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Enhancing Crop Yield Prediction with IoT and Agricultural UAVs: A Comprehensive Review

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Abstract

INTRODUCTION: Rapid development in the field of the Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) is allowing them to be utilized across multiple sectors like industrial manufacturing, healthcare, defense, etc. In the agricultural industry, IoT and UAVs are also proving themselves as one of the most promising technologies. These technologies have opened the door to numerous innovative opportunities in precision agriculture, particularly in predicting crop yields more accurately and efficiently. Traditional methods for crop yield prediction were based on manual sampling and statistical models, which proved to be time-consuming and less accurate.
OBJECTIVES: This paper mainly contributes to the comprehensive study of IoT and UAVs in crop yield prediction. It highlights how data-driven methods, sensor technologies, and remote sensing enhance decision-making in precision agriculture.
METHODS: The paper discusses traditional practices for crop yield prediction and their limitations. It explains the architecture of IoT and its various layers, including a detailed study and comparison of different IoT sensors, microcontrollers, and communication standards. The paper further focuses on the potential of UAVs for yield prediction, including details of different types of UAV platforms, control strategies, and communication standards. Additionally, the paper explains the benefits and limitations of integrating IoT and UAVs for more accurate crop yield prediction.
RESULTS: The study demonstrated that IoT-enabled monitoring and UAV-based remote sensing improve crop prediction accuracy.
CONCLUSION: Overall, this paper presents the transformative capability of integrating IoT and UAV in modernizing the process of crop yield prediction and other precision agriculture practices. As a future scope, the paper focuses on the use of edge/fog computing, mobile apps, and AI chatbots to enhance the power of IoT and UAVs in crop yield prediction.

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1. Introduction

By 2050, the world's population will reach about 10 billion people and food demand will increase by 70% [1]. To meet this high demand, we need to improve the rate of food production. Traditional farming practices are fraught with challenges and are more prone to crop loss. One of the greatest challenges humanity is currently facing includes sustainable production of food for a growing population. To enhance crop productivity, we must apply the principles of precision agriculture. Precision agriculture involves the implementation of smart agriculture for better yield.

Smart farming involves the use of new technologies that have evolved through the fourth industrial revolution, such as Artificial Intelligence, Robotics,

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IoT, and UAVs [2] [3]. The use of these technologies increases the quantity and quality of production by utilizing resources to the maximum level and minimizing the environmental impact. Figure [1] shows the benefits of smart farming, including production; reducreducreduceder use; Improved crop quality; Pest and disease detection; and better sustainability [4].

The Prediction of crop yield is crucial for maintaining economic and ecological balance, promoting sustainable growth. An effective crop yield prediction has a significant impact on efficient use of resources [5]. Nowadays, the use of remote sensing techniques is ideal for collecting data to predict crop yield, as it provides quantitative and timely information [6] [7].

IoT is the emerging technology that allows multiple devices to connect remotely. It is gaining importance in almost all sectors, including health, industry, agriculture, and communications, among others. In agriculture, the IoT remotely monitors plants and crops, collecting information using sensors and instruments [8]. The IoT helps monitor crop health and water levels for irrigation, ultimately leading to improved crop yields.

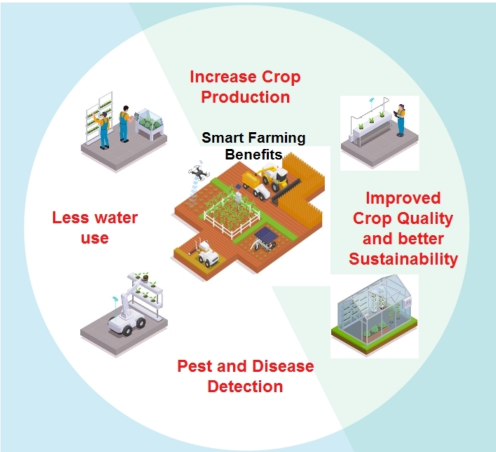

Figure 1: Benefits of Smart Farming

UAVs, or Unmanned Aerial Vehicles, are flying devices without pilots that are now available to the public at affordable prices. It has a Global Positioning System (GPS), brushless motors, propellers, and flight controllers [9]. The use of UAVs is increasing rapidly in the agricultural sector. It is replacing satellites and other remote technologies. Unlike satellites and other aircraft, UAVs fly at lower altitudes, which allows them to take clear photographs[10].

2. Crop yield Prediction Techniques

Forecasting crop yields is one of the most challenging tasks for farmers. Since the beginning of humanity, our ancestors have employed various techniques to predict the yield of their crops. Those traditional methods were usually manual and required extensive personal experience. Slowly and gradually, with the advancement of time, many modern technologies have evolved, which have been proven to be more efficient [11].

2.1. Traditional Methods

Conventional methods for predicting crops usually involve the experience and knowledge of farmers. They studied the local climate of the area, the historical yield of the crop, and soil conditions to predict the future yield. They also developed weather-based forecasting, in which farmers analyze weather parameters such as rainfall, temperature, and humidity to estimate their yield. Traditionally, farmers also used various crop growth models, in which predictions were based on factors such as the date of planting, crop species, soil type, weather conditions, and water availability. Depending on these factors, they made simulations and predicted the yield.

2.2. Limitations of traditional methods

Traditional crop yield prediction technologies had numerous drawbacks. They were highly dependent on data. Primarily, the available datasets were limited to historical weather records and yields, which may not accurately represent large-scale factors such as soil conditions, climate change, or diseases and pests in crops. Those technologies were not as accurate and precise as they were based on farmers' knowledge and experience, which are subject to biases. Their knowledge may fail under unpredictable natural conditions. They also proved to be inaccurate when applied to large-scale regions[12]. Traditional practices were not efficient for real-time monitoring of the crop and its factors, making it challenging to take targeted measures for crop management.

2.3. Introduction of IoT and UAVs as alternative methods

To overcome the drawbacks of traditional techniques of crop yield prediction, various modern methods emerged, which include data analytics, Machine Learning (ML), Deep Learning (DL), IoT, UAVs, etc. [13]. These modern technologies were more promising in terms of accuracy and timely prediction. Of all modern technologies, the introduction of IoT and UAVs has revolutionized present farming practices. IoT involves the use of sensors, actuators, and other devices in the field to collect real-time data [14]. The collected data are used for analysis and decision-making regarding crop management, irrigation, and pest control[15]. The use of UAVs, often referred to as drones, is also gaining popularity in the field of agriculture due to their potential for real-time crop monitoring[16]. UAVs are equipped with cameras and sensors that help capture aerial images of crops to monitor their health, observe crop growth patterns, and detect diseases and pests[17].

3. Internet of Things (IoT) for crop yield prediction

IoT in agriculture involves the use of various embedded sensors to create a network of interconnected devices that can collect and share data. IoT enables farmers to collect data on crop growth, soil conditions, and environmental factors. The Adoption of IoT devices for agriculture is increasing rapidly. Currently, the United States, Germany, and Japan are dominating other countries in sensor technologies[18]. When talking about IoT architecture for smart agriculture, we can divide the architecture into four major layers: (1) IoT Sensors, (2) Communication Technology, (3) Database and Server technology, and (4) Users [19]. This illustration is presented in Figure [2].

3.1. IoT sensors

Sensors are small devices that measure various conditions, such as temperature, light, and motion, and convert them into digital values. Sensors are required to make farming "Smart". The yield of any crop depends significantly on various parameters, including weather conditions, soil nutrients, and soil moisture. With the help of multiple sensors, we can easily monitor and collect data, then analyze it to make informed predictions for the future. Table [1] represents the emerging implications of the sensor in the field of crop yield prediction.

Smart sensors (sensors equipped with chips) are capable of recording various environmental and soil parameters with higher accuracy. These sensors are installed throughout the field and then begin collecting data regarding soil and crop health. The collected data are then transferred in real-time to a centralized platform, where they are processed for further analysis and the development of predictive models to predict crop yield [34]. Here is a detailed step-by-step procedure of how sensors work for the prediction of the yield of any crop:

1. **Installation:** Sensors are wisely installed throughout the agricultural field to record the various factors related to crop growth. Soil sensors are buried inside the soil. Crop health monitoring sensors are placed above the crop, and weather stations are installed on the ground.

2. **Data Collection:** All sensors continuously measure all the parameters related to crop yield. Soil sensors measure soil moisture and soil nutrients. Crop health sensors monitor the health of leaves and temperature, while weather stations measure rainfall, temperature, humidity, and wind speed.

3. **Data Transmission:** Sensors transmit data to a centralized database by utilizing wireless communication over the internet. This centralized database may be located on the farm or in any other remote location.

4. **Data Integration:** The data collected from various types of sensors is integrated into a centralized database and is converted into a structured form. This integrated data enables farmers to access all data from a single location.

5. **Data Analysis:** After data collection and integration, the prepared dataset is further analyzed using advanced data analytics techniques, like ML algorithms, to uncover different trends and patterns and predict crop growth and yield.

6. **Crop Yield Prediction Models:** Data collected from sensors are used to develop predictive models that forecast the yield of the crop.

3.2. IoT Controllers

IoT Controllers manage and control all the devices connected to them, including sensors, actuators, and other connected devices. They serve as the developers' board to collect data from sensors, process it, and perform actions using the actuators. In agriculture, various microcontrollers are used to manage and automate different activities, enhancing crop productivity. Table [2] discusses the various IoT controllers with respect to other parameters.

Arduino is the most commonly used microcontroller, but it lacks WiFi capabilities, which limits its suitability [35] [36]. Various Arduino boards, including the Arduino Uno, Arduino Nano, and Arduino Mega, are used as needed. NodeMCU (ESP8266) is another widely used controller. It relies on wireless connectivity, which makes it more user-friendly and easy to store data on the cloud [37][38] [39] [40]. Raspberry Pi is also a powerful controller with multimedia support and numerous connectivity options, making it suitable for complex IoT applications [41] [42] [43]. The controller, equipped with an ESP32, provides Wi-Fi and Bluetooth connectivity. It has more GPIOs and other connectivity options [39] [44] [45] [40]. Giant Board and Particle Photons are the new boards that are gaining popularity in the field of agriculture for various applications [46] [47].

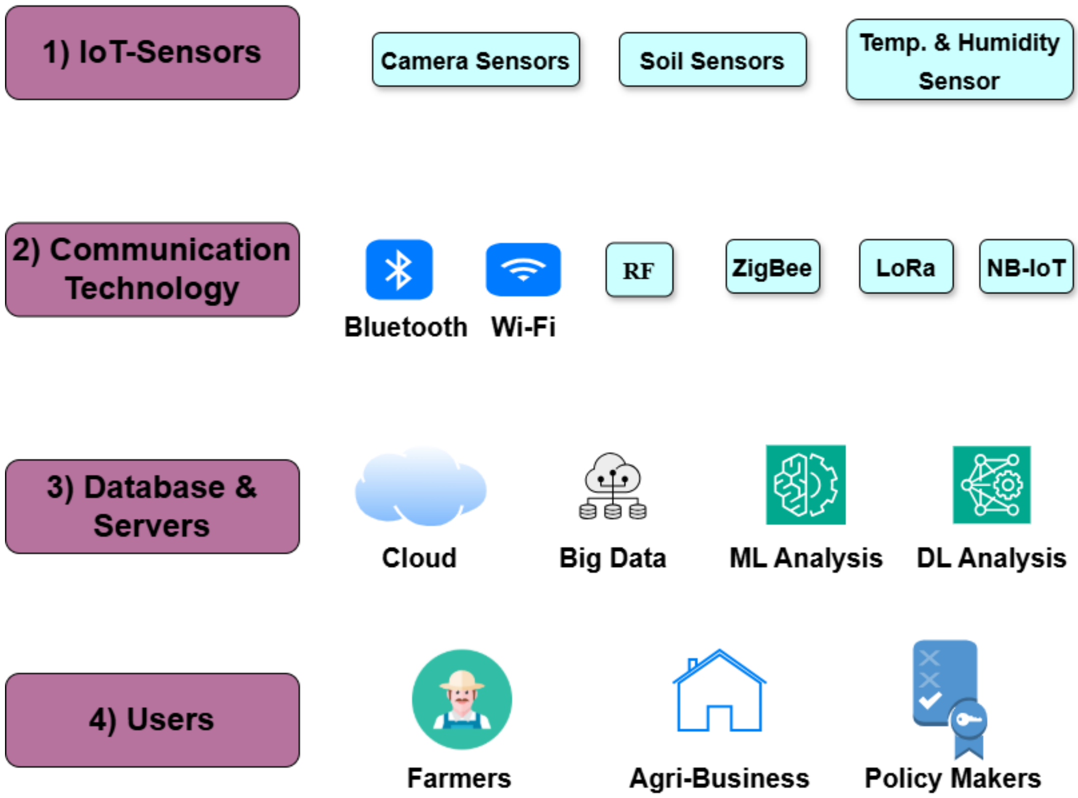

Figure 2: IoT Architecture for Agriculture

Table 1. Comparison of different IoT Sensors used in Agriculture

Sensor Type	Use	Methodology of Sensor	Ref.
Optical Sensors	They are used to monitor vegetation index, growth of crop, detect pests and diseases, monitor water use, etc	They work by measuring the absorbance rate of red and infrared light through an object (leaf).	[20], [21], [22], [23]
Electrochemical Sensors	They are used to detect soil moisture content, soil nutrients, soil electrical conductivity, temperature, soil pH, and other parameters.	They work by using an ion-selective electrode that senses different ions.	[24], [25], [26]
Mechanical Sensors	They are used to detect mechanical properties such as wind speed and pressure, soil compression or displacement.	They work by measuring the mechanical resistance in soil.	[27]
Dielectric Sensors	They are used to measure soil moisture content.	They work by measuring the dielectric constant of soil.	[28], [29], [30]
Location Sensors	They measure the range, height, and distance of any area.	They work upon images taken from GPS satellites.	[31], [32], [33]

3.3. IoT Communication Standards

When we discuss IoT communication, we primarily refer to the manner in which data is exchanged between IoT devices, such as sensors, gateways, and other platforms. Transmission of field data is a crucial component of agricultural IoT. IoT Communication standards refer to the set of protocols and technologies that facilitate the exchange of data. Wireless Sensor Networks (WSNs) have

Table 2. Comparison of different IoT Controllers used in Agriculture

Controller	Processing Power	Memory	Connectivity	I/O Interfaces	Power Consumption	Cost	Ref.
Arduino	Low	Limited	Limited (USB, UART)	Limited	Low	Low	[35], [36]
Node-MCU	Moderate	Moderate	WiFi, USB	GPIO, SPI, I2C, UART, ADC	Moderate	Low-Moderate	[37],[38], [39], [40]
ESP-32	Moderate-High	Moderate-High	WiFi, Bluetooth	GPIO, SPI, I2C, UART, ADC, PWM	Moderate	Moderate	[39], [44], [45], [40]
Rasberry-Pi	High	Moderate-High	WiFi, Ethernet, Bluetooth, GPIO	GPIO, SPI, I2C, UART, USB	Moderate	Moderate-High	[41], [42], [43]
Giant Board	High	Moderate	WiFi, Bluetooth, GPIO	GPIO, SPI, I2C, UART	Low	Moderate-High	[46]
Particle Photon	Moderate	Moderate	WiFi, USB	GPIO, SPI, I2C, ADC, PWM	Low	Moderate	[47]

been utilized for various applications, including agriculture, to enhance crop yields. WSNs are a boon for farmers as they are cost-effective [48]. These communications define the way data is exchanged, its format, and the encryption techniques used. These standards also ensure the authenticity and security of data. The IoT devices used in agriculture typically come in various shapes and sizes, and they often employ different communication technologies. The IoT communication standards provide a common framework to communicate with each other. Several IoT communication standards are utilized in the agricultural field to connect and exchange data between various devices, sensors, and other platforms. Some commonly used IoT communication standards are: (1) WiFi, (2) Bluetooth, (3) ZigBee, (4) Long Range Wide Area Network (LoRaWAN), (5) Sigfox. Table [3] shows the comparison of some commonly used IoT communication standards in the field of agriculture.

WiFi. WiFi is one of the most commonly used technologies in agriculture. It is primarily used in controlled environments, such as indoor farming and greenhouses. It helps us to transmit data at high speed from the farm to any cloud-based platform. This transmission of data from the field to the cloud enables us to monitor various agricultural parameters, such as soil nutrient content, soil moisture, temperature, and humidity, in real-time. Malhotra et al. [49] proposed a system in which they collected agricultural data like soil moisture, temperature, humidity, sunlight, and CO_2. The collected data was stored in a gateway and then transmitted to a server using a WiFi network. Fathy et al. [38] developed an IoT-based irrigation system utilizing light cryptography. Communication was established between NodeMCU, ESP8266, and Raspberry Pi using WiFi. Juan et al.[50] proposed a SAgric-IoT framework that combines IoT and CNN-based approaches for monitoring environmental and physical variables, facilitating early disease prediction. They collected the data from sensors and a camera and transferred it over the internet using a WiFi interface. They stored the data in the cloud, analyzed it, and made a disease prediction with an accuracy of over 90%. Murali et al. [51] proposed an IoT-based soil nutrient classifier and crop recommendation system using different sensors and Arduino. They used the ESP8266 as a WiFi module. WiFi is used as their communication standard to transmit the field data to the cloud over the internet.

Bluetooth. Generally, Bluetooth is used for short-range wireless communication. It is used in agriculture to connect devices and enable them to share data for real-time monitoring and control. Yunseop [52] et al. proposed an irrigation system to conserve water and increase crop productivity. They used low-cost Bluetooth communication to transmit signals from sensors and controllers to the base station. Nongye et al. [53] designed a Bluetooth-based system for monitoring and controlling crop growth parameters in a greenhouse. Gu-zhah Hong et al. [54] utilized a Bluetooth module to develop an Integrated Control Strategy (ICS) system for irrigation, aiming to conserve electricity and water usage.

Zigbee. Zigbee technology offers low-power, low-data-rate wireless communication capabilities. It follows a mesh networking topology to connect devices and communicate data over short distances. The Zigbee communication standard is utilized in agricultural activities, such as crop monitoring in greenhouses and controlling crop irrigation in confined areas. It offers a cost-effective and reliable solution. Peng Gao et al. [57] proposed a system to predict soil moisture and electrical conductivity of citrus orchards using sensors and used the Zigbee network to group data in a remote server. Swapnil et al. [58] proposed a Zigbee module-based IoT system to collect natural and soil parameters from different field locations and aggregate data over the cloud. Gangawar et al. [59] described a framework for an agro-ecological resource management system. They proved it to be a low-cost solution, as they utilized the Zigbee communication standard, which is a lightweight wireless sensor network. Yinjun et al. [60] used ML/DL algorithms for the accurate detection of disease in tomato farms. They collected real-time soil data from the farm and aggregated it on the edge server. For data transmission, they used the Zigbee communication standard.

LoRaWAN (Long Range Wide Area Network) . It offers a long-range, low-power wireless communication service. This communication standard is primarily used in large agricultural setups to connect remote devices and sensors, enabling them to transmit data over long distances. It is suitable for monitoring weather and crop health in bigger farms in rural areas. Mushran et al. [62] utilized the LoRaWAN communication standard to develop a wide-area Alternate Wetting and Drying (AWD) system for rice crop irrigation. Singh et al.[63] presented a LoRaWAN-based IoT framework for farmers to monitor soil moisture, temperature, humidity, and other weather conditions, making the system more efficient and optimized. Y.N. Goh et al. [64] deployed LoRaWAN-based sensors for the monitoring of soil moisture, pH levels, and temperature in an oil palm farm. Using the LoRaWAN communication standard, they transmitted the collected data from remote locations to a centralized server.

Sigfox. Sigfox is a wide-area network technology that consumes very low power. It provides long-range connectivity for IoT devices set up in remote and rural areas. This feature of Sigfox makes it suitable for use in large agricultural areas with limited infrastructure, making it a cost-effective solution. Gennaro et al.[67] used Sigfox's low-power, long-range feature to transmit data collected from the sensors deployed in water bodies to a centralized server. They built a system to monitor water quality and detect pollution in water bodies. Ahumada et al. [68] created a sustainable and intelligent solution for monitoring and operating irrigation in farms. They collected real-time soil data and weather data and transferred it to the cloud using the Sigfox communication standard.

4. UAVs for Crop Yield Prediction

Use of UAV-based data can significantly improve the prediction accuracy of the yield of any crop [69]. UAVs, or drones, are helping farmers and analysts collect aerial data flexibly at high resolution with improved spatial and temporal granularity [70]. Using UAVs, we can monitor crops and collect data at any time, as it is not affected by cloud cover and other weather conditions, unlike satellites [71]. There are many advantages of UAVs and drones over both satellites and manual monitoring [72]. Figure [3] explains some of them. These advantages of UAVs have expanded their applications to various other areas of agriculture, including fertilizer spraying,

Table 3. Comparison of different IoT Communication Standards

Standard	Range	Data-rate	Powe consumption	Security	Ref.
WiFi	Short to medium range	Upto several Gbps	Moderate to High	WPA2, WPA3	[49], [38], [50], [51], [55]
Bluetooth	Short range and wireless	Upto several Mbps	Low to moderate	AES encryption	[52], [53], [54], [56]
Zigbee	Short range and wireless	Upto 250 kbps	Low to Lower	AES encryption	[57], [58], [59], [60], [61]
LoRaWAN	Long range and wireless	Upto 50 kbps	Ulta-Low	AES encryption	[62], [63], [64], [65], [66]
Sigfox	Long range and wireless	Upto 1000 bps	Very Low	AES encryption	[67], [68]

weed detection, disease detection, and seed plantation, among others [73]. The deployment of UAVs for crop yield prediction encompasses various leading technologies, including different types of UAV platforms, sensor types, various communication protocols for UAVs, and control methodologies.

4.1. UAV Platform Types

UAV platforms deployed in agriculture are primarily categorized based on their design type, payload capacity, flight range, and flight time. Talking about the types of UAV platforms, UAVs are mainly of three types: a) Rotatory Wings UAVs, b) Fixed wings UAVs, and c) Hybrid UAVs.

Rotary-Wings UAVs. Rotary wings UAVs have 4 to 8 rotors. It can hover and take off vertically. It has a flight time of typically 15 to 40 minutes, with an average speed of 5 to 15 meters per second. These are easy to fly and deploy, making them suitable for smaller fields. They are also ideal for complex terrain. Ge et al. [74] used a rotary wing UAV embedded with a Red-Green-Blue(RGB) camera for maize yield prediction. They integrated classification with regression to improve the accuracy of yield prediction. Yang et al. [75] also used a rotary wing-based UAV embedded with an RGB camera for the development of a field-based plot extraction technique. By using this technique, they achieved higher plot extraction accuracy as compared to existing methods. Liu et al. [76] used a DJI Phantom 3(a rotary wing-based UAV) for the yield estimation of maize crop. As a result, they found a high correlation between UAV-based data and ground data.

Fixed-Wing UAVs. Fixed-wing UAVs have an airplane-like structure, and they use wings for lift. It has a flight time of approximately 45 to 120 minutes with an average speed of 15 to 25 m/s. It usually uses a runway for the launch and a parachute for landing. They are generally used for large-scale monitoring due to their high endurance and range. They have better aerodynamic performance than rotary-wing UAVs. Bending et al. [77] used eBee (a fixed-wing UAV) embedded with a multispectral camera for the mapping of canopy height and vegetation in a wheat crop field. Moghimi et al. [78] deployed a fixed-wing UAV embedded with a hyperspectral camera for the high-throughput yield phenotyping of wheat crop. Their work proved the potential of UAV-based hyperspectral images for more accurate yield prediction.

Hybrid UAVs. These UAVs combine the agility of rotary-wing UAVs and the endurance of fixed-wing UAVs. Their flight time is about 60 to 90 minutes. They are capable of hovering like multi-rotors and have a long range. They are suitable for high-resolution aerial mapping and scouting of large fields. They are costlier than the other two UAVs. Tsouros et al. [79] used a fixed-wing based UAV named WingtraOne VTOL for the monitoring and data collection of olive orchards. As a result, they achieved high spatial accuracy. Pretto et al. [80] developed an integrated aerial-ground robotic system for crop monitoring and intervention. In this system, they utilized the capability of a hybrid VTOL UAV, which proved to be very efficient.

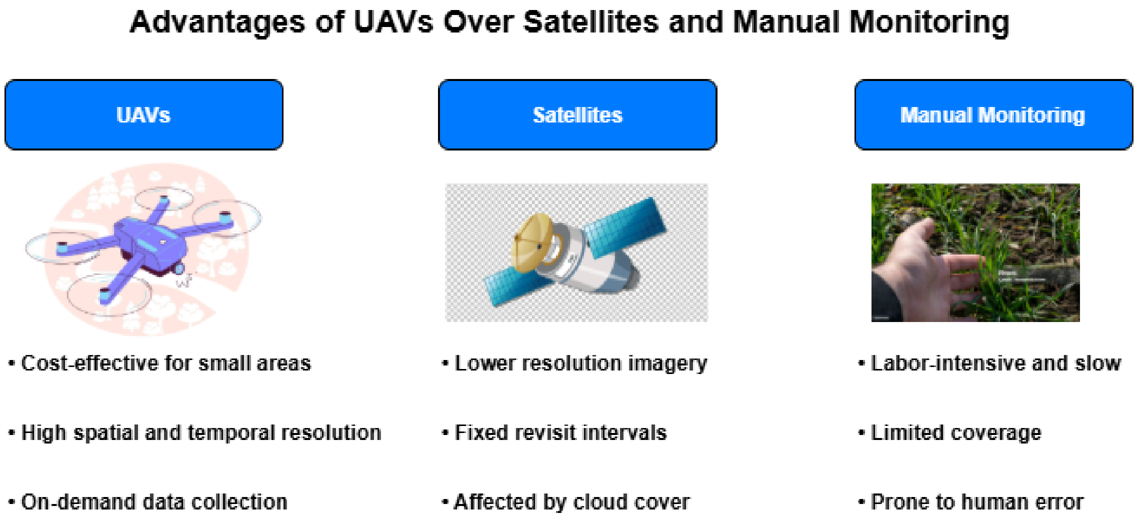

Figure 3: Advantages of UAVs over satellites and manual monitoring

Table 4. Comparison of different UAV Platform Types

UAV Platform	Flight time	Coverage	Payload	Cost	Launch	Usage	Ref.
Rotary-wing	15-40 min	10-50 ha	Light-moderate	Low	No runway required	Small crop field monitoring, Spot spraying	[74] [75] [76]
Fixed-wing	45-150 min	100-500 ha	Moderate	Moderate to high	Runway or catapult required	Bigger crop field monitoring, Yield prediction	[77] [78]
Hybrid	6–190 min	150-400 ha	High	High	No runway required	Medium and varied terrain crop field monitoring, Crop mapping with high accuracy	[79] [80]

4.2. UAV Sensors

UAVs have gained significant importance in precision agriculture. It is widely used for predicting crop yields. UAVs, when equipped with various sensors, provide timely data with high resolution. This data enhances the decision-making power of the farmers. There are basically six types of UAV sensors: 1) RGB (Red-Green-Blue) Cameras, 2) Multispectral Sensors, 3) Hyperspectral Sensors, 4) Thermal Infrared Sensors, 5) LiDAR (Light Detection and Ranging) Sensors, and 6) Multi-modal (Fusion) Sensors.

RGB (Red-Green-Blue) Cameras. RGB cameras utilize the visible spectrum to capture images. They are affordable and easy to use. They are mainly used for plant growth monitoring, crop disease detection, and measuring canopy cover [81]. RGB images can be used to derive the Vegetation Index (VI), which indicates the crop health and crop yield. Hang Yin et al. [82]

conducted a study examining the use of UAV-based RGB imaging to predict biomass in potato crops across various growth stages. They analyzed the color and texture features from the collected images and developed a model that effectively estimates the biomass in potatoes.

Multispectral Sensors. These sensors are used to collect data and images across a specific wavelength. They include visible and Near-Infrared(NIR) spectra. They are used primarily for calculating VI, such as Normalized Difference Vegetation Index (NDVI), which is used to analyze plant stress and vigor. Multispectral images are used to monitor chlorophyll content in leaves, measure Leaf Area Index (LAI), and assess other physiological parameters, which help predict crop yield. Herrero-Huerta et al. [83] used a multispectral sensor-based UAV to predict the yield of the soybean crop. They analyzed the UAV-collected data using ML algorithms and achieved high accuracy in yield prediction.

Hyperspectal Sensors. These sensors provide high spectral details about the object by capturing data across many narrow, continuous spectral bands. It helps in detecting nutrient deficiencies in plants, diseases, and other factors affecting crop yield, even before they are visible to the naked eye. Zongpeng Li et al. [84] utilized a hyperspectral-based sensor-based UAV to predict the yield of winter wheat. They analyzed the UAV-based data using ML algorithms and predicted the accurate yield of the wheat crop. They proved the potential of hyperspectral imaging with ML technologies in precision agriculture.

Thermal Infrared Sensors. UAVs equipped with thermal sensors are used to measure the temperature around the crop, indicating water stress and transpiration rates within the crop. This data helps inform wise decisions regarding crop irrigation. Yulin et al. [85] conducted a study that combines UAV-based thermal and multispectral imaging along with ML techniques to predict the yield of wheat crop with better accuracy.

LiDAR (Light Detection and Ranging) Sensors. LiDAR sensor-based UAVs emit laser rays for measuring distances. They are used to create high-resolution 3D maps of the crop canopy and terrain, which are then used to assess biomass, plant height, and other plant characteristics. LiDAR-based data helps in estimating the plant volume and biomass, which ultimately helps in accurate yield prediction. Zhu et al. [86] used both LiDAR data and multispectral images to assess the biomass of the maize crop, thereby predicting the actual yield of the crop.
Table [5] clearly shows the comparison of different UAV-based sensors with respect to their Spectral band, Resolution (both Spatial and Temporal), Cost of implementation, and their application in precision agriculture.

4.3. Communication Protocols for UAVs

The functionality of UAVs greatly depends on the effective communication protocols. They are responsible for the effective transfer of data from UAV sensors to control stations, which facilitates real-time monitoring of crops and enables the prediction of their yield. Several factors play a significant role in selecting the appropriate communication protocols. These factors include data range, transmission range, power consumed, etc. Several communication protocols are used in agriculture for predicting crop yields.

MAVLink (Micro Air Vehicle Link). This protocol is nowadays mainly used in UAVs. It is a lightweight communication protocol specifically designed for communication between UAV sensors and ground-based control stations. It utilizes telemetry messages for facilitating real-time communication. Mogili et al.[87] proposed a drone system using the capabilities of the MAVLink communication system for various agricultural applications, such as water stress management and crop harvesting. This drone proved to have great potential in enhancing crop management activities to increase crop productivity.

IEEE 802.15.4 based protocols. IEEE 802.15.4-based protocols encompass protocols such as ZigBee and IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN). These protocols basically offer low power consumption and have the ability for mesh networking. They are suitable for short-range communication. These protocols are often used for transmitting environmental data, such as temperature and soil moisture, to UAVs and control stations, which helps in crop yield prediction. Kumar, J.N.V.R.S. et al.[88] developed a drone system to measure environmental parameters like soil moisture and temperature using the IEEE 802.15.4 communication protocol, which includes HyLaR-OF-M (an intelligent routing algorithm) to choose the best way of data traveling depending upon factors like signal, availability of sensors, and battery power. Their system proved to be more reliable and helpful in collecting real-time crop data.

Table 5. Comparison of different UAV-based sensors

Sensor type	Spectral bands	Resolution (Spatial)	Resolution (Temporal)	Uses	Cost	Ref.
RGB Camera	R, G, B(Visible)	High	High	Plant growth monitoring. Canopy cover, Phenotyping.	Cheap	[82]
Multispectral	NIR, Red edge	Medium	High	NDVI, Chlorophyll Content monitoring, LIA, Stress detection	Moderate	[83]
Hyperspectral	Contiguous, narrow	Variable	Medium	Plant grown monitoring, Canopy cover, Phenotyping, Nutrient deficiency monitoring, stress and other disease detection	Very high	[84]
Thermal infrared	Infrared	Medium	Medium	Irrigation management	Moderate	[85]
LiDAR	It uses laser pulses	Very High	Medium	3D maps of canopy cover and terrain	Moderate	[86]

LoRaWAN (Long Range Wide Area Network). LoRaWAN is basically a long-range, low-power networking protocol. It is ideal for wireless devices. It is a wide-area network-based protocol that is most suitable for large-scale agricultural field monitoring. It enables the transfer of data collected using sensors from remote fields to UAVs and central servers, which aids in crop yield prediction [89]. Xu Tao et al. [90] proposed a decentralized framework using UAVs for intelligent crop monitoring. Since the monitoring was done in large-scale farms, they utilized LoRAWAN as the communication technology.

Wi-Fi (IEEE 802.11.Standards). It serves short to medium range communication with high data rates. It is utilized in various applications for real-time data transmission. Wi-Fi facilitates high-throughput data transfer from UAVs to ground-based stations, aiding in the analysis of yield. Brinkhoff et al. [90] introduced a low-cost framework that utilizes an IEEE 802.11 Wi-Fi communication platform to measure various factors, such as soil moisture and temperature, for real-time monitoring. The collected data are then transferred to a cloud platform, which enables informed decision-making.

Bluetooth Low Energy (BLE). This communication protocol offers short-range communication with less power consumption. It is utilized for connecting UAVs with nearby devices and sensors to collect local data on plant health, which helps in building yield prediction models [69].

Cellular Networks. These communication networks include 3G, 4G, and 5G networks. They enable real-time data transfer by providing wide-area coverage and high data speed. UAVs are equipped with these networks to allow the transmission of a large amount of data from sensors to cloud platforms, where they can be further analyzed and used for yield prediction.
Table [6] represents the detailed comparison of different types of communication protocols used in UAVs for effective crop yield prediction.

4.4. UAV Control Methodologies

UAVs' control methodologies refer to the mechanisms and algorithms that enable UAVs to manage their flights and maintain stability in the air. They address the environmental impacts of drones during their flight. These control methodologies manage the speed, altitude, and navigation of UAVs, ensuring they fly safely and accurately. For an effective and accurate crop yield prediction, UAVs must have the ability to fly efficiently over large and uneven terrain-based fields to collect high-resolution images and other sensor read parameters data. For this, several UAV control methodologies are available.

Table 6. Comparison of different Communication Protocols for UAVs

Protocol	Standard	Comm. range	Rate of data transfer	Power consumption	Uses	Ref.
MAVLink	UAV Protocol	Medium	Low-Moderate	Low	Used in Communication of Telemetry-based messages for real-time monitoring	[87]
ZigBee	IEEE 802.15.4	10-100 M	250 Kbps	Very low	Used in recording and transmitting environmental data to UAVs and ground-based stations	[88]
LoRaWAN	LoRa Alliance	2-15 Km	0.3-50 Kbps	Very Low	Used in transmission of remote field data to UAVs and data stations	[88]
Wi-Fi	IEEE 802.11	50-100 M	10s of Mbps	Moderate High	Used in transmission of high-resolution data from UAVs	[90]
BLE	Bluetooth SIG	Less than 100 m	1 Mbps	Very Low	Used for connecting UAVs to nearby sensors and other devices	[69]
Cellular(4G/5G)	LTE/NR	10-30 Km	High (> 100 Mbps for 5G)	Moderate	Used for synchronization of UAVs and cloud platform	[69]

The PID (Proportional-Integral-Derivative) Control methodology primarily helps maintain altitude during steady flight. However, they are not suitable for changing environmental conditions, such as locations with high-speed winds. Sairoel Amertet et al. [91] implemented hybrid fuzzy PID controllers in UAVs to precisely monitor their crops and predict crop yields. They demonstrated that these control methodologies enabled them to enhance their adaptability to varying agricultural conditions. Yunling Liu et al. [92] developed a UAV-based variable spray control system. They integrated the potential of the Radial Basis Function (RBF) neural network with the PID control methodology. This system effectively improved the pesticide spraying process. Their results demonstrated that the RBF-PID-based controller outperforms traditional PID and fuzzy PID controllers, resulting in improved crop management and yield prediction. Model Predictive Control (MPC) is another control methodology that can predict the future behavior of UAVs and optimize their control accordingly. They help in precision farming by enabling UAVs to manage their flight in real-time. It ensured the accurate collection of field data even in areas with disturbances and uneven terrain [93]. MPC can manage complex agriculture processes, helping to improve precision agriculture practices [94]. Fuzzy Logic Control methodology is capable of mimicking humans. It performs decision-making using linguistic variables. It can handle varying crop conditions with imprecise inputs and make informed decisions. This Fuzzy Logic Control helps UAVs to perform well in diverse environmental conditions in agriculture [95]. Next comes the Neural Network-Based Control methodology, which can learn from data and adapt to environmental changes over time. It is usually used in applications that require real-time decision-making. When integrated with ML, it helps UAVs to map the crop yield zone.

Table 7. Comparison of some existing review papers with the this study.

Paper (Source & Year)	Focus / Scope of Review	Traditional Practices Discussed	IoT Coverage	UAV Coverage	Integration Discussion
Mustafa et al. (2024) [96]	Discusses Bibliometric review mapping research trends in crop yield prediction using UAV and ML technologies.	X	X	✓	X
Dibal et al. (2022) [97]	Gives an overview of IoT-based solutions for climate-smart agriculture in Sub-Saharan Africa.	✓(in African context)	✓	X	X
Yuan et al. (2024) [98]	Comprehensive SLR on UAV-based imagery for crop yield prediction.	X	X	✓	X
Muruganantham et al. (2023) [99]	Presents ML models and IoT use cases in agriculture; emphasis on data analytics.	Partial	✓	X	X
This Paper *(Purnima et al.)*	Discusses traditional crop yield prediction methods and their limitations; focuses on IoT (sensors, controllers, communication standards) and UAV (platforms, control, communication), discusses benefits, limitations, and future scope.	✓	✓	✓	Conceptual

Table 8. Summary of Research Gaps and Future Scope

Research Gap	Future Scope	Ref.
No fixed and standard protocol or framework for data collection and processing.	Development of an open-source and standard framework for data collection and processing to support comparisons and model transferability.	[100], [101]
Limited ML Models that are reliable for diverse field conditions, geographies, and seasons.	Develop more varied datasets and adoption of models that are uncertainty-aware and have an ensemble approach	[102], [103]
Difficulty in integrating UAV imagery with real-time sensor data.	Use edge computing and low-latency AI models to facilitate the integration of heterogeneous data.	[104], [105]
Negligence in local crop production and smallholder farming systems.	Research should be extended towards local crops and regions with low resources.	[106], [107]
Economic Viability, as these technologies have high deployment and operational costs, and also have complex calibration.	Development of cost-effective, modular, and easy-to-use UAV/IoT platforms.	[108], [109]
Limited Use of Explainable AI models	Promote the use of Explainable AI approaches that are transparent to farmers, making it easy to trust them.	[102], [103]

5. Comparison with Existing Reviews and Related work

Most of the available reviews emphasize mainly system implementation, automation, or model performance without discussing the transition from traditional crop yield prediction techniques to modern sensor-driven techniques. In contrast

, this paper uniquely provides a comparative review that shows three stages of evolution of crop yield prediction techniques: traditional methods, IoT-based techniques, and UAV-based systems. Table [7] highlights the comparison of this review article with some existing related work, making its contribution clearer.

6. Overall Research Gap

Although there has been significant growth and advancement in technologies such as IoT, UAVs, remote sensing, and ML in the field of crop yield prediction, several research gaps still hinder the scalable and robust development of precision agriculture. Table [8] briefly explains the overall research gaps found after reviewing the various papers related to this field.

7. Conclusion

The integration of IoT and UAVs in agriculture represents a significant advancement in precision agriculture, particularly in predicting crop yields. Through this review, we highlight the potential of IoT and UAVs to overcome the challenges and limitations of traditional crop monitoring and crop yield prediction systems. Over the past few years, data-driven decision-making has taken over conventional intuition-based decisions. IoT-based sensing devices, such as soil moisture sensors, temperature and humidity sensors, and soil nutrient sensors, enable the collection of real-time data to enhance the process of crop yield prediction. On the other hand, UAVs equipped with RGB cameras, multispectral cameras, hyperspectral cameras, and thermal cameras have the potential to analyze plant health, stress, canopy cover, and other factors over large agricultural fields. Through this comprehensive review, we have concluded several key findings: 1) Both IoT and UAVs play complementary roles in precision agriculture. IoT-based sensors provide ground-level data in real-time, whereas UAVs provide high-resolution spatial images and data across time. Together, they form a powerful fusion system that enhances the accuracy and reliability of crop yield predictions. 2) The integration of both IoT and UAV technology has dramatically improved the efficacy of crop yield prediction models. The real-time and high-dimensional datasets generated by IoT-based sensors and UAVs have improved the performance of ML and DL approaches used for yield prediction. 3) These technologies have improved the scalability and adaptability towards a wide range of crops and environmental conditions. 4) Introduction of IoT and UAV technologies promotes environmental sustainability. By enabling precise agricultural practices for crop management, they focus on reducing agricultural waste and lowering environmental impact.

7.1. Challenges

Along with several benefits of using IoT and UAV technologies, there are many challenges related to them: 1) Since the data collected by IoT-based sensors and UAVs are heterogeneous in nature, their fusion is a complex process. 2) The lack of internet in any underdeveloped or developing regions makes it difficult to transmit and store data in real-time. 3) The cost and technical expertise required for using IoT-based sensors and UAV technologies serve as a big barrier for some farmers.

7.2. Future scope

There are many promising future steps for improving the potential of IoT and UAVs in crop yield prediction: 1) Introducing edge computing and fog computing with IoT and UAV nodes can significantly reduce the dependency on cloud platforms, thereby allowing real-time decision making. 2) Introducing mobile apps and voice assistants with local language support will help farmers to use these systems efficiently, even with less technical knowledge. 3) Introduction of chatbots linked to IoT and UAV systems can greatly help farmers to analyze their crops and recommend actions accordingly.

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