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Implementation of drone technology for farm monitoring & pesticide spraying: A review

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A B S T R A C T

The world receives more than 200 thousand people in a day and it is expected that the total world population will reach 9.6 billion by the year 2050. This will result in extra food demand, which can only be met from enhanced crop yield. Therefore, modernization of the agricultural sector becomes the need of the hour. There are many constraints that are responsible for the low production of crops, which can be overcome by using drone technology in the agriculture sector. This paper presents an analysis of drone technologies and their modifications with time in the agriculture sector in the last decade. The application of drones in the area of crop monitoring, and pesticide spraying for Precision Agriculture (PA) has been covered. The work done related to drone structure, multiple sensor development, innovation in spot area spraying has been presented. Moreover, the use of Artificial Intelligent (AI) and deep learning for the remote monitoring of crops has been discussed.

1. Introduction

The population is increasing rapidly, which is making food security a challenging task. According to Food and Agriculture Organization (FAO) of the United Nation, more than 815 million people are chronically hungry and 64% of the chronically hungry are in Asia. The world needs to increase food production by approximately 50% by the year 2050 to feed a population of nine billion [1]. On the other hand, the basic resources for agriculture production such as land and water are becoming scarcer every day [2,3]. In a study done in 2018, it has been revealed that 9.2% of people on earth had extreme degrees of food availability problems [4]. Any further decreases in the amount of food will result in a very pathetic condition. There was also a moderate level food insecurity problem (i.e. up to 17.2% of the total populace), which means that they did not have customary access to nutritious and adequate food. The combination of moderate and extreme degrees of food availability problem carries the approximate 26.4% of the total populace [4].

The crop production and food supply networks were severely affected by the COVID-19 pandemic [5–8]. The basic requirements in the field of agriculture like labor, seeds, fertilizers, and pesticides were not available timely to many

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farmers and has resulted in less production [5,6]. Many Asian countries are at a developing stage, and they are confronting with the issue of a high populace and their agrarian efficiency is much lower when compared with technologically advanced nations. India is facing a similar issue. This is due to its low-level agriculture technology, lesser power availability, and unskilled farmers, etc. Almost 73% of the Indian population is dependent on the agriculture sector directly or indirectly. Indian farming is still being done in a conventional manner. Farmers are using conventional techniques for seed planting, composts and pesticides application, etc. [9]. The traditional techniques used for pesticides and fertilizer spraying require more time and are less effective, thus there is a need for technological advancement in this segment [9,10]. COVID-19 pandemic made the monitoring of crop, fertilizer, and pesticide spraying very difficult for conventional farmers [5,11]. The utilization of Drone in agriculture is a suitable solution to overcome these difficulties [12]. Utilizing proper information collected by drones, agronomists, rural specialists, and farmers may improve their activities to increase the yields [13,14].

For smart farming and Precision Agriculture (PA), aerial remote sensing is considered to be one of the most important technology. Aerial remote sensing, with the help of drones, utilizes the images of different wavelengths and measures the vegetation indices to recognize the several conditions of crops [15]. In the past decades, manned aircraft or satellites were used for capturing desired images that were utilized for precision agriculture [16]. Capturing images by using manned aircraft is a very costly affair and the problem with satellite images is that image spatial resolution is not as good as desired in most conditions. Moreover, the availability and quality of images depend upon the weather conditions [17,18]. An advancement in Unmanned Aerial Vehicle (UAV) technologies and reduction weight of payload devices has shifted the remote sensing of crops through this technology. This technology is less expensive, time-saving, and captures high-resolution images in a non-destructive way [19,20].

Drone monitoring systems help the farmers for observing the aerial views of the harvest. This gives information related to the water system, soil variety, pests, and fungal infestations. Crops images, collected by the drones, have information in the range of infrared and visual spectral. Different features from these images can be extracted, which gives information about the health of plants in a manner that cannot be seen with the naked eye. Another important feature of this technology is its capability to monitor the yield regularly i.e. on each week, or even at each hour. The frequent availability of crop information helps farmers to take corrective action for better crop management [21,22].

Applications of drones in precision farming can be studied based on the payload devices. Payload is actually the weight a drone can carry. The two main categories studied here are crop health monitoring, and pesticide spraying. In this paper, after a brief introduction about the use of UAV technology in the agriculture field, their different types used for agriculture monitoring have been reviewed. Further, a discussion about capturing high-resolution images and their analysis for crop health monitoring are done. Improvements in pesticide spraying drone and development of a drone capable for spot spraying has been reviewed.

2. Agricultural drone

Initially, the drone was originated as a military tool and was given different names such as Unmanned Aerial Vehicle (UAV), Miniature Pilotless Aircraft, or Flying Mini Robots. Nowadays it is being utilized in the business sector, infrastructure sector, farming, security, insurance claims, mining, entertainment, telecommunication, and transport sector, etc. The drone has a powerful market opportunity as is evident from the data given in Table 1. Such a broad application of drones has resulted in a very fast improvement in drone technology, thereby making it more user-friendly day by day.

Nowadays, the application of small unmanned aerial vehicles (UAVs) is growing at a very fast rate in agribusiness [23–25]. Drones are semi-automatic devices that are continuously shifting toward fully automatic devices. These devices have an enormous potential for agricultural planning and related spatial information collection. In spite of some innate barriers, this technology can be utilized for productive data analysis [12].

Initially, UAVs were radio-controlled devices operated by a pilot from the ground, however, modern drones are GPS-based autopilot aerial vehicles. The type of cameras, sensors, controlling devices depends on the application of a drone. The three main types of UAVs platforms are Fixed-wing, Helicopter, and Multi-copter [4].

Fixed-wing UAV: These UAVs have stationary wings in the shape of an aerofoil which creates the lift needed when the vehicle reaches a certain speed. A commonly used Fixed-wing UAV is shown in Fig. 1(a).

Helicopters: It has a single set of horizontally rotating blades attached with a central mast for producing lift and thrust. This type of UAV is shown in Fig. 1(b). A helicopter is capable of vertically take off and land, fly forward, fly backward, and hover at a particular place. These features allow the use of helicopters in congested and remote areas where fixed-wing aircraft are unable to operate.

Multi-copters: Rotorcraft with multiple sets of horizontally rotating blades (typically 4–8) have the capability to provide lift and control movements of UAV as shown in Fig. 1(c).

In the past decade, the unmanned aerial vehicle (UAV) market was captured by fixed-wing and helicopters. Nowadays, the use of small drones in precision agriculture has shifted focus towards multi-copters that at present covers almost 50% of the available UAV model [13]. The advantages, disadvantages, and applications of fixed-wing drones, helicopters, and multi-copters are summarized in Table 2.

Performance of tiny sensors (accelerometers, magnetometers, gyros, and pressure sensors, etc.), used in drone technology, is continuously increasing and their size is reducing day by day [26–28]. Moreover, the development of powerful processors, GPS modules, and increment in the range of digital radios is a continuous process, and thus drone technology is also improving. New innovations in embedded systems and motors have made it possible to reduce the size of UAVs and improved their payload capability. This further leads to a better controlling of the drone for monitoring of remote fields [29–33].

Table 1 – Utilization of drone in different sectors [10].

S.No.	Industry	Drone application	Budget (Source: PwC (2016))
1	Infrastructure	Investment monitoring, Maintenance, Asset inventory	$45.2 bn
2	Agriculture	Analysis of soils and drainage, Crop health monitoring, Yield prediction, Pesticides and fertilizer spot spraying	$32.4 bn
3	Transport	Delivery of goods, Medical Logistic	$13.0 bn
4	Security	Monitoring lines and sites, Proactive response	$10.5 bn
5	Entertainment and Media	Advertising, Entertainment, Aerial Photography, Shows and Special Effect	$8.8 bn
6	Insurance	Support in claims settlement process, Fraud detection	$6.8 bn
7	Telecommunication	Tower maintenance, Signal broadcasting	$6.3 bn
8	Mining	Planning, Exploration, Environmental impact assessment	$4.3 bn

(a) (b) (c)

Fig. 1 – Types of UAVs (a) Fixed wing drone (b) Helicopters (c) Multi-copter drone.

The integration of Artificial Intelligence (AI) has revolutionized the use of semi-controlled drones for farm monitoring [34,35]. The decision of a semi-controlled drone was purely based upon the sensor output as shown in Fig. 2. AI system has its own decision-making power, which has made it a useful tool for real-time data analysis. This decision-making power of AI is based upon previous training. Real-time data analysis has improved farm productivity through mapping spatial variability in the field. The crude data (of crops in agricultural fields) collected using drones are fed to the analytical models for analysis and further remedial actions are taken to improve the yield. Drones can perform soil health scans, assistance in irrigation, fertilizers application, crops health monitoring. Moreover, it provides useful data analysis to estimate farming yield [36].

Satellite image utilization for data analysis has its limitation in the case of small plants. Moreover, the availability of satellite images depends upon weather and light conditions. Unmanned Aerial Vehicle (UAV) provides a better solution for image data collection since they can capture desired location images from the desired height and at the desired frequency automatically. Moreover, drone-based technologies can analyze the data instantaneously and can be used as a fully automatic device for pesticide, and weed.

3. Crop health monitoring

Daily monitoring of crops is performed by the farmers to detect any potential threats such as diseases, pests, and slow rate of growth. The traditional methods for monitoring crops were visual inspection and collecting ground samples manually from random locations. For more than 50-years, color and infrared photography captured by different platforms have been used for monitoring crop growth [37]. A camera-mounted drone identifies the crops with diseases or deficiencies using advanced image data analytical tools [38,39]. Drones in the agricultural sector are mainly used for field mapping and crop monitoring, shown in Fig. 3. Investigation and analysis of UAV application for crop monitoring has been carried out in this section.

A vegetation indices map can be created with the help of images captured by the drone-mounted camera. Crop information such as crop disease, nutrients requirements, and water stress can be estimated on the basis of these indices [40]. Vegetation indices help in differentiating between healthy, unhealthy plants and weeds [41]. These indices are based on the image spectrum of crops and the image spectrum is related to the health condition of the crop as shown in Fig. 4. There are solid relationships between harvest yield and vegetation indices estimated at certain harvest stages [42]. These relationships play a great role to monitor the yield.

Drones in the agriculture field perform many activities that help in monitoring crop health and assists to take corrective actions and thus prevents the spoiling of crops. Some applications of drones in crop health monitoring are summarized in Table 3.

For effective crop monitoring, the selection of sensors to be used along with drones is very important. The sensor selection mainly depends upon their applications such as disease detection, nutrients detection, and water status identification, etc. Researchers have worked on the improvements of drones continuously and developed task-specific drones for crop monitoring. However, the UAV system made its breakthrough in the agriculture sector in around 2011, most likely

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Table 2 – Different types of aerial imaging system used in precision agriculture.

Types of Aerial platform	Commercial agriculture drones[68]	Price range	Applications in agriculture	Advantages	Disadvantages
Piloted aircraft[40]	• M-18 Dromader • PZL-106AR Kruk • Grumman Ag Cat	Very High	• Crop scoutingFertilizer and pesticide spraying for larger areaDrought monitoringSecurity, and surveillance	• High speed • High flight time • Rough use in severe weather condition • Higher payload weight • Can cover well over hundreds of hectares of crop fields in a short period	• High operating cost • High altitude Flight • Problem in inspection of isolated small fields • Need skilled pilot • May be dangerous • Noise and vibration
Single Rotor Helicopter (UAV) [53]	• Yamaha RMAXR22-UVR66 spray systemAlign Demeter E1SR20 and SR200 of rotomotion	High	• Large area pesticide sprayingIn remote area where high payload capability is needed-Crop height estimationsSoil and field analysisCrop classification	• Controlled by the autopilot software • High payload capacity • Higher flight time • Higher speed • Strong and durable • Access to remote areas • Petrol or gasoline powered unmanned aerial vehicle • Vertical take-off and the ability to land vertically • Hover, and fly forward, backward	• Some area in the crop field is not covered properly while spraying • Heavier • Costly setup • High altitude flight • Noise and vibration • Stability problem • High initial and maintenance cost
Fixed Wing [12,23,31]	• AgEagle RX60 • eBee Ag • Precision Hawk Lancaster 5 • Sentera Phoenix 2Trimble UX5	Medium-High	• Large area monitoringLarge area crop growth monitoringCrop health status monitoringFertilizer and pesticide spraying	• Simpler architecture • Easier maintenance process • Long endurance and range • Higher flight speed • Larger average • Greater energyefficiency • Greater ability to survive • Gliding capability	• Limited accessibility • Less wind resistance • Difficulties in launching • Difficulties in landing • Harder to Hover • Harder to fly • More training needed • High initial and maintenance cost
Multi-copter [50]	• DJI Phantom 4 PRO • AGCO Solo • Sentera Omni Ag • SenseFly eXom • AgBot • InDago AG	Low -Medium	• Nutrition, and crop stress considering local field needsSpot pesticide sprayingSmall field monitoringcrop height EstimationsSoil and field analysisWater stress calculation	• Site-specific management • Low altitude flight capability • Better stability • Stable fixed flight capability • High payload capacity • Low speed flight capability • Ability of vertical landing and take-off • Swarm of UAVs can be used for better control • Pre-programmed flight plans • Better accessibility	• low speed • low payload weight capability • Complex architecture • Difficult maintenance process • Limited flying time and range • Lower flight speed • Less energy • Low battery life • Stability problem in bad weather condition

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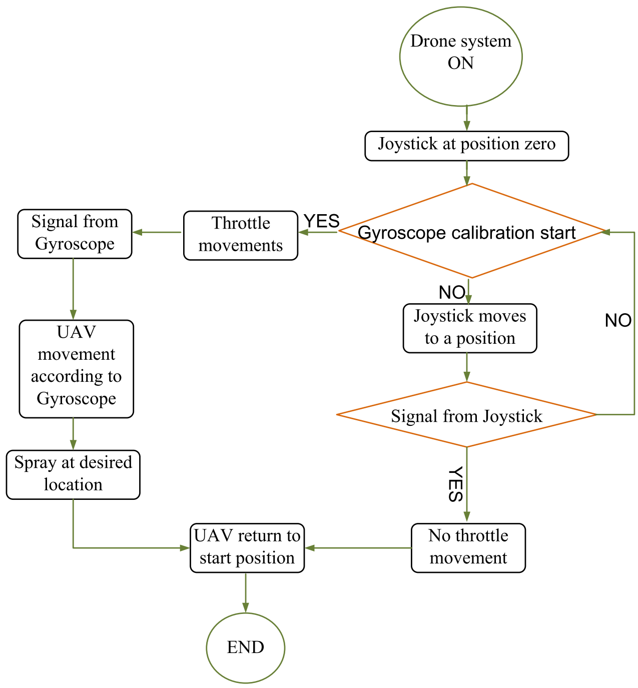

Fig. 2 – Workflow diagram of sprayer drone.

because the drone technology, as well as payload devices, became affordable and easy to use [43].

In 2010, A digital color-infrared camera system was developed by E. Raymond Hunt Jr. et al. [44] for wheat field monitoring. Vector-P UAV (from IntelliTech Microsystem) controlled by an autopilot computer program was used to capture the photograph at user-selected points. The camera system was lightweight and compact in size suitable for small UAV systems. Image data were successfully analyzed for crop condition and soil types; this analysis was based upon Green Normalized Difference Vegetation Indices (GNDVI). This system was lacking precise control and image capturing was possible only at selected points.

In 2012, An unmanned aerial vehicle (UAV) named VIPtero was developed by Jacopo Primicerio et al. [45]. This was used for site-specific vineyard management. It was an autonomous hexacopter capable of site-specific operation with a multispectral camera. The designed "VIPtero" platform was an economical and environmentally sustainable device with improved efficiency. It showed a good capability to perform the specified task with improved control. However, it needed improvement in the payload capability of the system and further miniaturization of sensors.

In 2015, Hassan-Esfahani et al. [46] proposed a remote sensing technology, named "AggieAir", for agricultural application. It had the capability of capturing images in RGB (Red Green Blue), Near Infrared (NIR), and thermal spectrum. It provided high-quality multispectral image data for crop health monitoring. It successfully estimated the crop leaf canopy volume, crop tissue nitrogen, chlorophyll, and soil moisture. Machine learning was applied for site-specific information estimation that needs to be improved for better performance.

In 2016, Santesteban et al. utilized a drone system for the study of water status in vineyard crops [47]. Aerial thermal images captured by drone were used for estimation of instantaneous as well as seasonal water status in the crop. The health condition of crops was analyzed based upon Crop Water Stress Index (CWSI). Thermal images were captured using the high-resolution camera in a 7.5 ha farm. A wide range of CWSI values was obtained (0.28–0.69). It showed that water status measurement based on CWSI is significant for crop health analysis. Data achieved through image processing were compared with the manually collected data and it was found that there was a minor deviation between them. It was concluded that the thermal data captured by drones provided significant and accurate results (based on CWSI) about water status in the vineyard.

In 2017, Paredes et al. have proposed a simple multispectral image system for UAV-based agricultural applications [48]. A lower-order system, utilizing several cameras for capturing multispectral images, was developed. It synchronized successfully with the flight controller and data acquisition system. Algorithms proposed for image acquisition and trigger checking were successfully implemented. However, this system has limitations of low flight altitude of drone and image acquisition rate due to the resolution of the camera.

(a) (b)

Fig. 3 – UAV application in agricultural field (a) Field mapping (b) Crop monitoring.

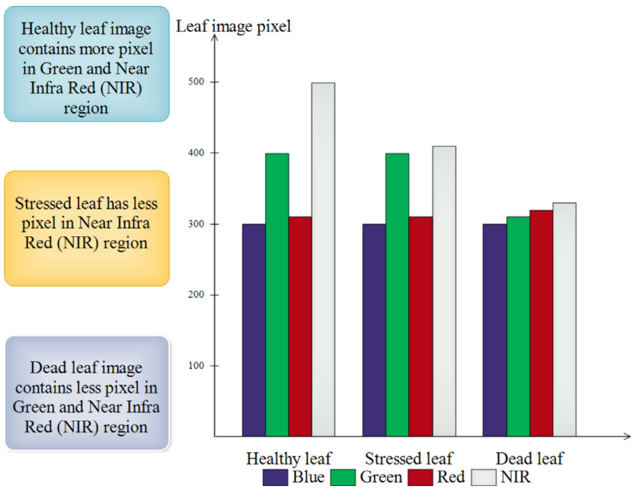

Fig. 4 – Relation between plant health and image spectrum.

In 2018, Arnab Kumar Saha et al. proposed an IOT based real-time crop data monitoring drone system [49]. Smart sensors and modules were employed for real-time data analysis. The proposed solution was integrated with the drone using Raspberry Pi 3B module. The system was trained with machine learning algorithms to predict the health condition of crops. This system was user-friendly and gave a more accurate condition of crop health as compared to other available drone systems. However, it was more complex in structure and had a weak security.

In 2019, Jack et al. proposed a system for estimation of soil properties based on the square of Visible Atmospherically Resistant Index (VARI) [50]. Soil pH in the pineapple crop field has been predicted and results were compared with laboratory tested pH data, the R-squared value of comparison was about 51%. A linear relationship between VARI and soil pH was presented. Estimation of soil properties using the proposed method was useful in predicting essential soil nutrients and pH. It was concluded that laboratory soil analysis for monitoring crop plantation is prohibitively expensive as compared to the proposed method in the long run. The designed system needed improvement in sensors for better results.

In 2020, Su et al. have proposed an automatic yellow rust disease monitoring system using UAV [51]. A multispectral camera has been used for the data collection. It captured the five different spectrum bands which are RGB, extra RedEdge, and NIR. The proposed system relied on U-Net for semantic segmentation. Image segmentation performance was improved due to extra band utilizations. The Random Forest algorithm-based deep learning process was used for the classification of the image data. Deep learning is Convolutional Neural Network (CNN) based Machine learning (ML) process. ML is a popular technique for visual data analysis and result prediction. A workflow diagram of this technique is shown in Fig. 5. The raw data collection using suitable sensors and processing of the collected data is done in the data acquisition and processing blocks. The collected data is converted into useful data through cleaning and grouping. Deep learning model consist of a well-written computer program.

The model was trained and validated with refined data for the collection of desired information from the crop. The trained system was deployed in the field for problem analysis. It was observed that the segmentation and disease detection capabilities of the system was improved. However, vegetation indices performance has been reduced. The performance of the system can be improved by using other deep learning networks and better data labelling.

Some important outcomes have been extracted from research done in crop monitoring during the last decade. In recent years, many crop condition-monitoring methods were developed based on remote sensing data. These crop condition monitoring methods can be classified as direct monitoring methods, image classification methods, and IoT based crop monitoring.

The direct monitoring methods are based upon crop condition monitoring indices (such as Normalized Difference Vegetation Index, NDVI and leaf area index, LAI, etc.). These methods are easy to use and needed fewer data. However, due to their short theoretic foundation, they are hard to use in complex areas.

Table 3 – Summary of utilization of drone in crop health monitoring.

Farming jobs	Image-based data utilization	Advantages over other aerial imaging systems
■ Crop scouting[12,40] ■ Crop health monitoring [34,48,50,51] ■ Field surveying (before planting)[34] ■ Nitrogen recommendation[48] ■ Yield monitoring [12] ■ Plant stress monitoring[38,50] ■ Drought assessment [66] ■ Senescence analysis [67] ■ Leaf Area Indexing[44] ■ Tree classification[30] ■ Pesticide spraying at desired spot[29,58] ■ Fertilizer spraying[24,58]	■ Plant height estimation ■ Plant count ■ Plant health monitoring ■ Calculation of nutrients present ■ Disease classification ■ Weed detection ■ Relative biomass estimates ■ 3d / volumetric data (piles, patches, holes and hills)	■ Cheaper imaging ■ Greater precision ■ Earlier detection of problems ■ More frequent index reporting ■ React more quickly ■ Site-specific management ■ Low altitude flight capability ■ Better stability

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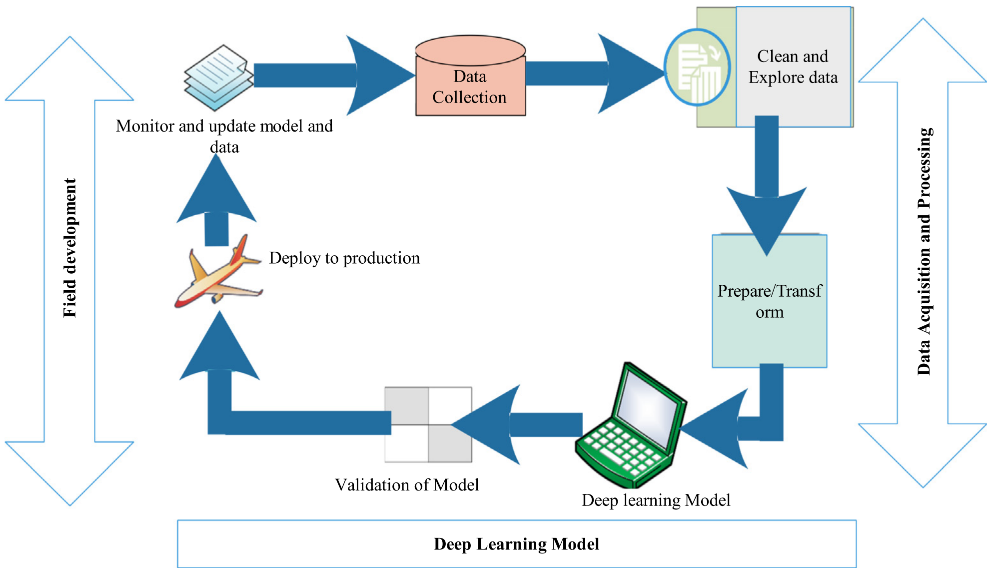

Fig. 5 – Workflow diagram of deep learning-based system used for precision agriculture.

Fig. 6 – UAV based Spraying system being used in (a) Paddy field (b) Tea crop and (c) Banana trees.

Image classification methods are based upon supervised and unsupervised learning algorithms. These methods visualize the results effectively and are user-friendly. A continuous improvement in machine learning, computer vision, and AI technologies is making it more accurate and user-friendly. This technology needs good programming skills and latest equipment. Moreover, calibration is needed, for the classification model, in the case of real-time applications.

IoT-based technology utilizes the different types of sensors for the collection of crop data and these data are analyzed using a simulation model. This technology is efficient in resource utilization, enhances data collection, needs less time, and minimizes human efforts. This technology has some drawbacks such as; complexity, security, and privacy.

4. Pesticide spraying

This section is about research and developments in UAV-based pesticide spraying systems. Till date, mostly conventional methods for pesticides application are being used in various parts of the world. The manual mechanical sprayer is the most common tool for conventional pesticide application. Manual spraying of the pesticides affects human beings and may lead to diseases like cancer, hypersensitivity, asthma, and other disorders [52]. Additionally, conventional methods have several other shortcomings such as extra chemicals use, farm labor shortage, lower spray uniformity, environmental pollution, and less area coverage. These conventional methods cause a higher cost of pesticide application and are less effective in controlling pests and diseases. To overcome these shortcomings, a drone-mounted sprayer is being employed. The application of drone-mounted sprayers in the field has enhanced the coverage ability, increased the chemical effectiveness, made the spraying job easier and faster. Nowadays, Drone is capable of carrying up to 40-liter pesticide tank and follow pre-mapped routes to spray crops according to the requirements. Drones are showing great potential in covering the fields with difficult access for tractors and aircraft. Some images of drone-mounted sprayer are shown in Fig. 6 [53].

A flow chart of drones with an integrated spraying system is shown in Fig. 7. The basic components of any drone are Brushless Direct Current Motors (BLDC), Electronic Speed Control (ESC), Flight controller, Camera, Transmitter, and

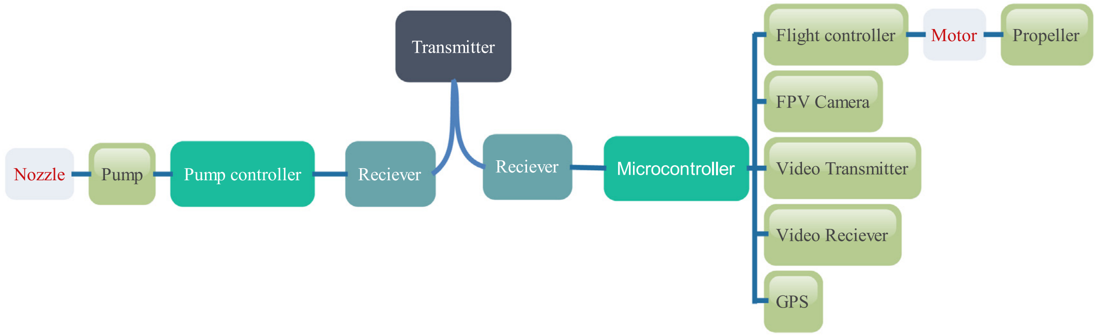

Fig. 7 – Flow chart of Semi controlled UAVs for pesticide application.

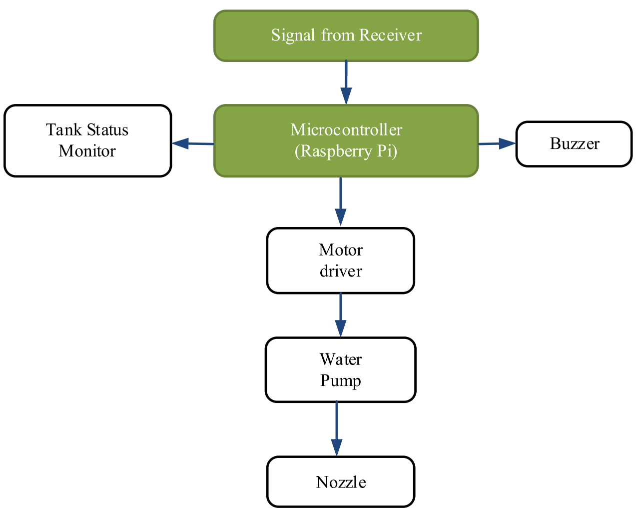

Fig. 8 – Blocks of a fully automatic pesticide spraying system.

Receiver. The main parts of any spraying system are the pump and its controlling system. In accessories: Accelerometer, gyroscope, GPS are used for controlling the drone.

To design a drone for spraying application, the first step is to estimate the payload. Components of the drone are selected after the calculation of payload. Battery selection depends upon the current and voltage requirements of the drone modules. Finally, the frame of the drone is designed that depends upon the number of arms and payloads.

First UAV (unmanned helicopter) for pesticides application was developed by Yamaha Motor Co. Ltd., Shizuoka Japan in 1983. The stability and controllability of this helicopter were not suitable for utilization in the field. Many researchers have worked on the stability and controllability of UAVs as well as their spraying systems. In this sequence, Y. Huang et al. had built a sprayer for UAV-based pest management in small fields [54]. Pulse Width Modulation (PWM) based controller was used for controlling this UAV system. This system gave satisfactory results in vector control applications. Moreover, it was suitable for use at tough reachable sites.

In 2010, Zhu et al. proposed a PWM regulator-based preprogrammed and remotely controlled helicopter for pesticide spraying in the agriculture field [55]. A fixed frequency PWM (TL494), data acquisition system and software developed along with a guided system were used. PWM controller was tested on LabVIEW 8.2 software and after that, it was analyzed by using different control signals to get the optimum result. A designed spraying system with a PWM controller has the ability to enhance the efficiency of pesticide applications in the field. The system was remotely controlled, however, the telemetry system used for signal transmission was not precise.

In 2017, Bruno S. Faiçal et al. proposed an adaptive control approach for pesticide spraying using UAVs in dynamic environments [56]. Static configuration was inefficient in changing weather conditions. Environment system (AdEn) Software system was created which had two parts: (i) Collector and Actuating (CollAct), and (ii) OPTImization Core (OPTIC). CollAct inspected the weather conditions and accordingly, route changing parameters were updated. Route optimization was achieved by OPTIC as per the actual weather condition. The experimental results showed that the performance of the proposed pesticide sprayer system has been enhanced in the tested scenario. However, there was a need for the development of an automatic sprayer system with lower costs.

In 2017, He Luo et al. proposed a genetic algorithm-based multi-UAV system for the optimization of pesticide spraying tasks [57]. Maximizing the profit of pesticide spraying was

Table 4 – Comparison of different machine learning algorithms used in agriculture.

Algorithm	Application	Experimental data	Testing Accuracy
ANN [59]	Pesticide spraying	60 m × 80 m field divided in 10 m × 10 m units	99.97%
CNN (VGG)[65]	Crop Disease Detection	Openly available database of 87,848 photographs	99.53%

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selected as the main optimization task. Planning flight trajectory was another important task in pesticide spraying using multiple UAVs. A combination of Dubins Team Orienteering Problem (DTOP), Variable Time Windows (VTW), and Variable Profits (VP) models, was proposed for the path allocation of UAVs. An analysis based upon two majorly factors affecting the efficacy of the task was done. These factors were amount of pesticide to be sprayed and the temperature of the environment. The designed model was found to be more accurate than the regular manual procedure of pesticide application. The model was tested for only a rectangular field, and its efficacy for different shaped fields was not verified.

In 2017, Spoorthi et al. developed a drone name Freyr for uniform spraying applications in the field [58]. A user-friendly android app was developed with Wi-Fi interface. A smart controller board (Arduino Mega-2560) was used to control the system process. Freyr drone had an ability to rout any field portion irrespective of shape. It was useful for low-level farming. However, technical knowledge was required by the farmers for using the developed android app.

In 2018, B. Balaji et al. designed a hexacopter using a Raspberry Pi controller to make the agriculture technologies farmer-friendly [59]. Python language programming was used for disease and weed detection in crop monitoring applications. Various sensors like water level sensors, LDR, and DHR were connected to get the data corresponding to the real condition of the crops. It was concluded that almost 20–90% saving is possible in terms of chemical, water, and labor using this technology. However, this system needed an improvement in the payload of the drone.

In 2019, Sheng Wen et al. designed a UAV integrated variable spray system that was based upon an artificial neural network (ANN) [60]. Utilizing sensor data, ANN model, and data acquisition, a program was written in Keil Software for applying pesticides as per the requirement. Software named UAVDDPS was designed to predict droplet deposition. The ANN model predicted the deposition rate of chemicals and accordingly, the flow rate of the spray system was regulated. An experiment was conducted in a paddy field and it was found that the ratio of droplet deposition to prescription value in each unit is approximately equal. The error between the predicted droplet deposition and actual droplet deposition was found to be less than 20%.

In 2019, Kislaya Anand, Goutam designed a drone named AeroDrone for field monitoring and chemical spraying [61]. The aim was to minimize the time of spraying and the loss of pesticide. A simulation platform was proposed to assign the mission on the field and to check the sensibility and accuracy of this plan. Results proved that the work performed by this quad-copters integrated system was efficient and the

Table 5 – Image Processing Sensors used in precision agriculture.

Sensor	Features used	Advantages	Disadvantages
Visible (RGB) Camera [50]	Colour, Size, Shape, Edges, Surface	• Easy to identify by visual inspection. • Cheap and small in size • Small payload for UAV • High resolution camera • Easier to use	• Have only three bands • Unable to detect many features • Unable to find irregularities in data • Needs higher image resolution
Multispectral Camera [51]	Appearance and geometrical features, NVDI	• Images in more spectrum bands than the Red Green and Blue (RGB) can be captured • More information than an RGB digital image • Captures spectral bands near infrared (NIR) • Provide information about reflectance of visible light and vegetation indices.	• Needs computer • More heavy and more costly • Images captured depends on the climatic conditions • Image resolution limits • The altitude at which the UAV can fly and the image acquisition
Hyper spectral Camera [51]	RVI and NDVI Indices	• Creates images using thousands of narrow bands • Multidimensional datasets • Can detect more features than multispectral camera • Acquires entire at each point	• Need fast computers • More costly and complex • More difficult to use. • Big data storage capacity is needed • High payload
Thermal Camera [29,48]	Crop Water Stress Index (CWSI)	• Have greater spectral and spatial resolutions. • Quick determination of canopy surface temperature • Small size • Low weight	• Thermal images depend upon weather condition • Accuracy of the system depends upon the resolutions of camera. • Model that estimates plant water status, depends upon many variables

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mission time of each quadcopter was almost the same. This scheme showed good results however it was only tested for a rectangular farmland.

In 2019, Martinez-Guanter et al. have designed and developed an aerial pesticide spraying system that considered the limitations of payload [62]. It was designed using low-cost material so as to make a low-budget drone. UAV with approximately 6 kg take-off weight, with GNSS receiver and telemetry system was designed. The modular nozzle had two configurations, one has four nozzles with 250 mm spacing and the other has a single anti drift nozzle. Pump speed was controlled from a remote-control station. The pumping range was between 0.10 ltr/min to 0.22 ltr/min. A PWM-based control system was used for autonomous application. The efficiency and reliability of the hardware system were tested in super-high-thick olive and citrus plants. The experimental results showed that the developed system was able to save approximately €7/ha in comparison to the previously used system.

In 2020, Karan Kumar Shaw et al. has designed an octocopter with a lower weight spraying system [63]. Payload was determined by considering the sizes of the tank storage (that was 6 Litres), fluid density, nozzles (fine spray), and pump. According to payload requirement, 8 Brushless Direct Current (BLDC) motors, Electronic Speed Controller, Propeller, 12 V pump, FPV camera, video transmitter, and LI-PO battery were selected for system design. This octocopter design was good for farm monitoring, however, there was a need to change the manually controlled system into an AI-based autonomous system to improve its performance.

During recent years, a lot of changes can be observed in the drone flight controllers as well as in the spraying systems. The spraying system upgraded from a semi-controlled device to AI-based fully automated system. The blocks used in a fully automatic pesticide spraying system is shown in Fig. 8. A fully automatic pesticide spraying system is capable of spot spraying by analysing the real-time data. It does not require any human efforts in chemical spraying, that makes it a great choice toward safer and more economical system [64,65].

In precision agriculture, different tasks that need an aerial image processing system are crop monitoring, and pesticide spraying. Image processing efficiency of the system depends upon aerial platforms, machine learning algorithms, and image capturing systems. A comparative study of the different aerial platforms has been presented in Table 3. Moreover, comparative studies of the other two factors have been presented in Table 4 and Table 5 respectively.

5. Conclusions and future challenges

This research paper presents the state-of-the-art development of drone technology for precision farming. The Paper covers two main fields of drone applications in the area of Precision agriculture: crop monitoring, and pesticide spraying. In particular, change in drone structures, development of sensors for data collection, innovation in pesticide spraying drone, implementation of deep learning, and AI in remote monitoring of crops has been addressed. It has been concluded that there is a ramp in drone application for precision agriculture after 2017. This is due to the reduction of weight, cost of UAVs, and increment in payload capability. Drones used in crop health monitoring and livestock detection are mainly multi-copter and fixed-wing types. The size and cost of these drones are continuously reducing day by day. Unmanned Helicopters are used mainly in pesticide or fertilizer spraying due to their high payload capacity. However, the application of multi-copters is continuously increasing in pesticide spraying. Multi-copters are a better option for spot spraying because of more stability in flight. Drone cameras have evolved a lot in their weights, size, and resolution. Cameras are shifting from RGB to multispectral cameras due to more feature extraction requirements.

The controllers of the drones are improved from a basic microcontroller to AI-enabled Arduino Uno and Raspberry Pi. Drone technologies are continuously shifting from semi-controlled to fully automated systems due to advanced research in embedded systems, data transmission, and data analysis. The implementation of machine learning in drones has made it possible to create a farmer-friendly system. Still, there are many issues related to the application of drone technology in the agriculture sector, which needs to be resolved to increase the adoption rate of drones. The major challenges are the cost of technology, limited battery life of drones, vision destruction, literacy about technology to end-user, and shortcomings of image processing and data analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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