Agrociencia

MODERN AGRICULTURE SYSTEMS: ENHANCING PRECISION FARMING THROUGH ADVANCED AERIAL TECHNIQUES

Mayuranathan **Mani**[1], Dhivya **Baskar**[2],
Sathish Kumar **Pakkarisamy Janakiraman**[3], Surendran **Rajendran**[4*]

[1]SRM Valliammai Engineering College. Department of Computer Science and Engineering. Kattankulathur, Tamil Nadu 603203, India.
[2]Karpaga Vinayaga College of Engineering and Technology. Department of Artificial Intelligence and Data Science. Chengalpattu, Tamil Nadu 603308, India.
[3]Panimalar Engineering College. Department of Computer Science and Engineering. Chennai, Tamil Nadu 600123, India.
[4]Saveetha Institute of Medical and Technical Sciences. Saveetha School of Engineering, Department of Computer Science and Engineering. Chennai, Tamil Nadu 602105, India.
* Author for correspondence: dr.surendran.cse@gmail.com

Citation: Mani M, Baskar D, Pakkarisamy Janakiraman SK, Rajendran S. 2025. Modern agriculture systems: Enhancing precision farming through advanced aerial techniques.
Agrociencia. https://doi.org/ 10.47163/agrociencia.v59i8.3551

Editor in Chief:
Dr. Fernando C. Gómez Merino

Received: July 09, 2025.
Approved: November 18, 2025.
Published in Agrociencia: November 20, 2025.

ABSTRACT

In modern agriculture, early detection and treatment of crop diseases and pests are necessary for increasing yields and ensuring food security. Traditional methods are labor-intensive and time-consuming, leading to inefficiencies and delayed responses. This research presents a solution using drones for continuous monitoring and automated spraying of fertilizers and pesticides. Drones equipped with multispectral, thermal, and red, green, and blue (RGB) cameras collect high-resolution images of fields, which are then processed using machine learning techniques such as YOLOv5 for disease detection and Random Forest for fertilizer classification. Data is transmitted to an Internet of Things (IoT) platform, where it i1s analyzed to generate vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which offer information on crop health. Upon detecting a disease, the system automatically triggers the drone's spraying mechanism, ensuring targeted management. Field trials demonstrate the system's ability to accurately detect diseases and optimize resource usage, improving crop health and yield. The integration of IoT enables real-time monitoring and alerts, allowing farmers to make informed decisions promptly. This study demonstrates the potential for combining drone technology, machine learning, and IoT to revolutionize agriculture, providing a scalable and efficient solution to modern farming challenges.

Keywords: Agriculture, drone technology, fertilizer spraying, Internet of Things, machine learning, triggering, real-time monitoring.

INTRODUCTION

To address the rising need for nourishment and ensure food stability objectives, modern agriculture increasingly relies on polymer coverings such as agricultural plastic sheets

(Du *et al*., 2024). Pesticide and fertilizer use is a widespread agricultural practice that protects crops from pests and diseases while enhancing yield and productivity. However, the residues these chemicals leave on food can pose significant health risks to consumers. Severe exposure can lead to acute toxicity, and long-term accumulation has been associated with hormonal disruptions, neurotoxicity, and even cancer.

Inappropriate or excessive use of fertilizers and pesticides has a negative impact on crops over time, leading to nutrient imbalances in the soil and reducing crop yields. Pesticide overuse often results in pest resistance, requiring stronger chemicals that further harm plants (Chen *et al*., 2024). Environmental consequences include soil degradation, water pollution from runoff, and air pollution from chemical volatilization. Technologies available for the application of fertilizers and pesticides include tractor-mounted sprayers, manual sprayers, robotic sprayers, and drone sprayers.

The manufacturing sector is evolving with the incorporation of cutting-edge technologies, marking the shift from conventional methods to Industry 4.0 and beyond (Dalenogare *et al.*, 2018; Ghobakhloo, 2020; Askerbekov *et al*., 2024). Technologies such as the Internet of Things (IoT), innovative analytics, radio-frequency identification (RFID), automated storage systems, and robotics tackle particular tasks, enhancing logistics and distribution coordination, stock management, and worker safety (Raj *et al*., 2020). Amid these innovations, Unmanned Aerial Vehicles (UAVs), usually referred to as drones, and their interconnected systems within the outline of the Internet of Drones (IoD), are notably transformative.

Several industries are progressively adapting drones for commercial applications to improve workflow optimization, enhance worker security, and optimize stock control (Maghazei and Netland, 2019; Ayamga *et al*., 2021). Drone adoption has expanded rapidly, with an increasing number of registered UAV units and certified pilots contributing to broader agricultural and industrial applications (The Drone Girl, 2024). The market for commercial drones was estimated at USD 19.89 billion in 2022, with forecasts indicating a compound annual growth rate of 13.9 % until 2030 (Grand View Research, 2024). Increased use in industries such as construction fuels this expansion, with drones reducing surveying durations by 85 %, thereby improving project efficiency and safety. Technological progressions and flexible regulatory frameworks worldwide, including those implemented by the US Federal Aviation Administration, have bolstered this upsurge, with more than 500 000 drones recorded for commercial purposes in the USA by 2021 (Choi *et al*., 2023).

Several recent innovations highlight the transformative potential of drones in agriculture. For example, Singh *et al*. (2024) developed an intelligent farming UAV equipped with IoT technologies that use machine learning methods, such as TensorFlow Lite with an EfficientDetLite1 model, to recognize objects from a specialized dataset trained on three crop types, including pineapple, papaya, and cabbage, achieving an inference time of 91 ms. Meesaragandla *et al*. (2024) proposed a cutting-edge strategy with increased adaptability and a more structured methodology compared to conventional techniques, leading to an impressive 60-fold boost in efficiency.

Detecting weed clusters can be achieved through image capture with drones, followed by processing and spraying. Rathore *et al*. (2024) introduced a Field Area Calculation (FAC) system using a drone, which captured images and calculated the area through image processing and Gauss's area formula (surveyor's formula). The results were compared to satellite images. The proposed method demonstrated improved performance and yielded results that closely matched expectations. Jonak *et al*. (2024) presented a technique combining a YOLOv5 classifier with high-resolution imaging using a full-frame Sony Alpha A7R IV sensor mounted on a DJI Matrice 600 drone. Their study also emphasized selecting an appropriate super-resolution method to enhance low-resolution aerial images, improving the accuracy of crop and weed detection.

Roma *et al*. (2024) used a DJI Mavic 2 Pro UAV to capture visible light images in an area characterized by complex terrain features, such as peaks and valleys. A dataset of plastic film samples was constructed, and the parameters of the U-Net deep learning model, integrated into ArcGIS Pro, were continuously adjusted and optimized to achieve accurate plastic film identification. Meanwhile, Trappey *et al*. (2023) proposed a method that employs Object-Based Image Analysis (OBIA) and Digital Elevation Models (DEM) to segment and classify images and orthomosaics, enabling the extraction of key plant metrics such as canopy area, height, volume, and NDVI.

Through an in-depth literature review, Song *et al*. (2023) analyzed both patent and non-patent literature in the field of agricultural drones and established a knowledge framework for UAV technologies. Additionally, extensive macro- and micro-level patent evaluations were performed to assess patenting trends and identify leading technologies in the agricultural drone sector. In line with ongoing drone applications, Subramaniam *et al*. (2023) designed a device featuring a circular storage system with a hammer-driven release mechanism. The release outlet is positioned 50 cm below the drone's frame within the airflow zone, and the storage unit comprises eight cylindrical compartments, each 38 mm in diameter, enabling the deployment of up to 56 balls in a single operation.

Automation and precision technologies have focused on improving efficiency, accuracy, and resource management in crop management practices. Goodrich *et al*. (2023) aimed to enhance and optimize crop-dusting with agricultural drones by developing an advanced reservoir design and a stabilized release mechanism to improve the precision and efficiency of the application. Ghafar *et al*. (2023) introduced a novel approach that utilizes a progressive gap-minimization algorithm to reduce sensor redundancy and determine optimal sensor placement across four types of agricultural fields. In addition, a genetic algorithm was applied to optimize multi-agent flight trajectories for sensor scanning within a simulated agricultural environment using a robust agent-based model.

Recent innovations in agricultural automation and precision spraying have focused on improving efficiency, reducing chemical use, and enhancing crop monitoring. Moradi *et al*. (2024) developed a two-wheeled agricultural robot equipped with a camera, wireless controller, and mobile app, enabling precise spraying of fertilizers and pesticides, automated robot movement, and continuous monitoring of crop health and growth. Similarly, Zhou *et al*. (2023) designed a dynamic fertilization management system for liquid fertilizers, combining accurate variable-rate application with deep fertilization technology using a fuzzy Proportional-Integral-Derivative (PID) algorithm. Honrao and Awadhani (2023) proposed an oscillating nozzle agriculture sprayer, which applies pesticides directly to plant spoilage and fruits, reducing waste and minimizing chemical usage.

Advances in informatics facilitate decision-making and promote sustainable farming. Deepa *et al*. (2024) proposed Agri-Ontology, a framework for structuring heterogeneous agricultural data through Natural Language Processing (NLP) techniques and ontology construction. Using BERT and Jaccard similarity, they extracted relationships from the Agrovoc dataset and used a BiGAN framework for performance evaluation, achieving an accuracy of 94.64 % and outperforming existing approaches. Building on this work, Deepa *et al*. (2025) introduced Agricultural Advancement using NLP (AA-NLP), an ontology-based framework that combines NLP techniques to process unstructured agricultural data. The system integrates named entity recognition, sentiment analysis, and semantic similarity to transform textual inputs into structured ontological knowledge, enhancing information retrieval, classification, and decision-making.

Bhargavi *et al*. (2024) proposed Smart Agriculture Computing using Quantum Natural Language Processing (SAC-QNLP) to improve decision-making and resource management. By integrating quantum computing with NLP, the framework processes large agricultural datasets more efficiently than classical methods. Simulation results showed higher forecasting accuracy and scalability, highlighting its potential to enhance productivity and sustainability. Selvaraj *et al***.** (2025) developed a hybrid model combining Vision Transformer (ViT) and Convolutional Neural Network (CNN) for multi-disease detection in coffee plants. The approach integrates a counterfactual recommendation system to suggest suitable management and preventive measures. Their model achieved 98.81 % accuracy on 1056 images and was deployed in the Affogato app to support small-scale farmers with sustainable crop management.

From the reviewed literature, it is clear that although drones and machine learning are applied for crop monitoring, weed detection, and spraying, several limitations remain. Many models are dataset-specific and fail to generalize across different crops and environments. Approaches like U-Net or OBIA need large datasets and high computational power, limiting real-time use. Furthermore, some studies focus solely on detection without providing management recommendations or enabling automated spraying, and manual calibration of sensors and spraying systems can further reduce accuracy. These gaps remark the need for an integrated, IoT-enabled framework capable of real-time detection, classification, and precise spraying. In response, this work proposes a novel technology that combines drones and robots for continuous crop health monitoring and the targeted application of fertilizers and pesticides.

MATERIALS AND METHODS

This study proposes the use of advanced agricultural drones for the continuous monitoring of crops. High-resolution cameras capture crop images, which are then transmitted via Wi-Fi to an IoT-based cloud platform for storage and preprocessing using cloud computing services. The preprocessed data are analyzed using machine learning techniques such as YOLOv5, which trains and validates models to detect the presence of diseases or pests. Once identified, relevant features are extracted and classified using a Random Forest algorithm, allowing the system to recommend suitable management. Based on these recommendations, the drone autonomously applies the appropriate fertilizers or pesticides in precise quantities.

Crop image dataset

The proposed method allows pest and disease detection using cameras, followed by the application of appropriate management via drones. Images of maize and tomato crops, collected at different time intervals to capture variability in growth stages and environmental conditions, are included in the dataset provided by Kwabena *et al*. (2023) for crop pest and disease detection. The dataset was divided into two categories: (i) raw images, comprising 10 734 samples, including 5389 maize (*Zea mays* L.) and 5435 tomato (*Solanum lycopersicum* L.) images; and (ii) augmented images, which were further split into training and testing sets containing 50 835 images (23 657 maize and 27 178 tomato samples) and classified into 12 categories according to pest and disease symptoms: seven for maize (healthy, fall armyworm, leaf blight, maize streak virus, leaf spot, grasshopper, and leaf beetle) and five for tomato (healthy, tomato leaf curl virus, leaf blight, *Septoria* leaf spot, and *Verticillium* wilt). All images were stored in .jpg format, with dimensions of either 3024 × 4032 or 4032 × 3024 pixels. Images were captured under diverse background conditions, including white, illuminated, dark, and natural settings.

IoT cloud integration

Collected crop data were transmitted to the IoT cloud using wireless communication technology. The Wi-Fi module established a TCP/IP connection with the cloud and transmitted images through a Representational State Transfer Application Programming Interface (REST API) web service. To ensure data reliability, image files were sent in chunks. Upon reaching the cloud server, the data were securely stored in Google Cloud Storage for subsequent processing and analysis.

In the proposed system, the Internet of Things (IoT) plays a central role in enabling real-time connectivity, data management, and decision-making. The IoT framework functions as an intermediary between the agricultural field and the cloud platform by collecting images from drones and transmitting them securely via Wi-Fi 6 and REST API protocols. Once uploaded, the IoT infrastructure enables seamless integration with machine learning models (YOLOv5 and Random Forest) for automated disease detection and management recommendation. Furthermore, IoT provides real-time alerts and feedback through connected devices, allowing remote monitoring of crop health. This integration ensures continuous surveillance, low-latency data transmission, and automated drone activation for spraying operations, thereby increasing the efficiency of pest and disease management while providing actionable, cloud-based insights for precision agriculture.

Machine learning algorithm

You Only Look Once version 5 (YOLOv5) is an advanced one-stage object detection algorithm widely recognized for its speed and accuracy in real-time applications. It consists of three major components: the backbone, neck, and detector. The backbone extracts and processes image features using Convolutional Neural Networks (CNNs), while the neck bridges the backbone and detector by generating multi-scale feature maps through a Feature Pyramid Network (FPN), enhancing detection of objects of varying sizes. The detector then predicts bounding boxes and class probabilities to identify the target objects.

In this study, YOLOv5 was used to analyze drone-captured images of crops and accurately detect symptoms of pest infestation and plant diseases in real time. Its lightweight architecture enables low-latency processing on edge devices, making it ideal for agricultural drones that must handle large image datasets during flight. Once the affected regions are detected, a Random Forest algorithm classifies the identified diseases or pests and recommends appropriate fertilizers and pesticides based on learned patterns from the training dataset.

By integrating detection and recommendation, the proposed machine learning framework minimizes human error, accelerates decision-making, and supports precision agriculture by ensuring that each crop receives timely and targeted management. YOLOv5 was selected for its superior performance compared to traditional two-stage models such as Faster R-CNN, achieving an overall accuracy of 96 %, with 95 % precision and 93 % recall in this work. These results are consistent with previous findings (Jonak *et al*., 2024; Singh *et al*., 2024), confirming YOLOv5's suitability for high-performance, real-time detection of crop pests and diseases in dynamic agricultural environments.

The detector used sophisticated feature maps to identify the bounding boxes and class possibilities of each identified object. YOLO segments the input image into a grid, with each cell responsible for detecting multiple bounding boxes and assigning confidence scores. Class labels are then allocated to the boxes with the highest scores, enabling real-time detection and classification of multiple objects simultaneously. The overall workflow of the proposed system is illustrated (Figure 1).

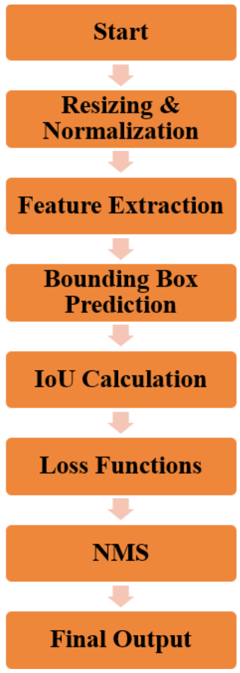

Figure 1. Schematic representation of the proposed disease detection process.

Training and testing

In this study, a dataset of 50 835 images was utilized and divided into two subsets: 80 % (40 668 images) for training and 20 % (10 167 images) for testing. All images were resized to a uniform resolution of 256 × 256 pixels to ensure consistency across the dataset. This approach enabled the machine learning model to learn from a wide range of conditions and visual features. The training subset was used to develop a robust detection model, while the testing subset served to evaluate its accuracy and overall performance.

Management recommendation

After the detection of diseases and pests, the Random Forest algorithm was used to recommend suitable fertilizers and pesticides. As a robust ensemble learning method widely applied in classification and regression tasks, Random Forest was trained using datasets encompassing major maize and tomato diseases and pests, along with their corresponding treatments (Table 1). These combinations, derived from established agronomic practices and prior research, allowed the model to generate precise, data-driven, and condition-specific treatment recommendations.

Following the detection of crop diseases and pests, the Random Forest algorithm was used to recommend appropriate fertilizers and pesticides. Gini impurity measures the degree of impurity at a node within a decision tree, representing the probability that a randomly chosen element would be incorrectly classified:

Table 1. Pest and disease management recommendations of maize (*Zea mays* L.) and tomato (*Solanum lycopersicum* L.) provided by the Random Forest algorithm.

Crop	Disease	Suitable fertilizer	Suitable pesticide
Maize	Northern leaf blight (*Exserohilum turcicum*)	Nitrogen-rich fertilizer	Mancozeb, Azoxystrobin
	Gray leaf spot (*Cercospora* sp.)	Potassium-rich fertilizer	Propiconazole, Tebuconazole
	Common rust (*Puccinia* sp.)	Phosphorus-rich fertilizer	Chlorothalonil, Mancozeb
	Corn borer (*Ostrinia nubilalis*)	Nitrogen-rich fertilizer	Permethrin, *Bacillus thuriniensis*
	Armyworm (*Spodoptera frugiperda*)	Potassium-rich fertilizer	Spinosad, Lambda-cyhalothrin
	Corn rootworm (*Diabrotica* sp.)	Phosphorus-rich fertilizer	Bifenthrin, Clothianidin
Tomato	Early blight (*Alternaria* sp.)	Nitrogen-rich fertilizer	Chlorothalonil, Mancozeb
	Late blight (*Phytophthora infestans*)	Potassium-rich fertilizer	Copper fungicides, Mancozeb
	Septoria leaf spot (*Septoria lycopersici*)	Phosphorus-rich fertilizer	Chlorothalonil, copper fungicides
	Tomato hornworm (*Manduca quinquemaculata*)	Nitrogen-rich fertilizer	*Bacillus thuringiensis*, Spinosad
	Whiteflies (*Bemisia* sp.)	Potassium-rich fertilizer	Imidacloprid, Neem oil
	Aphids (*Aphis* sp.)	Phosphorus-rich fertilizer	Pyrethrin

$$Gini = 1 - \sum_{i=1}^{n} (p_i)^2$$

where p_i represents the probability of class i at a particular node.

Entropy quantifies the amount of uncertainty or randomness in a dataset:

$$Entropy = -\sum_{i=1}^{n} p_i log_2(p_i)$$

Information Gain (IG) measures the effectiveness of a split in a decision tree by measuring the reduction in entropy achieved after the split:

$$IG = Entropy(parent) - \sum_{j} \frac{N_j}{N} Entropy(child_j)$$

where N_j represents the number of samples in child node j and N is the total number of nodes.

The Out-of-Bag (OOB) error is used to estimate the generalization performance. It is calculated as the average error for each training instance, using only the trees that excluded that instance in their bootstrap samples.

$$OOB\ Error = \frac{1}{N}\sum_{i=1}^{N} I(y_i \neq \hat{y}OOB, i)$$

where N denotes the total number of training instances, y_i is the actual label, and $\hat{y}OOB, i$ is the predicted label from the OOB samples.

Feature importance measures the contribution of each feature in predicting the target variable. It is computed as the average decrease in impurity across all trees in the forest whenever a feature is used for splitting:

$$Feature\ Importance = \frac{1}{T}\sum_{t=1}^{T}(\frac{\Delta\ Impurity(t)}{Number\ of\ splits}$$

where T is the total number of trees, and Δ *Impurity*(t) is the decrease in impurity for tree t.

Implementation of the UAV-based precision spraying

The spraying process in the proposed system was implemented using the onboard mechanism of the Yamaha RMAX drone. This robust and versatile UAV is widely used in agricultural and industrial applications. It was introduced in the 1990s and has become a leading platform for precision spraying, crop monitoring, and data acquisition. It features a two-stroke liquid-cooled engine that ensures stability and endurance during flight and a 28 L payload tank connected to a multi-nozzle spraying system for uniform and efficient distribution of liquid fertilizers and pesticides (Figure 2).

Once the algorithms detect and classify crop diseases or pests, the corresponding treatment recommendations are transmitted to the drone controller via an IoT-based communication platform. The variable-rate control unit automatically adjusts nozzle flow according to the severity and spatial extent of the detected infection. This precision-targeted spraying approach minimizes over-application, reduces chemical wastage, and limits environmental exposure. The RMAX operates at a flight altitude of 2–3 m above the crop canopy and applies treatments in optimized swath patterns with overlap correction to ensure even coverage. Compared with manual spraying,

Figure 2. Schematic representation of the Yamaha RMAX- Unmanned Aerial Vehicle (UAV) spraying mechanism used in the proposed system.

this system provides higher accuracy, lower environmental impact, and greater efficiency in large-scale agricultural operations. The technical specifications of the Yamaha RMAX are summarized (Table 2).

Performance metrics such as accuracy, precision, recall (sensitivity), and F1-score are essential for evaluating the effectiveness of machine learning models. Accuracy measures the proportion of correctly predicted instances out of the total number of instances. Precision evaluates the proportion of correctly predicted positive cases among all predicted positives, while recall (or sensitivity) measures the proportion of actual positive cases that are correctly identified by the model. The F1-score represents the harmonic mean of precision and recall, providing a balanced measure of both. These metrics are computed based on the values of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

Table 2. Technical specifications of the Yamaha RMAX-Unmanned Aerial Vehicle (UAV) used in the proposed spraying system.

Specifications		Details
Dimensions	Length	3.63 m
	Width	0.72 m
	Height	1.08 m
Weight	Empty weight	64 kg
	Maximum takeoff weight	94 kg
	Payload Capacity	28–31 kg
Power and Performance	Powerplant	Water-cooled, two-cylinder, two-stroke engine
	Main rotor diameter	3.115 m
	Endurance	Approximately 1 h per flight
Usage and Approvals	Countries used	Japan, Australia, South Korea, United States
	US Federal Aviation Administration approval	Approved for agriculture operations including pesticides and fertilizers spraying
	Flight condition	Flight below 60 m, within visual line of sight

RESULTS AND DISCUSSION

The confusion matrix (Figure 3) illustrates the classification performance of the model across three classes (0, 1, and 2). The model accurately predicted Class 0 in 68 instances, while 13 instances of Class 0 were misclassified as Class 2.

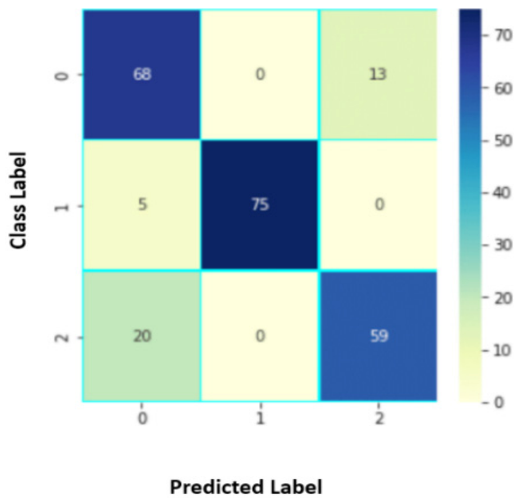

Figure 3. Confusion matrix illustrating the classification performance of the model across three classes (0, 1, and 2).

For Class 1, the model demonstrated high accuracy, correctly predicting 75 instances with only five misclassifications in Class 0. For Class 2, the model correctly identified 59 instances but misclassified 20 instances as Class 0. These results indicate that the model performs well for Class 1 with minimal error, whereas Class 2 has the highest misclassification rate, particularly with Class 0. Overall, the model maintains good classification accuracy but shows variability across classes, which indicates that it requires refinement in distinguishing between Classes 0 and 2.

The performance of YOLOv5 and Random Forest classifiers for crop disease detection and treatment recommendation demonstrated superior performance (Table 3). Both models achieve high accuracy, but Random Forest consistently outperformed

Table 3. Performance metrics of YOLOv5 and Random Forest for crop disease detection and treatment recommendation.

	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
YOLOv5	96	95	93	94
Random Forest	97	96	95	95.5

YOLOv5 across all metrics, with slightly higher precision, recall, and F1-score. This demonstrates that Random Forest provides more reliable and consistent predictions for the dataset, supporting accurate treatment recommendations.

Drone-based spraying offers several advantages over traditional manual spraying in agriculture. By reducing direct contact with chemical fertilizers and pesticides, drones minimize health risks to human workers. Additionally, drones cover larger areas in less time, whereas manual spraying is more labor-intensive and time-consuming. Over the long term, drones prove to be cost-effective by lowering labor expenses and optimizing the use of fertilizers and pesticides, while human spraying incurs higher labor and equipment costs. Drones provide real-time monitoring and dynamic adjustments during application. Overall, drone-based spraying is safer, more efficient, and more economically advantageous compared to conventional human spraying techniques.

The comparison of agricultural drones (Table 4) highlights differences in payload capacity, flight duration, coverage area, and spraying efficiency. The DJI Agras T20 and Yamaha RMAX each support payloads of up to 20 kg, making them suitable for large-scale field operations (Yamaha Motor Co., 2017; DJI, 2020). The Yamaha RMAX further demonstrates the longest reported operational endurance (60–90 min), a spray width of approximately 7 m, and a control range of up to 10 km, enabling wider coverage per mission (Zhang and Kovacs, 2012; Yamaha Motor Co., 2017). The DJI Agras T20, while operating with a slightly shorter flight time, can spray up to 30 ha per deployment (DJI, 2020).

Other platforms, such as the DJI Agras MG-1S and Yuneec H520E, offer lower payload capacity and shorter endurance, making them more appropriate for medium- or small-scale fields (Tsouros *et al*., 2019). Lightweight fixed-wing models like the Parrot Bluegrass and SenseFly eBee X provide longer flight times but are limited in

Table 4. Comparative specifications of agricultural drones for crop spraying applications.

Drone Model	Payload Capacity	Maximum Flight time	Coverage area per flight	Spray width	Spray system	Control range
DJI Agras T20	20 kg	15–20 min	Up to 30 ha	5 m	Four-nozzle system	5 km
DJI Agras MG-1S	10 kg	10–15 min	Up to 10 ha	5 m	Four-nozzle system	2 km
Yuneec H520E	5 kg	30 min	Up to 5 ha	4 m	Two-nozzle system	1.6 km
Parrot Bluegrass	1.8 kg	25–30 min	Up to 7 ha	2 m	One-nozzle system	2 km
SenseFly eBee X	1.6 kg	50–60 min	Up to 20 ha	3 m	Variable	5 km
Yamaha RMAX	20 kg	60–90 min	Up to 10 ha	7 m	Six-nozzle system	10 km

payload and spray volume, reducing their utility for dense crop coverage (Radoglou-Grammatikis *et al*., 2020). Overall, based on payload capability, flight endurance, and spray coverage, the Yamaha RMAX remains well-suited for large-scale fertilizer and pesticide applications.

CONCLUSION

This study established a precision spraying system for crops that applies suitable fertilizers and pesticides based on real-time detection of diseases and pests. The framework integrates the YOLOv5 model for accurate identification of multiple crop diseases and pests, while the Random Forest algorithm processes this information to recommend the appropriate fertilizers and pesticides. The Yamaha RMAX drone, equipped with a multi-nozzle spraying system, was employed to execute precise chemical application. By combining detection, recommendation, and automated spraying, the system reduces chemical wastage, minimizes environmental impact, and enhances overall crop management efficiency. This integrated approach not only improves precision in crop protection but also supports sustainable farming by optimizing the use of agricultural inputs.

The framework can be further advanced through improvements in sensor technology, autonomous drone navigation, and predictive modeling for crop management. Incorporating blockchain technology could enhance data security and traceability, while assessing environmental impacts would strengthen sustainability. Additionally, addressing socio-economic factors, such as making the technology accessible to small-scale farmers, could maximize its benefits, contributing to food security, rural economic growth, and broader adoption of precision agriculture practices.

REFERENCES

Askerbekov D, Garza-Reyes JA, Ghatak RR, Joshi R, Kandasamy J, Nascimento DLM. 2024. Embracing drones and the Internet of drones systems in manufacturing–An exploration of obstacles. Technology in Society 78: 102648. https://doi.org/10.1016/j.techsoc.2024.102648

Ayamga M, Akaba S, Nyaaba AA. 2021. Multifaceted applicability of drones: A review. Technological Forecasting and Social Change 167: 120677. https://doi.org/10.1016/j.techfore.2021.120677

Bhargavi G, Das M, Banumathi S, Malarvizhi E, Surendran R. 2024. Leveraging NLP and quantum computing for advanced agricultural solutions. *In* 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA). Institute of Electrical and Electronics Engineers. Coimbatore, India, pp: 900–906. https://doi.org/10.1109/iceca63461.2024.10800767

Chen C, Hussain Z, Liu J, Zaman M, Akhlaq M. 2024. Innovative technologies in sprinkler irrigation: An overview. Agrociencia 58 (7): 1–18. https://doi.org/10.47163/agrociencia.v58i7.3191

Choi U, Moon C, Ahn J. 2023. Energy minimization of dynamic multi-UAV communication network for cooperative multihop data gathering. IEEE Transactions on Aerospace and Electronic Systems 59 (3): 3082–3099. https://doi.org/10.1109/taes.2022.3221031

Dalenogare LS, Benitez GB, Ayala NF, Frank AG. 2018. The expected contribution of Industry 4.0 technologies for industrial performance. International Journal of Production Economics 204: 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

Deepa R, Das M, Thilakavathy P, Prabhu AB, Surendran R. 2024. Harvesting knowledge: An innovative ontology framework for agricultural advancement using NLP methodologies. *In* 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT). Institute of Electrical and Electronics Engineers. Tiruchirappalli, India, pp: 1–7. https://doi.org/10.1109/iceeict61591.2024.10718542

Deepa R, Jayaraman V, Srinivasulu S, Umamageswari B, Surendran R. 2025. Agri-ontology: A novel ontology framework for agricultural domain. *In* 2025 International Conference on Electronics and Renewable Systems (ICEARS). Institute of Electrical and Electronics Engineers. Tuticorin, India, pp. 1151–1157. https://doi.org/10.1109/icears64219.2025.10941477

DJI (Da Jiang Innovations). 2020. DJI AGRAS T20 support. Shenzhen DJI Sciences and Technologies Ltd. Shenzhen, China. https://www.dji.com/mx/support/product/t20 (Retrieved: October 2025).

Du X, Huang D, Dai L, Du X. 2024. Recognition of plastic film in terrain-fragmented areas based on drone visible light images. Agriculture 14 (5): 736. https://doi.org/10.3390/agriculture14050736

Ghafar AS, Hajjaj SSH, Gsangaya KR, Sultan MTH, Mail MF, Hua LS. 2023. Design and development of a robot for spraying fertilizers and pesticides for agriculture. Materials Today: Proceedings 81: 242–248. https://doi.org/10.1016/j.matpr.2021.03.174

Ghobakhloo M. 2020. Industry 4.0, digitization, and opportunities for sustainability. Journal of Cleaner Production 252: 119869. https://doi.org/10.1016/j.jclepro.2019.119869

Goodrich P, Betancourt O, Arias AC, Zohdi T. 2023. Placement and drone flight path mapping of agricultural soil sensors using machine learning. Computers and Electronics in Agriculture 205: 107591. https://doi.org/10.1016/j.compag.2022.107591

Grand View Research. 2024. Commercial drone market size, share and trends report 2030. Grand View Research. San Francisco, CA, USA. https://www.grandviewresearch.com/industry-analysis/global-commercial-drones-market (Retrieved: October 2025).

Honrao DV, Awadhani LV. 2023. Design and development of agricultural spraying system. Materials Today: Proceedings 77: 734–738. https://doi.org/10.1016/j.matpr.2022.11.417

Jonak M, Mucha J, Jezek S, Kovac D, Cziria K. 2024. SPAGRI-AI: Smart precision agriculture dataset of aerial images at different heights for crop and weed detection using super-resolution. Agricultural Systems 216: 103876. https://doi.org/10.1016/j.agsy.2024.103876

Kwabena MP, Akoto-Adjepong V, Adu K, Ayidzoe MA, Bediako E, Nyarko-Boateng O, Boateng S, Donkor FE, Bawah FU, Awarayi S, *et al*. 2023. Dataset for crop pest and disease detection. Mendeley Data V1. https://doi.org/10.17632/bwh3zbpkpv.1

Maghazei O, Netland T. 2019. Drones in manufacturing: Exploring opportunities for research and practice. Journal of Manufacturing Technology Management 31 (6): 1237–1259. https://doi.org/10.1108/jmtm-03-2019-0099

Meesaragandla S, Jagtap MP, Khatri N, Madan H, Vadduri AA. 2024. Herbicide spraying and weed identification using drone technology in modern farms: A comprehensive review. Results in Engineering 21: 101870. https://doi.org/10.1016/j.rineng.2024.101870

Moradi S, Babapoor A, Ghanbarlou S, Kalashgarani MY, Salahshoori I, Seyfaee A. 2024. Toward a new generation of fertilizers with the approach of controlled-release fertilizers: A review. Journal of Coatings Technology and Research 21 (1): 31–54. https://doi.org/10.1007/s11998-023-00817-z

Radoglou-Grammatikis P, Sarigiannidis P, Lagkas T, Moscholios I. 2020. A compilation of UAV applications for precision agriculture. Computer Networks 172: 107148. https://doi.org/10.1016/j.comnet.2020.107148

Raj A, Dwivedi G, Sharma A, Lopes De Sousa Jabbour AB, Rajak S. 2020. Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. International Journal of Production Economics 224: 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Rathore R, Ahamad S, Soni A, Dewangan AK, Jain A. 2024. Agriculture field area calculation using drone camera: Method and framework design. SN Computer Science 5 (2). https://doi.org/10.1007/s42979-023-02577-4

Roma E, Catania P, Vallone M, Orlando S. 2024. Assessing the effectiveness of pruning in an olive orchard using a drone and a multispectral camera: A three-year study. Agronomy 14 (5): 1023. https://doi.org/10.3390/agronomy14051023

Selvaraj K, Selvanarayanan R, Venkatesan SKG, Rajendran S. 2025. Future-proof coffee plant disease detection based on counter-factual recommendation with a hybrid vision transformer and convolutional neural network model. Agrociencia 59 (4): 1–24. https://doi.org/10.47163/agrociencia.v59i4.3385

Singh E, Pratap A, Mehta U, Azid SI. 2024. Smart agriculture drone for crop spraying using image-processing and machine learning techniques: Experimental validation. IoT, 5 (2): 250–270. https://doi.org/10.3390/iot5020013

Song C, Wang Q, Wang G, Liu L, Zhang T, Han J, Lan Y. 2023. Study on the design and experiment of Trichogramma ball delivery system based on agricultural drone. Drones 7 (10): 632. https://doi.org/10.3390/drones7100632

Subramaniam R, Hajjaj SSH, Gsangaya KR, Sultan MTH, Mail MF, Hua LS. 2023. Redesigning dispenser component to enhance performance crop-dusting agriculture drones. Materials Today: Proceedings 81: 166–172. https://doi.org/10.1016/j.matpr.2021.03.015

The Drone Girl. 2024. The state of drones in 2024: How many drones are registered in the U.S., and how many pilots are certified? San Francisco, CA, USA. https://www.thedronegirl.com/2024/04/01/drones-in-2024 (Retrieved: October 2024).

Trappey AJC, Lin GB, Chen HK, Chen MC. 2023. A comprehensive analysis of global patent landscape for recent R&D in agricultural drone technologies. World Patent Information 74: 102216. https://doi.org/10.1016/j.wpi.2023.102216

Tsouros DC, Bibi S, Sarigiannidis PG. 2019. A review on UAV-based applications for precision agriculture. Information 10 (11): 349. https://doi.org/10.3390/info10110349

Yamaha Motor Co. 2017. RMAX industrial unmanned helicopter: Product specifications. Yamaha Motor Corporation. Iwata, Japan.

Zhang C, Kovacs JM. 2012. The application of small unmanned aerial systems for precision agriculture: A review. Precision Agriculture 13 (6): 693–712. https://doi.org/10.1007/s11119-012-9274-5

Zhou W, An T, Wang J, Fu Q, Wen N, Sun X, Wang Q, Liu Z. 2023. Design and experiment of a targeted variable fertilization control system for deep application of liquid fertilizer. Agronomy 13 (7): 1687. https://doi.org/10.3390/agronomy13071687