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A Survey on Automation Challenges and Opportunities for IoT based Agriculture

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Abstract—Agriculture automation is a major concern and a contentious issue in every country. This study provides a comprehensive assessment of the obstacles and potential associated with automating agricultural practises using IoT (Internet of Things) technology. It begins with an introduction that highlights the prior work and discusses the proposed proposal, which is centred on IoT and machine learning applications and breakthroughs in irrigation systems. The report digs into several IoT applications in agriculture, including crop and soil management, drone field surveillance, cattle and resource management, and pesticide/fertilizer tracking. It delves into the breakthroughs made possible by IoT and machine learning, particularly in smart irrigation systems, livestock monitoring, drone technology, precision agriculture, and integrated pest management. The paper thoroughly examines the challenges associated with automating irrigation practises, such as interoperability, data storage, connectivity, hardware and software maintenance, security concerns, data collection, environmental variability, cost, infrastructure, privacy, and adoption by small-scale farmers. The survey finishes by synthesising the important findings and emphasising the crucial need of overcoming these problems in order to successfully adopt IoT-driven agriculture automation.

Keywords-: IoT, Agriculture, Smart farming, Crop Monitoring, Machine learning

I. INTRODUCTION

Farmers can select various acceptable crops for plants of a wide variety and discover the right insecticides. The quality and quantity of agricultural products decrease significantly due to plant disease. The research into the diseases of plants is based on a study of obvious patterns in plants. Inefficient agricultural production, monitoring plant health and diseases plays a vital role. First, a specialist in this field performed the plant disease surveillance and analysis were performed by a specialist in this field [1]. It requires a lot of effort and a lot of work time. Image processing techniques may be used for the detection of plant diseases. Symptoms of the disease are most common on the fruits, leaves, and stems. The symptoms of the disease are the disease-sensing plant leaves. However, most diseases generate a particularly visible spectrum, such that a qualified expert's first experience in identifying plant diseases involves naked-eye inspections [2],[3].

A plant pathologist should be able to accurately monitor typical symptoms to detect plant diseases properly and accurately. Diseased plant symptoms may lead to erroneous diagnoses since amateurs and hobbyists may have greater difficulties. Drip irrigation, ditch irrigation, and sprinkler systems are the conventional irrigation techniques. The automated system instead of the conventional methods may quickly rectify this issue. The present irrigation technique employs a uniform, non-optimal water distribution [4],[5]. Therefore, technology is used to monitor agriculture, which farmers need. A wireless sensor-based monitoring system has been created in addition to the standalone monitoring station, consisting of several wireless sensor nodes and a gateway. This technology offers a unique, wireless, and simple way to solve space and time problems. In addition to using farm surveillance technology to automate irrigation systems, machines require some intelligence to understand the agricultural data collected so that the data may anticipate the output instead of following the conventional rule-based algorithm. So, "machine learning" [4], an integral component of artificial understanding, plays a major role in making it possible for machines to learn without human interference. In crop selection and yield, machine learning has its applications in which several effective machine algorithms [6],[7],[8] determine the input and, therefore, the output of crop choice, resulting in a forecast. Various machine learning methods are used in crop selection using a variety of variables, such as Artificial Neural Networks (ANN), K-Nearest Neighbor, and Decision trees. In addition to crop selection and yield, machine learning has also been used in crop disease predictions [9].

Detection of crop diseases and classification were performed using support vector machines in the early stages. Pattern recognition, a machine learning branch, was also used to identify diseases from crop leaves. So, it is obvious that wireless sensors are used to monitor crop selection and yield and crop disease prediction, depending on the system and machines. However, no study has been published so far that predicts and analyses agricultural data collected for irrigation automation. Moreover, most systems are semi-automotive or automated, limited to a narrow region, and some human involvement is still needed based on the actuation forecast, and so on. This article offers a state-of-the-art farming solution. Wireless sensor network fields should be created across the farm fields and even in the home gardens to control all field sections' irrigation using IoT (Internet of Things) and machine learning methods. The study presented provides the most efficient solution for the agricultural requirements and irrigation demands based on several open sources, internet databases, and machine learning techniques (Classification and Regression).

The requirements for irrigation vary with crops and with seasons, too. With the continual growth of the human population, the pressures on the agricultural sector will increase. Thus, Agri-technology and precision agriculture have become more important nowadays. Using hi-tech software applications to evaluate various factors, such as weeding detection, crop prediction, yield detection, crop quality, and many other machine-learning methods, is also called digital agriculture [10]. This article will cover the many applications in agriculture for ANN, ML, and IoT and numerous models that support precision agriculture.

I. BACKGROUND

In [11], it is discussed how to detect tea pests with a high accuracy of 99.99% by using radial basis function networks with 31 hidden layers. It is exclusive to tea crops, though. Its application of 31 hidden-layer radial basis function networks demonstrates the potential of deep neural networks for tea crop-specific pest detection, providing very accurate pest management. Given to resource constraints in the late 1980s, [12] uses a rule-based expert system for general crop pest detection and control, with an emphasis on insect-related problems. The effectiveness of the rule-based expert system in identifying and controlling insects in general crops demonstrates its usefulness.

Paper [13] highlights the potential of neural networks in food dryness patterns by using artificial neural networks with three hidden layer neurons to identify dryness in mangoes and cassava. While pointing out the limitations with regard to temperature predictions, the use of a basic artificial neural network with three hidden layer neurons highlights the viability of using neural networks for food quality monitoring. In [14], the potential for crop prediction is demonstrated by using artificial neural networks with 9 to 5 neurons in the hidden layer to predict the development of jute crops by backpropagation. Its use of artificial neural networks with diverse hidden layer neuron configurations predicts the development of jute crops with success, suggesting that, with the right training, it may be able to forecast the growth of other crops as well.

In [15], fuzzy logic is used to classify various fruits in MATLAB. However, misclassification is a problem that can be fixed by including texture and colour information. While highlighting its effectiveness, the use of fuzzy logic for fruit categorization in MATLAB admits that misclassification problems still need to be addressed, maybe with the addition of other information like colour and texture. In [16], neural networks and SVM are used for wheat categorization. The neural network achieves a greater accuracy of 94.5%, providing more exact results at a reduced computing cost. The accuracy and cost effectiveness of neural networks are superior to SVM when compared to neural networks for wheat classification, which motivates more research into feature sets for various wheat varieties.

In [17], 84% accuracy in live image testing is attained with the use of CNN-based disease diagnosis in tomato plant monitoring, taking soil and moisture parameters into account. Its application of CNN-based disease detection for IoT-enabled tomato plants shows that remote monitoring and disease identification are feasible, as evidenced by the satisfactory accuracy of live image testing. In order to anticipate agricultural illnesses based on leaf analysis and achieve high disease detection accuracy, [18] focuses on using drones and deep learning. The potential for high-accuracy leaf-based disease detection is highlighted by its use of drones and deep learning for crop disease prediction, highlighting the significance of this technology in contemporary agriculture.

To enhance crop management and yields, [19] uses IoT and a variety of sensors to gather data on field conditions. With an emphasis on soil and environmental aspects, it demonstrates the advantages of data-driven decision-making for crop management through the integration of IoT and diverse sensors into farming practises. In [20], sensor monitoring is used for certain crop regions, but irrigation is not automated, and security issues are not addressed. This leads to better grape quality and lower costs. Despite not taking automation or security into account, the use of sensors for targeted crop monitoring eventually leads to better grape quality, lower costs, and more energy-efficient crop management.

In contrast to spectral-based techniques, [21] achieves superior performance in identifying wheat rust illness by utilising unmanned aerial vehicles and deep learning algorithms. Improved segmentation accuracy for RGB photos is demonstrated by the use of UAVs and deep learning algorithms to detect rust disease in wheat fields, highlighting the benefits of spectral-based classifiers.

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Table I: A comprehensive overview of research works on crop management

Paper	Research Contribution	Opportunities Discussed	Challenges Mentioned	Technologies Discussed	Contribution/Metrics
[11]	Tea pest detection	DNN for crop-specific pest detection	Resource constraints and exclusive to tea crops	Radial basis function networks with 31 hidden layers	High accuracy (99.99%) in tea pest detection
[12]	Rule-based expert system	General crop pest detection and control	Resource constraints and limited to insect-related problems	Rule-based expert system	Effectiveness in identifying and controlling insects
[13]	Food dryness patterns	Food quality monitoring	Temperature predictions	ANN with three hidden layer neurons	Viability of using neural networks for food quality monitoring
[14]	Crop prediction	Forecasting growth of crops	Lack discussion of crop development hindering factors	ANN with diverse configurations	Successful prediction of jute crop development
[15]	Fruit categorization	Improving misclassification with texture and color information	Misclassification issues need additional information	Fuzzy logic in MATLAB	Effectiveness in fruit categorization
[16]	Wheat categorization	Wheat variety classification	Cost-effectiveness compared to SVM	Neural networks and SVM	Accuracy of 94.5% in wheat categorization
[17]	CNN-based disease diagnosis	Remote monitoring and disease identification	Focus limited to tomato plant monitoring	CNN-based disease detection for IoT-enabled tomato plants	Satisfactory accuracy in live image testing - 84% accuracy in live testing
[18]	Drones and deep learning	High-accuracy leaf-based disease detection	Anticipating agricultural illnesses	DL	High disease detection accuracy based on leaf analysis
[19]	IoT and sensor data for crop management	Data-driven decision-making for crop management	Emphasis on soil and environmental aspects	IoT and diverse sensors	Advantages of data-driven decision-making for crop management
[20]	Sensor monitoring for grape quality	Better grape quality and lower costs	Automation and security issues not addressed	Sensor monitoring for targeted crop regions	Better grape quality, lower costs, and energy-efficient management
[21]	UAVs and deep learning for wheat rust	Improved segmentation accuracy for	Lack of propoer analysis of	Unmanned aerial vehicles and DL algorithms	Superior performance in identifying wheat rust illness

		wheat rust disease detection	spectral-based techniques		

II. Proposed Idea

This survey presents a detailed analysis of features of the technologies IoT and ML in agriculture, and the existing limitations in their integration. As demonstrated in Figure 3, we map the limitations of automation in agriculture using ML and IoT to specific characteristics of IoT and ML in agriculture demonstrates the complex relationship between technology and agricultural practices. Limiting data quality and connectivity is particularly critical in the context of remote monitoring and predictive analytics capabilities, as these capabilities rely on consistent data transfer and accurate information to make informed decisions. High initial costs associated with IoT and ML implementation directly impact the adoption of advanced precision farming techniques and remote monitoring systems, which can provide significant benefits but often require significant investments. Privacy and security concerns, on the other hand, underscore the importance of protecting sensitive agricultural data, especially in predictive analytics applications based on data-driven insights. The challenge of adapting to local conditions highlights the need for personalized precision farming solutions tailored to specific agricultural environments and highlights the role of ML in fine-tuning algorithms and strategies to optimize agricultural outcomes.These limitations and characteristics are interrelated and their interaction significantly influences the successful integration of ML and IoT technologies into the agricultural sector.

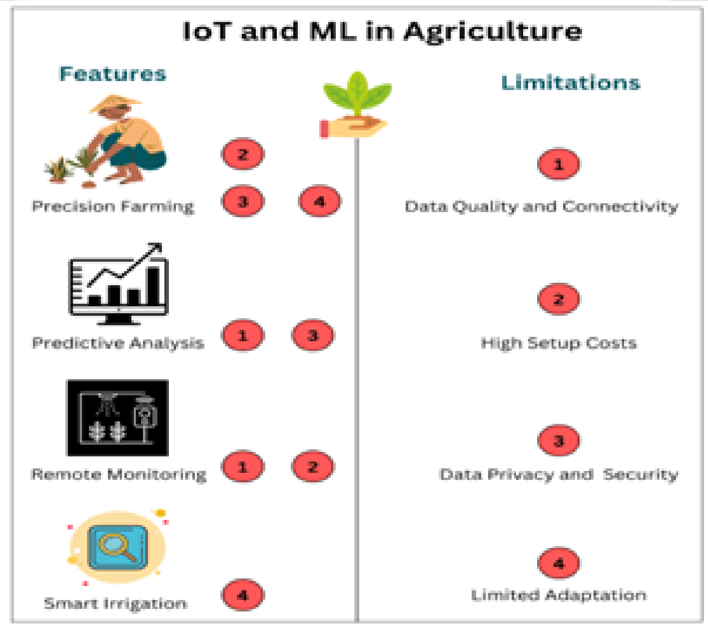

Figure 3: Mapped features and limitations of integration of IoT and ML in Agriculture

Paper Objective: This comprehensive assessment examines the characteristics of IoT and ML technologies in the context of agriculture, with a particular emphasis on understanding the existing limits in their integration. A thorough review of existing literature and research articles was conducted. The research technique entails examining and synthesising material from many sources on the applications, benefits, and problems of incorporating IoT and ML in agriculture. The survey focuses on mapping the limitations of agriculture automation utilising ML and IoT to specific aspects of these technologies. The study throws light on crucial issues such as data quality, connection, upfront expenses, privacy, security concerns, and the difficulty of adapting to local conditions. The survey intends to give insights into the successful integration of ML and IoT technologies into the agricultural industry by revealing the interconnected nature of these constraints and characteristics.

With IoT's acceptance in many industries, including households, vehicles, and even towns, the opportunity to make anything intelligent is enormous. IoT technology is being used in agriculture, and smart farming has developed

III. Applications and Advancements of IoT and ML in Irrigation Systems

This section deals with the applications and advancements of IoT and ML in irrigation systems.

A. Applications of IoT in Agriculture

via the Internet of Things (IoT) and precision. Figure 4 illustrates the many sectors of IoT utilized to produce smart agriculture.

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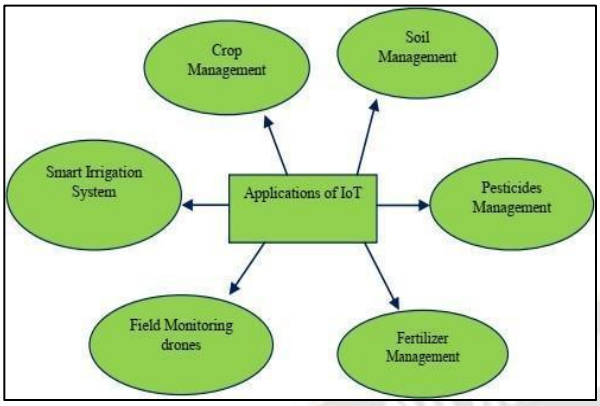

Figure 4. : Applications of IOT in Smart Farming

B. Crop Management using IOT:

Crop management system allows detection of agri-cultural crop development of diseases in leaves, weeds, and water levels, and insect detection and animal in- cursion. Farmers can identify the needs for crops and correctly predict their development. The soil features, meteorological conditions, moisture, temperature, etc., are the factors to be observed on farms. Crop surveillance involves crop health identification and monitoring. IoT sensors and RFID chips can identify plant and agricultural diseases. Supervised and unsupervised algorithms can analyzing data from IoT sensors and RFID chips to detect patterns and anomalies in crop health, diseases, and environmental factors, enabling proactive decision-making for optimal crop management [22].

C. Soil Management:

IoT soil monitoring shows how soil conditions and characteristics vary. Each farmer must understand soil management. The soil's pH value, temperature, and humidity These are key factors for soil characterization and for making correct fertilizers and plant selection decisions. Decision trees and random forests automate soil characterization by analyzing data from soil monitoring to predict optimal pH levels, temperature and humidity for specific crops, simplifying soil management decisions for farmers [23].

D. Field Monitoring using drones:

These make the agricultural data collection using agricultural drones, also known as UAVs (uncrewed aircraft), utilized in smart farming. The drone may also do additional activities, including prior human work, such as planting, preventing pests and infection, cultivation sprays, and crop tracking, besides monitoring capabilities [24]. Computer vision algorithms facilitate agricultural data collection using drones by enabling real-time image analysis for tasks such as pest detection, disease detection and crop tracking.

E. Cattle Monitoring and Management

Like other fields of application, IOT farming sensors may be connected to animals on a farm to monitor their health and performance. The monitoring and surveillance of livestock helps to collect information on animal health, welfare, and the actual location of stocks. Sensors in animal monitoring can detect ill and injured animals to be separated from the herd by farmers to prevent pollution. Farmers also assist in decreasing labor costs by using drones to track livestock [25].

F. Pesticides and Fertilizer Management:

Monitoring the amount of pesticides in crops may help farmers get better outcomes. When a farmer rains, a pesticide may have to be given more frequently, but the effects on different parts of the field during a storm may cause the excess or under of pesticides in various places. They may control the chemical levels using soil or above-ground sensors near plants. We can understand the pests and their activity, location, and trends in managing pesticides and fertilizers. We classified the difficulties of using IOT in agricultural fields in this part based on the technical issues in agricultural fields. In agricultural areas where just basic Internet connection is a problem if, new technologies like IoT, big data, and cloud computing are included. If farmers have engaged in smart farming, there are some difficulties that farmers should know [26].

Table II: Summary of IoT applications in agriculture, their uses, and limitations

IoT Application	**Uses**	**Limitations**
Crop Management System	● Detection of crop diseases in leaves, weeds, and water levels	● Dependency on accurate data from sensors and RFID chips ● Challenges in integrating diverse data sources for comprehensive analysis
Soil Monitoring	● Variation of soil conditions and characteristics	● Reliance on accurate pH, temperature, and humidity data

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		• Potential challenges in maintaining and calibrating soil monitoring sensors
Field Monitoring using Drones	• Agricultural data collection through drones • Tasks such as pest detection, disease detection, and crop tracking	• Limited battery life and range of drones • Dependence on clear weather conditions for effective drone operation
Cattle Monitoring and Management	• Monitoring animal health and performance • Surveillance of livestock location and welfare	• Need for effective connectivity in remote areas with livestock • Potential privacy concerns regarding continuous monitoring of animals
Pesticides and Fertilizer Management	• Monitoring and managing the amount of pesticides in crops	• Challenges in precise control of chemical levels based on localized conditions • Technical issues related to Internet connectivity in rural agricultural areas

4.2 Advancements of IoT and ML in Agriculture

A. Precision Agriculture

It employs sensor technology for rigorous monitoring, allowing for optimal resource utilisation, real-time data-driven decision-making, and reduced environmental impact. However, its implementation may be costly at first and requires reliable and integrated sensor data.

G. Smart Irrigation Systems

It uses IoT-connected sensors to manage water more efficiently, resulting in better crop health and less water waste. Their success, however, is dependent on continual connectivity and operational correctness.

H. Livestock Monitoring

Wearable sensors and IoT devices are used in livestock monitoring to detect early symptoms of animal health issues, improving breeding decisions and overall herd health. There exists constraints about continuous monitoring and the dependability of wearable sensors.

I. Drone Technology

Drone Technology for Crop Monitoring allows for faster data collection and early disease identification, but it has limits in terms of battery life, range, and weather sensitivity.

J. Integrated Pest Management (IPM)

IPM with IoT-based systems enables precise pest management and reduced chemical usage, but proper identification and response to various insect populations pose obstacles. These developments demonstrate the potential of IoT in agriculture while emphasising the importance of resolving technological complexity and context-specific requirements for successful application.

Table III outlines several recent advancements in IoT-based agriculture, each offering distinctive approaches, advantages, and limitations.

Table III: Advancements in IoT-based agriculture, advantages, and limitations

Advancements	**Approaches**	**Advantages**	**Limitations**
Precision Agriculture	Use of sensors for precise monitoring	• Enhanced crop yield through optimized resource utilization • Real-time data for decision-making • Reduced environmental impact through targeted inputs	• Initial high implementation costs • Dependency on accurate sensor data • Potential challenges in integrating diverse sensor data sources

Smart Irrigation Systems	IoT-connected sensors for water management	• Efficient water usage based on real-time data • Improved crop health through controlled irrigation schedules • Reduced water wastage and costs	• Reliance on consistent connectivity for remote areas • Potential technical issues with sensor malfunctions or inaccuracies
Livestock Monitoring	Wearable sensors and IoT devices for animal health	• Early detection of health issues in livestock • Improved breeding and management decisions • Enhanced overall herd health and productivity	• Privacy concerns regarding continuous monitoring of animals • Reliability and durability of wearable sensors
Drone Technology for Crop Monitoring	UAVs equipped with IoT sensors for field analysis	• Rapid data collection for crop health assessment • Early detection of diseases or pests • Improved efficiency in large-scale field monitoring	• Limited battery life and range of drones • Dependence on favorable weather conditions for effective operation
Integrated Pest Management	IoT-based systems for pest monitoring and control	• Precise pest identification and control • Reduced chemical usage through targeted application • Enhanced ecological balance in agricultural ecosystems	• Complexities in accurately identifying and responding to diverse pest populations • Potential dependency on accurate data inputs

IV. Challenges in Automation of Irrigation Practices

This section outlines the five major difficulties facing agriculture in using IOT technologies.

A. Standard problems of interoperability

The IOT technologies used to transmit information amongst all the interlinked IOT devices in an agricultural environment. These devices communicate with the connections and standards via a single protocol. Therefore, interoperability is the hardest reality. Heterogeneous data from various sensors can hardly be integrated (like moisture sensor, soil sensors, temperature sensor etc.) We have to invest a lot of effort and cost creating one standardized protocols for all IOT devices [27].

B. Massive Agriculture Data Storage Issues

Large volumes of data from various IOT devices linked in an agricultural area (such as sensors, cam- eras, weather stations.) We require a big repository to store such an enormous amount of data. The database does not store data enough for an enormous amount of data to manage. The best performance for storage and latency would be technologies, such as Cloud Computing and Fog Computing [28].

C. Issues concerning connectivity

Connecting to the IOT device with the database or cloud is a significant problem because it is too difficult to make wireless connection. Low Internet connectiv- ity in farms is the fundamental issue. Most farms are in rural regions with inadequate connection to the internet for fast transmission speeds. In addition, crops, severe weather, and other physical obstacles may obstruct communication cables. In the future, 5G technologies using the space-based Internet may be the answer.

D. Implementation and maintenance of hardware and software

We must choose the hardware and software tools and methods to build an Agri-based solution. Sensor quality, improved data storage, and sophisticated data analysis instruments. The quality of sensors. The findings depend on the correctness and dependability of the data. Given the potential of sensors installed for field monitoring by animals, strong wind, rain, etc., hardware maintenance in agriculture is a challenge. To solve this contrait, the hardware needs to be robust and durable.

E. Issues of security

In using IoT on farms, an understanding of the safety concept is needed, and they developed safety rules. Intelligent agriculture and IOT technologies involve dealing with large volumes of data from many sensors, thus increasing the number of possible safety gaps for data theft and assaults by criminals. Agricultural data security is an intuitive and difficult job. Many farms utilize drones to provide data to agricultural equipment. These devices have minimal or no data security linked to the Internet, such as server passwords or authentication for remote access.

F. . Data Collection and Annotation

The gathering and annotation of massive, high-quality image databases is one of the major issues. A wide-ranging dataset is necessary for deep learning models to learn and generalize patterns for precise classification successfully successfully. However, gathering such datasets with labeled photographs of plants and flowers may be labor-intensive, time-consuming, and expensive. Additionally, it takes rigorous work and subject expertise to ensure the correctness and consistency of annotations for different plant species and flower varieties. The performance of the trained model can be significantly impacted by insufficient or erroneous labeling, which can result in decreased classification accuracy and dependability. To develop reliable and efficient models for accurate plant and flower identification, academics and practitioners in agriculture automation must overcome this data gathering and annotation difficulty.

G. Environment Variability

Due to various environmental factors, including climate, soil composition, and cultivation techniques, plants and flowers can display substantial differences in their look and development patterns. As a result, it may be difficult for the ML model trained on one set of environmental circumstances to reliably and generally categorize plants and flowers in many environments. The model must learn to adapt to different situations to achieve strong generalization, as well as to recognize key properties that are less sensitive to environmental changes. To improve the model's capacity to recognize plant and floral traits across various environmental contexts, this task calls for advanced data augmentation approaches, transfer learning, and fine-tuning tactics. To provide accurate plant care suggestions and efficient automation in agriculture across various geographic regions and agricultural methods, robust generalization is essential.

H. Cost and Infrastructure

Implementing IoT in agriculture necessitates a major upfront investment in sensor deployment, connectivity infrastructure, and data processing systems, which presents a big hurdle for farmers with limited financial resources. Rural areas may lack sufficient network and electrical infrastructure, which increases costs and impedes seamless IoT integration.

I. Data Privacy and Security

The capture and transfer of sensitive agricultural data via IoT devices raises privacy and data security concerns. To avoid unauthorised access or data modification, it is critical to protect this information from cyber threats, which necessitates strong encryption mechanisms and tight access controls.

J. Interoperability

Compatibility and interoperability of multiple IoT devices and systems from diverse vendors is a significant concern. To ensure seamless communication and data exchange among various sensors and platforms, standardised protocols and interfaces are required, reducing integration difficulties.

K. *Adoption by Small-scale Farmers*

Small-scale farmers frequently encounter barriers to adopting IoT due to issues such as limited technology literacy, insufficient financial resources, and a lack of awareness about the potential benefits. It is critical for wider adoption among this group to tailor cost-effective and user-friendly IoT solutions while providing necessary training and support.

V. Conclusion

Monitoring agriculture is necessary to reduce the number of human interventions in practice. Day by day, food demand reaches its highest level, and it is extremely difficult to meet growing demand without using new techniques in agriculture. The primary focus is agricultural monitoring, which helps decrease work and improve output. Agriculture monitoring. An analytical analysis of the different research papers on crop surveillance is provided and its most concentrated parts and gaps or areas not covered are also noted. They provide a comprehensive evaluation of several publications, crop surveillance, the detection of diseases and farm management. Some problems have been raised from the studies that need study and testing in the future, as well as communication technologies and IoT hardware platforms. There are also questions, problems and future guidelines for study. The whole discussion has profoundly explained distinct elements of the

IoT in agriculture and how these studies could be treated to provide efficient and ingenious scenarios for agriculture. The growth of farm automation leads to many loopholes in these systems and the alarming necessity to protect agricultural land. This paper proposes a system using sensors, IoT, and machine learning to automate conventional agriculture operations.

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