

# A Review on Implementation of IOT And Robotics In Smart Agricultural Farming

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**Abstract-** The aim of this study is to review various modern approaches of IOT and smart techniques in agriculture to aid sustainable crop production because of increasing world population, climate variations, and propelling demand for the food are the hot discussions these days. Focusing on expert systems, robots developed for agriculture, sensors technology for collecting and transmitting data, in an attempt to reveal their potential impact in the field of agriculture. None of the literature highlights the application of IOT techniques and robots in (Cultivation, Monitoring, and Harvesting) to understand their contribution to the agriculture sector. current paper presents review on various IOT techniques and use of Robot for smart farming.

**Keywords-** IOT, Agriculture robot, smart farming, sensors, cultivation, monitoring, harvesting etc

## I. INTRODUCTION

Technological advancements have revolutionized almost all sectors, particularly agri-culture, in the modern world. As the global population continues to grow, the demand for food is expected to rise significantly, placing immense pressure on the planet's resources. Agricultural robots are poised to play a pivotal role in meeting this growing demand while ensuring sustainable food production. By optimizing resource usage, reducing waste, and enhancing productivity, these machines can contribute to a more food-secure and environmentally responsible future. The adoption of agricultural robots is also expected to accelerate the development of smart farming infrastructure. Advanced sensor networks, data analytics platforms, and cloud-based services will become increasingly common place, enabling farmers to make better-informed decisions and manage their operations more efficiently. This data-driven approach to agriculture will help minimize risks, reduce uncertainties, and optimize the allocation of resources. they can help farmers reduce costs and make better decisions". Agricultural robots are transforming the industry, from boosting productivity to promoting sustainable farming practices, ensuring a brighter and more prosperous future for all. Article focuses on the use of robotics and precision

agriculture in agriculture 4.0 and provides a detailed description of the many types of agricultural robots used, as well as the techniques and hardware used for their operation and monitoring. Future trends in precision agriculture and robotics are also discussed, including the use of multi-objective control algorithms and artificial intelligence in low-cost mobile robots for planning the best path while accounting for energy efficiency, soil type, and obstacles.

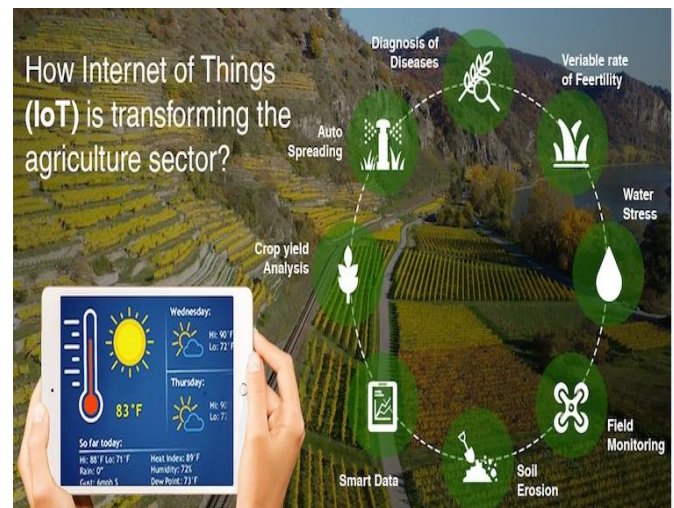


Fig 1. IOT application in agriculture

The internet of things provides efficient ways to assist the farmers and researchers in the agricultural crop production sector. Moreover, it assists the decision making by making various information readily available when it comes to soil, water, pesticides, fertilizers, and manures. Climate change and global warming are the burning issues of the world, with a lot of studies and resources being spent to ensure a better future for the coming generations.

## II. LITERATURE SURVEY AND RELATED WORK

Smart farming is a technique that uses advanced technology to optimize yield and efficiency in agricultural production. In Lohchab et al. (2018), explored the application of IoT technologies in smart agriculture. Subsequently, in a

2020 review article, Sharma et al. (2020) focused on the use of artificial intelligence and machine learning in smart agriculture. Furthermore, in a 2021 review article, Ratnaparkhi et al. (2020) discussed the implementation of sensor technologies and Geographic Information Systems (GIS) for smart agriculture. Finally, in a recent 2022 review article, Botta et al. (2022) examined the integration of robotics and automation in smart agriculture. Some topics that very little has been addressed in smart agriculture are: the integration of smart agriculture with the circular economy and environmental sustainability, the development and application of artificial intelligence and machine learning technologies in pest and disease identification and management, increased focus on optimizing water use and irrigation management in response to climate change and limited water availability, improved connectivity and interoperability of systems to facilitate large-scale adoption and implementation, and the development of specific low-cost solutions for small farms and rural communities in developing countries to improve food security and reduce rural poverty.

### III. EXISTING SYSTEM

In the existing system, there is no source of informing the farmer about the condition of his paddy field via SMS. If any of the sensors goes beyond the set limit or any problem occurs to the motor he can only know by opening the web server. To avoid this situation, we are developing the proposed system, in which the farmer can know immediately if any of the sensors goes beyond the threshold level by SMS

### IV. IOT TECHNIQUES USED IN AGRICULTURE

The problems associated with various agricultural activities can be solved by implementing IOT techniques. The research work has provided numerous methodologies in the field of agriculture, and it is presented below.

#### 4.1 Climate Change and Its Effects on Various Crops: A Need of Smart Crop Production

Climate change has severely impacted agriculture worldwide. Rising temperature, fluctuations during day and night temperature, and seasonal variability in the rainfalls has increased the intensity of extreme weather events, i.e., droughts, flash floods [40–43], and incidence of disease occurrence have increased [44]. Efficiency of production systems has been affected, and the impact of climate change has triggered the need for and the adoption of climate-smart adaptation options to sustain productivity and availability throughout the year. Such adaptation options and technologies need to be adopted in almost all aspects related to agricultural

crop production, such as soil–water dynamics, nutrients, and fertilizers [41,45] management, improvements in crop types and evaluations [46], applications of beneficial elements [47], organic amendments in soil [48], fisheries, livestock, and poultry, and farm mechanization, as indicated in Figure 1. Temperature is one of the critical factors in crop production.

Decision and planning are very important in agriculture. The sudden change in climate affects the farmer's planning in the crop growth cycle. Shahjalal et al. [9] have worked on the FL model to analyze climate change's consequences on agricultural production. With this study, farmers can make the right decision to plant crops. Further, the application of FL for an understanding of carnation seedlings and their growth cycle parameters, such as shape, is presented by Fujiwara [10]. His-work presents the FL with an image processing algorithm and achieves a 97% judgment rate. The agriculture processes are complex, and it requires much effort to perform them within time. By considering this aspect, Nassiri et al. [11] have worked on the packaging of good tomatoes using FL based classification model.

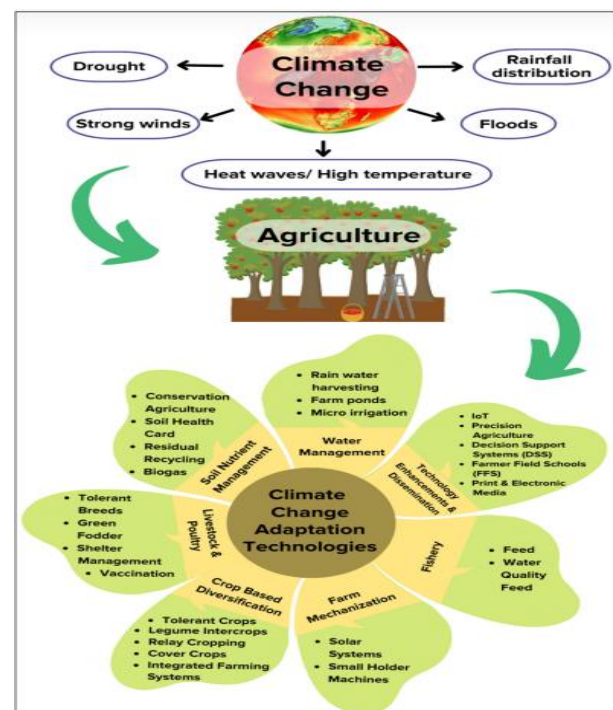


Fig 2. Climatic impact on agriculture and adaptation technologies

#### 4.2 Yield Prediction in Smart Agriculture

Crop yield is an important entity, and yield prediction is a salient and challenging task in agriculture. Soil properties, meteorological data and seasonal fluctuations, seed quality, harvesting methods, monitoring of pests and diseases, managing nutrient deficiencies, and maintaining water requirements for the crops are all contributing factors for

predicting the overall yield of a plant or crop. Precision agriculture has been used for years and now researchers are considering the use of variable rate technologies, sensor monitoring, and management systems to ensure better crop health, improved productivity, and better quality of the produce. Sensor- and drone-assisted quality monitoring of horticultural crops, yield predicting sensors on harvesters of various agronomic crops, and use of the internet and real time data simulators are receiving attention day by day, particularly for their use in large scale crop production.

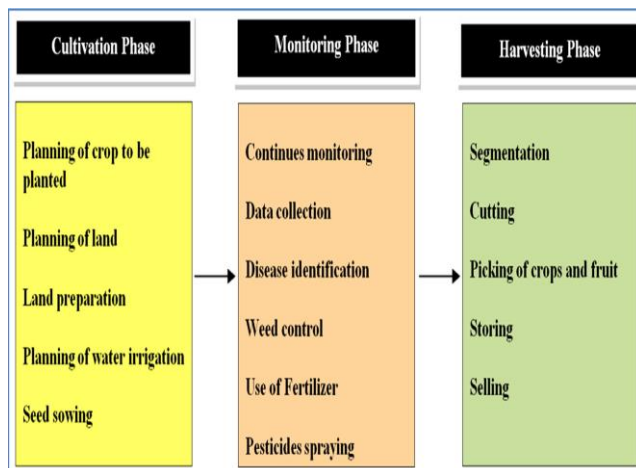


Fig 3. Implementation of IOT techniques in agriculture activities

### 4.3 Smart irrigation technique in Agriculture

The water cycle has been substantially altered by climate change, which has also increased the severity of droughts. Hence, efficient water use in agricultural systems is a basic concern in the current scenario. The losses of water under limited water availability have gained a lot of interest in these days, when a major part of the world is susceptible to drought each year. Traditional and manual irrigation systems fail to accomplish water-saving goals, and are unable to supply water efficiently. Smart irrigation is a technique which is countering this problem efficiently by not just providing efficient water use, but also saving it for the future. Additionally, smart irrigation reduces the input costs, which provides relief to the farmers. Manual irrigation requires manpower for daily observations and scheduling irrigations by observing plants or crops in fields, but a sensor-assisted irrigation system detects soil moisture available in the soil profile and initiates the irrigation, making irrigation control better than the manual, whereas a decision-support-system-assisted irrigation system integrates soil moisture sensors and climate sensors to observe water demand and control irrigation application for crops (Figure 2). The development of accurate and effective irrigation systems has been aided by the revolution in decision-support-assisted irrigation systems,

brought about by advancements in technology. This not only incorporated soil moisture and climate sensors, but also an internet-assisted cloud system for real-time data observation. Dynamic simulation models are linked to examine the effects of irrigation on crop growth and productivity estimation. Moreover, in accordance with data analysis and yield predictions, an irrigation Quantity has been finalized and is supplied through an automatic irrigation control system. A remote control or mobile application is also linked up with this system for easy understanding and usage of the modern irrigation

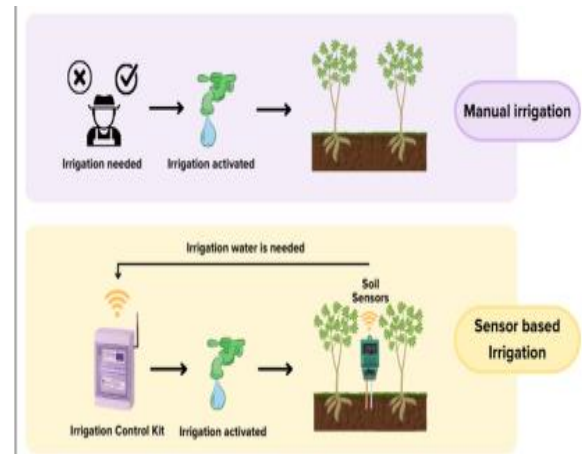


Fig 4. Manual versus smart sensor based irrigation application

### 4.4 Mobile robotics in agriculture

The emerging field of agricultural mobile robotics is UGV and UAV (Prakash et al., 2020). The main applications of mobile robotics in farming are:

- Identify the state of the crop and corresponding application of chemical products, fumigation, or harvesting, as required by the fruit or plant.
- Mobile handling through collaborative arms (harvesting, fruit handling).
- Collection and conversion of helpful information for the farmer.
- Selective application of pesticides and avoidance of food waste.

Interest in mobile robotics in agriculture has grown considerably in the last few years due to its ability to automate tasks such as planting, irrigation, fertilization, spraying, environmental monitoring, disease detection, harvesting, and weed and pest control (Araújo et al., 2021). Furthermore, mobile robotics in smart farming uses a combination of emerging technologies to improve the productivity and quality of agricultural products (Bechar and Vigneault, 2016).

UGV are robots that control can be remote (controlled by a human operator through an interface) or fully autonomous (operated without the need for a human controller based on AI technologies) (Araújo et al., 2021). The main components of UGV are locomotive, manipulator and supervisory control systems, sensors for navigation, and communication links for information exchange between devices. The main locomotion systems used are wheels, tracks, or legs. To properly operate UGV in the field, they must meet size, maneuverability, efficiency, human-friendly interface, and safety requirements

The main issue of mobile robotics in agricultural fields is to perform multiple tasks (obstacle avoidance, tracking, path planning, crop data collection, disease detection, among others) autonomously with reduced hardware for low-cost robots that can be acquired and implemented by farmers. Furthermore, path planning is an essential application of smart agriculture that focuses on optimizing routes and movements of agricultural machinery to improve efficiency and reduce production costs (Nazarahari et al., 2019). Another application of multi-objective control in path planning is the optimization of fertilization and pesticide application in crops. According to a study by Zhao et al. (2023), multi objective control can optimize the routing of pesticide and fertilizer application machinery to reduce the number of inputs used and improves application efficiency.

Finally, a study proposes a Residual-like Soft Actor-Critic (RSAC) algorithm for agricultural scenarios to realize safe obstacle avoidance and intelligent path planning of robots.



Fig 5. mobile robot used in agriculture

## V. SMART FARMING

Smart farming is based on the information provided by sensors placed on an agricultural field (Ahmed et al., 2016); Machine Learning (ML) models could learn patterns to support the farmers’ decision-making (Mammarella et al., 2020; Shorewala et al., 2021). These sensors joined with a microcontroller sending data constantly, are considered part of the IoT. Besides, data might be processed in big servers allocated in the cloud (cloud computing). However, IoT devices are often a rigid solution since they are placed in a single location. Therefore, Autonomous Robotic Systems (ARS) can walk around crops taking data from the whole farm and providing accurate information (Ozdogan et al., 2017; Kamilaris and Prenafeta-Boldu, 2018). This combination of sensors, data analysis, and robots provides farmers with a smart farming application. The objectives of smart farming are to increase crop yields, minimize costs, and improve product quality through using a modern system.

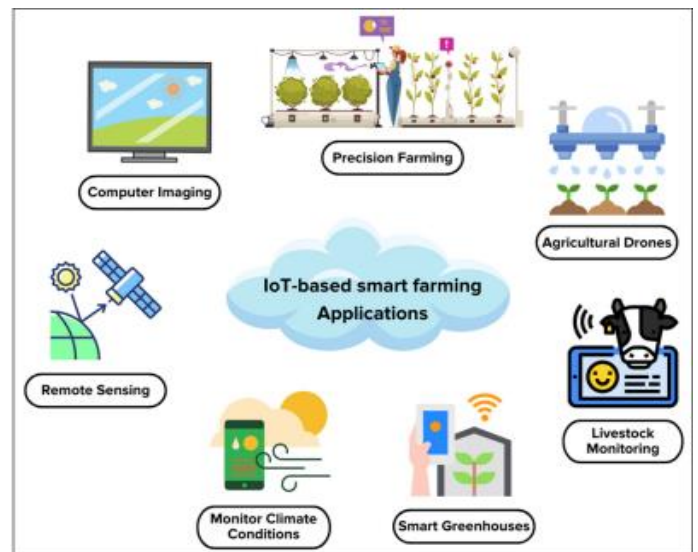


Fig 6. IOT based smart farming (Future of agriculture)

## VI. CONCLUSION

The main aim of the proposed investigation is to carry out a systematic study of IOT techniques in the field of agriculture. The recent smart strategies for various crop management approaches, as well as the technologies associated with yield predictions and enhancements, are explained. It has been shown that implementation of smart techniques and IoT is necessary to boost the productivity of crop production systems.

The application of robots and autonomous systems in farming has raised the standard of farming and becoming more popular. The application of the agriculture robot in the

monitoring phase, followed by the harvesting phase, is more as compared to the cultivation phase. Future work will go on to explain the new emerging challenges and constraints, to accept and adopt the modern advancements for smart farming.

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