Journal of Computer Science

Original Research Paper

Sustainability Through Connectivity: IoT Influence on Agriculture

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Article history
Received: 06-01-2024
Revised: 17-05-2024
Accepted: 04-07-2024

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Abstract: Today's smart farming has ushered in a new era of agriculture, one where information and communication technologies seamlessly integrate with the latest equipment in machinery and sensors based in high-tech farming systems. This transformative shift is driven by the latest technologies notably the IoT and cloud computing which are poised to revolutionize farming practices by introducing robots using artificial intelligence into the agricultural landscape. While these advancements hold immense promise, they also bring forth a set of formidable challenges. To investigate the profound impact, of innovative farming underpinned by the IOT on advancing sustainable agriculture. Through an in-depth exploration of empirical evidence and scholarly research, it rigorously examines how IoT technologies optimize resource allocation, foster precision farming practices effectively address environmental concerns in agriculture. That empowers farmers to optimize their practices, improve crop yields navigate the complex interplay of technology and tradition in modern farming.

Keywords: Traditional Farming, IoT-Based Agriculture, Sustainable Agriculture, Wireless Sensors

Introduction

Sustainable agriculture, characterized by its eco-friendly practices, is the cornerstone of our ongoing efforts to secure lasting food production while simultaneously safeguarding the environment and ensuring the well-being of future generations (Srisruthi *et al*., 2016). It not only promotes farming methods that support both farmers and essential resources but also aligns with economic viability and ecological integrity. Sustainable agriculture encompasses a multifaceted approach that includes soil conservation, the preservation of water resources, the enhancement of biodiversity, and the cultivation of a natural and healthy environment (Duflo *et al*., 2011).

The pivotal role of sustainable agriculture extends beyond mere food production, it serves as a linchpin in conserving natural resources, and curbing biodiversity loss mitigating the ominous specter of greenhouse gas emissions (Obaisi *et al*., 2022). It harmonizes the imperative of meeting the current global food demand with the equally pressing need to secure the health of our planet for generations to come. Smart farming, an innovative approach that seamlessly integrates technology and agriculture, has emerged as a potent force in realizing the goals of sustainable agriculture (Latake *et al*., 2015).

The urgency of this transformation cannot be overstated. In countries like India, where agriculture forms the bedrock of the economy, the challenges loom large. Despite a surge in agronomic output, the agricultural workforce has dwindled from nearly 72% in 1951 to just 45.1% in 2011 (Foster and Rosenzweig, 2010). The economic survey of 2018 predicts that this trend will continue, with agricultural workers comprising only 25.7% of the total workforce by 2050. The attrition of the farming populace depends is different factors,

DOI: 10.3844/jcssp.2025.96.110

including escalating farming costs, diminishing per capita productivity inadequate soil stewardship, and rural-to-urban migrations in pursuit of more lucrative occupations.

However, amid these challenges, we stand on the cusp of a digital revolution a moment when technology can be harnessed to reconnect farming with the digital realm, enhancing the connectivity and empowerment of farmers (Ganeshan and Vethirajan, 2021). The fusion of agriculture and wireless technology has the potential to revolutionize the agricultural landscape, But the path to sustainable agriculture is not without its complexities.

In this context, Factors in irrigation patterns, such as nutrient content, and soil type pest resistance must be individually assessed both in terms of quality and quantity of crop. Achieving the full potential of agriculture requires an intricate dance with spatial where crop rotation and annual growth cycles play pivotal roles (Adhiguru and Devi, 2012).

In the following chapter, we embark on a journey through the transformative landscape of smart farming based on sustainable agriculture where technology and tradition converge to shape the future of food production. We explore the application of IoT-based and different cutting-edge technologies, shedding light on their potential to redefine agriculture's boundaries and address its most pressing challenges.

The evolution of agriculture stands as a testament to humanity's relentless pursuit of innovation, efficiency sustainable food production. This historical voyage through the annals of agriculture, from its origins in ancient times to the modern frontier of Smart Farming, reveals a captivating narrative marked by technological advancements, environmental challenges an unwavering commitment to agricultural excellence.

Ancient Agriculture to the Traditional Era 1.0: In the distant past, agriculture was the lifeblood of human survival, ushering in what we now recognize as the Traditional Era 1.0. This epoch relied upon human toil and the strength of beasts of burden, with rudimentary tools like sickles and shovels defining the agricultural landscape. It was an era characterized by labor-intensive cultivation, a period that yielded modest productivity.

In Fig. (1), The Rise of Agricultural Era 2.0: The 19th century heralded a transformative era in agriculture with the introduction of steam engines and the proliferation of machinery. This marked the genesis of Agricultural Era 2.0, a time promising heightened farm efficiency and productivity. This era arrived with a sobering cost the widespread adoption of chemicals and machinery ushered in a troubling era of chemical pollution.

The Emergence of Agricultural Era 3.0: This epoch saw the advent of robotic techniques, programmed agricultural machinery other cutting-edge innovations that revolutionized agricultural processes (HBGEA, 2019).

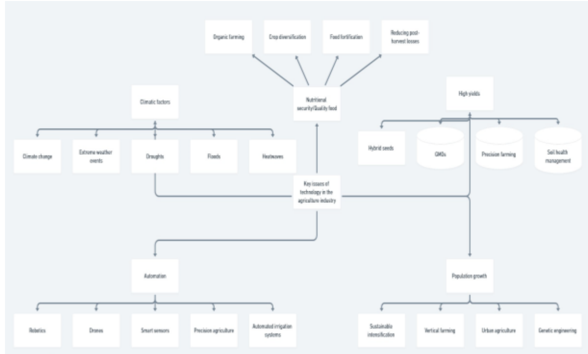

Fig. 1: Agriculture industry key issues of technology

The current agricultural era 4.0-smart farming: This amalgamation of technologies has birthed the epoch of Smart Farming, fundamentally reshaping agriculture in profound ways. With the deployment of cost-effective sensor and network platforms, Era 4.0 emphasizes production efficiency, minimal water and energy utilization, and a reduction in environmental footprints (Dagar *et al*., 2018). big data analytics offer real-time insights into agricultural conditions, endowing farmers with the power to make informed decisions. Artificial intelligence is seamlessly integrated into IoT devices, enabling astute and timely decision-making by farmers.

Around the world, multilateral organizations and developing countries alike have recognized the transformative potential of smart farming technologies and have championed their adoption to bolster agricultural output. These technologies hold the promise of revolutionizing farming practices from the very inception of crop sowing to the final stages of harvest, and storage transportation. This modern agricultural paradigm leverages an array of sophisticated ICT tools, including the IoT base GPS, the latest sensors, robotics, precision equipment, and actuators data analytics to comprehensively address the evolving needs of farmers and offer tailored solutions to there is big challenges. The integration of these innovative technologies injects precision and timeliness into decision-making processes while significantly enhancing crop productivity.

In Fig. (2), Smart agriculture, underpinned by robust monitoring systems, addresses an array of challenges in crop production, particularly concerning variations in soil characteristics, climatic factors soil moisture levels (Dagar *et al*., 2018). These advancements empower spatial management practices that not only boost crop yields but also curtail the excessive use of fertilizers and pesticides. Notably, Artificial Neural Network (ANN) models are instrumental in Smart Irrigation Water Management (SIWM), which furnish real-time data on irrigation efficiency, water productivity indices the precise demands and supplies of irrigation water (Palombi and Sessa, 2013).

DOI: 10.3844/jcssp.2025.96.110

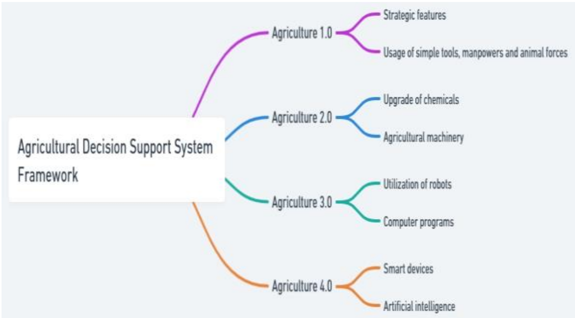

Fig. 2: Agricultural decision support system framework

The IoT Revolution in Agriculture

IoT's integration into agriculture marks a transformative shift in the sector. This research-driven exploration underscores the profound impact of IoT on modern agriculture, highlighting its potential to address the pressing challenges faced by the global agricultural community while driving innovation and efficiency in farming practices. (Prathibha *et al*., 2017).

The Incorporation of IoT in Agriculture Offers a Plethora of Advantages

Data-driven decision-making: IoT devices generate Lage amount of data amounts of data providing farmers with invaluable insights into their operations. This data allows for informed, data-driven decisions on matters such as planting, and irrigation fertilization (Kidd, 2012).

Resource optimization: IoT devices facilitate precise resource management. In real-time soil moisture data or deploying pest control measures only when needed, farmers can optimize the use of water, and energy pesticides, reducing waste and environmental impact.

In Fig. (3), Enhanced productivity: IoT-enabled machinery, such as automated tractors and harvesters, can work efficiently day and night, enhancing productivity and reducing labor costs.

Environmental stewardship: IoT supports sustainable farming practices by reducing the overuse of resources, minimizing pollution lowering the carbon footprint of agriculture.

Crop resilience: Early detection of crop stress or disease allows for timely intervention, preserving crop health and minimizing yield loss.

Components of IoT-Based Monitoring and Control Systems in Agriculture

Sensors: At the heart of IoT-based systems lie a diverse array of sensors. These sensors are strategically deployed across fields and farmlands to monitor a myriad of parameters. Soil sensors, for instance, gauge moisture levels, and nutrient content pH, while weather sensors track temperature, humidity, wind speed precipitation. Additionally, drones equipped with cameras and multispectral sensors capture high-resolution images and data on crop health, detecting early signs of stress or disease. Livestock wearables collect data on the health and behavior of animals's smart irrigation systems use moisture sensors to optimize water usage. All these sensors contribute to a comprehensive data pool for precise decision-making (Prathibha *et al*., 2017).

Data transmission: IoT-based systems rely on seamless data transmission from sensors to central hubs or cloud-based platforms. Connectivity technologies such as Wi-Fi, cellular networks, or low-power, long-range options like lora want to ensure that data flows consistently and in real time from the field to the central system.

Data analytics: The deluge of data generated by sensors is subjected to advanced analytics. Machine learning algorithms and artificial intelligence models process this data to extract valuable insights. For instance, predictive analytics can forecast crop yields, disease outbreaks, or optimal harvest times, guiding farmers in their decision-making processes.

Control mechanisms: IoT-based systems do not stop at data collection and analysis; they also offer control mechanisms. Automated actuators can be triggered based on sensor data, allowing for precise control of irrigation, pest control, or even livestock feeding. This level of automation ensures timely responses to changing conditions, increasing resource efficiency and reducing waste (Kidd, 2012). The transformative power of the Internet of Things (IoT) has begun to sweep across diverse industries, including healthcare, trade, communications, and energy agriculture. This technological marvel enables devices to connect remotely, heralding a new era of efficiency and intelligence in various sectors, with smart farming being a prominent example (Tognoni *et al*., 1999). In the context of agriculture, the IoT is poised to revolutionize the way farmers operate, enhancing performance sustainability across the entire agricultural landscape.

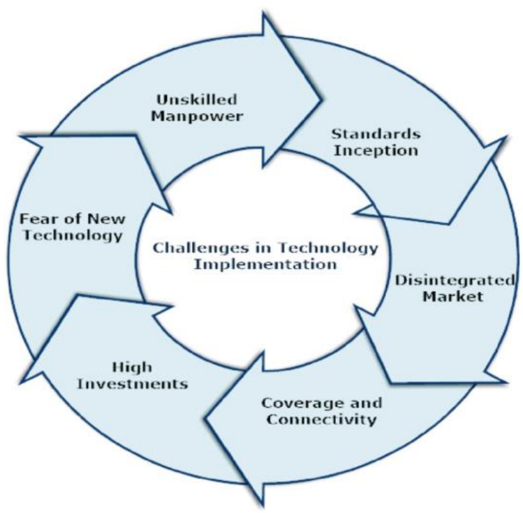

Fig. 3: Challenges in technology application

DOI: 10.3844/jcssp.2025.96.110

Monitoring and Data Retrieval

One of the IoT's primary contributions to agriculture lies in its ability to remotely monitor both plants and animals while retrieving vital information through mobile devices and sensors. Farmers can assess real-time weather conditions and anticipate production levels with the help of sensors and instruments connected to the IoT. Additionally, the IoT has revolutionized water harvesting and management practices, enabling precise control of water flow, assessment of crop water requirements, optimized timing of water supply significant water savings (Kipp, 2010). Through sensor networks and cloud connectivity, data related to soil and plant needs can be monitored and managed remotely, contributing to resource conservation and improved crop production (Kidd, 2012).

Enhancing Crop Health

One of the most significant challenges in agriculture is maintaining crop health by detecting and addressing nutrient deficiencies and pest diseases. The sheer scale of modern farms makes manual monitoring of each plant impractical. Here, the IoT proves invaluable, providing a means to remotely monitor and manage crop health through a network of sensors and intelligent data analysis. This technology empowers farmers to detect and respond to crop issues promptly, marking a significant milestone in modern agriculture (Tavakoli and Khoshkam, 2013).

Fundamentals of IoT Applications in Agriculture

In the realm of agriculture, the Internet of Things (IoT) is ushering in a new era characterized by accessible, cost-effective interactive tracking platforms that consolidate a wealth of information on traditional agricultural methods, techniques, implements, crop management, pests, diseases more (Muangprathub *et al*., 2019). This transformation is crucial for achieving sustainable agriculture and ensuring the efficient utilization of resources. Here, we delve into the fundamentals of IoT applications in agriculture:

- Interactive agriculture: One of the defining features of IoT applications in agriculture is its interactive nature. It provides users with easy access to a vast repository of data through various devices, including computers and mobile phones (Muangprathub *et al*., 2019). This accessibility empowers farmers with real-time information, enabling informed decision-making and precise resource management
- Robust models: Agriculture is characterized by its diversity, complexity patio-temporal variability. Uncertainties regarding crop yields, weather patterns facility management abound. Robust models are essential to navigate these challenges successfully. IoT technologies enable the development of sophisticated models that can handle the intricacies of agriculture, providing valuable insights and predictions.
- Scalability: Farm sizes vary widely, from small-scale operations to large agricultural enterprises. IoT solutions in agriculture must be scalable to accommodate this diversity. The deployment and testing of IoT technologies should be designed with scalability in mind, allowing for gradual expansion without incurring exorbitant expenses.
- Affordability: Affordability is a paramount consideration in the agricultural sector, where cost-effectiveness directly impacts the success of farming endeavors. IoT solutions, therefore, need to strike a balance between functionality and cost. Standardized platforms, products, tools services can contribute to affordability, ensuring that farmers can access these technologies without prohibitive expenses.
- Sustainability: Sustainability is a pressing concern in modern agriculture, given the economic pressures and intense competition on a global scale. IoT applications play a crucial role in addressing sustainability challenges by facilitating efficient resource utilization, reducing waste optimizing production processes. These technologies enable farmers to make environmentally conscious decisions, ultimately contributing to the long-term viability of agriculture (Muangprathub *et al*., 2019)

Technologies Used in Smart Farming

Global Positioning System (GPS)

In the world of modern agriculture, the Global Positioning System (GPS) is like a digital map that can pinpoint your exact location. It does this by receiving signals from satellites orbiting the Earth and using them to calculate your latitude (how far north or south you are), longitude (how far east or west you are) even your elevation (how high or low you are) (Medela *et al*., 2013). Imagine having a super-accurate map that can follow you as you move around your farm. Now, think about how valuable this information is for farmers. It allows them to know precisely where everything is happening in their fields. Are there pests in one corner? Is the soil quality different in another area? Are there weeds growing in a particular spot? With GPS, farmers can answer all these questions and more in real time (Brewster *et al*., 2017).

In Fig. (4), It's like having a farm map that updates itself as things change, helping farmers make decisions like where to plant seeds, where to apply fertilizers or pesticides when, and where to water their crops.

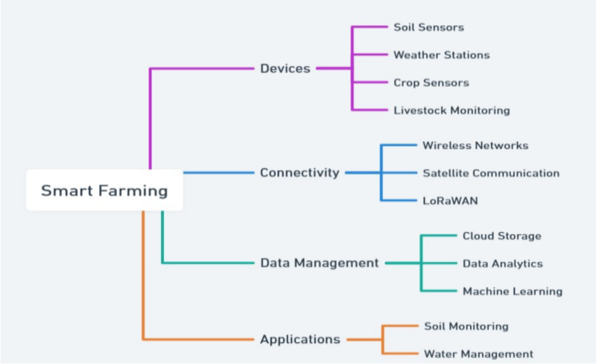

Fig. 4: Components of smart farming

Sensor Technologies

Sensors are like the eyes and ears of smart farming. They use various techniques, like measuring light, checking electrical conductivity, or using ultrasound, to gather important information about the farm's environment (Chen *et al*., 2004). These sensors can do things like telling you what kind of soil you have, and how much moisture is in it even if your crops are stressed or healthy. It's like having a team of tiny detectives investigating your fields 24/7. Things like soil moisture, nutrient levels, sunlight exposure even the color of their leaves can make a big difference in their health. Sensors help monitor all these factors and more. They make sure the conditions are just right for your plants to thrive. For example, if a sensor detects that the soil is too dry or that a plant is getting too much sunlight, it can send a signal to a computer or a farmer's mobile phone. There are many types of sensors used in agriculture, each with its own job. Some measure temperature, others check humidity some even keep an eye on things like carbon dioxide levels or air pressure 22 (Farooq *et al*., 2020). These sensors are not only reliable but also portable and durable. They can be placed throughout the farm to collect valuable data on crop conditions. What's great is that these sensors can work on their own or be part of a larger system, depending on what the farmer needs. It's like having a network of farm helpers who report back on everything happening in the fields.

Variable-Rate Technology (VRT) and Grid Soil Sampling

Variable-Rate Technology (VRT) is like the precision instrument of farming. It's all about customizing the delivery of things like seeds, and fertilizer pesticides based on a detailed map created using Geographic Information System (GIS) data (Batte and VanBuren, 1999). This map tells farmers exactly where and when to apply these inputs in varying amounts across their fields. Think of it as a tailor-made suit for your crops, ensuring they get exactly what they need, right where they need it. To create these maps, farmers use a technique called grid soil sampling. This involves systematically collecting soil samples from a grid pattern that covers the entire field. The samples are like puzzle pieces that, when put together, form a map showing the soil's characteristics, like nutrient levels, across the entire area. These maps serve as the foundation for VRT. Farmers load these maps into a special machine that adjusts the number of inputs it delivers based on the map's instructions (Berntsen *et al*., 2006) and Han and Kamber (2001). It's a bit like having a GPS-guided robot that knows exactly where to plant seeds, apply fertilizer, or spray pesticides in just the right amounts. This technology is a game-changer for managing soil fertility and optimizing nutrient distribution in fields. It means that no two areas of a field are treated the same way if they have different nutrient needs. Grid sampling helps pinpoint these differences. Instead of blanket treatments that can lead to over-fertilizing in some areas and under-fertilizing in others, VRT ensures precise and efficient use of resources. It's like giving each part of your field a customized nutrition plan for better precision agriculture (Ojo and Ilunga, 2018).

Geographic Information System (GIS)

It's a high-tech way to create detailed maps and make sense of all the data related to your farm. This includes information about soil types, nutrient levels, the lay of the land, irrigation systems, drainage, chemical applications crop production (Ojo and Ilunga, 2018). Essentially, GIS helps farmers understand their farms like never before. Imagine having a digital toolbox that can compile, store, retrieve, and analyze information about your farm's geography and characteristics. That's precisely what a Geographic Information System (GIS) does (Ehlers, 2008). GIS databases provide a wealth of information that forms the basis for making informed decisions on the farm. It's like having a treasure trove of information at your fingertips, allowing you to see how different elements on your farm are connected and how they affect crop growth and productivity. GIS can help farmers assess current farming practices and explore alternative approaches by layering and analyzing various types of data. It's like having a powerful microscope to zoom in on specific aspects of your farm and make better decisions based on the big picture.

Crop Management

Satellite images are like the eyes in the sky that provide crucial information about what's happening in your fields. These images reveal variations in soil conditions and how crops are performing, all influenced by factors like the terrain (Tucker *et al*., 1980). This means farmers can keep a close eye on essential factors like seeds, fertilizers pesticides that directly impact yields and efficiency. Satellite images offer near real-time information over vast regions, allowing farmers to monitor their crops' health and growth. The relationship between the color and reflectance properties of plants, especially in the red and near-infrared spectrum, can provide valuable insights into vegetation health and crop production. It's like having a remote control for your crops, where you can see how they're doing without even stepping into the field. By interpreting these images and comparing them to previous seasons, farmers can predict crop yields before harvest. This early estimation helps with planning and decision-making. Automated systems gather and process data, monitor farm operations, predict weather, create field maps, track soil nutrients provide a range of functionalities that simplify farm management. It's like having a personal assistant who takes care of various aspects of crop production and farm operation. (Chowdhury *et al*., 2020)

Soil and Plant Sensors

Think of soil and plant sensors as your farm's health monitors. These devices provide real-time data on crucial factors like soil moisture, pH levels, temperature even pollution (Sudduth and Hummel, 1993). They help create the ideal conditions for crop growth, manage stress factors boost yields. For instance, these sensors can measure vital nutrients like Nitrogen (N), Phosphorus (P)potassium (K) in the soil. Some sensors use near-infrared reflectance to gauge surface and subsurface soil nitrogen levels, while others predict Soil Organic Matter (SOM) by analyzing spectral reflectance (Daniel *et al*., 2011). It's like having a laboratory right on your farm, analyzing soil samples on the spot. Additionally, soil sensors can detect changes in Electrical Conductivity (ECa) on the field's surface, which is sensitive to variations in soil texture and salinity (Potamitis *et al*., 2019). They can even help identify soil insects and pests using various technologies. It's like having a team of detectives who are always on the lookout for potential issues in your soil.

Precision Irrigation in Pressurized Systems

Recent advances in irrigation systems have introduced smart machines equipped with GPS-based controllers and sensor technologies. These machines monitor soil and climate conditions and adjust irrigation parameters like flow and pressure to maximize water efficiency (Afzaal *et al*., 2020). They hold the promise of more precise and sustainable water use in agriculture.

Yield monitor: Yield monitors are like the harvest detectives. They continuously measure crop yield as the grains flow through the harvesting equipment. Some yield monitors work by bouncing microwave energy beams and measuring the energy that bounces back, while others rely on GPS receivers to create yield maps based on location data (Naorem *et al*., 2019). These maps provide insights into yield variations across the field.

Software: Software is the digital brain that brings everything together on the farm. It handles tasks like mapping, data processing, and analysis interpretation (Dinkins and Jones, 2013). With the right software, farmers can generate maps that show soil properties, and nutrient status yield data. It's like having a powerful tool that helps make sense of all the information collected from various sources on the farm. In essence, these technologies represent the modern farmer's toolkit, empowering them to make data-driven decisions, optimize resource use enhance productivity while reducing environmental impact.

Applications in agriculture: By embracing sensor and IoT technologies, agriculture is undergoing a transformation, reinventing traditional practices and addressing various challenges. Wireless sensors and IoT are providing solutions to many longstanding issues in agriculture, such as land suitability, drought monitoring, irrigation, and pest control yield optimization. The following sections delve into some key applications that leverage advanced technologies to boost efficiency and revolutionize farming.

Soil Mapping and Plant Monitoring

Soil analysis is the first step in understanding a field's nutrient status. GPS and field-specific data help determine soil nutrient deficiencies at different crop stages (Dinkins and Jones, 2013). Various factors like topography, soil type, texture, cropping pattern fertilization affect soil fertility. Soil mapping, aided by a range of sensors, tracks properties like water-holding capacity, and texture absorption rate, helping prevent soil degradation and issues like erosion, and salinization pollution.

Drought poses another challenge to crop productivity. Remote sensing techniques provide valuable soil moisture data, assisting in remote drought analysis. Satellite-derived soil moisture maps contribute to the calculation of the Soil Water Deficit Index (SWDI), which aids in predicting agricultural drought based on soil properties (Martínez-Fernández *et al*., 2016; Vågen *et al*., 2016). For instance, IoT-based mobile applications equipped with sensors and IoT connectivity help farmers monitor soil and ambient parameters, such as temperature, humidity leaf wetness. This data collection process, from seeding to harvest, is vital for enhancing crop productivity and quality, particularly in grape cultivation.

Irrigation

With desertification looming over many regions and half the world's population living in water-scarce areas, efficient water management in agriculture is crucial (Saiz-Rubio and Rovira-Más, 2020). Controlled and efficient irrigation systems like drip and sprinkler systems help conserve water resources. Factors like soil type, precipitation, irrigation method, and crop type requirements influence water demand estimation. The integration of air and soil moisture control systems with wireless sensors optimizes water resource use. IoT techniques, such as Crop Water Stress Index (CWSI) based water management, predict water requirements based on crop canopy, air temperature other data sources (Yuan *et al*., 2004). Climate data, sensor inputs satellite imaging contribute to these predictions, allowing for precise water usage tailored to each field.

Site-Specific Nutrient Management

Fertilizers are essential for plant growth, but their misuse can harm soil, plants the environment. Site-specific nutrient management under smart agriculture calculates precise nutrient quantities, minimizing negative impacts on soil and the environment (Xue and Su, 2017). Factors like soil type, crop type, yield goals weather conditions influence site-specific soil nutrient fertilization. IoT-based fertilization techniques estimate the spatial distribution of nutrients. Technologies like GPS, geo-mapping, and Variable Rate Technology (VRT) autonomous vehicles play a significant role in smart fertilization. Techniques like fertigation and chemigation, which involve water-soluble fertilizers and soil amendments, further improve fertilization efficiency (Lavanya *et al*., 2020).

Crop Pest and Disease Management

Pests and diseases can cause significant crop yield losses, estimated at 20-40% annually worldwide. Traditional pest control methods involving pesticides pose health and environmental risks (González-Briones *et al*., 2018). IoT-based devices, including robots, and wireless sensors drones, offer real-time monitoring, modeling disease forecasting, enhancing the effectiveness of pest and disease management (Villarrubia *et al*., 2017). IoT-driven disease and pest management rely on detection and image processing. Remote sensing imagery and field sensors collect data on plant health and pest presence. Automated traps capture, count identify insect types, sending data to the cloud for analysis (Newlands, 2018). Robotics equipped with multispectral image sensing devices and precision spraying nozzles can detect and control pests with high precision under IoT management systems.

Yield Monitoring and Forecasting

Yield monitoring involves tracking yield, moisture content produce quality. Quality is influenced by factors like pollination and environmental conditions (Khattab *et al*., 2019). Crop forecasting predicts yield before harvest, aiding farmers in planning, decision-making quality analysis.

Maturity monitoring determines the optimal harvest time, considering factors like fruit color and size. Predicting the right harvest time maximizes crop quality and production, assisting with market management strategies. Satellite imagery and optical sensors, including RGB and multispectral sensors, are used for crop monitoring and yield estimation (Wietzke *et al*., 2018). These technologies are crucial for ensuring optimal harvest and market opportunities.

Role of IoT in Advanced Farming Practices

Greenhouse Farming and Protected Cultivation

Greenhouse farming, one of the oldest smart farming methods, involves growing plants in controlled environments. IoT technology has breathed new life into this practice, enabling crops to flourish regardless of external weather conditions. Success in controlled environment crop production hinges on factors like shed structures, wind control materials, aeration systems, precise monitoring parameters decision support systems (Akkaş and Sokullu, 2017). IoT-enabled greenhouses use sensors to monitor internal parameters like humidity, temperature, and light pressure. These smart greenhouses automate farm operations, protecting plants from hailstorms, winds, ultraviolet radiation, and insect pests. For instance, hibiscus plants are nurtured with the ideal wavelength of light during the night, guided by data from sensors that monitor temperature and humidity. Such practices have resulted in a 70-80% reduction in water requirements IoT facilitates direct communication between farmers and consumers, optimizing efficiency and profitability (Kodali *et al*., 2016). Additionally, automated IoT systems enhance the productivity of greenhouse-grown rose plants by monitoring and controlling various parameters like humidity, mist, CO_2 levels, UV light intensity, pH, EC value, nutrient solution levels, and temperature pesticide amounts (Tripathy *et al*., 2021).

Hydroponics

Hydroponics, a subset of hydroculture, involves growing plants without soil to maximize greenhouse farming benefits. IoT plays a significant role in this context by facilitating precise measurement and monitoring of nutrient content in water solutions, which is crucial for plant growth. IoT-enabled systems detect various parameters in real time, ensuring optimal conditions for crop growth. A wireless-sensor-based prototype, for instance, monitors nutrient concentration and water levels in a soilless cultivation system (Sambo *et al*., 2019). Automated smart hydroponics systems, integrated with IoT, comprise input data, and a cloud server output data component. They enable remote monitoring of lettuce cultivation by analyzing real-time data on parameters like pH levels, nutrient-rich water solutions, and room temperature humidity, thus enhancing crop management. Another hydroponic technique, the deep flow technique, employs IoT-enabled sensors integrated into Raspberry Pi to monitor pH, temperature, humidity water levels in the hydroponic reservoir, ensuring proper water circulation (Usman *et al*., 2018).

Vertical Farming

Vertical Farming (VF) addresses issues of soil erosion and water overuse associated with traditional agricultural practices. IoT is instrumental in maintaining precise control over plants' growing conditions, reducing resource consumption increasing production while requiring minimal ground surface. VF has proven to be highly effective in increasing yields and reducing water consumption compared to conventional farming. In VF, carbon dioxide levels are crucial Non-dispersive infrared (NDIR) CO_2 sensors play a vital role in tracking and controlling conditions (Benke and Tomkins, 2017).

Phenotyping

Phenotyping is an emerging technique in crop engineering that links plant genomics with ecophysiology and agronomy. It is indispensable for crop breeding, allowing the quantitative analysis of crop traits like pathogen resistance and grain weight. IoT-based phenotyping is designed to observe and measure crop characteristics and traits, facilitating crop breeding and digital agriculture (Paul *et al*., 2019). This approach employs sensing technologies and image-based phenotyping to analyze biostimulants and understand their mode of action. Trait analysis algorithms and modeling help establish relationships among genotypes, phenotypes growing conditions, enhancing the understanding of crop behaviours and their response to various stresses.

Barriers to Implementing Smart Farming Technologies

The adoption of technology in farming systems is a process influenced by a multitude of heterogeneous factors, each exerting its unique impact (Foster and Rosenzweig, 2010). While technology integration into agriculture has bestowed accuracy, efficiency relief from time constraints, several barriers still impede the widespread adoption of smart farming technologies:

- Cost of technology: The very technologies designed to enhance agricultural productivity also raise concerns about the potential replacement of human labor. Many countries, especially those heavily reliant on the agricultural workforce, grapple with the challenge of balancing the benefits of automation with the social and economic implications of reduced employment. The implementation of advanced devices and technologies demands substantial financial investments, posing affordability challenges for farmers who are accustomed to traditional tools and methods.
- Lack of financial resources: Farmers often rely on financial support, including loans, to sustain their operations. Unexpected calamities such as droughts, floods, pest infestations diseases can significantly impact crop yields, making it challenging for farmers to repay loans or secure future financing.
- Literacy status of farmers: The level of education among farmers presents a substantial hurdle in the adoption of smart farming technologies, especially in developing countries. Effectively utilizing these technologies requires not only technical skills but also the ability to process and apply information. Education plays a crucial role in enhancing farmers' digital literacy, enabling them to manage and make informed decisions using smart farming tools (Khan *et al*., 2007). However, in many developing nations, farmers often lack formal education and technical skills, making it challenging for them to embrace new technologies (Khan *et al*., 2007). The complexity of some smart farming tools and their user interfaces can be intimidating for farmers, further hindering their adoption. Bridging the digital literacy gap is essential to unlock the benefits of smart farming Agri-tech companies must ensure that their technologies are user-friendly and accessible to all, regardless of literacy levels.
- Lack of integration between systems: Effective smart farming often relies on seamless integration between various systems, including production, and property management decision-making tools. Bridging the gap between agricultural and information sciences requires robust communication between interdisciplinary groups and academics. Enhancing user effectiveness is a priority during the development of information systems timely access to high-quality data is essential for informed decision-making. Integrating data sources to generate actionable information and knowledge is a crucial step in advancing smart farming technologies.
- Telecommunications infrastructure: Farmers often operate in rural areas where arable land is more abundant than contaminated land. However, the reliability of data transmission, particularly through mobile phones and tablets, is hindered by inadequate telecommunications infrastructure. Smart farming relies on real-time internet connectivity to leverage information effectively. Additionally, the control systems for various agricultural inputs, such as fertilizers, and pesticide seed volumes, require robust internet connections for optimal performance. While mobile internet access has expanded in rural areas, signal quality and speed remain limiting factors.
- Data management: The proliferation of sensors in agriculture generates substantial amounts of data. However, farmers face challenges in organizing and utilizing this data effectively. Weather stations, for example, generate valuable data, but farmers may lack the necessary knowledge to interpret and apply this information. Complex data management systems,

DOI: 10.3844/jcssp.2025.96.110

combined with issues of acceptability and usability, can lead to incorrect calculations and hinder data-driven decision-making. Ensuring that data is accessible and presented in a user-friendly manner is essential for farmers, consultants other stakeholders involved in the agricultural production process.

- Current challenges and future expectations: In the context of the 2030 Agenda for Sustainable Development, aiming to eradicate hunger by 2030, it's concerning that over 800 million people worldwide currently face food shortages (Fróna *et al*., 2019). As the global population continues to grow, demands on food production are increasing, necessitating improvements in both food and cash crop cultivation

With the global population projected to reach 10 billion, agriculture faces the monumental task of ensuring a sufficient food supply for this expanding population. The availability of arable land is finite further expansion is restricted. This constraint requires the exploration of new agricultural practices and technologies to optimize existing land use. Tackling climate change and curbing greenhouse gas emissions is an urgent concern. Agriculture must adapt to changing climate conditions while minimizing its environmental impact. These challenges demand a comprehensive revaluation of agricultural practices, including water management, land utilization, and rural Labo climate adaptation. The migration of rural populations to urban areas is not only diminishing rural communities but also contributing to an aging farming population. This demographic shift poses challenges for both labor and production in agriculture.

The ongoing reduction in arable land and the need to adapt to specific geographic and ecological conditions emphasize the significance of advanced technologies. In Fig. (5), Abrupt weather changes, including droughts, groundwater depletion soil degradation, are adversely affecting crop production. Additionally, excessive use of (Tzounis *et al*., 2017).

Future of Agriculture

The future of agriculture is poised to be closely intertwined with artificial intelligence and big data services. This convergence will lead to integrated systems that encompass farm machinery and management throughout the entire agricultural cycle, from seeding to production forecasting (Villa-Henriksen *et al*., 2020).

Future of Agriculture

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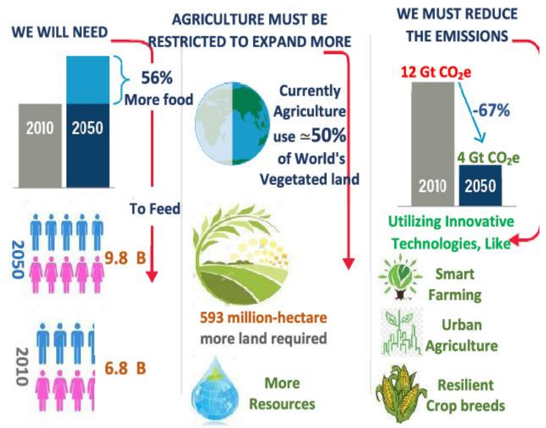

Fig. 5: The key challenges agriculture is expected to confront by 2050

Key technologies and methods are expected to drive sustainable agriculture:

- Communication: The success of the Internet of Things (IoT) in agriculture hinges on seamless connectivity between devices (Ayaz *et al*., 2019). Mobile services and smartphone technology, particularly in developing countries, offer promising prospects for enhancing crop yields. Low-Power Wide Area technology (LPWA) is expected to play a significant role in smart farming due to its improved coverage, and low power consumption cost-effectiveness
- Wireless sensors and IOT: Wireless sensors deployed across fields provide real-time information to farmers for data-driven decision-making. These sensors, coupled with GPS technology, enable comprehensive monitoring of crop growth and terrain features. The IoT's role in optimizing crop management is expected to expand, particularly with the transition to fifth-generation (5G) cellular mobile communication technologies. By 2050, the agricultural sector is projected to host around 29 billion IoT-based components, generating millions of data points daily (Villa-Henriksen *et al*., 2020)
- Drones and unmanned vehicles: Drones have become essential tools for monitoring crop growth, and precision spraying data collection in challenging terrains. They offer advantages in terms of speed, coverage precision over traditional machinery. Robotics, including automated seeding, transplanting harvesting, further enhance productivity (Chang *et al*., 2017)
- Vertical farming and hydroponics: Vertical farming and hydroponics address the challenges of shrinking arable land and urbanization while reducing water consumption. These methods leverage advanced technologies, particularly the IoT, to make agriculture more efficient and sustainable

DOI: 10.3844/jcssp.2025.96.110

- Performance analysis using machine learning: Data analytics and machine learning play crucial roles in crop production. Machine learning algorithms help identify the most suitable genes for crop production, matching seed varieties to specific climate conditions. Machine learning also aids in product classification and quality assessment, streamlining the agricultural value chain (Hassan *et al*., 2019)
- Renewable energy, microgrids smart grids: Smart farming relies on significant energy consumption for sensor placement, GPS usage data transmission. Incorporating renewable energy sources, smart grids microgrids in agriculture addresses long-term energy challenges and enhances sustainability (Aslam *et al*., 2020)

Results and Discussion

Data mining techniques involve predictive modeling, cluster analysis, and association and sequence (or market-basket analysis).

A decision tree is a machine learning technique that allows us to estimate a quantitative target variable (for example, profit, loss, or loan amount) or classify observation into one category of a categorical target variable (for example, good/bad credit customer; churn or do not churn) by repeatedly dividing observations into mutually exclusive groups. The algorithm commonly used to construct decision trees is known as recursive partitioning and the common algorithms are CHAID (Chi-square Automatic Interaction Detection), CART (Classification & Regression Tree), and C5.0. This study will focus on using CART in building the decision tree. Decision trees represent a supervised approach to classification. Weka uses the J48 algorithm, which is Weka's implementation of C4.5 (Adhiguru and Devi, 2012) Decision tree algorithm. J48 is actually a slight improvement to the latest version of C4.5. It was the last public version of this family of algorithms before the commercial implementation of C5.0 was released.

Association Rule Generation

Apriori is an association rule algorithm that is implemented in Weka software. In the third phase, model building and evaluation, the apriori algorithm was used to generate association rules from the clustered as well as non-clustered selected dataset. Different attributes were given to apriori in an effort to generate meaningful rules. As state, the occurrence frequency of an itemset is the number of transactions that contain the itemset. This is also known as the frequency or support count of the itemset. If an item satisfies the minimum support count, then it is a frequent or large item set.

The Apriori algorithm generates strong association rules from these frequent or large items. According to the apriori property, which is the base for the apriori association rule algorithm, all nonempty subsets of a frequent itemset must also be frequent. Thus, a number of interrelated rules can be generated from large or frequent itemsets.

The five steps required to process the data in order to generate an association rule are:

Step 1: Discretizing the data
Step 2: Formulating target episodes
Step 3: Determining the minimum confidence and support for apriori analysis
Step 4: Generating the rules
Step 5: Selecting the rules

Software Issue

Weka

The WEKA software was developed at the University of New Zealand. A number of data mining methods are implemented in the WEKA software. Some of them are based on decision trees like the J48 decision tree, some are rule-based like ZeroR and decision tables some of them are based on probability and regression, like the Naïve bayes algorithm. These are explained next.

Experimental Datasets

In this research, we have used Rainfall and Temperature data from Sagar District M.P. from 1997-2010.

Data Preparation

The process of data cleaning and preparation is highly dependent on the specific data mining algorithm and software chosen for the data mining task. The researcher attempted to prepare the data according to the requirements of the selected data mining software, Weka, and the selected data mining algorithm, apriori. Weka is a multi-functional data mining software (O'Grady and O'Hare, 2017). The major data mining functions incorporated in the software are data preprocessing, classification, association, clustering, and visualizing input and output. Apriori is the only association rule algorithm implemented in Weka.

In Fig. (6), As a result, we might also additionally argue that statistics mining has benefited agriculture. In this study we've mentioned Data mining withinside the area of Agriculture and the usage of open supply device referred to as WEKA.

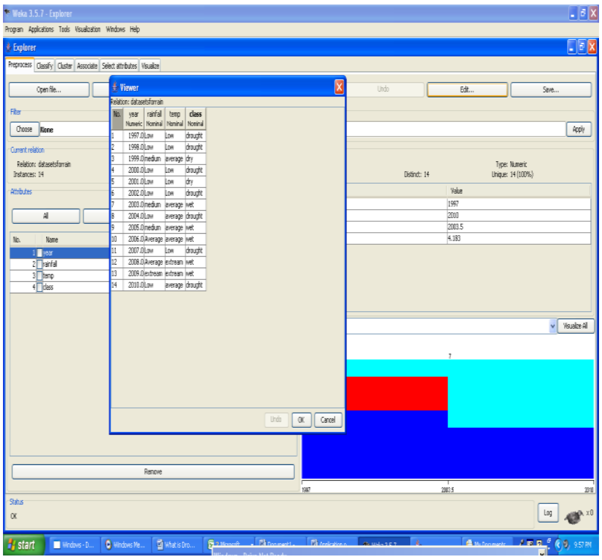

Fig. 6: Weka results in Agricultural decision support system

Experiment 1:

=== Run information ===
Scheme: Weka. Associations. Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation: Datasets for rain-weka. Filters. Unsupervised. Attribute. Remove-R1
Instances: 14
Attributes: 3
Rainfall
Temp
Class
=== Associator model (full training set) ===

Apriori
=======
Minimum support: 0.1 (1 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 18
Generated sets of large itemsets:
Size of a set of large itemsets L (1): 10
Size of a set of large itemsets L (2): 18
Size of set of large itemsets L (3): 8
Best rules found:

1. Class=drought 7 ==> rainfall=Low 7 conf:(1)
2. Temp=Low 6 ==> rainfall=Low 6 conf:(1)
3. Temp=Low class=drought 5 ==> rainfall=Low 5 conf:(1)
4. Rainfall=medium 3 ==> temp=average 3 conf:(1)
5. Rainfall=Average 2 ==> class=wet 2 conf:(1)
6. Temp=extream 2 ==> class=wet 2 conf:(1)
7. Temp=average class=drought 2 ==> rainfall=Low 2 conf:(1)
8. Rainfall=Low temp=average 2 ==> class=drought 2 conf:(1)
9. Rainfall=medium class=wet 2 ==> temp=average 2 conf:(1)
10. Rainfall=extream 1 ==> temp=extream 1 conf:(1)

Experiment 2:

=== Run information ===
Scheme: Weka. Classifiers. Trees. J48 -U -M 2
Relation: Dataset for rain-weka. Filters. Unsupervised. Attribute.Remove-R1
Instances: 14
Attributes: 3
Rainfall
Temp
Class
Test mode: evaluate on training data
=== Classifier model (full training set) ===
J48 unpruned tree

Rainfall = Low: drought (8.0/1.0)
Rainfall = medium: wet (3.0/1.0)
Rainfall = Average: wet (2.0)
Rainfall = extreme: wet (1.0)
Number of Leaves: 4
Size of the tree: 5
== Evaluation on training set ===
=== Summary ===

Correctly classified instances	12	85.7143 %
Incorrectly classified instances	2	14.2857 %
Kappa statistic	0.7455	
Mean absolute error	0.1468	
Root mean squared error	0.2709	
Relative absolute error	35.9018 %	
Root relative squared error	60.3821 %	
Total Number of Instances	14	

=== Detailed Accuracy by Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0.143	0.875	1	0.933	0.929	drought
0	0	0	0	0	0.729	dry
1	0.111	0.833	1	0.909	0.978	wet

=== Confusion Matrix ===
a b c <-- classified as
7 0 0 | a = drought
1 0 1 | b = dry
0 0 5 | c = wet

Conclusion

The pressing challenges of diminishing arable land and the surging food demands of a growing global population necessitate the development of more intelligent and efficient crop production methods. Food security in the context of sustainable agriculture is a

DOI: 10.3844/jcssp.2025.96.110

concern that should be on everyone's radar. To this end, the proliferation of new technologies geared towards augmenting crop yields and fostering the adoption of farming as a respected profession, especially among innovative young individuals, holds paramount significance. This study underscores the pivotal role played by a multitude of technologies in the realm of agriculture, with a particular emphasis on the Internet of Things (IoT). These technologies are instrumental in elevating the intelligence and effectiveness of agricultural practices, thereby aligning them with the demands of the future.

By shedding light on the current challenges confronting the agriculture industry and providing insights into its prospective future, this study aims to serve as a guiding compass for scholars and engineers. It underscores the undeniable importance of every parcel of farmland and underscores the imperative of leveraging sustainable IoT-based sensors and communication technologies to maximize crop production, ensuring a food-secure future for all.

Acknowledgment

To our families and all those who matter in our lives

Funding Information

The authors have not received any financial support or funding to report.

Author's Contributions

Manmohan Singh: Carrying out the experiment, collecting and verifying the analyzed data; prepared the draft of the manuscript and approved the final manuscript.

Shaheen Ayyub and Dharmendra Sharma: Member of the Laboratory experimental / implementation monitoring and approved the field data.

Vikas Prasad and Amol Ranadive: Correction of the translation of the manuscript in English, experimental monitoring, member of the Laboratory /implementation, and approved the field data.

Smita Sharma and Vinod Patidar: Members of the Laboratory, preparation of the nursery, implementation monitoring collection of data.

Sudheer Kumar: Design the research plan and supervised this study. Design the research plan, supervised this study approved the final manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

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