abnormally marked by a professional diagnosis; deal with any missing values; divide the period by combining the sliding time window; classify the traffic by performing a cluster analysis within the same time interval period based on the abnormal cycle. Features: The supervised learning method is used to create a leak detection model. In the actual detection process, traffic data is searched for the previous 0.5, 1 and 1.5 hours, and the likelihood of anomalous traffic in each period is computed. Traffic data is input at a predetermined time. After weighing and thoroughly calculating the chance of traffic abnormality at that precise instant, the system is queried to determine the probability of abnormal traffic at that moment. Using the defined leakage confidence level, it is possible to ascertain whether leaks are occurring right now. A leakage alert will sound on the intelligent agriculture information monitoring service platform in the event of a leak.

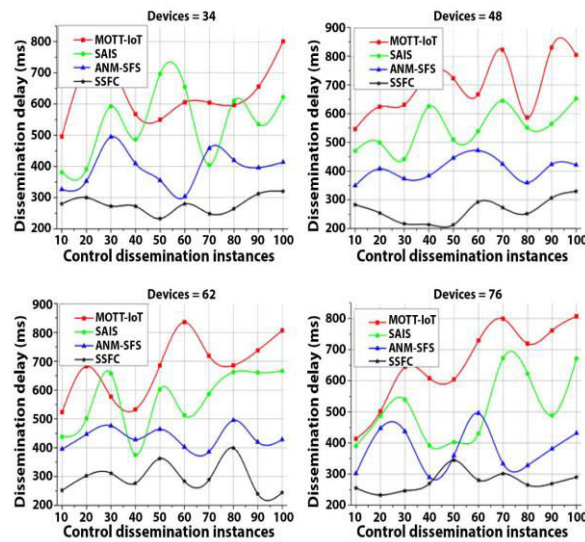


Figure 6. Dissemination delay analysis of SSA with respect to other competing methods.

Many problems need to be solved in big data-driven smart sensing for precision farming, despite the noteworthy advancements that have been made in this area. Among these include the need for continuous innovation in AI algorithms and sensor technologies, privacy and data security concerns, integration issues with existing farm management systems, and interoperability issues across various sensor networks. Some possible future research directions include developing autonomous robotic systems for in-situ data collection and precision farming, integrating Internet of Things (IoT) devices for seamless connectivity, and utilizing blockchain technology for safe and transparent data sharing among actors. In summary, big data-driven smart sensing systems enabled by AI technologies hold great potential to revolutionize precision agriculture through large-scale data-driven decision-making. Real-time data analytics may help farmers maximize resource use, boost agricultural output, and enhance environmental sustainability. However, addressing present problems and embracing new advancements will be necessary to fully realize precision agriculture's potential in feeding the world's growing population while safeguarding its finite resources.

5. RESULTS AND DISCUSSION

In conclusion, big data-driven smart sensing techniques combined with artificial intelligence (AI) methodologies constitute a significant advancement in precision agriculture and provide previously unheard-of opportunities to completely transform agricultural practices. With the integration of data analytics, artificial intelligence (AI), and state-of-the-art sensor technologies, precision agriculture has the potential to achieve previously unheard-of levels of productivity, sustainability, and efficiency.

Farmers now have access to real-time data on crop health, weather patterns, soil conditions, and environmental factors thanks to smart sensing technologies built on big data that enable continuous monitoring of a variety of agricultural indicators. Large amounts of data are collected at high temporal and geographical resolutions by these systems using a variety of sensors, such as weather stations, spectrum sensors, and soil moisture sensors.

Artificial intelligence is deemed indispensable for the assessment and interpretation of data collected by smart sensing devices. Machine learning algorithms that examine historical data to identify patterns, correlations, and anomalies provide predictive analytics for crop growth, insect infestation, and disease outbreak. It is simpler to predict production, categorize crops, and identify weeds when deep learning models are used for tasks like time-series analysis and picture recognition.

The integration of AI-driven analytics into precision agriculture systems enables the development of decision support systems (DSS) that offer farmers actionable guidance. Weather forecasts, soil properties, crop characteristics, and market demand are just a few of the many factors that these systems consider when optimizing planting dates, irrigation methods, fertilizer treatments, and pest control strategies.

Precision agriculture uses big data and artificial intelligence to address many of the fundamental problems facing modern farming, including resource constraint, environmental degradation, and climate variability. Through improved resource use, improved crop quality, and increased environmental stewardship, big data-based smart sensing for precision agriculture promises to feed the world's growing population while ensuring the long-term viability of agricultural enterprises.

However, challenges like data security and privacy, interoperability issues, and the need for continual innovation must yet be resolved if big data-based smart sensing in precision agriculture is to live up to its full potential. Prospective research and development endeavors need to focus on surmounting these challenges and propelling the amalgamation of big data, artificial intelligence, and smart sensing technologies to construct a more efficient, prosperous, and enduring agriculture system.

In order to improve the operational devices' accuracy in a smart farm scenario, this research presented a smart sensing-based function control approach. In terms of lowering uncertainty in the collection and exchange of control information, this method works well. The uncertainties are found via BM learning, which uses different restrictions to distinguish certainties in information analysis and control distribution. Several restrictions occur when using analysis and control distribution to filter the least amount of uncertainty. The non-recurrent analysis of the BM is used to minimize uncertainty resulting from unsynchronized input and control flows. Regarding the provision of tardiness-free solutions, this procedure occurs instantaneously for different densities of sensors and devices.

6.CONCLUSION

Smart farming is an area of potential application where different intelligence and communication technologies are used to enhance the outcomes of the agricultural process. Agricultural situations feature multi-level operations that are automated by intelligent decision-making systems and smart sensors. This article presents the smart sensor information processing method for controlling the functions of agricultural machinery. This method, called "smart sensing agriculture," aims to identify and minimize uncertainty in information processing. To manage uncertainties in information processing, devices with effective layered processing are employed. According to the recommendations provided by the output, the allocation of device controls happens initially. Training sets and limits are especially used to filter analysis and regulate distribution in order to improve the accuracy of the devices. The performance of the proposed SSA is investigated using experimental analysis and real-time data set using a range of metrics, such as analysis time, analysed rate, dissemination delay, uncertain controls, and correctness. According to the study, the proposed SSA

achieves the following: 14.2% analysis time, 19.1% shorter dissemination delay, 23.4% uncertain control, 8.17% accuracy, and 6.47% high analyzed rate. The experimental investigation showed the same thing, speeding up and improving the accuracy of analysis for the recommended technique by reducing analysis and dissemination time as well as unclear controls.

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