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REVIEW

Smart Agriculture Based on Internet of Things Using Drones: A Survey

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Abstract

Researchers have studied the potential of unmanned aerial vehicles (UAVs) for real-time visual data acquisition and processing using potent deep learning (DL) algorithms over the past few decades. In this regard, drone use in smart cities has become one of the most common uses in recent years. UAVs and the Internet of Things (IoTs) are two popular technologies being used in smart agriculture that are ushering in a new era of agriculture by replacing traditional farming methods. The combination of drones and IoT has the potential to drastically change our lives through real-time data collection and analysis that will enhance life quality and provide a high quality of service (QoS). UAVs can provide farmers with up-to-date information on their fields, enabling them to make informed decisions about the use of farm inputs. In this paper, this review focuses on the use of UAVs in smart agriculture for pest and crop disease management, plant growth monitoring, yield estimation, weed control, fertilization, phenotypic measurement, soil moisture assessment, pesticide use, and nutritional status evaluation to improve productivity and environmental sustainability. In addition, we outline how UAV technology fits into smart agriculture. The goals of this review were to: (1) assemble information on the application of UAVs in smart agriculture in general in various scenarios; (2) discuss their benefits and limitations in a variety of applications in UAV-based agriculture; (3) cover the key ideas of drone architecture, drone sensors in smart agriculture, drone applications in smart agriculture using remote sensing, and IoT architectures and challenges for smart cities; and (4) offer a survey of all the most recent prior studies on IoT, besides the UAV strategy used in smart agriculture. Therefore, a literature review was conducted using 135 research articles that are relevant to UAV applications in smart agriculture and other general information about how well UAVs can be used in smart agriculture, collected from the research articles mentioned earlier. The study concluded that UAV-based crops can be an effective method for monitoring and management to improve yield and quality and significantly benefit social, economic, and environmental aspects. We conclude that two of the most significant technologies that change conventional farming methods into a new understanding of intelligence are IoT and UAV. However, UAVs should also take into account some of the difficulties in smart agriculture, including high initial costs, regulations, inclement weather, policy, and communication failures.

Keywords: Drone, Internet of things, Smart agriculture, Precision agriculture, Smart city, Unmanned aerial vehicles

1. Introduction

An agricultural nation's overall development is greatly influenced by its agricultural sector. It is among the most important elements in any economy's ability to survive. Historically, the production of food and crops was the only activity associated with agriculture (El Hoummaidi et al., 2021). Today, more than 7 billion people are fed by agriculture worldwide, and the United Nations (UN) projects that by 2050, there will be about 10 billion people on the planet (World Population Clock: 8.1 Billion People (LIVE, 2023) - Worldometer). Moreover, unexpected pandemics have triggered a severe risk to food security and economic growth (Já et al., 2020). Better information on seasonal agricultural production that is made available as soon as possible is crucial to enhancing food security and updating as

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conditions change (Pé and rez-Escamilla, 2017). Issues related to agricultural products and food safety are currently garnering international attention and receiving support from governments across numerous nations and regions (Gupta et al., 2021). The traceability of the agri-food supply chain food safety and quality can be guaranteed by internet of thing (IoT)-based systems, which may encourage consumers to have faith in food safety as shown in Fig. 1 (Costa et al., 2012). Researchers have long offered a variety of creative ways to increase agricultural productivity, including using greenhouses (van et al., 2019), vertical farming (Gray and Nuri, 2020), and even emerging technologies such as satellites and aircraft (Mazzia et al., 2020) to develop more reliable solutions. Nowadays, farmers are using different modern technologies to ensure productivity increases (Bouguettaya et al., 2022).

Governments and the private sector use remote sensing through unmanned aerial systems (UAS) extensively for mapping soil properties, types of crop classification, water stress detection of crops, crop disease monitoring, and crop yield mapping (Kwan et al., 2020; Tan et al., 2019; Istiak et al., 2023). There is a necessity to divert toward the IoTs which aid administrators in more effectively overseeing, managing, organizing, and optimizing food supply chain procedures (Verdouw et al., 2016). Images of plants that are used to detect diseases can be captured by IoT-enabled systems, preprocessed, and sent to distant labs. Utilizing remote sensing for land use (Yang et al., 2004; Lin et al., 2011) and agricultural monitoring (Xiao et al., 2006; Ozdogan et al., 2010) since the space era has been widely adopted by satellites. Massive crop yield estimation now heavily relies on machine learning (ML) algorithms as a decision-support tool (Chlingaryan et al., 2018; van Klompenburg et al., 2020). One of the main tenets of contemporary agriculture is crop classification, which attempts to classify plant and crop varieties into distinct categories while identifying their geographic distribution. Having effective information about the crops can benefit farmers and government authorities, as it can enhance their decision-making skills (Kwak and Park, 2019; Yang et al., 2020a).

Deep learning and UAV-based remote sensing have surfaced as novel technologies that could be vital to the productivity of agriculture and the world's food supply in the future by automating

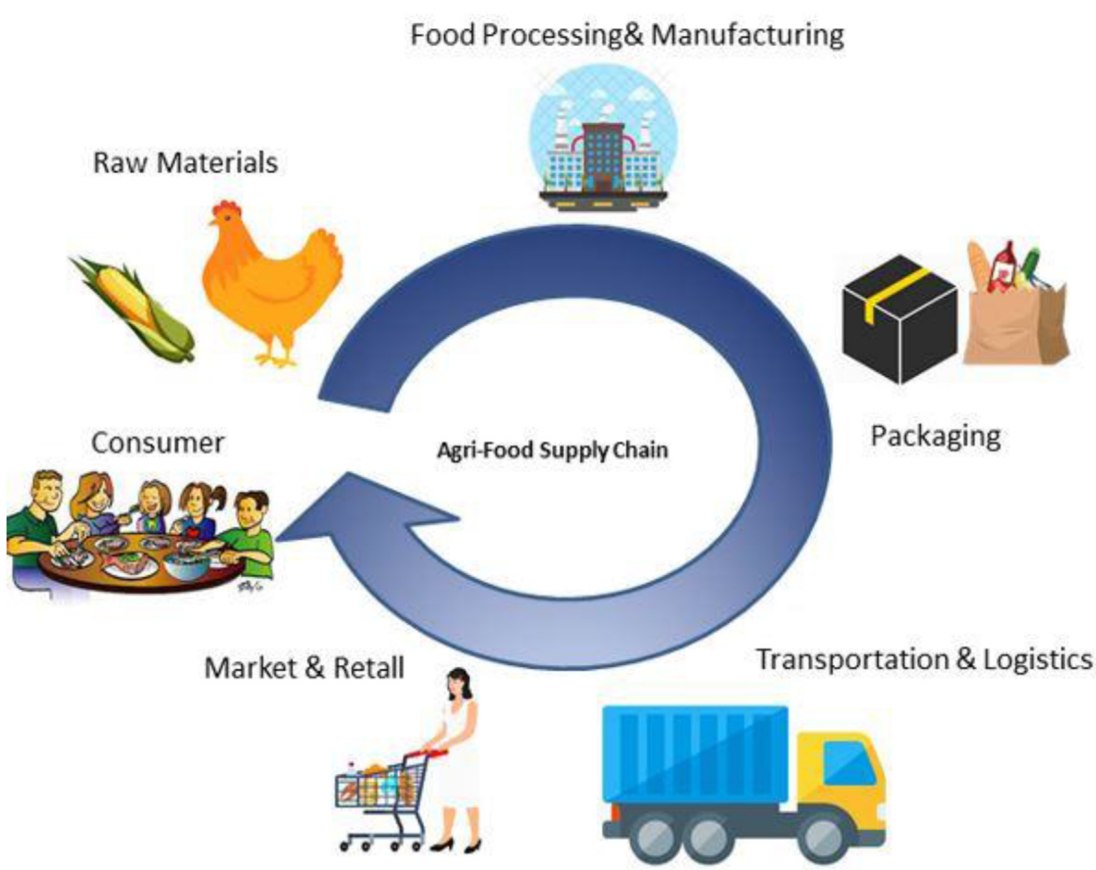

Fig. 1. Agri-food supply chain (Costa et al., 2012).

various tasks, such as plant and crop identification. UAVs offer the best tradeoff between spatial, temporal, and spectral resolution in addition to their high flexibility, low cost, small size, and real-time data acquisition capabilities (Bouguettaya et al., 2022). The three primary concepts that UAVs execute are perception, decision-making, and action execution. When dealing with complex data, the conventional machine learning methods for classifying various crop and plant types from aerial imagery can be inefficient and time-consuming. DL algorithms, however, have shown promise as a potential remedy for these problems (Bouguettaya et al., 2022) and have been reinvigorated, producing numerous outcomes in agricultural applications (Yang et al., 2021). Thanks to technological advancements, UAVs can now gather detailed crop information in the field. They can also see the outside world using various sensors (Bouguettaya et al., 2022), which are necessary in agricultural contexts (Comba et al., 2020). In addition, UAVs can support the computation of crop status indexes, including the plant scale (Primicerio et al., 2017) and the Normalized Difference Vegetation Index (NDVI) (Primicerio et al., 2015).

There are many restrictions that might be liable for the low output of crops, which can be overwhelmed by the use of drones in the agriculture field. These capabilities rework simple objects into intelligent devices that can run in real time, adjust to the conditions, and operate without human supervision or intervention. UAVs and IoTs are two of the most important and vital techniques that have evolved old-style farming practices into a novel viewpoint of intelligence in agriculture (Maia et al., 2017).

This survey differs from prior ones, where we are especially focusing on the new idea of drones and IoTs for ameliorative and increasing smart-city applications in agriculture. Therefore, the main contributions of this work are as follows:

(1) Assemble information on the application of UAVs in smart agriculture in general in various scenarios.
(2) Discuss their benefits and limitations in a variety of applications in UAV-based agriculture.
(3) Moreover, it also offers a survey of all the most recent prior studies on IoT, besides the UAV strategy used in smart agriculture, through a review and comparison of the most important applications and practices.

The paper is organized in the following way: in Section 2, the related work about the efforts to make use of unmanned aerial vehicles in agriculture is presented. Section 3 consists of the principal goals and the concept of smart cities. A general overview of the drone is summarized in Section 4, while Section 5 concludes the paper.

2. Related work

Recently, a number of studies have been conducted to monitor the health of various crops using various image processing techniques, as well as to identify particular crops using UAV RGB images. Istiak *et al.*'s study (Istiak et al., 2023) examined the viability of using UAVs for precision farming, decision-making, and action performance. Weicai Qin et al. (2023) provide a basis for scientific and reasonable spraying and control by agricultural drones, as well as for more in-depth research on the dissemination of powdery mildew spores and enhanced pest management. To identify vegetation in a particular area, Torres-Sanchez *et al.* (Torres-Sá et al., 2015) used an object-based image analysis on UAV images to calculate two vegetation indices: Excess Green (ExG) and NDVI. To increase grain yield, Wan *et al.* (Wang et al., 2020) extracted structural and spectral features from the red, green, and blue (RGB) images of rice fields during the growth period. Li et al. (2018) estimated the coverage of maize crops in farmland from its UAV image using the half-Gaussian fitting method. Three different types of tomato plants were evaluated for height, NDVI, and area covered using UAV RGB images by Enciso et al. (2019). Stroppiana et al. (2018) performed weed mapping by using an unsupervised clustering algorithm to identify weed and non-weed areas from UAV RGB photos of farmland.

A paradigm shift from traditional image processing methods to supervised learning techniques is occurring in crop classification methods from RGB images due to the development of various machine and deep learning topologies in the last few years. Using its UAV RGB images, Yang et al. (2017) assessed farmland for rice lodging. To assess how much spectral and spatial information contributes to overall accuracy, the authors calculated the single feature probability. An automatic algorithm for detecting palm trees was presented by Malek et al. (2014) to recognize randomly planted palm oil trees from UAV RGB images of the surrounding area. Scale-invariant feature transformation (SIFT) was used for feature extraction in the suggested identification process, and an extreme learning machine classifier was used for classification. Chew et al. (2020) used a transfer learning method from the pre-trained Visual Geometry Group (VGG-16) and ImageNet Convolutional Neural Networks (CNNs) modules to identify three distinct food crops (banana, maize, and legume).

To identify multiple crops from aerial images of land taken by UAVs, authors of Ref (Rebetez et al., 2016) proposed a hybrid classification module by combining a neural network that accepts image histograms as input and a CNN module that accepts raw images as input. Nevertheless, the combination of two neural networks lengthens the training period and complicates the classification procedure. In (Yang et al., 2020b), a multilayer CNN architecture is suggested for using UAV photos to analyze the phenology of rice crops. Using CNN, Bah et al. (2018) proposed a fully automatic learning framework to distinguish weeds from crops on agricultural land by taking RGB pictures of the crops with a UAV. Fan et al. (2018) used two multilayer CNNs to identify a tobacco plant that was on land in RGB photos taken by the UAV system in the area in question. Combining the Hough transform with classical CNN, Bah et al. (2020) created a novel CNN architecture called CRowNet to identify crop rows in cornfields based on photos taken by unmanned aerial vehicles. Using RGB photos taken by the UAV system, Kitano et al. (2019) used the U-net CNN architecture for maize plant identification and counting in farmland. For weed mapping in rice fields, Huang et al. (2020) used the CNN architectures AlexNet, VGGNet, Residual Network (ResNet), and GoogLeNet. There are two classes that are classified (rice and weed).

To avoid including non-crop areas in the training process that could lead to incorrect classification, Pandey and Jain (2022) first gathered high-resolution UAV images for various croplands. From these images, the candidate crop regions were extracted. Subsequently, a new CNN architecture known as the conjugated dense CNN (CD-CNN) is put forth, featuring Softsign and the Rectified Linear Unit (SL-ReLU) as the activation functions in convolutional layers. To learn features from candidate crop regions, the proposed CNN module does away with the need for independent feature extraction techniques. The suggested module achieves 96.2% accuracy when the experiment is run on a dataset of five distinct crops. The automated detection of weeds is a promising research area in precision agriculture. In the past, a number of motivated researchers have created a method for separating weeds from crops in digital photos. A support vector machine (SVM) classifier was used in (Ahmed et al., 2012) to discriminate between five different types of weeds and chili crops based on color, size-dependent, size-independent, and moment features. This computer vision-based automated weed detection system makes use of real field images.

Artificial neural networks (ANNs) and texture features extracted using a Color Co-occurrence Matrix (CCM) were used in (Li et al., 2009) to distinguish between crops and weeds. Ref (Haug et al., 2015) describes the process of separating a carrot crop from weeds based on photos taken with a BoniRob robot. Using Hu's invariant moments, monocot and dicot weeds are distinguished in Ref (Herrera et al., 2014). Using distinct shape features, sugar beetroot crops and weeds are distinguished in Ref (Bakhshipour and Jafari, 2018). SVM and ANN classifiers were used for the classification. These two classifiers' performances were assessed and examined. In (Lottes et al., 2020), plant stem position, spatial coverage of crops and weeds, and a fully convolutional network were used to discriminate between crops and weeds. Vegetable crops and weeds are classified in (Molina-Villa and Solaque, 2016) using color features and area thresholding. In this work, images from the farm fields were taken in natural lighting. Ref (Negrete, 2018) provides countrywide information on research projects carried out to identify pests, invasive plants (weeds), and crop diseases using computer vision techniques. The authors of Ref (Slaughter et al., 2008) examine the advancements made in autonomous weeding robot technology. They claim that the absence of reliable weed recognition methods is the primary obstacle to the development of commercial weeding robots. A brief discussion of the literature review is presented, as shown in Table 1.

As evident from Table 1, although there are already a lot of studies on different aspects of agriculture, there are still many restrictions that might be liable for the low output of crops, which can be overwhelmed by the use of drones in the smart agriculture field.

3. Smart City

The idea of smart cities begins with the combination of technology that desires to offer offerings more effectively and quickly to residents. Smart cities are considered the most important and essential IoT applications. A smart city is an urban environment that mixes communication technology, information, and advanced wireless sensors to assist in efficaciously managing the city's assets to indorse economic growth and enhance the existing standard requirements using the most advanced technology. An essential aspect of a smart city is the distribution of effective infrastructure and the lowering of the intake of resources and costs so as to enhance the overall performance and quality of services, spreading such services and conveniences

Table 1. Summary of the discussed related work.

Ref	Methodology	Pros	Cons
M. Istiak *et al.* (Istiak et al., 2023) (2023)	Determination of the impact of imaging modalities and imagery datasets in relation to agricultural applications, categorical evaluation of UAV configuration, and the feasibility assessment of UAVs in precision agriculture. In addition, the worldwide taxonomy of crops for which unmanned aerial vehicles are used is documented.	Perform a meta-analysis of recent studies on the use of UAVs for applications based on visual imagery in agriculture.	NA
Qin *et al.* (Qin et al., 2023) (2013)	They examine the impact of downwash airflow produced by a plant protection drone's flight altitude on the powdery mildew spores' horizontal, vertical, and ground distribution in wheat. Spore traps are used to track the evolving dynamics of airborne powdery mildew conidia.	The study offers a basis for scientific and reasonable spraying and control by agricultural drones, as well as for more in-depth research on the dissemination of powdery mildew spores and enhanced pest management.	The impact of airflow disturbance is closely linked to the release of powdery mildew pathogen spore numbers. The drone's rotor airflow has less of an impact on spore release in the early stages, when spore release is minimal.
Torres-Sanchez *et al.* (Torres-Sá et al., 2015) (2015)	An inventive Otsu-based thresholding Object-based Image Analysis (OBIA) algorithm was used to find vegetation in remotely sensed photos that were taken.	The classification error decreased as the object size increased until an optimal value was attained.	Once the ideal value was reached, increasing the size of the object led to larger errors, while the other parameters, like shape and compactness had little bearing on the classification accuracy.
Wang *et al.* (Wang et al., 2020) (2020)	To improve the prediction of grain yield, structural and spectral data taken from UAV-based images during the rice growing season is used.	Improving the accuracy of grain yield predictions and gaining effective crop growth monitoring.	NA
L. Li *et al.* (Li et al., 2018) (2018)	The half-Gaussian fitting method for FVC estimation (HAGFVC) is a novel approach for breaking down the Gaussian mixture strategy and estimating FVC.	The outcomes show that the HAGFVC approach can be applied correctly and effectively.	The prevalence of mixed pixels in LARS images, particularly at high altitudes above ground level or in the case of moderate vegetation coverage, caused other methods they tested to perform poorly.
J. Enciso *et al.* (Enciso et al., 2019) (2019)	A method for utilizing UAV data to measure crop height, canopy cover, and NDVI values in relation to time and space for three different tomato varieties during the growing season.	There was no discernible difference between the estimated UAV and manually measured crop heights, according to the computed paired t-test statistic.	Enhancements should be made to UAV crop growth and NDVI monitoring.
D. Stroppiana *et al.* (Stroppiana et al., 2018) (2018)	An unsupervised clustering algorithm was used to classify a multispectral orthomosaic that was created from images.	The most appropriate inputs were spectral indices, and SAVI and GSAVI produced the best results, with OA exceeding 94%.	NA

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Table 1. (continued)

Ref	Methodology	Pros	Cons
M. Der Yang *et al.* (Yang et al., 2017) (2017)	A thorough and effective UAV image classification method for agricultural areas. Image-based modeling and texture analysis yielded the digital surface model and texture information of the images in addition to spectral information.	A useful tool for evaluating rice lodging is their suggested hybrid image classification strategy, which combines spectral and spatial aspects.	NA
S. Malek *et al.* (Malek et al., 2014) (2014)	One suggested approach is to combine an active contour method based on Level Sets (LSs) with the keypoints of the ELM classifier to capture the shape of each tree.	The promising capabilities of their proposed framework were confirmed by the results of the experiments.	NA
R. Chew *et al.* (Chew et al., 2020) (2020)	A model pretrains using the publicly available ImageNet dataset and the VGG16 architecture, utilizing developments in deep convolutional neural networks and transfer learning.	At this scale, crops like maize and bananas can be categorized with great accuracy.	Legume crops, which are used in intercropping, can be challenging to reliably identify.
J. Rebetez *et al.* (Rebetez et al., 2016) (2016)	A hybrid CNN-HistNN deep neural network that can effectively classify a wide range of crops by utilizing both color distribution and texture patterns.	An enhancement in the performance of classification.	Many model parameters, like the number of layers and filters in the CNN, were absent from their analysis.
Q. Yang Rebetez *et al.* (Yang et al., 2020b) (2020)	A novel approach that uses RGB images to directly identify the main stages of rice growth.	The outcomes demonstrated the recommended deep learning method's outstanding performance in yield time estimation and phenology discovery in almost real time.	Early phenology is particularly difficult to distinguish because available data only spans a small portion of the growing season.
Bah *et al.* (Bah et al., 2018) (2018)	A novel fully automatic learning method for finding weed from UAV images that combines convolutional neural networks with an unsupervised training dataset.	The outcomes show performance that is comparable to supervised data classification.	NA
Fan *et al.* (Fan et al., 2018) (2018)	A novel deep neural network-based method is presented for identifying tobacco plants in UAV-captured images.	It performs well in accurately identifying and estimating the quantity of tobacco plants in UAV photos.	NA
Bah *et al.* (Bah et al., 2020) (2020)	A new method called CRowNet recognizes crops in UAV-captured images by using a convolutional neural network, the Hough transform, and a model created with S-SegNet.	The performance showed the best and most robust result when compared quantitatively with traditional approaches.	
Field data and superpixel standardization are not required for CRowNet.	NA		

Kitano *et al.* (Kitano et al., 2019) (2019)	Utilizing images of various maize crops taken with a UAV to improve techniques that allow for the counting of maize plants and the computerization of this process through computational vision and deep learning.	It is presented as a workable substitute for counting maize plants.	Experiments should be conducted to categorize other objects, like weeds and straws, that are present in the photos and may have an impact on the automated counting.
Huang *et al.* (Huang et al., 2020) (2020)	Using a partially Connected Conditional Random Field (CRF) for post-processing could greatly accelerate a fully connected CRF's inference speed.	Partially connected CRFs are more useful for developing accuracy, and combining partially connected CRFs with skip architectures can improve performance even more.	NA
Pandey and Jain (Pandey and Jain, 2022) (2022)	A unique CD-CNN architecture for the intelligent classification of multiple crops from RGB photos captured by UAVs, featuring a unique activation function called SL-ReLU.	It attains a strong differentiation capability across multiple crop classes with a 96.2% accuracy rate for the relevant data.	NA
F. Ahmed *et al.* (Ahmed et al., 2012) (2012)	Using a support vector machine to accurately distinguish between crops and weeds in digital photos.	The findings show that over a set of 224 images, SVM achieves accuracy levels above 97%. Notably, crops are not mistakenly labeled as weeds, and vice versa.	NA
Z. Li, Q. An (Li et al., 2009) (2009)	Four texture parameters were extracted using the HIS Color Co-occurrence technique (CCM): Angular Second Moment (ASM), Entropy (E), Inertia Quadrature (IQ), and Inverse Difference Moment or local homogeneity (IDM).	With a 78% classification accuracy, it offered the best classification performance.	NA
S. Haug and J. Ostermann (Haug et al., 2015) (2015)	A benchmark dataset for open computer vision tasks in precision agriculture, such as single plant phenotyping and crop/weed identification.	Providing a proposed evaluation method to allow comparison of different approaches.	One of the obstacles to advancement is the current dearth of publicly available datasets.
P. J. Herrera *et al.* (Herrera et al., 2014) (2014)	Proposed a method in which a collection of shape descriptors is used to identify weeds.	A high success rate for weed species identification.	NA
A. Bakhshipour and A. Jafari (Bakhshipour and Jafari, 2018) (2017)	A support vector machine and artificial neural networks were used to facilitate the vision system and the identification of the weeds through their patterns.	By using ANN and SVM, respectively, 93.33% and 96.67% of sugar beet plants were correctly classified.	NA
P. Lottes *et al.* (Lottes et al., 2020) (2020)	The technique makes use of an end-to-end, trainable, fully convolutional network that estimates the spatial extent of weeds and crop plants while also estimating the positions of plant stems.	The system's ability to adapt well to diverse environmental conditions and previously unexplored fields is essential for the practical application of such systems.	NA

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Table 1. (continued)

Ref	Methodology	Pros	Cons
C. A. Pulido-Rojas (Molina-Villa and Solaque, 2016) (2016)	The research provided a machine vision plan that circumvents lighting and sharpness issues during the acquisition stage and uses outdoor images to find weeds in vegetable crops.	In addition to specificity, sensitivity, and positive and negative expected values to estimate algorithm performance, an area-based classification is provided.	NA
J. C. Negrete (Negrete, 2018) (2018)	It explains how to identify pests, invasive plants (weeds), and crop diseases using computer vision techniques.	NA	NA
D. C. Slaughter *et al.* (Slaughter et al., 2008) (2007)	The development of autonomous weeding robots is reviewed by the authors.	NA	The primary obstacle impeding the advancement of industrial weeding robots is the deficiency of reliable weed identification methods.

ubiquitously (Khan et al., 2018). Smart City has become an umbrella acronym for several strategies with the aim of enhancing and improving the efficiency of upcoming cities and the satisfaction of lifestyles for their populations (Eckhoff and Wagner, 2018). Fig. 2 illustrates some smart city applications.

Effectively and successfully implementing smart city initiatives will lead to decreasing charges, further engaging more efficiently and actively with the populations. One of those strategies is the UAV, which can offer numerous applications for smart cities and generate a fantastic effect on civilization (Mohamed et al., 2020; Al-Turjman et al., 2020a). Drones may be spread flexibly and rapidly in lots of fields in smart cities, as they are more cost-effective than manned planes. In addition, they may be extra elastic in various situations and locations, in addition to chance hazard cases for people. Therefore, those drones' capabilities provide advantages for smart city applications (Nguyen et al., 2021). A conventional smart city architecture includes five important layers of progressive work on the data from the past layer, as demonstrated in Fig. 3: the business layer, application layer, middleware layer, network layer, and sensing layer. The sensing layer, additionally named the perception layer, comprises sensors that can obtain data. The information read by the sensing layer is passed ahead using the networking layer to the middleware layer through wireless network strategies. The middleware layer provides a generic interface that used information via database management services and different Application Programming Interfaces (APIs) to provide clients with services. The business layer is connected with the application layer and is used to foster and improve approaches and formulate procedures that assist in accomplishing the scheme totally (Syed et al., 2021; Serey et al., 2020).

3.1. IoT architectures for smart cities

The mixture of IoT and Artificial Intelligence (AI) is giving rise to a rising trend known as IoT that is opening up new routes to get digitization into the modern. IoT is a scheme that mixes numerous technologies and devices, eliminating the demand for human interference. This allows for the capability of having smarter cities across the world. Within the context of smart cities, IoT permits sensors to accumulate and drive data about the city's status to a central cloud, which is then treated and makes decisions. There are three structures where the handling of data can be implemented: fog, cloud, and edge models. Table 2 lists the personalities of every one of the three layers of the IoT

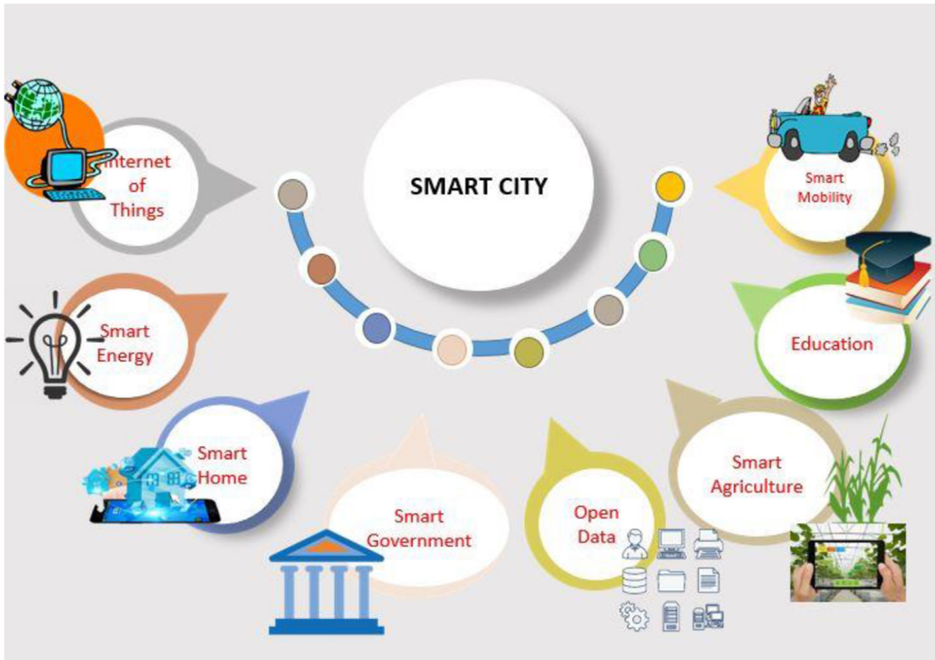

Fig. 2. Smart city (Syed et al., 2021).

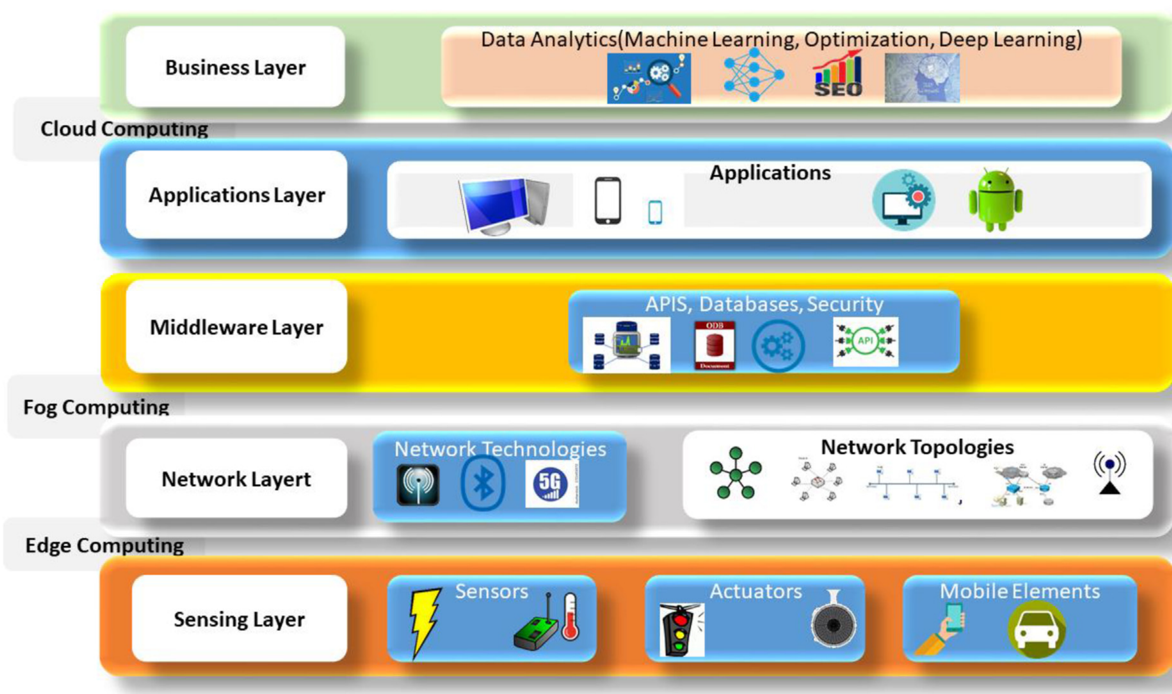

Fig. 3. Smart city architecture (Syed et al., 2021).

framework (Eckhoff and Wagner, 2018; Syed et al., 2021), and (Zhao et al., 2019). Interest in the direction of performance, productivity, and efficiency enhancements is coveted additionally across the agricultural sector (Balducci et al., 2018). Smart agriculture is becoming the best standard thanks to agricultural sensors and is becoming more common among farmers. IoT transmits the picked-up data from the surrounding environment to the Internet via service providers. This extra facilitates

Table 2. Comparing fog, edge, and cloud computing models.

Fog Computing Model	Edge Computing Model	Cloud Computing Model
It has contextual consciousness of the local sensing state.	Edge devices usually have information only about their private cases. Interchange technique is probable but restricted to the local neighborhood.	Contextual consciousness is a universal standard that includes all phases of its application.
Being nearby Fog, Edge can respond greatly rapidly to the data being transmitted from sensors and other devices, and by doing so, it can collectively transmit the information transmitted.	Rapidest decision creation is probable, but decisions will be founded on local situations.	Latency is rising, and decision-making can be delayed.
Uses heterogeneous information, however, within a minor area.	Commonly do not have access to diverse kinds of data.	Uses heterogeneous information from a diversity of sensing devices.
Medium network charge as data movement is decreased.	Minimum network charge.	High network charge.
Compared with cloud computing, it can increase and enhance privacy.	Greater privacy enforcement is possible than the Fog model.	Potential privacy hazard, as raw information might be transmitted to the cloud.
Extra powerful than the cloud model.	Maximum robustness as distributed decision creation happens.	It is less powerful as decision-making is centralized.
Less capable than other cloud devices.	Least capable.	Superior abilities in terms of sources.
Scalability is greater than the cloud.	Scalability is at its maximum.	Scalability is weak.

customers to examine the plotted or numerical data (Aliev et al., 2018). IoT has played a massively important role in the agricultural industry recently with a view to offering aid to farmers along with an increased observing system of water supply, humidity, and temperature, as well as an early detection system and disease observing (Kitpo et al., 2019). IoT is likewise used to accumulate sensor data from the field in order that data and recommendations from the machine learning algorithm may be accessible on a graphical user interface (GUI) platform, which makes it simpler to have nonstop monitoring of the farm (Araby et al., 2019).

A profitable and sustainable agricultural output is possible with smart agriculture, which will be based on a combination of creative uses of cutting-edge ICTs like the IoTs. The intricacy of the tasks carried out by farmers leads to the complexity of all the technologies used in smart agriculture. For farmers, sensor-based irrigation systems offer a promising solution. By gathering data from sensor networks, IoT technologies can lower the cost and expand the scope of sensor-based irrigation systems. The IoTs is a global network built on accepted communication protocols. It collects data using a variety of technologies, ranging from physically measured quantities to IoTs applications (Boursianis et al., 2022).

As evident from Table 2, while there are certain restrictions when using cloud computing for IoT data analytics, Fog is primarily intended for interactive IoT applications that require real-time responses. However, edge computing offers a great platform for the development of smart cities.

3.2. IoT challenges for smart cities

The technical difficulties related to using IoT in smart cities that have been the focal point for academics are presented in Table 3 (Syed et al., 2021).

As evident from Table 3, there is a brief debate on the difficulties that IoT scheme designers encounter while deploying innovative smart city applications. The technical difficulties related to using IoT in smart cities have been the focal point for academics. Therefore, there are still many restrictions that hinder the advancement of smart cities using IoT.

3.3. Applications of UAV in smart cities

These applications offer useful benefits for smart cities to enhance services's overall performance and

Table 3. Internet of things Challenges for Innovative Smart City.

Challenge	Meaning
Security and Privacy	They need to accept the truth, confidence, and sharing of clients. Propagation of sensors in smart cities may disclose the daily doings of clients as undesirable.
Smart Sensors	Smart city expansion would want all the devices to carry out tasks among themselves and exchange data to be reliable and robust.
Networking	Supplying networking with devices to stay linked is a huge mission.
Big Data analytics	Modern data analytics algorithms needed to be evolved, and those algorithms wanted to be appropriate to various data and changing natures.

citizens' quality of life (Mohamed et al., 2020). Table 4 Illustrates a summary of the challenging issues of UAV applications in smart cities.

3.3.1. Traffic monitoring and management

Traffic tracking and observation can enhance traffic systems in preference to conventional strategies. Several massive cities need smart traffic monitoring systems as a pressing requirement because of the improvement in traffic. UAVs may be used to gather and deliver a whole set of actual-time approximate data related to traffic overcrowding. UAVs can offer live feeds overlaying the congestion region and all neighboring regions. For example, in 2017, the Authority of Transport and Roads in Dubai observed their traffic and controlled vehicle accidents using drones (Syed et al., 2021; Mohamed et al., 2020; Nguyen et al., 2021).

3.3.2. Health emergency services

UAVs can also provide similar emergency offerings to citizens in public facilities when accidents and injuries happen within the city that restrict or cutoff transportation. In this regard, smart health pursuits make sure that healthcare is accessible to as many citizens as feasible through telemedicine offerings and get better diagnosis assistance from doctors utilizing AI. The widespread use of cellular telephones and health trackers may pick up real-time data related to people's health (Syed et al., 2021; Mohamed et al., 2020).

3.3.3. Agriculture management and environmental monitoring

Smart agriculture is the use of sensors embedded in crops and plants to measure diverse parameters to assist in decision-making and protection from pests, diseases, and so on. UAVs may be applied to assist agricultural approaches such as pesticides, seeds, water, and distributing fertilizers. They can also offer periodic rummaging of fields and their conditions. A part of the smart agriculture paradigm is precision agriculture, which entails sensors being located in fields to offer measurements and consequently permit targeted interest mechanisms to be deployed (Syed et al., 2021; Mohamed et al., 2020).

3.3.4. UAV-based surveying

Surveying has many implementations in civil engineering and in city control. However, most conventional surveying techniques consume massive time and effort. UAVs may be used effectively in surveying and geospatial activities in smart cities. UAVs can be characterized as accurate, rapid, safe, flexible, and inexpensive tools to execute various surveying activities needed for building projects or city administration systems. A UAV may be used to obtain three-dimensional (3D) mapping information for huge infrastructure projects (Mohamed et al., 2020).

3.3.5. Large-scale disaster management

Response and situation administration in huge-scale catastrophes, including volcanoes, terrorist

Table 4. A summary challenging issues of UAV applications.

UAV Application	Challenging Issues
Traffic monitoring and management	It needs low-latency communication and high-bandwidth necessities to transmit video streams to the control center. If protection isn't always robust and sufficient, we will be facing possible major sabotage incidents and hacking.
Health emergency services	It needs high security, reliability, safety necessities, and high development, production, and servicing costs. The possibility of incorrect use of the introduced medical elements. There is likewise a threat to humans in the event of crashes or malfunctions.
Agriculture management and monitoring	It does not have the ability to deal with various agricultural situations. Generally of low risk, however, a few mistakes may also cause damage to fields or crops.
UAV-based surveying	It does not have accurate measurement capabilities.
Large-scale disaster management	It needs trusted communication with the control centers. It does not have sufficient capability to cope with various catastrophic situations. Advanced coordination if more than one UAV is used. The deployed UAVs might not be capable of addressing all conditions if they are not designed to address them.
Merchandise delivery	It requires highly effective operations. It wishes integration with other different logistics systems. It does not have the capability to deal with the excessive weight and large payloads. Possibility of accidents that could result in property or product damages or injuries.
UAV taxi	It does not have the capability to hold excessive weight. It must have extraordinarily high reliability, high levels of self-independence, security, and safety requirements. It needs high improvement and preservation costs. Legal aspects associated with any accidents. Any accident might also increase the risk of accidents or death. Troubles and criminal outcomes might also arise. A growing quantity of UAV taxis in the air will lead to air congestion.

attacks, earthquakes, fires in forests or large infrastructures, and floods, are very challenging; however, in most of these situations, people and emergency groups cannot effortlessly and speedily attain the catastrophe regions or every other. At the same time, most of the infrastructure, including telecommunications structures and roads, may be destroyed. UAVs may be applied efficaciously in such situations. They may be used as reliable, safe, and flexible tools to screen, monitor, and offer real-time data about the recent situation (Mohamed et al., 2020; Nguyen et al., 2021).

3.3.6. Merchandise order delivery

UAVs may be used to deliver client orders in less time. Because a client gives an order online, she or he can take the order quickly through a delivery UAV specially designed for this application. UAVs are elastic enough to wag fast to various regions in cities for speedy delivery even in overcrowded areas (Mohamed et al., 2020).

3.3.7. UAV taxi

One of the basic objectives is to offer an autonomous, safe, and unmanned UAV taxi available on request. Another purpose is to, with the aid of greater direct routes, keep off the traffic congestion in massive cities. Dubai most recently executed its first test of a UAV taxi service as part of its smart city visibility. Although there are perfect benefits for this application, there are particular obstacles that need to be resolved (Mohamed et al., 2020; Dubai tests drone taxi service - BBC News).

Although there are numerous opportunities for UAV use to support a smart city, as Table 4 makes clear, any smart city that uses UAVs to further its economic development will greatly benefit from these opportunities. However, there are many UAV application issues.

4. Drone overview

4.1. Drone background

There are various terms used for a drone, including remotely piloted aircraft (RPA) and a UAV. It is an aircraft deprived of a pilot on board as shown in Fig. 4. UAVs are planes that work by remote control using onboard computers. Nowadays, UAVs are one of the most essential areas of technology because of their speedy improvement and applications in any aspect of the actual world (Khan et al., 2018; Nguyen et al., 2021; Altawy and Youssef, 2016; Vattapparamban et al., 2016; De Rango et al., 2017; Chung et al., 2020; van der Merwe et al., 2020; Ayamga et al., 2021) Satellites lack flexibility for the reason that they cannot be mobilized quickly and are difficult to use when needed. A UAV, considered a current innovation in far-flung sensing, could ride to triumph over those disadvantages. It permits spectral resolution and a higher spatial resolution (Nguyen et al., 2021; Michels et al., 2020). The drone approach can result in significant secondary benefits and advantages, including decreasing pollution, preserving resources, decreasing power consumption, growing preparedness for emergencies, and having access to dangerous and disaster areas (Alsamhi et al., 2019a). The four principal sorts of drones are illustrated in Table 5 (van der Merwe et al., 2020; Michels et al., 2020; Macrina et al., 2020; Hafeez et al., 2023).

Fig. 4. A typical commercial drone (Qin et al., 2023).

Table 5 clearly illustrates the four primary drone types: fixed-wing, single-rotor, multi-rotor, and hybrid, their applications, and their strengths and weaknesses. The design and technology of flapping wings are more complex compared with those of fixed and rotary wings, due to their complex aerodynamics. Hybrid systems use either a single-rotor, multi-rotor, or ducted fan configuration to allow a VTOL capability and then transition to fixed-wing flight to enable greater endurance.

4.2. Drone architecture

Usually, any UAV structure includes three principal elements: Unmanned Aircraft (UmA), Ground Control Station (GCS), and Communication Data-Link (CDL) as shown in Fig. 5 (Al-Turjman et al., 2020b; Yaacoub et al., 2020).

4.2.1. Flight controller

It is considered the drone's central primary processing unit. Apart from maintaining drone stability while in flight, it also receives and interprets sensor

Table 5. *A summary of the Four Principal Sorts of Drones.*

Type	Vertical Takeoff and Landing	Flight Time	Payload Capacity	Cons and Pros
Fixed-wing	No It needs a minor operational footprint. Numerous of them want a flat and long arrival area that is free of hurdles inside the landing region and in the processes of takeoff and landing. Based on the location, those area necessities may be essential to fixed-wing drone processes.	High: It is the most effective because the lift produced by the wings decreases the quantity of energy required to maintain the drone airborne.	Medium-high	Their easier structure calls for much less complex repairs and maintenance. It is capable of conveying more payloads over extended distances using much less power. But it wants a steady air motion throughout the flight.
Single-rotor	Yes	Medium-high energy is constantly wanted to push the propellers and motors to keep the drone airborne and controlled. Single-rotor structures are normally more effective than multi-rotors.	Medium-high	They can fly and land vertically in a minor area, and as a consequence, they're extra agile in terms of maneuvering. But they have a higher servicing charge.
Multi-rotor	Yes	Low energy is constantly requested to push the propellers and motors to keep the drone airborne and controlled.	Low	The layout and model of flapping wings are more complicated than those of rotary and fixed wings. Their operational charges are normally excessive, and their flight period subsistence is decreased due to the intense power wanted for the flapping model.
Hybrid	Yes	Medium-high: The hybrid model uses a multi-rotor, single-rotor, or ducted fan arrangement to permit a VTOL ability, after which it moves to a fixed-wing to allow a better stay.	Medium	Combine fixed-, rotary-, and flapping-wing systems.

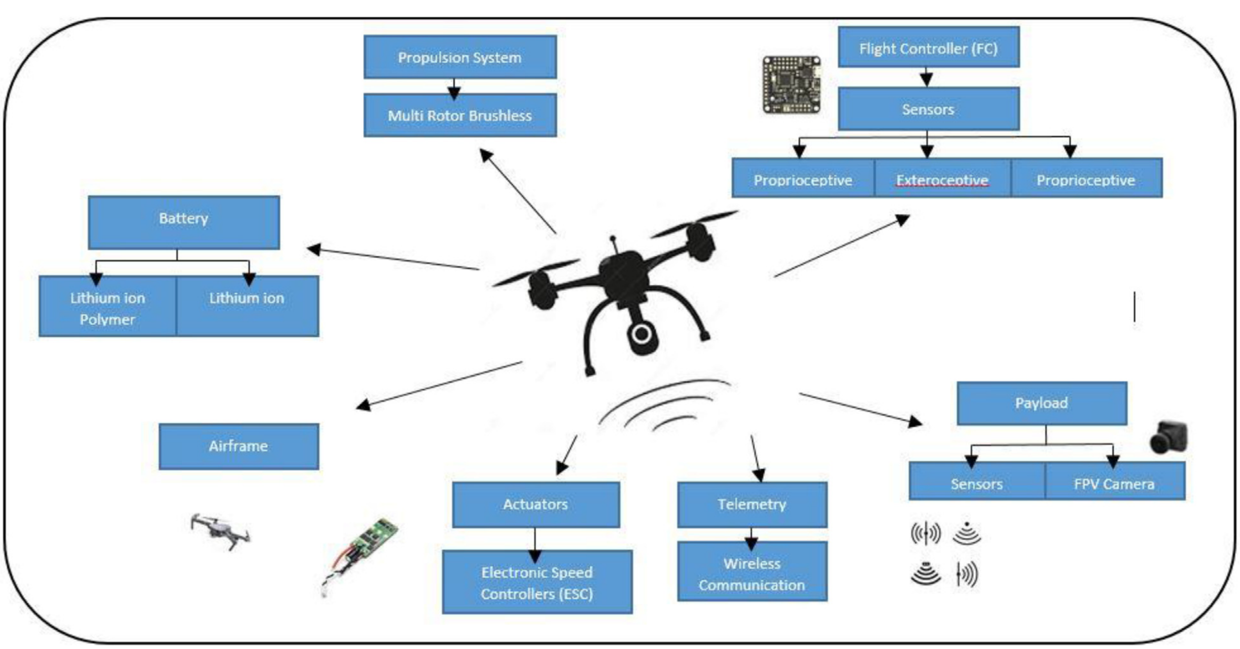

Fig. 5. Components of a drone (Al-Turjman et al., 2020b).

data, converts it into actionable information, and, depending on the kind of control, sends the updated state either directly to the actuator control units or to the Ground Control Station (GCS). The GCS communication interface is implemented by the flight controller. More specifically, the flight controller processes commands from the GCS and then modifies the deployed actuators. In addition, the flight controller can send telemetric signals to the GCS through a variety of transmitter channels. The flight controller can communicate with an external sensor unit or have several sensors integrated into it. The GPS module, accelerometer, gyroscope, magnetic orientation sensor, and electro-optical or infrared camera are among the sensors of the UAV system.

4.2.2. Ground control station

It is primarily dependent on an On-Land Facility (OLF), which offers people operators the essential competencies to govern and/or monitor UAVs at some stage in their operations from a distance. GCSs differ depending on their size, type, and drone tasks. Put differently, hobbyists use GCSs, which are small handheld transmitters, for their recreational mini and micro drones. The GCS is a sizable, self-contained building with numerous workstations used for tactical and strategic drones. Through a wireless link, a GCS and the drone exchange commands real-time data to create a virtual cockpit.

4.2.3. Data links

These are wi-fi links used to govern the data flow between the drone and the GCS. This relies on the operational range of UAVs. The UAV operating range determines the chosen communication link. Line-of-sight (LOS) missions, where control signals can be sent and received through direct radio waves, and beyond line-of-sight (BLOS) missions, where the drone is controlled through satellite communications or a relaying aircraft that can be a drone itself, are the two categories of drone missions based on their distance from the general control system (GCS).

4.3. Drone sensors in agriculture

UAVs contain various types of precisely smart devices, including time-of-flight (ToF) sensors. It may be managed remotely and flow independently without human intrusion (Trasviñ et al., 2017). The sensor network community is the connecting reality of our online world, which is the prime idea of IoT. Sensors may be categorized into two categories: active and passive. Active sensors expel energy and expose the reflection of that released energy. Passive sensors are the most popular kind used in agriculture and are used to measure the released or reflected energy from a scene. Active sensors are commonly heavier and far more expensive than passive sensors; however, they can produce repeatable data despite the changing circumstances surrounding them. Passive sensors are normally lightweight and have a minimum cost; however, they may be enormously influenced by the circumstances surrounding them (van der Merwe et al., 2020). Sensors are used in precision agriculture to measure the various environmental qualities wanted for the targeted application (Araby et al., 2019; Pawar and Chillarge, 2018).

4.3.1. Visible light

RGB sensors are the least costly and most popular passive sensor types used on drones (Amarasingam et al., 2022).

4.3.2. Broad band color infrared

These sensors are replacements for RGB sensors. This technique leverages the comparatively high degree of advancement connected to client camera evolution, leading to high-quality sensors with perfect directional resolution at a comparatively minimum cost, and it has been greatly used in agriculture.

4.3.3. Multispectral and hyperspectral

There is not any explicit definition of differentiation among hyperspectral and multispectral sensors. Data goodness is enhanced, mixed with lowering the fee and operational complexity, resulting from their unanticipated increasing use in agriculture (Amarasingam et al., 2022).

4.3.4. Thermal

Thermal cameras used in agriculture are passive sensors. The resulting thermal precision is suitable for most agricultural applications in which temperatures are analyzed relatively closely (Amarasingam et al., 2022).

4.3.5. Light detection and ranging (LiDAR)

LiDAR is a kind of active sensor that may be described as a holder of light and radar. The data in LiDAR excels at presenting topography data without the photo overlap requirement related to normal aerial imagery, thereby increasing topographical mapping efficiency (Amarasingam et al., 2022; Su et al., 2023).

4.4. Advantages of drones

Drones offer aerial photography at a significantly lower fee than using a small plane or helicopter. They may be bought for a portion of the price, and the electricity required to recharge them is tiny compared with the price of gasoline. Due to their small size, drones are an awful lot more maneuverable than planes or helicopters, making images smoother and faster. The reasons why drones are used may be almost divided into three classes (Chung et al., 2020; Macrina et al., 2020; Reinecke and Prinsloo, 2017).

4.4.1. Minimization of tour completion time or makespan

Completion time is the time needed to service all clients and go back to both vehicles to the depot.

Makespan = latest goes back time at the depot.

4.4.2. Minimization of the total cost

Include battery price, maintenance cost, and labor.

Total cost = cost of the tour.

4.4.3. Other objectives

Include minimizing the latency and maximizing the predicted range of clients served on the same day and clients within time windows.

4.5. Disadvantages of drones

Despite the many advantages of drones mentioned above, the efficient use of UAVs presents numerous problems that need to be addressed. Briefly, there are a few critical challenges that want to be highlighted. The unwelcome issues of drones are mentioned in Refs (Khan et al., 2018; Mohamed et al., 2020; Nguyen et al., 2021; Chung et al., 2020; Reinecke and Prinsloo, 2017). There is a limit to the batteries' capacity. Larger batteries can be used to make up for this, but doing so increases weight and the amount of power required to maintain the altitude. Batteries can only be recharged a certain number of times before they lose their usability and must be replaced, which is frequently an expensive process. The majority of nonmilitary drones have extremely short flight ranges in terms of both battery life and remote control signal. Since they are not waterproof, all but the most specialized drones can only be used in dry weather. Drones used for various civilian purposes in extremely crowded cities present significant safety concerns because they have the potential to crash and cause enormous damage. This could be the consequence of an operator error, a technical issue, poor equipment maintenance, or collisions in midair. Concerns regarding drones falling on public property have also been raised by severe weather conditions, including turbulence, lightning, and battery life lift capacity. Furthermore, there is a significant chance that airborne collisions resulting in extensive damage could occur because larger cities share their airspace with other commercial aircraft. The technology within commercial or recreational drones poses a greater security risk than the drones themselves. The services that the drones provide could be disrupted if attackers manage to take control of or destroy the technologies that equip the drones. Modules used for drone communication and navigation are susceptible to various security breaches. A drone's navigation system is made possible by GPS, which is readily spoofable due to its open nature and lack of authentication. Another potential attack that might result in the drone's communication system being taken over, with potentially dire repercussions for anyone in the vicinity, is Wi-Fi jamming.

4.6. Drone used in agriculture

Recently, drones in the agriculture field have carried out many activities that assist in tracking crop health, taking corrective actions, and, as a result, preventing damage to crops. Smart farming allows human beings who have even had little practice in farming to increase (Syed et al., 2021; Balducci et al., 2018; Hafeez et al., 2023; Guillén et al., 2021; Reshma et al., 2020; Jin et al., 2020a). Precision agriculture (PA) is a new idea in agriculture; it is described as a farm management strategy using information technology to manage, identify, and analyze the diversity of fields to ensure certain sustainability, protection, and profitability of the environment. PA is used to offer agriculture solutions through the use of an AI machine learning algorithm that is used for executing data prediction on data gathered by sensors (El Hoummaidi et al., 2021; Araby et al., 2019; Michels et al., 2020; Pawar and Chillarge, 2018). Most people agree that one of the best ways to improve plantation management techniques and get precise data for decision-making is through PA. The purpose of PA, a farm management technique, is to maximize crop productivity by applying inputs like water, fertilizer, and pesticides in the most efficient way possible using information and communication technology. Applying the right amount of agricultural input at the right time and place to increase yield quantity and quality is the primary goal of PA. It is a farming strategy that

Table 6. A Summary of using internet of things-based totally artificial intelligence in smart Agriculture-Related Works.

Ref	Idea and Objectives	Method	Results	Limitations	Dataset
Guillén et al., 2021	Evaluation of edge computing in crops for frost prediction by appreciating depressed temperatures out of long short-term memory (LSTM) models.	There are three IoT nodes. Sensors provide information every 10 min	Offering an excellent framework for driving edge computing as an actual opportunity for smart applications. Permit farmers to acquire a temperature prediction in actual time at their plots.	New variables need to be integrated into the LSTM to create a multivariate LSTM. Edge computing architectures are not capable of taking care of heavy workloads.	Two various crops in Murcia (southeast Spain).
Pratyush Reddy et al., 2020	A smart irrigation system predicts the water necessities for a crop.	A moisture, humidity, and temperature sensor forward data through a microprocessor. The consequences received through the decision algorithm are dispatched through a mail alert to the farmers.	The larger the data, the more correct the results will be.	NA	Datasets include the values of various scenarios in the farms to train the model exactly.
Jin et al., 2020a	The prediction of weather data, along with wind speed, humidity, and temperature, to enhance the yield and quality of crops.	An Empirical Mode Decomposition (EMD) technique is used to decompose the weather information, then a Gated Recurrent Uunit (GRU) network is trained, and lastly, the consequences from the GRU are delivered to gain the prediction result.	The proposed predictor can acquire correct predictions for the subsequent 24 h. Experiments primarily based on weather data affirm the improvement of the proposed strategy.	It is not always smooth to appropriately expect weather trends.	The accumulated hourly weather data, which includes humidity, temperature, and wind speed, in Beijing.
Reshma et al., 2020	The research goal is to determine the class of soil and the appropriate crop for the soil using category strategies.	An appropriate category method is selected based totally on the accuracy value.	The decision tree presents higher predictions than SVM in all overall performance metrics. An evaluation can be made to determine the perfect plants that may be cultivated within the offered soil type.	NA	Inside the college campus, which is sectioned into four various regions.
Jin et al., 2020b	Using a deep learning algorithm with a sequential two-level decomposition structure.	The two-level sequential decomposition structure was used to decompose the climate data. Then the GRU networks were trained as the sub-predictors for every component.	It can acquire the correct prediction of humidity and temperature and meet the wishes of precision agricultural production.	It is not facile to correctly expect the future trend.	In Ningxia, China, for wolfberry agriculture.
AlZu' et al., 2019	Yellowing leaves and sprinkles inside the soil have been spotted using multimedia sensors to discover the extent of plant thirstiness in smart farming.	Sensor reading has been used as a traineeship dataset pointing to the thirstiness of the plants, and deep learning was applied in the following phase to detect the optimal decision.	The tests performed in this study are promising.	NA	100 training records have been created, each of which contains 8 columns and a label.

Ale et al., 2019	Presenting a Densely Connected Convolutional Networks (DenseNet) based transfer learning strategy to discover plant diseases.	The performance has been compared with various photo entry sizes so as to locate the stability of the complexity raised through photo accuracy and performance.	The presented strategies can accurately find out plant diseases using the fewest computational resources.	NA	Actual-world dataset.
Araby et al., 2019	Precision agriculture is used to offer agriculture solutions using an artificial neural network algorithm.	A sensing network was deployed to collect data on some crops (tomatoes, potatoes, etc.), then gave this data to a machine-learning algorithm to obtain a warning message.	The system will supply all previous knowledge to the farmer in advance of making the right decision.	The gateway must transmit actions by itself and splash the field as wished.	Actual data, collected from CLAC is known as day-degree data.
Kitpo et al., 2019	Suggest an IoT system with a bot notice on tomato evolution stages.	The photo analysis was made by collecting deep learning for tomato detection, image processing for color characteristic extraction, and machine learning for six development stages of classification.	They can successfully classify the six stages of tomato increase using SVM classification with a weight accuracy of 91.5%.	We need to train with a larger dataset to enhance and achieve better accuracy.	The tomato dataset was gathered from Shinchi Agri-Green, the tomato greenhouse in Fukushima, Japan.
Web Enabled Plant Disease Detection System for Agricultural Applications using WMSN - Amrita Vishwa Vidyapeetham 2018	A Novel Web-Enabled Disease Detection System (WEDDS) primarily based totally on Compressed Sensing (CS) is proposed to stumble and classify the illnesses in leaves.	The suggested IOT-based total system includes six phases: image preprocessing, classification, image segmentation, image acquisition, compressed sensing, analysis, and feature extraction, in which the first four phases are executed at the sensor end, and the rest at the tracking site.	The suggested technique affords an overall detection precision of 98.5% and a classification precision of 98.4%.	NA	Carried out using a support vector machine classifier in MATLAB. The algorithm is carried out on the RPi board using the python language.
Aliev et al., 2018	The WSN strategy has been suggested to be beneficial for smart agri culture applications.	They developed a prototype device and an Android application that gets physical data and retransmits it to the cloud.	The suggested prototype device receives information from crops and makes it obtainable to the user.	NA	Istat statistical dataset, the industrial IoT sensors dataset, and the National Research Council (CNR) scientific dataset.
Balducci et al., 2018	Reveal how to control heterogeneous data coming from actual datasets that acquire biological, physical, and sensory values.	Focusing on the IoT sensor dataset, we utilized machine learning strategies and extra-standard statistical ones.	The forecast of pear and apple total crops could be generated with a neural network strategy with gain rates close to 90%. Regression and polynomial predictive strategies are extra desirable considering the kind of dataset.	Needing the design of completed tools, user interfaces, and machines that facilely adjust to a context subjected to normal news is not as facilely expected.	NA

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Table 6. (continued)

Ref	Idea and Objectives	Method	Results	Limitations	Dataset
Goap and Sharma, 2018	Proposing an IoT-primarily based totally smart irrigation structure in conjunction with a hybrid machine learning-based totally method to expect moisture in the soil.	The suggested algorithm makes use of sensors' information of the latest beyond the climate forecasted data for the next few days.	The system is completely purposeful, and the expected outcomes are very encouraging.	NA	The sensor node data is wirelessly amassed over the cloud using web services.
Pawar and Chillarge, 2018	The suggested system advises the farmer about the level of toxicity, the crop, water supply, and fertility of the soil.	For classification, the decision tree J48 algorithm is used, which is easy to execute and has greater accuracy compared with different category algorithms.	The precision of the J48 decision tree algorithm is better in comparison to different category algorithms.	NA	1. Crop Data Set: includes crop name, humidity, pH, temperature, and nutrients (Na, Mg, N, P, Cl, and Ca). 2. Fertilizer Data Set: includes fertilizer dates, crop name, and name.
Aruul et al., 2017	The main goal of the smart agricultural system is to develop the crop in the field.	The tracking technique entails accumulating information about the soil factors of the field. A Wi-Fi Sensor Network (WSN) is mounted to acquire that information and feature with the aid of sporadically importing it to the cloud.	LSTM networks have been discovered to be the right algorithm. The inferred consequences are compared with the optimal crop, and the best proper crop is intimated to the consumer through SMS service.	To enhance the reaction time, a distributed framework primarily based on fog structures might be constructed.	Agricultural University
Rodrí et al., 2017	With a view to offering the best-developing conditions for roses in a greenhouse, a wireless sensor has been designed and applied that supports data extracted from the agricultural surroundings, which includes light, temperature, and humidity.	The sensor network permits surrounding situations data collection and visualization in a mobile or web application, and after that, using data mining strategies, acquiring a prediction model with proper accuracy.	The SVMs appear to offer a great prediction model.	The need to set diverse algorithm configurations is being placed forth to discover higher outcomes.	Available at the Universidad de las Fuerzas Armadas (ESPE), Ecuador.
Maia et al., 2017	Determining an actual-time, in-situ agricultural IoT device planned to screen the soil and the surroundings.	The tracking nodes are established among the numerous locations in the field, with sensors to screen each environment and the soil.	Data were acquired via the IoT device in comparison with available data from two sources: (i) The CPTEC/INPE Center for Weather Forecasting and Climate Studies; (ii) Weather Underground.	NA	The Mirante de Santana station (in São Paulo city—the closest station from São Bernardo do Campo).
Kussul et al., 2017	A multiple-level DL technique for land cover and crop kind's category has been suggested using satellite imagery.	A conventional, completely linked multilayer perceptron (MLP) and the most commonly used strategy in RS society, random forest, are then examined with CNNs.	The structure with a group of CNNs outguesses the one with MLPs, permitting us to more accurately discriminate positive summertime crop types.	NA	They used Sentinel-1A images and Landsat-8 in Ukraine over the test site, JECAM.

Table 7. A synopsis of Drone in Agriculture-Related Works.

Ref	Idea and Objectives	Results	Limitations	Dataset
Wu et al., 2024	Eliminating the noise pixels from soil, shadows, and the Thermally Affected Zone (TAZ) from UAV images using an automatic image segmentation-based noise removal technique.	Automatic noise reduction and multi-criteria comprehensive evaluation have a lot of potential for quickly assessing winter wheat cultivars' resistance to drought in large-scale breeding trials.	NA	Dryland Farming Institute, Hebei Academy of Agricultural and Forestry Sciences, Hengshui, China. The station is located in the winter wheat-producing area of the North China Plain.
Tunca et al., 2024	By analyzing UAV data and ML models, this study attempted to address the need for quick, nondestructive Leaf Area Index (LAI) monitoring over wide areas.	The K-NN model and Extra Trees Regressor (ETR) had the highest accuracy. UAV data and ML techniques can estimate sorghum LAI precisely to support precision agriculture applications.	NA	At the Black Sea Agricultural Research Institute located in Samsun, Turkey's Bafra Plains.
Alzhanov and Nugumanova, 2024	ascertain the relative effectiveness of crop classification models that were either trained directly from the UAV multispectral images or using features from the Gray Level Co-occurrence Matrix (GLCM).	The fusion of GLCM features derived from a time series of images and the ExtraTreesClassifier emerged as the standout performers, achieving accuracy, precision, and recall of 0.87, 0.88, and 0.87, respectively.	Should increase the variety of crops being compared as well as the number of prototypes.	In the Eastern Kazakhstan region
Demir et al., 2024	Empowering agricultural systems that function in environments that depend on nature, allowing them to efficiently maximize the use of limited resources.	The models can be used in conjunction with soil data and UAVs to predict Isparta oil rose yield early on in organic farming systems.	It is advised that research be conducted in locations with meteorological stations under various ecological circumstances.	Isparta oil rose (Rosa Damascena Mill.)
Ribeiro et al., 2023	A two-step, automatic segmentation approach is suggested. To begin, divide the planted area into sections with crop lines and areas with unplanted soil using a convolutional neural network. Next, employ a refinement procedure designed to restore and enhance the lines that were previously identified.	The UNet performs best when it comes to crop line segmentation, achieving a higher Dice coefficient for the datasets examined. Moreover, the network's ability to segment images is enhanced when it is trained using a dataset that includes a variety of crops from different plantations.	The reconstruction produces a slight decrease in the Dice coefficient.	Aerial images showing areas of sugar cane cultivation and containing crop lines of varying widths and ages.
Xiao et al., 2023	Utilizing deep learning technology, Geographic Information Systems (GIS), and UAVs to track corn growth performance under various management scenarios.	The methods used in this study could be extrapolated to enhance other crops' cultivation procedures.	Variations in management practices caused differences in the emergence rate, and extended germination periods have negatively affected seeds' survival, resulting in a lower emergence rate.	In Hokkaido, the northernmost prefecture in Japan

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Table 7. (continued)

Ref	Idea and Objectives	Results	Limitations	Dataset
Cheng et al., 2023	Uses UAV-based multispectral and thermal information and site-observed air temperature to obtain the three UAV-based drought indices: the Three-Dimensional Drought Index (TDDI), the Normalized Relative Canopy Temperature (NRCT), and the Temperature Vegetation Drought Index (TVDI).	The comparison of consistency with VMC revealed that TDDI outperformed NRCT and TVDI. Additionally, compared to the other two, TDDI displayed noticeably superior temporal characteristics.	(1) Limitation on the acquisition time of a remote sensing image. (2) TDDI's scalability for increased use. (3) The applicability of TDDI for different vegetations.	Henan province, China
Gao et al., 2024	Provides a full pipeline for deep convolutional neural networks-based semantic weed and crop segmentation. The networks were validated using remotely sensed images from a UAV platform as well as field test data, having only been trained on field images.	Deep learning can be applied to multiple tasks and can integrate various sources of data. To guarantee that the suggested network is superior, preprocessing methods that minimize dataset disparities between two different domains must be used.	It is unknown how well the model performs in radically different growth stages.	East-Flanders Province, Belgium
Guo et al., 2023	To estimate maize LAI, hybrid inversion models (HIMs) were built using hyperspectral and multispectral data from UAVs, respectively.	Incorporating Active Learning (AL) into the HIMs can significantly increase the model's accuracy. Another independent dataset was used to validate the model, and it also produced results with high accuracy. When using the GPR-AL-HIM for LAI inversion, the hyperspectral data show an advantage over the multispectral data.	NA	In Tongzhou District, Beijing
Jin et al., 2024	Remote sensing images captured by an UAV were used to extract rice texture features for rice fertilizer decision-making.	Providing an effective technical method for predicting the amount of fertilizer that should be applied to rice with mechanization and precision.	NA	In northeast China
Samsuddin et al., 2023	Examine how well UAVs fitted with Vegetation Indices (VIs) can track the health of paddy plants at different phases of growth.	The NDRE index proves valuable for evaluating dense crops, offering insights for precision agriculture and crop management in Malaysia.	NA	In Malaysia
Bagheri and Kafashan, 2023	Providing a comprehensive analysis of UAV-based remote sensing, applications, and solutions to the issues in both forests and orchards.	Rotary-wing UAVs were employed more widely in orcha-forest research than fixed-wing types. Utilizing the Accumulative Research Index (ARI) index curve reveals that the monitoring and management of orcha-forest trees is a challenging and fascinating field of study on a global scale.	Advanced machine learning techniques should also be used to implement intelligent diagnostic systems for the detection of diseases, pests, and other deficiencies, as well as the physical characteristics of trees, biomass estimation, water and nutrient prediction, damage assessment, and other issues.	in orcha-forest environment

Vé et al., 2023	Provides an extensive dataset of LiDAR data that was gathered from vineyards in northern Spain.	Providing insights into vineyard morphology and development, thereby helping to optimize vineyard management strategies.	NA	Vineyards in northern Spain
Tunca et al., 2023	Two commercially distinct types of UAV thermal sensors have been tested, and their performance was assessed by comparing the calibrated ground thermal measurements.	In terms of correlation coefficients, both sensors have shown strong performance. The potential of calibrated UAV thermal sensors for precision agriculture tasks is demonstrated by this study.	NA	At the Black Sea Agricultural Research Institute, Samsun, Turkey
Krestenitis et al., 2022	Providing the exact boundaries of 3 types of common weeds in this type of crop, namely (i) Johnson grass, (ii) field bindweed, and (iii) purslane.	The dataset can be utilized both separately and in conjunction with additional datasets to create AI-based techniques for the automatic segmentation and classification of weeds.	NA	A cotton field in Larissa, Greece
Biglia et al., 2022	Concentrating on examining the effects on canopy spray deposition and coverage due to various UAV-spray system configurations.	The effectiveness of spray application is greatly impacted by the flight mode. When compared with the optimal UAV spray system configuration, the conventional airblast sprayer demonstrated lower ground losses and higher canopy coverage.	Field trials designed to assess the biological efficacy of the spray applications when using a UAV spray system are required to prove the reliability of these kinds of spray application techniques in trellised vineyards.	In an experimental vineyard
Amarasingam et al., 2022	Concentrating on the application of UAVs in the sugarcane sector to enhance productivity and environmental sustainability through the management of pests and diseases, yield estimation, phenotypic measurement, soil moisture assessment, and nutritional status evaluation.	Crop Remote Sensing (RS) using UAVs can be a useful technique for managing and monitoring sugarcane to increase yield and quality while also having a major positive impact on the social, economic, and environmental spheres.	Should also take into account a few of the difficulties faced by the sugar industry, such as the need to adapt to new technology, high startup costs, bad weather, poor communication, policy, and regulations.	Utilizing three bibliographic databases, including Google Scholar, Scopus, and Web of Science, and 179 research articles.
Pandey and Jain, 2022	CD-CNN achieves a strong distinguishing capability from several classes of crops.	It achieves an accuracy of 96.2% for the concerned data.	NA	Carried out at different locations in India. UAV images of five different crops, viz.
Yang et al., 2020b	The VPA approach was used to determine a continuous relationship between VI and PAI/biomass with phenology.	It performed robustly throughout the growing season.	It neglects the effectiveness of phenology, and the stopping of the piecewise technique can bring about abrupt adjustments in appreciation during the stage-transmission period.	Guangxi Province, in southern China, was selected as the experimental site.
Bhatnagar et al., 2021	Definition of an effective and robust strategy for using drone imagery as training to enrich satellite imagery for wetland classification.	The strategy is a robust, quick, and cost-effective method to map wetland habitats and discover their ecohydrological synergies.	The limited battery life of the drone. The alteration in altitude and coverage of the sun led to a modification in the view of society taken by the RGB sensor.	Clara Bog is situated in County Offaly in the midlands of Ireland.

(*continued on next page*)

Table 7. (continued)

Ref	Idea and Objectives	Results	Limitations	Dataset
Wan et al., 2020	Structural and spectral information was taken from UAV-based RGB and multispectral images to appreciate grain harvests and observe crop development status.	It can improve the output accuracy of grain harvests and achieve effective observation of crop development.	It should also be joined with crop development techniques to further clarify the relationship between crop harvest and meteorological parameters.	Grain-output Functional Area of Anhua, Zhuji City, and Zhejiang Province in China.
Alves de Oliveira et al., 2020	The first widespread assessment of the potential of drone-founded spectral faraway sensing and photogrammetry for guessing the biomass and quality parameters of grass swards for silage output.	Drone faraway sensing was an outstanding instrument for the exact and effective management of silage output.	NA	In the municipality of Jokioinen in southwest Finland.
Syifa et al., 2020	A Land Cover (LC) map was created from drone images taken by two classifier approaches, i.e., ANN and SVM.	Better consequences from the classifier SVM, which had a greater overall accuracy than the ANN classifier.	Continuation clarifications by forestry experts or researchers are necessary to check whether the PWD-specified trees are indeed diseased by PWD.	Anbi and Wonchang Villages, which are positioned in Chuncheon City, Gangwon Province, Republic of Korea
Jia et al., 2021	An innovative methodology was improved to guess soil. As levels from HRAI images.	Enriched Random Forests (ERF) and Random Forest (RF) algorithms achieved fine overall performance among the four machine learning algorithms. HRAI mixed with machine learning has the highest capacity to predict soil danger levels.	More data, together with the location and diverse basic data about the pollution resources, is needed from the local specialists in the suggested methodology.	Zhongxiang, Hubei, in southern China.
kavoosi et al., 2020	They used Landsat 8 OLI data and more images taken away by a drone over the carefully chosen plots for faraway sensing of CRC.	Landsat 8 OLI imagery has shown its capability for CRC assessment.	Landsat 8 OLI imagery is somewhat more precise than drone imagery for approximating CRC.	Badjgah, Empirical Station, College of Agriculture, Shiraz University, Shiraz, Iran.
Wu et al., 2019	They set up a novel drone-borne Ground-Penetrating Radar (GPR) for soil moisture mapping.	Showing the potential of drone-GPR for speedy, great-resolution mapping of soil moisture at the arena scale.	They were not apprehensive about some details, such as the standardization of the full-wave antenna technique.	In the Loess Belt area of Belgium.
Saha et al., 2018	In the suggested schema, there is an RGB-D camera for taking actual-time images and handling the images.	The SVM can act on a public dataset of yields and plants and, furthermore, forecast its outcomes with better accuracy.	NA	NA
De Rango et al., 2017	-The observation of the area for discovering the parasites and the assortment of drones to terminate them cooperatively.	The link-state way of announcing the help demand is commonly more appropriate.	The coming work should contain another parameter and the introduction of other assortments and observing approaches.	This map gathers data on already-visited fields.
Yallappa et al., 2017	A drone-mounted sprayer was advanced for the application of pesticide sprays onto yields.	It supports the development of coverage, boosts chemical efficiency, and turns out the spraying job faster and more easily without human interference.	The advanced drone-mounted sprayer can only carry a maximum of 5.5 l and a maximum of 16 min.	In the Research Farm of the University of Agricultural Sciences, Raichur, and Karnataka, India.

maximizes resource utilization with the goal of improving agricultural production and profitability. PA can help identify the ideal growing conditions for crops while preserving resources such as fertilizer and water. The UAVs in PA consist of various integrating sensors (hyperspectral, high-resolution RGB, multispectral, thermal, and LiDAR), data collection, image processing, internet connectivity, flight missions, and AI (Amarasingam et al., 2022; Su et al., 2023). An example of a drone that may be used for precision agriculture and fulfills the mentioned necessities is the Parrot Bluegrass (A review on the use of drones for precision agriculture - IOPscience).

4.7. Drone applications in agriculture using remote sensing

When comparing UAV sensing systems to ground-, aircraft-, and satellite-based sensing systems, there are a number of special advantages. For

Table 8. A summary of a drone fortified with internet of things devices and features of drone-related works.

Performances Measure	Ref	Main Goal
Selecting the more accurate path-planning with at least 95% accuracy for every case	Vannini et al., 2023	Harpia seeks to carry out agricultural application tasks with the least amount of human involvement
Drone energy consumption	Zhang et al., 2021	It reviews, assesses, classifies, and facilitates understanding various drone energy intake models
An Energy-Aware Drone Trajectory Planning Scheme	Kouroshnezhad et al., 2020	Instructs the drone effectively, decreases the localization period, and keeps the drone energy
Raise the flight period of drones by giving them obligatory charging in a cost-effective way	Hassija et al., 2020	A peer-to-peer dispensed network of drones and charging positions is a relatively talented selection to delegate drones to be used in numerous applications by increasing their flight period
Observe a group of dynamic or static aims, assuming a constant rate of battery capacity	Al-Turjman et al., 2020a	It decreases the overall number of drones wanted to control a surrounding setting while providing the most coverage, which in turn results in an extensive discount in cost
A drone-fortified IoT	Alsamhi et al., 2019b	Collecting data in real time and guiding SAR for the rescue of human lives
A drone fortified with an IoT	Lagkas et al., 2018	It can be prepared with sensors of the spectrum for at the same time mapping and localization, ultrasonic sensors for feel and hurdle-avoidance methodologies, and thermal sensors to screen the surroundings' ecological and climate circumstances
Drone Navigation for Effective Battery Charging in Drone Networks	Kim et al., 2019	The CBDN collects drone transit data and defines effective drone paths that allow for a decrease in the total QCM crowding stage using cloud-founded administration
Reducing energy ingestion, flying time, and latency of data gathering	Cao et al., 2017	Drone based on WSN for collecting data
High-quality energy efficiency	Motlagh et al., 2017	Results exhibit the adequacy of the suggested connection guidance mechanism on the one hand in terms of data packet dispatch rate and energy intake savings
Decreasing the energy ingestion of WSN during data gathering	Zhan et al., 2018	In WSNs, making use of a UAV as a mobile data adder for sensor nodes (SNs) is an energy-adequacy method to extend the network's existence
Enhance the lifetime of the drone battery	kavoosi et al., 2020	The effective combination of UAV and RFID strategies can offer extra data that can be used side by side with other structural systems, together with BIM techniques and project delivery chain administration software
Providing energy-effective relaying for a superior lifetime	Sharma et al., 2016	A combination of WSNs and UAVs can offer a solution to this immoderate use of energy resources
Flight period and fly hazard level	Yoo et al., 2016	Improvement of the flying course in UAV-aided IoT sensor networks
Decreasing missed resources and energy and guaranteeing security	Yu et al., 2016	It indicates that WDDS senses the sightless spots of huge factories or warehouses and covers a low drone flight time

instance, although accurate, the ground-based manual approach is expensive, labor- and time-intensive, terrain-dependent, and only offers insights into particular areas. In contrast, UAV sensing can avoid these issues because of its denser and wider coverage with less human intervention. When it comes to cost-effectiveness and accuracy, flexibility, and user-defined spectral−spatial−temporal image resolutions, UAV sensing outperforms manned aircraft and satellite-based sensing systems. It also has a flexible multiple-source data acquisition capacity thanks to various add-on sensing units. It is also mentioned that UAV sensing systems have the ability to serve as a relay or bridge between satellite- and ground-based sensing systems, greatly increasing the efficiency of ground-truthing satellite data for local agricultural applications (Su et al., 2023).

4.7.1. Seedling emergence assessment

The farm can be mapped with very high accuracy as a way to view the seedlings and identify regions where germination is failing. The required accuracy relies simply on the scale of the plant's leaves after emergence. Some crops have thin, wispy leaves at emergence, which can be harder to peer from above (e.g., wheat) (van der Merwe et al., 2020).

4.7.2. Weed detection and mapping

Weed mapping is a commonly used application of far-off sensing in agriculture, and drones provide advantages in this application because of the excessive degree of elasticity in locative accuracy. Multispectral imagery is usually most suitable for mapping weeds inside the crop field (van der Merwe et al., 2020).

4.7.3. Crop damage assessment

Drone mapping can be beneficial for the location and quantification of crop harm after climate events and for a huge variety of reasons, including pests and diseases (van der Merwe et al., 2020).

4.7.4. Water management

Restricted availability of water is one of the most considerable obstacles facing agriculture today, and pressures on water sources are anticipated to boom into the future. Protecting yields from drought-associated losses needs water administration systems that respond to converting water desires in close to real time (van der Merwe et al., 2020).

Tables 6 and 7 are a summary of the past efforts. The purpose is to explore the efforts to make use of UAVs in an agricultural setting, as they are able to reveal numerous aspects of farming that people cannot accomplish on their own.

As evident in Table 6 and in this survey paper, a nonexhaustive analysis is performed on the recent use of IOT and AI algorithms in smart agriculture applications. Although there are already a lot of studies on different aspects of agriculture, there are still many restrictions that might be liable for the low output of crops, which can be overwhelmed by the use of drones in the smart agriculture field.

As evident from Table 7 and in this survey paper, a nonexhaustive but systematic review is performed on the recent use of UAVs, which can be overwhelmed by the use of drones in the smart agriculture field using AI. Also, as illustrated in Table 8, it explains the main goal executed in the related works and their opportunity correlated to the performances of UAVs and drones equipped with IoT devices.

Also as evident from Table 8 and in this survey paper, a non-exhaustive analysis is performed on the recent use of a drone fortified with IoT devices and features of drone-related works.

5. Conclusion

We can deduce that UAVs could be of colossal assistance to the field of smart agriculture with the growth in the populace by way of their importance. It will not only lessen the period but additionally harvest superior farming primarily founded on examined data. As a result, this survey paper provides state-of-the-art improvement of the last research on drone strategies applied to smart agriculture. It contains important arenas for drone applications within the location of agriculture. Yet, there are numerous problems associated with the utility of drone strategies for the smart agriculture area that demand to be solved to raise the adoption ratio of drones.

In the future, ongoing studies ought to encompass extra experiments, strategies to lessen the intake of energy, boom the digits of various sensors, and authentication of the consequences by means of different calibrated sensors. Also, all the suggested structures ought to be executed and examined in the actual field.

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