Artificial intelligence and machine learning for the green development of agriculture in the emerging manufacturing industry in the IoT platform

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ABSTRACT
In recent years, greenhouse development has been innovative in agriculture based on information systems guidance with accelerated growth. The IoT provides an intelligent system and remote access technologies such as green infrastructure. The usability of information systems for effective training and producing intelligent systems and predictive models in organizational real-time based on machine learning and artificial intelligence (AI). Therefore, a Remote Sensing Assisted Control System (RSCS) has been proposed for improving greenhouse agriculture requirements. This proposed method utilizes artificial intelligence and machine learning technology for the green development potential industry’s ability to manage economic resources and increase innovative agriculture product development patterns. Thus, the key preconditions for increasing healthy food choices and promoting local and global organic farmers’ potential development are straightforward suggestions for developing an effective marketing strategy. The experimental results RSCS the highest precision ratio of 95.1%, the performance ratio of 96.35%, a data transmission rate of 92.3%, agriculture production ratio of 94.2%, irrigation control ratio of 94.7%, the lowest moisture content ratio of 18.7%, and CO₂ emission ratio of 21.5%, compared to other methods.

Summary of artificial intelligence and machine learning for the green development of agriculture using IoT platform
The green revolution has helped prevent and combine high-yielding crops, chemical fertilisers, and water for millions of people in developing countries (Maddikunta et al. 2021). However, due to the extensive inappropriate use of agrochemicals in particular chemical fertilisers, the green revolution cannot be seen as entirely green. Specific technologies of highly productive crops usually require a lot of fertiliser and water (Seyhan et al. 2021). The Greenhouse is a flexible plastic structure mainly designed for the production of the products inside. It can adapt crops’ growth approach to support plants’ requirements and improve crop quality and quantity. Since most traditional greenhouses, particularly in dry locations, numerous environmental factors such as moisture temperature and others have been ignored (Shakeel et al. 2020). Greenhouses normally require a set number of environmental control devices and require standard precise control and multi-parameter management. Fresh vegetables are one of the main foods in any family’s healthy routine (Pérez-Pons et al. 2021). However, the environment does not ensure food safety and crop plantation (Tran et al. 2021). In other circumstances, the workforce is not sufficient to monitor the planting process (Nguyen et al. 2020). Automated technology is used in agriculture to monitor crop development using a quadcopter and achieve massive emerging food manufacturing requirements (Manogaran et al. 2021). The design of mechanical, organic irrigation systems allows water resources easily accessible to the irrigation system to have been effectively allocated and maintained (Vangala et al. 2020; Sagheer et al. 2021). Crop productivity has shown to be an innovative evaluation given that crop field and plant strength are now an essential consideration by profit and food crops each day (Manogaran et al. 2019). One of the major challenges in current agriculture is the lack of knowledge on agricultural conditions and the reduction of emerging innovations (Manogaran et al. 2020). The development of remote sensing in the greenhouse environment has been
important for less costly innovations for farmers to recover production (Shamshiri et al. 2020). A greenhouse is a construct with a light source that can maintain temperature control, the required moisture, and light absorption for the healthy development of a production facility (Gao et al. 2020; Lv et al. 2020).

Agricultural production is a system that involves the detection, measurement of crops (Nasir et al. 2021). It is a technology for recognising greens, and messages are transferred to the server at this moment, and action is needed from the farmer given the information he obtains (Sekaran et al. 2020). The innovation that interfaces any except every limitation using advanced methods that present inventions can handle the IoT (Hsu et al. 2018; Gao et al. 2020). The integrated sensors innovations support the agricultural production industry for monitoring and comprise both the owner and the servant to improve green production. In the servant, various sensors are employed for temperature for monitoring the ammonium and moisture sensing. Farmers can monitor the food processes remotely over the mobile communication device.

Moreover, intelligent agricultural production systems there use several sensors for crop growth monitoring. This means that greenhouse factors such as CO₂, soil moisture, temperature, light can be monitored (Gupta et al. 2020). The unstable environment in greenhouse crops can affect plant development and reduce yield towards the end of culture (Zeb et al. 2020). This challenge can be addressed by applying IoT innovations in artificial intelligence applications for certain greenhouse factors controlling temperature range, water flow, light radiation (Abdel-Basset et al. 2020; Vadlamudi 2021). This agricultural instability can gradually increase with the emergence and this method has been involved in the continuous development of artificial intelligence (Arshad et al. 2020). Remote sensing data with high resolutions and real-time agricultural production crop yield sampling are appropriate machine-learning technology in commercial crop prediction (Saddik et al. 2021).

In the agricultural sector, machine learning is utilised to increase crop output and quality. Seed dealers use this agriculture technology to churn data to develop better crops. Pest control firms use them to identify different bacteria, pests, and vermin’s. Organisations/ cooperatives responsible for the production and distribution of vegetable/fruit/cereals/pulses or animal-based products make up an agriculture supply chain system. Agricultural products are employed as raw materials in various supply networks to create higher-value consumer products.

The main contribution of RSCM is described below:
- It improves greenhouse farming requirements by using RSCM
- It uses artificial intelligence for industry potential green development to control economic resources and increase the growth pattern of innovative agricultural products
- The results provide clear suggestions for developing an effective marketing strategy for green farm products and encouraging the potential growth of organic farmers locally and globally

Literature work
(Cioffi et al. 2020) initialised the adaptation and innovation in the manufacturing industry are of significant importance. This development was supposed to lead to the use of new technology in agricultural production. Manufacturing requires global prospects for agriculture smart production technologies to achieve sustainable development. Thus, the proposed work systematically analyzed research articles on artificial intelligence and machine learning (ML) in the industry. In this context, various AI-based approaches, including machine learning, were developed to achieve sustainable manufacturing by extensive research and development in Artificial Intelligence.

Waleed, M. et al. (Melović et al. 2020) evaluated this work to analyze the key elements that influence the success of green customers for the purchase of organic agricultural products. The relative importance of the index found health benefits as the key purchasing pattern from a specific manufacturing technique. The results indicated major components in connection with organic agriculture that leads mainly to green consumer choices. The regression analysis indicated that a consumer buying organic products daily are approximately less than a consumer who buys organic products weekly or monthly than the assumption that green products are healthier than non-organic products.

(Shamshiri et al. 2020) explored the commercial products closed-field agriculture a micro-climate analysis to deal with production uncertainty and increase profits. This research proposed an Internet-of-Things application to model-based microclimate parameter assessments in agricultural greenhouse systems. Therefore, this study suggested that the comfort index is a more revealing measure for comparing more green spaces based on the dynamic evaluation of microclimate parameters. The IoT sensor node and the simulation model provided farmers with a better understanding of how crop-growing environments get processed. The results of this study can help optimise control
systems for the more efficient production of greenhouse crops.

(Ferrag et al. 2020) introduced the threat model (TM) for green IoT-based agriculture security and privacy. This paper identified the study issues into safety and privacy challenges in green IoT agriculture in the environment. They classified the threat model to green IoT agriculture into the classes of green IoT-based agriculture, including assaults on privacy, authentication, con-property, availability, and integrity. The existing survey highlighted the remaining challenges for study and suggested potential strategic directions for research on security and privacy in green IoT agriculture.

(Xu et al. 2020) discussed the deep crop mapping model (DCMM) for the dynamic corn and soya mapping with increased spatial generalisation. Accurate crop mapping provides important and real-time information for supporting decision-making on large-scale estimations of agricultural production. A deep learning system called DeepCropMapping (DCM), based on a long-term framework with mechanisms for attention was created by merging multi-temporal and multi-spectral critical information for large-scale dynamic corn and soybean mapping. The results showed that the longer seasonal remotely sensed set would reduce uncertainty at all sites by monitoring the classification confidence for each level.

Wei et al. 2020 described the random forest regression algorithm (RFRA) for carrot ground truth yield. Carrot yield maps are an essential tool to encourage industry leaders to improve their precision agriculture, non-conventional and inaccessible. The goal was to develop a method for creating carrot yield maps using a database consisting of satellite spectral and carrot ground truth yields that use a random forest regression algorithm. Geo-referenced monitoring of the carrot yield was completed during crop development and satellite imaging was established. The RF regression algorithm applied in a database consisting of spectral segments was accurate and appropriate for predicting carrot yield.

Shaikh et al. 2021 Smart agriculture, aided by Artificial Intelligence (AI), is helping to assure agriculturalist long-term viability. Soil and irrigation management, weather forecasting, plant growth, disease prediction, and livestock management are all areas where AI is used. In this paper, we look at some of the most modern AI techniques used in these fields. We’ll look at the different AI algorithms that are employed and how they affect performance.

Kumar et al. 2021 Using artificial intelligence (AI) in smart agriculture is critical to the industry’s long-term viability. There are many areas of agriculture where artificial intelligence (AI) is being used. These areas include soil and irrigation management, weather forecasting, plant development, disease detection, and livestock management. A large part of our research is centred on AI algorithms, specifically on how they affect system performance. New AI approaches in various sizes are examined.

Ng and Mahkeswaran 2021 Urban farming has emerged due to rising food demand, unsustainable conventional agricultural practices, and shrinking arable land. Vertical farming and indoor farming are just a few of the methods. Aquaculture and aquaponics can also be used in urban farming. These strategies, on their own, will not be sufficient to transform farming; to do so; they must be used in conjunction with technological advancements.

Based on the survey, in existing TM, DCMM, RFRA methods, some issues include high precision, performance, data transmission, moisture content ratio, CO₂ emission ratio, irrigation control, and agriculture production. Therefore this paper, RSCS, has been proposed to monitoring crop production.

Remote sensing assisted control system (RSCS)

This paper provides an innovative approach for automated implementation and sensing in agriculture products. The report examined the integration of IoT technology in control networks and communication systems based on the actual condition of agricultural productivity. The sensing and acting system for agricultural and greenhouse production environments is applying IoT technology in agriculture. This proposed method uses to manage the economic resources of a green development potential industry and enhance innovative patterns of development of agricultural products. In an agricultural manufacturing industry sent over remote notices through the supporting platform, important temperature, moisture and ground signals are collected in real-time. To understand information to lead the production, it is essential to acquire real-time agricultural products’ data through the short message service, mobile, wireless system pattern. The system includes remote sensing monitoring equipment, data receiver remote acquisition applications, and mobile web applications. The data processing area monitoring system comprises an intelligent network, a connection device for the network, an information collection module and a system configuration control unit. The recipient of the remote sensor consists of a user interaction module, a network communication module and an access control module that can communicate with the remote sensing development tools of the
mobile app monitoring system through the network communication protocols.

Computer vision, robotics, and machine learning can all be used by farmers to combat weeds with artificial intelligence (AI). Thanks to artificial intelligence (AI), farmers can spray pesticides only where weeds are found, thanks to artificial intelligence (AI), which collects data on growing weeds. Because of this, a much smaller amount of chemicals was needed to treat the entire field. The use of artificial intelligence (AI) by farmers can help them detect regions of their fields that require irrigation, fertiliser, or pesticide treatment in real-time. Additionally, cutting-edge farming techniques like vertical agriculture may enhance food output while using fewer resources.

As a result of precision agriculture, farmers can use less water, fertiliser, and seed to increase yields. Using sensors and mapping fields, farmers may learn more about their crops at a micro-scale, conserve resources, and less impact the environment.

The concentration provides the farmer from remote locations with ground measurements that are remotely controlled greenhouse farming variables, such as CO₂, soil moisture, temperature and light, and controls for the on/off greenhouse can be made given the estimation of soil moisture. The use of the IoT technology for agriculture industry green development can improve the entire performance of each company and the manufacturing process. It can effectively encourage the communication of knowledge and transfer information between mobile applications.

**Figure 1** expresses the green agricultural development. Crop production is a major source of food for people that is the world’s food consumed. The grains, sugar crops, fruit and plant vegetables and oil crops comprise plant-based food. The massive amount of waste leaked in the soil and lost in the environment through the evaporation of ammonia and oxidising nitrogen fixation has led to an unstable vicious cycle. It has impared the development of increased environmental protection. To overcome the challenges of maintaining food security and environmental protection by establishing green crop production. A green crop production system is a requirement for green input and green management in agricultural land, as seen in **Figure 1**. This includes creating new crop plants, food crops and green pesticides to an integrated soil-culture control unit and developing rotating and intercropping crop systems to achieve a sustainable increase in high efficiency, high resource utilisation and environmental sustainability in agricultural production. The fundamental transformation of agricultural production from a traditional resource-based model with high ecological cost into increased productivity, high efficient resource use, and poor environmental impact is a significant change in the development of agriculture from purely intensive food production to sustainable production. The production of green crops includes green goods input management and output. The design of the agricultural system can improve adequate means soil quality and agricultural productivity, both essential if high-quality food is to be delivered significantly. Livestock production is an essential component of animal food production, such as meat, eggs and milk that contains nutrients that are easier to digest than many crops. It can supply key raw materials for industry, such as feathers and leathers in the textile and clothing industries needed for human existence. The contributions of animal crop production in agricultural emission to the overall emission of NH₃ and chemical oxygen consumption.

The data processing system generates a certain set of outputs for each stage of inputs and vice versa. Data, facts, information, and so on are interpreted from the inputs and outputs. The phrase information system is frequently used as a synonym for data processing or storage (codes) management systems. As a result, I’ve realised that agriculture must meet specific needs to produce food and keep providing it (yes, fibre too, and other non-food products, but mainly we are concerned with food production). Keep the soil healthy by following these guidelines: Keep the land fertile, and make proper water use.

Rural agricultural systems and livestock sectors are essential to residents’ livelihood and well-being. These are all essential contributions to climate change development, and there is no appropriate technology to manage livestock excess and crop production from the country’s most significant barriers to green agriculture. Green livestock systems such as the crop system can need green management throughout the production phase, including green housing. It offers essential resources for people’s daily lives and contributes to most rural people’s revenues.

Furthermore, these systems are viewed as essential to the stability and sustainable development of the producers of raw materials for the industry. The designs can be integrated so that practically all the materials used to feed the livestock can be supplied to agriculture. The excrement should be collected and used in the nutrient supply to crops. The risks of pollution from emission of animal contaminants from livestock systems, which can be used as essential nutrients for crop production, would be increased by non-connected and interconnected animal mass cultivation. To transform the integrated systems of animal crop production from a single system to a diverse quality in the agriculture...
market should be optimised. Agricultural and livestock farming can be combined to increase the efficiency of nutrient usage all through the food industry considered in such systems.

Precision agriculture, also known as precision farming, is made possible by artificial intelligence (AI) systems. These systems help enhance overall harvest quality and accuracy. Artificial intelligence (AI) technology aids in the detection of plant disease, pests, and nutritional deficiencies in farms. When using artificial intelligence (AI) sensors, you may identify which weeds need herbicide application and then pick which herbicide to use in that area. The greenhouse is mainly used to produce seasonal and non-seasonal crops, produce high-quality flowers and vegetables, and construct a tissue culture nursery for a nursery. There are numerous advantages to using a greenhouse.

The supply of green food is one of the people’s significant demands, and its focus is on safe, high-quality, nutritious food for the rural environment. Rapid progress has been made on green food in economic, ecological, social and brand impact green food. Now faced with several major obstacles to which continued improvements should be addressed in green food development. These challenges include the current level of products and higher demand for high-grade nutritious green foods. It is an imbalanced production plan, mostly short storage agricultural and a lack of resources on marketplace development. The recommended healthy diet includes cereals and vegetables that account for the total consumption of food and grains and fruit and vegetables in the overall food production. The proposed proper nutrition includes consuming whole-food grains, fruits and vegetables, and fruits and vegetables.

Figure 1. Agriculture Green Development.
due to imbalances in food production and consumption requirements. The development of the green food industry challenges increasing food security, nutrition security, climate change, water supply decrease and biodiversity loss. Food processing, healthy diet and food safety for agriculture green development have helped achieve green agricultural production, green storage and healthy human life. Products from the industry upstream and downstream can match the green input requirements for agricultural livestock production and market food quality standards. A green market and industry interconnection model can be introduced to support green economic and business development through e-commerce based on green industry and machine learning algorithms. This can be required to connect internet information transmission methods for increasing connectivity into the green environmental industry agriculture products and distribution. Technological innovation transmission and precision management are desperately necessary with the requirements of green products, and related technology services can be associated with crop-animal systems development.

Increased plants and animals must be produced to provide food demands, rapid population increase and living standards. However, the ecosystem is experiencing huge stress. The wheat crop summer corn rotation system is lost in the ecosystem with new higher fertilising huge stress. The wheat crop and industry interconnection model can be introduced to support green economic and business development through e-commerce based on green industry and machine learning algorithms. This can be required to connect internet information transmission methods for increasing connectivity into the green environmental industry agriculture products and distribution. Technological innovation transmission and precision management are desperately necessary with the requirements of green products, and related technology services can be associated with crop-animal systems development. Increased plants and animals must be produced to provide food demands, rapid population increase and living standards. However, the ecosystem is experiencing huge stress. The wheat crop summer corn rotation system is lost in the ecosystem with new higher fertilising huge stress. The wheat crop and industry interconnection model can be introduced to support green economic and business development through e-commerce based on green industry and machine learning algorithms. This can be required to connect internet information transmission methods for increasing connectivity into the green environmental industry agriculture products and distribution. Technological innovation transmission and precision management are desperately necessary with the requirements of green products, and related technology services can be associated with crop-animal systems development.

Figure 2 elaborates the machine learning agriculture supply chain. Machine learning is used during the production phase for weather prediction, disease detection, plant identification and soil nutrient management. Machine learning (ML) is used for estimating demand and planning production in the processing phase. The main application fields of ML in the distribution stage are inventory management and consumer analysis. Figure 2 presents the fundamental environment for machine learning agriculture presenting the results of the analysis. In an agricultural supply chain, the initial process is preproduction. In this phase, activities include prediction of crop production, the prognosis of soil qualities and irrigation. An accurate forecast of soil qualities is essential, and it helps to efficient land management techniques. A study that soil prediction leads to a better understanding of the processes of the soil ecosystems. Effective soil management practices drive the effective agricultural and environmental system. In this phase, ML applications include developing a decision support system in dry and semi-arid regions to predict product quality and improvement of smart agricultural production. Agricultural crop yield is essential in promoting better management of crops and plans to market. As once crop yield in a given location is predicted, extra input for agriculture can be planned according to soil and crop demands such as nutrients, agricultural inputs and production schedules. ML and signal processing methods are used for improving decisions in crop production prediction in improved agricultural systems. The estimation and evaluation of rates assisted in harvesting and improved field efficiency in coordination. A summary of several ML algorithms used for agricultural production prediction is presented in this paper.

According to the Food and Agriculture Organisation (FAO), about 1.3 billion people rely on livestock for their livelihoods and food and nutrition security. Livestock farming strategies help conserve biodiversity and sequester carbon in the soil and biomass at the local level. All living species (including humans) in a specific location, as well as nonliving components like air, water, and mineral soil, interact in an ‘ecological system’ (ecology). There are no hard and fast rules when it comes to ecosystem borders.

The study results demonstrate that the ML technique can deal with nonlinear difficulties and better predict all three soil properties examined. This paper uses the auto-adaptive evolutionary algorithm to improve the architecture of the extreme learning devices to estimate the soil temperature each day. A new ML technique is presented to address crop selection issues and enhance the crop net yield rate to improve crop yield over the
season. Accuracy in soil prediction contributes to effective techniques of soil management. Figure 2 gives a collection of several ML methods for soil learning. The management of irrigation has an important effect on crop quality and quantity. Irrigation development and management are designed to visually analyze when, where and how much irrigation can be conducted. The soil moisture, precipitation data, evaporation data and weather predictions use an effective irrigation system to determine better. To maintain the balance of climate, hydrological and agricultural processes for long-term agricultural sustainability, efficient irrigation management in agriculture plays an important role. Simulation and optimisation approaches are the basis for the ML algorithms for developing effective irrigation management systems. For predicting evaporation in storage release management, ML is employed in irrigation management. Figure 2 identifies the various ML algorithms used to develop irrigation systems. Ecosystem processes ‘occur at a wide range of scales,’ according to previous research. Internet of Things (IoT) security vulnerabilities is still a problem. Because of a lack of Internet of Things (IoT) legislation, Compatibility issues are a problem. Restricted resources; high expectations from customers. Data collected by remote sensing can be used to identify and monitor crops. They become a powerful tool for making crops and agricultural plans when organised in a Geographical Information System (GIS) with other characteristics.

The production phase of ML plays an essential role in predicting the weather, identifying plants, diagnosing diseases, managing livestock, location management of nutrients, harvest and crop quality. In the crop production phase. The weather prediction includes sunlight, precipitation, moisture, and humidity leading to the optimal water use for planning and decision-making irrigation. The various ML algorithms employed in weather prediction are listed in Figure 2. Effective ways to protect crops cover early identification, biotic stress, abiotic and biotic stress factor nutrient diagnoses, and crop failures. Innovative agriculture technology site-specific management enabled the detection of insect diseases and

![Figure 2. Machine Learning Agriculture Supply Chain.](image-url)
crops previous to actual conditions. A high spatial and temporal information density is essential for effective site-specific management and early detection of plant diseases. Many studies have proposed the use of real-time platforms to detect diseases to improve diagnostic accuracy. Management of crop quality is essential as it helps to achieve the appropriate product market price. Crop quality management approaches, such as nutrient control, provide excellent targeted homogeneous crops/field regions requiring similar processing. Prediction and clustering are the most extensively used ML techniques for nutrient management. Combinations of a crop model and global sets of grids have become an enabling environment for predicting crop yields. More particular ML uses throughout the production phase are presented in the following section. The final agricultural process carried out in the field is harvesting following crop development. The crop production estimations give farmers helpful information for planning and resource allocation for harvesting and after harvesting operations. At this level, the ML algorithms focus on predicting crop yield using remote sensing data. Used a set learning model to evaluate and compare the soil properties and the prediction of coffee production with random forests and regression analysis during the harvest. For predicting changes to crop colour during the harvest stage, ML methods are implemented. The element can provide professional soil nutrient testing and analysis at certified laboratories to help identify deficiencies and improve soil fertility for high-yielding crops. Plants rely on nutrients found in soil to thrive.

The large industry at this phase is the prediction of demand and production planning of agricultural goods. The inedible raw data are converted into a more helpful and stable food for feeding in the processing phase. Grinding, heating, grilling, smoking, drying, and frying are some notable processing procedures. The processing results in physical changes of the goods and, depending on the techniques utilised, both adverse and beneficial effective impacts. The agricultural products are packaged and ready for distribution and retail phases after the processing phase. The study focussed on the processing and management of waste to reduce carbon impact. Prediction of demand food in general inventory management prevents over-stressing, overproduction and overuse of resources. The distribution and retail phase combines the production and final usage of food and completes the farm with the fork cycle. The packed agricultural product is then forwarded to the distribution facilities and storage during the delivery process. Before reaching the maximum consumer, the majority of the products go through a distribution process. Several studies used genetic algorithms and focused on transportation problems, minimising damage to the goods, trip distance, and goods quality. The integrated manufacturing and distribution scheduling challenge uses association rules mining to find a cloud-based issue with the storage and distribution storage location. In addition, ML algorithms are used to evaluate transportation, inventory management and payment delays. ML has developed local food chain systems that ensure food safety and sustainable development in the transportation network.

In this study, much effort has been made to create smart cultivation patterns with IoT technologies in agriculture. By examining numerous crop complications and problems, IoT offered a staggering transformation to agriculture. The current trend towards innovation anticipates farmers to detect the organisation of those problems face, such as water management deficits in agriculture and productivity issues using IoT farmers and technology. The challenges faced by IoT have detected all these issues providing cost-effective solutions to reducing challenges. Technology-based remote monitoring networks enable us to collect and communicate information from devices (sensors) to the cloud server. Information collected by the sensors effectively evaluates the whole system for data on various environmental circumstances. Monitoring ecological conditions and yield productivity is the assessment factor for the crop. Numerous variables significantly impact yield productivity, efficient agricultural field management, soil and crop surveillance, moving undesirable objects, assaulting wild animals. Moreover, IoT provides detailed management for limited assets that ensure the optimum use of IoT to improve productivity.

Figure 3 shows remote sensing in smart agriculture with IoT technologies. The system demonstrates agricultural developments that create cost-effective and straightforward realistic interactions by safety and perfect connectivity between individual greenhouses, live stocks and farmers. The IoT-based agricultural system uses IoT devices to facilitate the production of animals and monitoring in real-time. IoT helped develop agricultural production patterns, including cloud platforms database schema, applications, security difficulties, and challenges. Different IoT techniques and standards in agriculture have been implemented across several organisations and individuals globally. However, a sensitivity measure has been carried out in the IoT-based agri-environmental setting to understand crop developments. This paper divides several difficulties and developments IoT-based intelligent agriculture transform to develop the enhance agricultural growth.
In this research, farming practices have been included from research as a resource following IoT: Identifying relevant IoT supporting components essential technology for smart agriculture. A detailed analysis has been developed on IoT’s communication network, including cloud infrastructure and application interface, topologies, devices are connected in agriculture protocols. There have been discussions on several application fields and related mobile and sensor applications. IoT-assisted agriculture highlighted security and privacy challenges. Industrial developments in IoT-based agriculture analyze the major manufacturing fields currently researching this field. Measures for the standardisation of smart IoT agriculture established by various countries are discussed. Finally, there have been highlighted the challenges and issues that can be improved in agriculture-based IoT technology.

By measuring reflected and emitted radiation from a distance, remote sensing detects and monitors an area’s physical features (typically from satellite or aircraft). Researchers can ‘feel’ things about the Earth by using cameras that collect remotely sensed images. Non-destructive nutrient detection uses optical sensors that employ reflectance spectroscopy to measure soil particle and nutrient ion energy reflectance/absorption and electromagnetic sensors that use ion-selective membranes. The method for irrigation of agricultural production depends on its capability to maintain the soil. The irrigation manager aims at keeping soil moisture between low and higher limits. The higher limit indicates that the soil has more water holding capacity and the lower limit is the barrier of the soil’s moisture content.

\[ F = \nabla e[\text{avg}(S(t), R(t))], \quad F \in [f_u, u = 1, ..U] \] (1)

As evaluated in equation (1), the soil moisture is calculated \( F \). Here, \( e \) indicates average volume soil moisture and rainy level propagation \( [\text{avg}(S(t), R(t))] \) is the average volumetrically moisture content of the ground. \( f \) is the irrigation farmland it depends on the soil capability \( R(t) \) and soil moisture \( S(t) \). The preconfigured set of labelled soil \( [f_u, u = 1, ..U] \) in agriculture production the \( u \) is the upper bound denotes the water retention capacity.

**Figure 3.** Remote Sensing in Smart Agriculture with IoT Technologies.
Soil moisture between low and higher limits in agriculture production is shown in Figure 4. Irrigated agriculture’s purpose is to keep soil moisture content within the lower and higher limitations. The upper bound defines the highest water retention capacity of the soil. In contrast, the lower bound indicates the soil moisture content level anything below the lower bound signals the necessity for irrigation. The ability of the earth (i.e. water retention) to activate the irrigation plan on agriculture is essential.

\[ s(t) = \sigma(F, \text{avg } S(t)) \] (2)

As described in equation (2) and Figure 4, the maximum soil water retention is defined. When the soil type is identified as the maximum capacity of soil water holding capacity \( s(t) \) is calculated. \( \sigma(.) \) is an actual correlation, identical to that defined in this paper, between plant species and soil moisture.

\[ s(t) = 1000 \times S(t)q_i \] (3)

As determined in equation (3), the depth of moisture content is evaluated. In the irrigation process, the soil water retained immediately at the root of the crop \( s(t) \) at a time instant \( t \) represents the depth of moisture content \( mm \) water and is determined. Where, \( q_i \) indicates the plant root thickness of the metre, the volume quantities of soil are. The groundwater deficit \( mm \) of the farmland and at time \( t \) shall be as follows in equation 3:

\[ s(t) = s(t) t - s(t) t \] (4)

As determined in equation (4), the upper boundary of water stress is calculated. The upper boundary of water stress \( s(t) \) can be zero. When \( s(t) \) achieves the maximum soil water retention \( s(t) t \) and \( s(t) t - s(t) t \) irrigation can not be required. However, for the time being, a value level is measured by using the expertise of farms.

\[ M_{eq} = EN \times M \rightarrow MMJ = M_/ (EN) \] (5)

As explored in equation (5), the nitrogen nutrition index is computed. Different plants attribute \( M_/ \), total \( M \) in the ground biomass the nitrogen nutrition index \( M_{eq} \) are analyzed to test the quality of grain \( M \). These signals are typically used to evaluate the requirement for crop fertiliser and adjust usage. The nitrogen consumption \( M_{eq} \) is calculated using multiplicand with the appropriate \( M_/ \) percentage of the plant part by the plant dry biomass \( EN \).

\( MMJ \) is a measurement based on the idea that with increasing biomass \( M_/ \) decreases. To calculate measured \( M_/ \) with essential indicating the lowest \( M_/ \) required for achieving maximum biomass at a given stage of development, the experimental diffusion curve that reflects the connection between \( EN \) values can be used. \( MMJ \) levels \( <1 \) show a deficit of \( M \) and \( MMJ \) values \( >1 \) show an excess of \( M \).

\[ M_{eq} = M_{ST} - M_{cor} \overrightarrow{100} \rightarrow PFP = X_{eq} / M_{cor} \] (6)

As suggested in equation (6), the fertiliser level is discussed. To enhance the fertilising stage of the process, standard fertilisation quantity \( M_{ST} \) are adjusted using measurements. In the presence of the higher level of absorbance, \( M \) fertiliser levels for \( M_{eq} \) are computed on each sector.

The correction factor at pixel \( J \) in the environment \( M_{cor} \) is calculated by reducing the \( M_{ST} \) according to the proportional reflection intensity changes at point \( J \) and \( X \), is calculated.

\[ AFR(\%) = M_{eq} = M_{eq}(MC) \overrightarrow{100} \rightarrow PFP = X_{eq} / M_{cor} \] (7)

As explored in equation (7), the actual recovery of fertiliser is determined. Three different measures evaluated nitrogen use efficiency: the actual recovery of fertiliser (AFR), usually referred to as recovery efficiency, is used to measure \( M \) fertiliser recovered by plants. Therefore, \( M_{eq} \) From the MC plot as a soil supply measurement Mis detracted from consumption and divided for the fertiliser applied from the status change. The total \( M_{eq} \) (AFR total) and \( M_{eq} \) in the plant foods are calculated for AFR crop.

In the measurement of the association between the crop yield in the fertilised field \( X_{eq} \) and \( M_{cor} \). Of this plot, a part factor productivity \( PFP \) is estimated.

\[ D = Y \times Q_1 - M_{cor} \times Q_M \] (8)

Where, \( X \) is a crop yield, \( Q_1 \) is an applied fertiliser, \( Q_M \) is the used N fertiliser cost. Costs are, respectively, for crop yield \( D \) and fertiliser \( M \).

Storage moisture in the intermediate plant root, as shown in Figure 5. The irrigation water is absorbed into the nutrient broth after reaching the surface area from the irrigation device. The amount of infiltrated water is separated into two parts: the amount accumulated within the intermediate plant root zone and the amount discharged downward beyond the plant root zone. The water balance in the plant is based on mass conservation, which stipulates that the change in soil surface storage moisture content of a plant root zone is equal to the amount of irrigation provided.

\[ \Delta S = \frac{P_{in} - P_{out}}{\Delta t} \] (9)

As calculated in equation (9), the storage moisture is
accumulated. \( \Delta S \) is the differential in storage moisture in the intermediate plant roots. \( P_{in} \) is the amount of irrigation water and \( P_{out} \). The evapotranspiration of the crop is as follows: is the quantity of water evaporated. The reference point for evapotranspiration is established using the methodology for the controlled greenhouse environment.

\[
DT = L_f - DT_0 = J - R - E - \Delta S \quad (10)
\]

As calculated in equation (10), the crop evapotranspiration is evaluated. In which, \( DT \) is crop evapotranspiration, \( L_f \) is crop-coefficient, \( J \) is corresponding to irrigation water quantity, \( R \) is the quantity of waste, \( E \) refers to water absorption measurement. The proposed RSCS monitors the agriculture product to achieve high precision, less moisture content, reduced \( \text{CO}_2 \) emission level, enhanced performance, high data transmission, irrigation control, and increased agriculture production.

**Result and discussion**

In agricultural productivity, effective crop management strategies had been a major focus to discuss present problems and potential requirements efficiency of agricultural production resource utilisation. It has been demonstrated to be an efficient and comprehensive technology for the quantification of field-based information. The development of intelligent agricultural production is guided by remote sensing when field data from artificial sensors are generally accessible. Several evaluations are accessible for remote sensing applications and recent studies have focused on the possible use of remote sensing and nutritional conditions in agriculture products. The system designed offers new ways of accessing information which the communication services can rapidly access. Farmers have simple conditional statements that help connect with applications and respond to fast change requests for processes; the process control can be altered less time to real requirements. Data collected by various remote sensor devices in the experimental greenhouse can be applied to control electro valves, lights and electric pumps using soil, water quality conductivity, air and land temperature, ambient temperature and humidity to devise alternative standards. The results can be studied using remote sensing based on the practical values of the IoT device for greenhouse factors such as \( \text{CO}_2 \), soil moisture, temperature and light for crop and crop growth components plant. In addition, water usage in greenhouse irrigation is compared with the predicted consumption required in soil usage using the provided information. The simulation parameters of green development of agriculture production outcome of RSCS as shown in Table 1.

**Precision ratio (%)**

The technical application of precision in agricultural production focuses on improving the interaction of normal foods with agriculture products, energy, moisture, fertiliser and chemicals. Precision agriculture can enhance simplified methods and massively strengthen the status of the field. Agriculture and intelligent, data-centred and multi-storage agricultural processing are now updated with advanced technology to promote innovative and precise farmers. The efficient implementation of production, precision, and adequate irrigation control are essential to complete crop demands, prevent errors, and impact the environment in agriculture and associated water management. Furthermore, farmers’ experience, farmers’ ability and a perception that the tested sample demands the information required for agricultural precision and involvement in

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**Figure 4.** Soil Moisture between Low and Higher Limits in Agriculture Production.
workshops and demonstrations have an essential influence on the acceptability of precision agriculture.

The precision ratio (%) is shown in Figure 6. In combination with data preprocessing technologies, this innovation utilises best-performing data for various resources to improve resource efficiency and provide an effective and personalised workplace environment for increasing agricultural production.

**Performance ratio (%)**

Evaluation measurement of device aims of standard results quantitative, effectiveness, lead time and a suitable method to remove the indications and evaluate intelligent information to adjust crop production performance. This shows that major performance measures and effects can be effectively assessed using updated source systems. Improved technology enables a sensor to learn its solution from the point of view of data processing by interaction with an external environment. The preferred solution is for predicting data analysis and enhanced technology for fundamental decision-making challenges. In conjunction with data preprocessing technologies, this development uses different data sources to improve resource performance and provide an effective and personalised work environment for improving agricultural production.

The performance ratio (%) and moisture content ratio (%) are shown in Figure 7. Maintaining proper plant development and good crop yields requires a sufficient moisture level. Irrigation does not restore moisture to the crop and therefore a temperature controller. Consequently, it is easy to understand that the crop has various requirements for moisture content, depending on its environment and stages of development. Therefore, a farmer’s main challenge is improving the production, storage and effective use of moisture contents. Moisture is the value reflecting the amount of moisture in the ground of the standard solution. The potential moisture content of plants and soil is indicative of the moisture content. Several ML approaches on the wet soil samples have been influenced by soil moisture content. The soil moisture measurements, soil moisture and evaporation information are used to evaluate and manage the environment of an efficient agricultural field. Weather

![Figure 5. Storage Moisture In The Intermediate Plant Root.](image)

![Figure 6. Precision Ratio (%).](image)

| Table 1. Green Development Agriculture Production Outcome of RSCS. |
|-----------------|--------|------|------|------|
| Parameters       | TM     | DCMM | RFRA | RSCS |
| Precision Ratio (%) | 56.7   | 65.2 | 76.6 | 95.1 |
| Performance Ratio (%) | 58.1   | 65.5 | 80.6 | 96.5 |
| Moisture Content Ratio (%) | 68.6   | 44.3 | 38.9 | 18.7 |
| Data Transmission Rate (%) | 67.8   | 72.3 | 83.3 | 92.3 |
| Co2 Emission Level (%) | 65.1   | 56.7 | 30.6 | 21.5 |
| Irrigation Control Ratio (%) | 64.2   | 76.4 | 87.7 | 94.7 |
| Agriculture Production Ratio (%) | 56.4   | 68.7 | 84.7 | 94.2 |
predictions, including sunlight, precipitation, evaporation and moisture, influence the appropriate water use for planning irrigation. A comparative analysis can be carried out to control the soil’s moisture content to assess predictor variables and AI performance.

**Data transmission rate (%) and CO₂ emission level (%)**

Innovation has pointed out that low-cost industrial IoT can enable industrial production efficiency to improve and develop emissions and pollution reduction. However, carbon emissions are responsible for major light industrial pollutants and total industrial wastewater emissions. Artificial intelligence and major organic for all aspects of the agricultural value chain are developed and implemented, moving food towards green development. The development mode based on the internet of things is essential for producing high efficiency, low costs, low emissions, and energy efficiency for the agriculture industry. Using the energy usage modes of handling and Co₂ emissions from environmental pollution introduced contributions of capital and labour into the manufacturing process. They produced energy usage and inputs from emissions into the atmosphere. Agricultural organisations reduced priority to protecting the environment, released more emissions control waste, and increased carbon emissions indices. Further required energy conservation and reduction objectives and related regulations have been proposed and the agriculture environmental pollution has been reduced.

Figure 8 (a) data transmission rate and Figure 8 (b) CO₂ emission level. The overlap interaction refers to the time and quantity of data generated during the transmission of each phase of the check process. A technique is preceded by the rapid ‘recognition rate’ for data transmission at which delay features of the platform are measured by test vibrations and the automated system instantly modifies the delaying information in the data sensor by sampling to determine the correct connection interruption tolerance levels and the equaliser transmission rate begins at this point. The data transmission process characteristics are evaluated during transmission to make adjustments and modifications that are decreased if the transmission potential implementation is required to the major power output signal. If such a signal is received during real-time, the protocol cannot be achieved and the source node can be blocked. Sensors are used to monitor crop growth, including moisture, weather, soil and farming field. The collected data is encrypted and then immediately uploaded to a database server of agriculture production.

**Irrigation control ratio (%)**

There have been no substantial variations among the average values, quantity, density, lightness, toughness and pH of the cucumber crop for irrigation under IoT system implementation utilising a moisture sensing and digitised scheduling technique. The irrigation control water applied by the sensing control results in significantly increasing yields for the consumer crop’s length, breadth, weight, and dry matter production. This finding is related to an ideal supply of the medium moisture content of the crop-root area.

Table 2 shows the irrigation control ratio (%). The findings showed that the irrigation control with average moisture significantly increased the oxygen levels and the crop quantity and potential production of each plant. At the same time, timing system irrigation controlled a significant increase in the average capacity temperature. The IoT platform provides deep connectivity to monitor, control, and regulate the greenhouse’s climate and supply systems and irrigation.

**Agriculture production ratio (%)**

The production efficiency has been the accessible huge resource to promote increased production of healthy foods and wealth for agricultural production. The various benefits of IoT nutritional recommendations to final farmers are essential in the nutrition environment.
of greens production and distribution. The various assessments of crop values are essential to the use of information by farmers and the challenging agricultural decision on an existent crop, soil and environmental data.

Table 3 shows the agriculture production ratio (%). Agriculture production has been the available massive product to increase crop production for agricultural production and create rich alternative crops. Several analyses are essential to the nutritionally based production and delivery system for the large-scale data nutritional food production services for end-users of the approach. Such factors produce an agricultural imbalance in this country that calls for realistic solutions to improve agricultural production in line with local environmental conditions. The soil-based greenhouse culture that cultivates in specific preset environmental parameters is one of the acceptable solutions. This technique considerably relieves the impact of problematic climatic and rural shortages in similar dry areas, increasing agricultural production and food consumption. Thus, the experimental results RSCS show when compared to threat model (TM), deep crop mapping model (DCMM), random forest regression algorithm (RFRA).

**End notes**

An intelligent irrigation system based on an AI to predict soil moisture content is presented in this study. It focuses on essential agricultural requirements such as saving groundwater quality and cultivation by regulating the irrigation functioning. IoT platform’s durability is dependent mainly on the maximum energy consumption of the sensor nodes. This evaluation provides a solution to information involving AI and agriculture and food production industry vision methods. This article suggests that the list of agricultural production can grow the main business and use the benefits of agriculture to industrialise the manufacturing production and make it more vital and active using the green management approaches and focusing on the agriculture production. Therefore the results are obvious suggestions for developing an effective marketing strategy for green agricultural products to improve healthy food choices and support the potential growth of agricultural products in the local and global areas. The RSCS achieved the highest precision ratio of 95.1%, the performance ratio of 96.35%, data transmission rate of 92.3%, agriculture production ratio of 94.2%, irrigation

| Number of Devices | TM    | DCMM | RFRA | RSCS |
|-------------------|-------|------|------|------|
| 10                | 55.6  | 65.6 | 77.1 | 88.4 |
| 20                | 56.1  | 66.7 | 78.3 | 88.9 |
| 30                | 57.3  | 68.4 | 79.9 | 90.1 |
| 40                | 58.3  | 69.3 | 80.1 | 90.4 |
| 50                | 59.2  | 70.1 | 82.3 | 91.3 |
| 60                | 60.1  | 72.3 | 84.6 | 92.5 |
| 70                | 61.2  | 73.1 | 85.3 | 93.4 |
| 80                | 62.1  | 74.8 | 86.1 | 93.5 |
| 90                | 63.6  | 75.4 | 87.0 | 94.5 |
| 100               | 64.2  | 76.4 | 87.7 | 94.7 |

**Table 3. Agriculture Production Ratio (%).**

| Number of Devices | TM    | DCMM | RFRA | RSCS |
|-------------------|-------|------|------|------|
| 10                | 45.6  | 57.1 | 68.4 | 85.6 |
| 20                | 46.7  | 58.3 | 68.9 | 86.1 |
| 30                | 48.4  | 59.9 | 70.1 | 87.3 |
| 40                | 49.3  | 60.1 | 74.4 | 88.3 |
| 50                | 50.1  | 62.3 | 75.3 | 89.2 |
| 60                | 52.3  | 64.6 | 78.5 | 90.1 |
| 70                | 53.1  | 65.3 | 80.4 | 91.2 |
| 80                | 54.8  | 66.1 | 82.5 | 92.1 |
| 90                | 55.4  | 67.0 | 83.5 | 93.6 |
| 100               | 56.4  | 68.7 | 84.7 | 94.2 |
control ratio of 94.7%, and the lowest moisture content ratio of 18.7%, CO2 emission ratio of 21.5%, compared to other methods.

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