SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 5.1, (2026), pp. 29-43
Open Access. Online & Print

DOI: 10.5281/zenodo.12511003

A DEEP LEARNING BASED MODEL FOR CROP YIELD PREDICTION USING UAV-BASED CROP HEALTH MONITORING

Praveen Kumar K[1]*, S H Manjula[2]

[1,2] *Department of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bengaluru – 560001, Karnataka, India.*

Received: 01/12/2025
Accepted: 02/01/2026

Corresponding author: Praveen Kumar K (pksjp2013@gmail.com)

ABSTRACT

Capacity planning in precision agriculture can be achieved through crop yield prediction. UAV analysis assists in the observation of crop health for several kinds of plants so that yield analysis can be performed. Estimating yield through empirical field survey data is a widespread practice It takes a lot of time and offers smudge output in actual field conditions. The Proposed system uses different Unmanned Aerial Vehicles (UAV) with Deep Learning models for performing an automated crop health monitoring system. It also allows for estimating yield based on data from unmanned aerial vehicles. In this research article, we propose a framework based on Machine Learning (ML) techniques for estimating the crop yield from UAV-based crop health monitoring. The framework that we propose uses a Convolutional neural network (CNN) model that uses a fine-tuned ResNet50 architecture. It uses a consecutive classification scheme to classify the UAV based aerial images into Healthy, Stressed and Infected crop classes. The yield of a crop will be predicted by using the previously predicted variables. The dataset used for training and testing the CNN model is PlantVillage. The five-fold cross-validation of the model resulted in an accuracy of 96.2%, precision of 95.7, recall of 96.8 and F1 of 96.2%. The 87model was used on aerial images taken in real-time from fields for evaluation of generalized efficiency. The model preserves its power to generalize, with a 90.0% accuracy and an F1 score of 87.4%. Regression metrics were used to evaluate the yield prediction results quantitatively. The approach proposed obtained 0.42 t/ha MAE (mean absolute error), 0.58 t/ha RMSE (root mean square error), and high $R2$ ($R2$ = 0.91), relating to good correlation between predicted and ground truth values. The findings of statistical significance analysis were evaluated quantitatively to indicate the difference between approaches, which revealed that the proposed method statistically significantly outperformed the traditional yield estimation methods at p < 0.01. The incorporation of CNN inference and UAV control logic for selective spraying has led to a substantive 31% reduction of pesticide use along with an impacted area spraying accuracy of 87.2% depicting smooth operation of the system.

KEYWORDS: UAV-based agriculture, Crop health monitoring, Crop yield prediction, Machine Learning, Deep Learning, Convolutional Neural Networks, Precision agriculture, Remote sensing

1. INTRODUCTION

The world's food systems would not have been possible without agriculture, especially in regions where agriculture is the sole livelihood for most of the population. It is predicted that by 2050, the global population will exceed 9 billion people. We will have to respond with increased food production, that also requires to be more efficient and sustainable [1]. Conventional farming has limitations with respect to the data driven insights required for precision farming to deal with the increasing challenges faced by farming for example, traditional farming systems have faced the challenge of delayed detection of disease outbreaks and pest attacks; inefficient utilization of water, fertilizers and pesticides; and poor yields. Due to technological evolution in automation, sensing and communication engineering techniques have been developed for agriculture management. The deployment of an Unmanned Aerial Vehicle helps in monitoring the targeted field at an unprecedented resolution on demand. Unmanned aerial vehicles equipped with imaging sensors are capable of obtaining the information related to crop health, water stress, pest and disease infestation at field scale. UAV images have significantly higher spatial resolution and temporal resolution than the satellite images. As a result, the use of UAVs produces timely prescription decision-making precision. UAV-based tool will be helpful for farmers and stakeholders with further integration of IoT-components. The main objective of the IoT-based environment monitoring system project is the environmental condition assessment if needed [2].

However, in case of AI, especially Deep Learning (DL), UAV based system can prove to be a game changer. UAV images can be used for intervention and automation of crop health identification and quantification by various deep networks. For example, Convolutional Neural Networks can be modified for image classification applications, while sequence architectures like Long Short-Term Memory would work for yield estimation and growth trend analysis. Most UAV-based systems continue to depend on visual inspection, manual inspection, or fixed interval pesticide spraying. One of the most significant gaps in the present-day scenario is using a unified and intelligent UAV framework capable of real-time monitoring and in-flight actuation control for intervention. There have been many attempts made so far, but they are either for monitoring of the crops or they require offline processing or human-in-the-loop supervision. To fill this gap, we present SmartSpray, a Deep Learning-based UAV framework for real-time classification for crop health state and expert spraying. Unlike most UAV uses for which offline processing or manual reverse control is needed, we allow onboard CNN inference for real-time detection of stressed/infected crop states. After detection, the relay controller is triggered for in-flight spraying of the affected areas of the crop. The controlled-use framework decreasing the agrochemical application in disease-causing areas can significantly lower the disease impact [3].

The primary objective of this research is to design and implement a cost-effective, scalable, and autonomous UAV-based precision agriculture system that integrates Deep Learning with real-time field operations for crop health assessment and yield prediction. Specifically, the objectives of this work are: (i) to develop a CNN-based model for classifying crop regions as healthy, stressed, or infected using UAV-acquired imagery; (ii) to model crop yield prediction by correlating UAV-derived crop health indicators with yield outcomes using Machine Learning techniques; (iii) to design an autonomous relay-controlled spraying mechanism that responds to CNN-based detections; (iv) to validate the system using both the PlantVillage dataset and real-world UAV field imagery; and (v) to evaluate operational benefits in terms of yield prediction accuracy, chemical savings, spraying precision, and response time [4].

Key contributions included a lightweight CNN model which is able to classify the in-flight crop health, and can be deployed on edge-computing platforms. On the PlantVillage dataset, we achieved 96.2 % validation accuracy and a 90.0 % accuracy under field conditions. Merging of the classification model with an Arduino model of a spraying system giving 31% reduced usage of agrochemicals with 87.2% affected-area spraying accuracy. The system's performance, which is almost in real-time with an average inference time of 0.9 s per image-patch, supports fully autonomous operation of the UAV. The system has been developed to address the need to modernize the crop monitoring and application of various resources. Food demand is increasing, cultivable land is diminishing, and climate uncertainty is rising. Accordingly, it is necessary to develop an intelligent, economical, and environmentally-friendly system for farmers. Several difficulties are faced by growers, like late diagnosis of disease, use of heavy/light chemicals and product estimation by empirical judgment. Hence, the cost is increased and yield is reduced. Due to technological advancements in UAV hardware, embedded AI computing and miniaturization of sensors, intelligent data-driven systems can now be deployed actively in the field at relatively low cost.

2. LITERATURE REVIEW

Machine Learning and Deep Learning are the leading technologies for plant diseases. The latest studies done in Agriculture technology (AgriTech) field show that the Machine Learning and Deep Learning techniques deployed Unmanned Aerial Vehicle (UAV) have good potential for use in crop health monitoring, disease detection and yield prediction. These technologies rely on sensors attached to the drone for data collection. Computer vision and Machine Learning algorithms are used for the analysis of the data generated. Data from RGB, thermal and multispectral sensors mounted on UAV, in the form of a color image, is useful to detect and identify disease in a crop. Using data-driven models for image data offers a dovetailing approach by which decisions can be taken at the farm level. As an example, the work on crop disease detection using RGB images from the UAV camera with CNN models by Zhou et al. [5] achieved 89.5% accuracy. The downside of their method, nonetheless, is the absence of an actuation mechanism for UAV operation, as well as the realization of a real-time intervention at the level of the field. In a similar manner, Patel et al. [6] perform a case study on yield estimation using LSTM models with multispectral UAV data and get an accuracy of 85.3%. Just like that, their work is limited because it relies on post-processing. They failed to suggest any crop health classification at the image level or action in real-time. Agro Deep Learning Framework is another work proposed by Evaluated advances semantic segmentation models composed of DeepLabV3+ and SegFormer Softmax [8] Using UAV imagery, they obtained 91.0% accuracy for crop segmentation. The lightweight models performed remarkably well concerning segmentation efficiency. Nonetheless, they cost too much to use. Did not make a consideration.

Lee [9] his colleagues described different surveys on Deep Learning techniques for UAV images data in agriculture. They explained about a number of things like algorithm design, dataset properties and model generalizability. The emerging design trends like lightweight models, edge computing and data compression were also discussed. Yet, real-time data analytics and flight control are not of existing use in closed-loop agricultural systems. According to the authors, this carbon auctioned for crop farming may lead to bad consequences. Jain et al. [10] surveyed various Machine Learning techniques for precision agriculture using UAV. They detailed various ML-based models and their pros and cons. Moreover, there is a requirement to concentrate monitoring, analytics, and autonomous actions into one system to allow effective field-level intervention. Essentially, this system can enhance efficiency, but detailed research is needed to trace this area. According to [11] Rao et al., a drone image data-based framework has been proposed by using CNN. In suboptimal imaging conditions, their framework correctly classified several disease classes. Nonetheless, the framework does not enable decision-making or autonomous spraying in real time. The Multi-vision Monitoring (MVM) system, proposed in Li et al. [12], reproduces the constrained scenario and does multi-vision learning for multi-task processing. Using UAV-acquired RGB image and video data, the MVM framework simultaneously observes crop conditions and identifies farm operations. The framework obtains good overall accuracy and also proves the strength of multi. Multi-Source data Fusion of Satellite and UAV Images for Crop Monitoring using Machine Learning. The study suggests the fusion of satellite and UAV information to conduct crop surveillance using Machine Learning. Estimation of the crop biomass and leaf area index improves through multisource data integration. Also, UAV image has a complementary role for improvement.

2.1. Research Gap and Motivation

Despite notable progress in UAV-based crop monitoring and Deep Learning–driven agricultural analytics, a significant research gap remains. Most existing systems are restricted to offline image analysis, post-flight processing, or analytics dashboards that require human intervention for decision execution, with limited emphasis on quantitative crop yield prediction derived from UAV-based crop health indicators. Very few frameworks support real-time inference combined with autonomous agrochemical application during UAV flight [14]. Moreover, yield estimation in many prior studies relies on empirical or historical models that are weakly coupled with real-time crop health conditions, limiting their predictive reliability. Furthermore, the lack of end-to-end closed-loop integration between crop health classification, yield prediction, and physical actuation results in delayed responses and inefficient resource utilization. The proposed work addresses this gap by introducing a unified, Deep Learning driven UAV framework that performs onboard crop health classification, models crop yield prediction using health-based indicators, and immediately initiates selective pesticide spraying [15]. By tightly coupling sensing, predictive analytics, decision-making, and actuation, the system enables accurate yield forecasting, precise intervention, and autonomous, resource-efficient agricultural operations. This closed-loop design advances the state of the art in precision agriculture by moving beyond isolated monitoring and analytics toward real-time, intelligent field intervention [16].

2.2. System Design

The UAV based Machine Learning framework proposed system design is for crop yield prediction through crop health monitoring. In contrast to conventional UAV sensing systems that heavily rely on visual field inspection or spraying operations at predefined schedules, the suggested framework combines UAV sensing with IoT-enabled hardware for field-level crop yield prediction powered by Machine Learning models. [17] The drone is capable of sending image data along with a sequence of environmental parameters for ensuing analysis of crop health. Correctly evaluating the health of crops at the ground can help to provide an accurate assessment of yield at the field level. The proposed system shows the enhancement of the overall system effectiveness and crop yield prediction accuracy with the help of UAV image processing-driven Machine Learning in the agricultural field. The Physical Architecture is divided into two parts i.e Device and programme. The hardware architecture has three parts. Structure of system, Driving force and Power supply. According to the paper [18], various UAV platforms are available to facilitate the stable flying of UAVs, support their payload, and embed a computer on the UAV platform. One of the more sought-after drone chassis that is found in the market is the modular Quad copter chassis. A drone essential mounting frame is built into the quad copter chassis that provide a chassis. The mid-frame holds the arms supporting the motors. The whole structure is chassis. One very popular modular chassis is DJI Flame Wheel F450.The propulsion system is made up of components that help the drone to gain height and stay in the air like a bird. It contains a machine part.

The navigation of the UAV uses four control axes: roll, pitch, yaw, and throttle. A flight mission of an unmanned aerial vehicle (UAV) can be considered either a waypoint-based flight or an adaptive path for field coverage based on the coverage requirement of the mission. The radio transmitter-receiver has manual over-ride control for field deployment safety. The RGB camera and thermal sensor are used for crop health monitoring. An RGB camera is being installed on the UAV for aerial photography. The thermal sensor monitors the stress levels of the plant. We use MPU-6050 for motion sensing and data and inertial measuring. The information goes through an edge shape computing unit mounted on UAV or sent to the ground station for further processing. A wireless communication device is used for exchanging information between system components and monitoring station. Depending on the requirements either ZigBee or Wi-Fi communication module is used. Both implementations use two transceivers; one is operated on a UAV while the other is placed at a monitoring station.

The development of smart cities and the use of smart technologies are becoming the focus of Machine Learning. For example, using Machine Learning, automatic face recognition is a Machine Learning application. These procedures are also used in NPL, processing, and generation and the same is useful in image processing. The Convolutional Neural Network, or CNN, is used to identify the objects in an image. Data from the field is acquired by the system on a real-time basis. The data can then be viewed on the farmer's smartphone. Ultimately, the field is sufficiently watered either with a decision-making system or by the farmer [20].

The figure above provides an overview of the system flow. UAV's initial flight over the agricultural field follows the mission flight path to collect images and other parameters required to determine crop health. Next, it sends this data for crop health evaluation to the health calculation system using CNN model. Moreover, health estimates will be aggregated in relation to each unit area time. The combined output is sent to the yield prediction model for final crop yield forecasting. The values of predicted yield and crop health will be sent to remote dashboard for visualization. The final step is for the UAV to land on the base station post-mission.

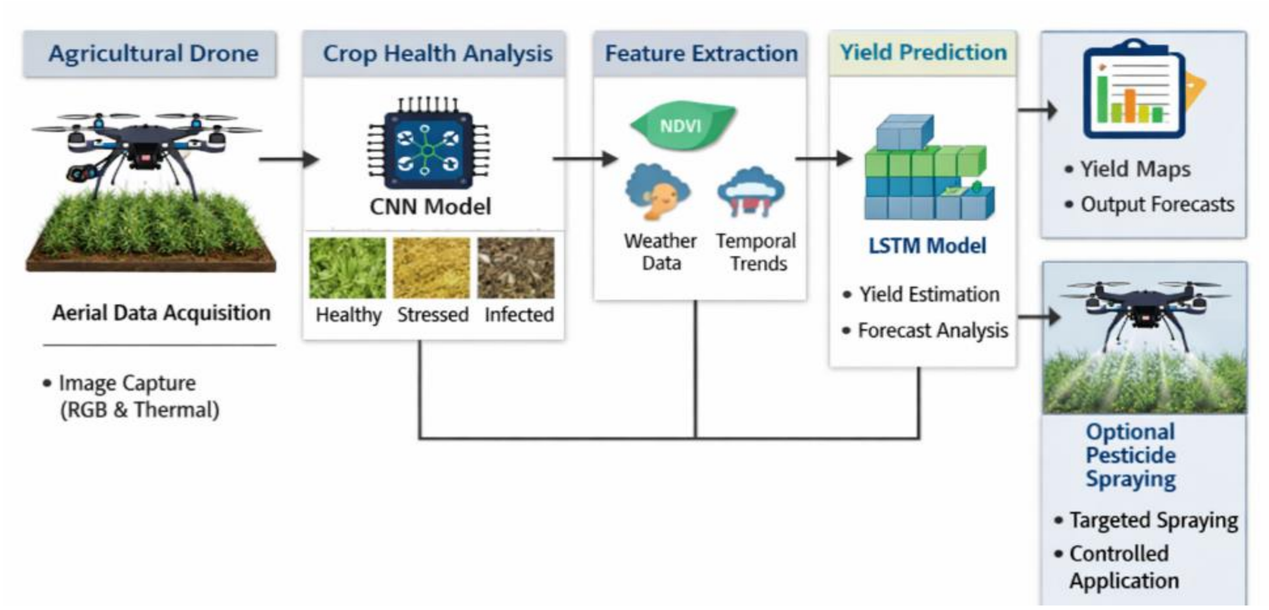

Figure 1: Methodology Flow Chart

3. METHODOLOGY

The framework for UAV-Based crop monitoring and yield prediction is presented in the overall architecture given in Figure 1. It shows the full system workflow from the deployment of UAVs and aerial data acquisition to Machine Learning-based crop health analysis and downstream decision making. The on-board computer communicates with the sensing modules. The computer will compute some edge computing to perform some activities on the fly as is seen in figure.

Figure 2: Agricultural Drone Design

Figure 2 illustrates the construction and working mechanism of the agricultural drone employed in this study. The integrated architecture of the UAV platform containing sensors, onboard processing units, power distribution units and communication units. The organization of functions allows for the assembly of imaging sensors, microcontrollers, and actuation units (optional) without causing any disturbance to the flight stable [21].

The drone's quadcopter chassis used in this study has been shown in Figure 3 with the detailed mechanical framework [22].

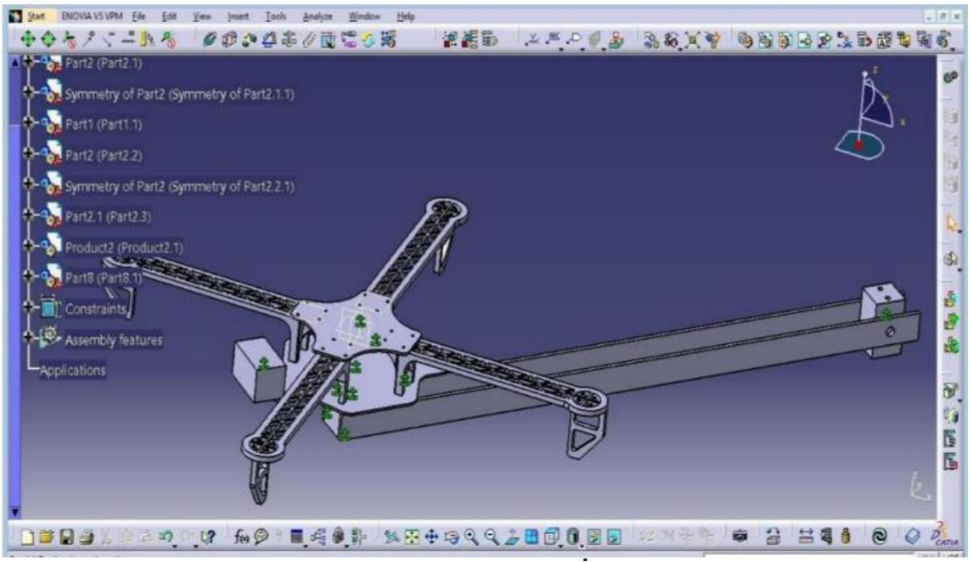

Figure 3: Drone Chassis

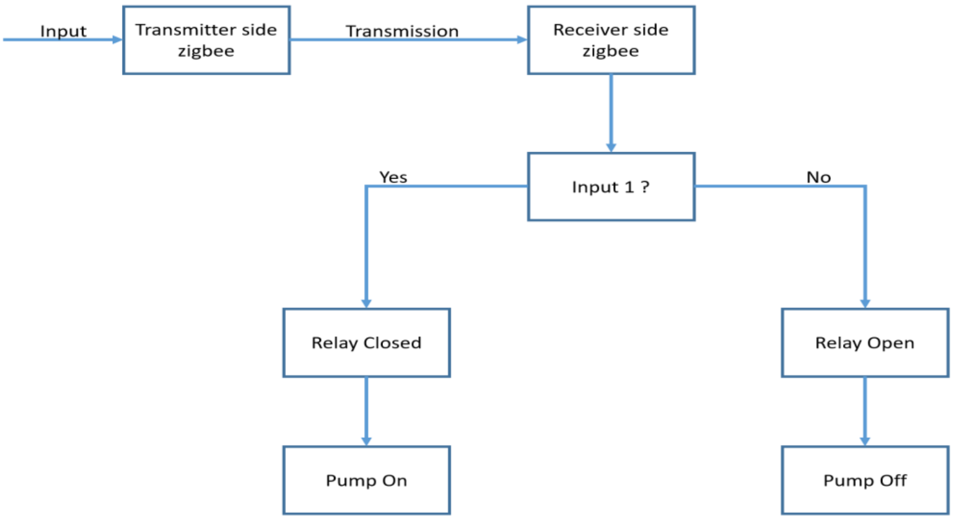

Figure 4: Working of Spraying Module

Figure 4 features the working of pesticide spraying unit, which shows the working of spraying module which consists of relay-controlled pump, pesticide tank and nozzle assembly. The design is such that it selectively sprays the pesticide or medicine as per the classification result (i.e. whether healthy or not) given by the neural network. The spraying forms the secondary task in the proposed framework. Nonetheless, the spraying module demonstrates the UAV based crop health assessment practical applicability for selective and targeted intervention in the field.

3.1. Calibration of the Quadcopter

The proposed UAV BCCD system requires a calibration procedure to ensure stable flight, accurate sensing, and consistent Machine Learning based inference. The calibration process employs sensor-bias correction, stabilization of control-loops, and synchronization of ML inference with onboard sensor streams, besides using the classic mechanical electrical tuning method [23]. Using these methods ensures precise manoeuvrability, wide-area quality sensing, uniform sensing of crop health, and robust crop yield prediction. Let a_m be the raw accelerometer measurement vector, b_a be the accelerometer bias vector, and S_a be the accelerometer scale and misalignment matrix, the calibrated acceleration vector. We denote roll, pitch, and yaw angle respectively by the symbols φ, θ, and ψ. With $u(t)$ the PID controller output, $e(t)$ the control error, and the proportional, integral, and derivative gains being K_p, K_i and K_d respectively. Let T denotes the thrust, ρ refers the air density, A denotes the propeller disk area, P refers the electrical power, V is the battery voltage, and I is the current [24]. To refer to the CNN confidence score in Machine Learning inference, we use p_{CNN}, and to refer to the confidence threshold, we use τ.

A. Firmware Installation and System Initialization

The flight controller's firmware which is the part that will control the UAV is the first step. Therefore, Mission Planners and technologies are used. The Arduino Mega 2560 was flashed at a baud rate of 115200. The firmware provides a basic low-level control framework for the autopilot. The firmware also fuses and stabilizes the sensors. In addition, it communicates with onboard computing modules, sending high-level manual and automatic pilot commands. Following the completion of the firmware, the UAV may fly autonomously or be remotely piloted. This indicates it operates on waypoint missions [25].

Figure 5: Accelerometer Calibration

B. Accelerometer Calibration and Orientation Stability

To assign a class label to every pixel of an input hyperspectral image (HSI), successful classification of HSI is important for HSI analysis. This is done by exploring the spectral content and spatial information of the HSI for classifying pixels in classes or thematic map types. Pigments are generally used to analyze spectral content. The Budding Color Theory from an artist or physicist is used to bias decisions about the spectral property of a pixel during classification. Hue, brightness, and color content are the three distinct color elements in this object coloring system. Hue indicates the colour, whereas intensity the lightness or darkness of a colour. If the intensity of a pixel's luminance is more than another pixel's luminance intensity. The saturation of a pixel refers to its concentration. Therefore, a small pixel will look duller than another one.

Figure 6: Compass Calibration

Figure 7: Radio Calibration

Figure 8: Extended Tuning Setting Parameters (PID Tuning)

C. Compass Calibration and Heading Estimation

Metallic components and electrical interference cause distortion in magnetometer reading. Compass calibration can identify the problem and correct it. The output vector m of a magnetometer reading is the actual magnetic field vector m in a respective relationship, and the raw measurement $m_m = S_m.m + b_m$. where m refers to the real magnetic field Also, m_m denotes a certain magnetic field which is specified by the calibrator. A compass calibration actually determines the S_m and b_m respectively the parameters of S_m and b_m can adjust the magnetic field to the earth's magnetic field. The tilt-compensated magnetometer value can be used to measure yaw(heading). Consequently, yaw of heading motion which is marked in figure 5.

D. Radio Calibration and Control Mapping

Radio calibration records the input at the transmitter that produces a body rate command at the control input at the receiver. The roll, pitch, and yaw control inputs must be given the value $u = 2(PWM - PWMmin)/(PWMmax - PWMmin) - 1$. Furthermore, it should provide the value $0 \le u \le 1$ for the throttle channel. PWM is the pulse width modulation output of the radio controller and u is the normalized control input. PWMmax, PWMmin are the radio controller maximum and minimum output limits. Radio calibration ensures that the UAV movement corresponds to the input from a radio control stick. This is required to ensure it [28].

E. PID Tuning for Stable Flight Control

In the UAV, motor speeds are controlled. The PID controller issues the control signal.

$u(t) = K_p \cdot e(t) + K_i \cdot \int e(t)dt + K_d \cdot (de(t)/dt)$

For implementation, a discrete version of this design shall be used, where the control output is a function of the error value at the current point and also the previous instant of time. If the PID system is tuned properly, the quadcopter will be able to hold its position stably, track the trajectory without oscillation and will be able to resist the wind disturbance (29). Figure eight depicts the Extended Tuning interface which allows one to tune the PID gains.

F. Machine Learning Inference Initialization and Calibration

Upon starting up the system, the CNN crop health classification model is loaded into memory and connected with image acquisition pipeline. With each image frame taken, it is categorized Healthy, Stressed or Infected class with a confidence score pCNN. To ensure reliability in the prediction process, the threshold is fixed at $\tau = 0.85$. A prediction is judged as believable only if $pCNN \geq \tau$. The CNN crop health data was used to extract temporal crop health indicators.

$$Xscaled = (X - Xmin) / (Xmax - Xmin)$$

By means of this normalization process, consistency in historical training features and live field features is established. The model used for predicting the yield of a crop, after normalizing these values of the different features, finally will yield crop yield based on the health of the crop [32].

G. Power, Thrust, and Energy Calibration

In order to hover steadily, the thrust T produced by the propulsor system must satisfy this inequality. T is greater than or equal to mg. In this equation, g represents the force of gravity, m is the UAV's total mass (including payloads). As a result, the thrust per motor for a quadcopter is approximately T/4. By applying momentum theory, we will find the induced velocity as. Velocity is equal to the square root of tension divided by twice the density and cross-section area. Here, ρ denotes the air density, while A signifies the area that the propellers sweep. We follow that to find induced power. P equals T multiply with nuElectrical power P Battery Management Path motors propellers from Battery Path-1 is made up of propulsion power PT and Cruise Power [33].

H. Servo Torque Calibration for Mechanical Actuation

By using Torque = Force × distance, the torque requirement of mechanical components like adjustable nozzles can be calculated. A load of about 0.5 kg applied at 0.25 m requires a torque of about $0.5 \times 0.25 \times 100 = 12.5$ kg-cm.

3.2. Simulation Results

The section experimental results and analysis is about the experimental results and performance analysis of the proposed UAV based crop health framework and operational intelligence to machine-learning based crop yield prediction. The outcomes are detailed and interact through three different experiments. The first one is an evaluation of the CNN model using the PlantVillage dataset. The second one is a validation on real-time UAV-acquired aerial imagery. Finally, an operational efficiency analysis of intelligent and selective pesticide spraying. These experiments together show the practical ability of intelligent learning machine models on UAV platforms for accurate crop health assessment as well as the resulting operational intelligence in precision agriculture.

3.3. CNN Performance on PlantVillage Dataset

The training and validation of the CNN model was performed by a labeled subset of PlantVillage dataset containing 50,000 labeled images of crop leaves. 6,000 images were picked for this study which included 2000 samples per class of Healthy, Stressed and infected crops. The resized images, with the size of 224 × 224, normalized images were created by rotation, flipping, and zooming to create generalization for the proposed model. In addition, we adopted a transfer learning approach on ResNet50 architecture as our base model that was fine-tuned to learn disease-based and stress-based visual features.

Table 1: CNN Performance Metrics on PlantVillage Validation Set

Metric	Value (%)
Accuracy	96.2
Precision	95.7
Recall	96.8
F1 Score	96.2

We split the training dataset with 80:20 training-validation ratio. As indicated in Table 1, the CNN model attained a notable performance on validation with an accuracy, precision, recall and F1 score of 96.2%, 95.7%, 96.8% and 96.2% respectively. This illustrates that the model can distinctively classify healthy, stressed, and infected crops. A high recall value means that a sufficient number of affected crops has been found, allowing further yield estimation and decision-making after this step.

Table 2: CNN Performance Metrics on UAV Field Validation Dataset

Metric	Value (%)
Accuracy	90.0
Precision	86.0
Recall	89.0
F1 Score	87.4

3.4. UAV Field Validation Results

An important aspect of this study is the deployment of the trained CNN model on UAV based imagery to identify the functionality of our proposed model at the field level. The aerial field images, used for testing, were taken by our agriculture UAV platform at a flight height of 15 m and 20 m. Moreover, the photographs taken served to generate 100 labelled image patches of the three classes. In addition, these patches of images were labelled by agriculture experts for ground truth labelling. The field images show much higher variation as compared to above PlantVillage images. This is due to the effect of changes in lighting conditions, shadows, overlapping of leaves, and also motion blur effects. Despite facing those challenges, the CNN model's performance can still remain high, with an overall accuracy of 90.0%, a precision of 86.0%, a recall of 89.0%, and an F1 score of 87.4% as shown in Table 2. The comparative performance analysis of the suggested model is done on the PlantVillage dataset and UAV based field-level data. It can be seen in Figure 9. There is slight performance degradation in field data, nonetheless the result suggests sustainable generalization performance for aerial view.

Table 3: Spraying Efficiency of CNN-Based UAV System

Parameter	Value
Chemical Usage Reduction	31%
Affected Area Precision Sprayed	87.2%
Time Saved per Hectare	16 minutes

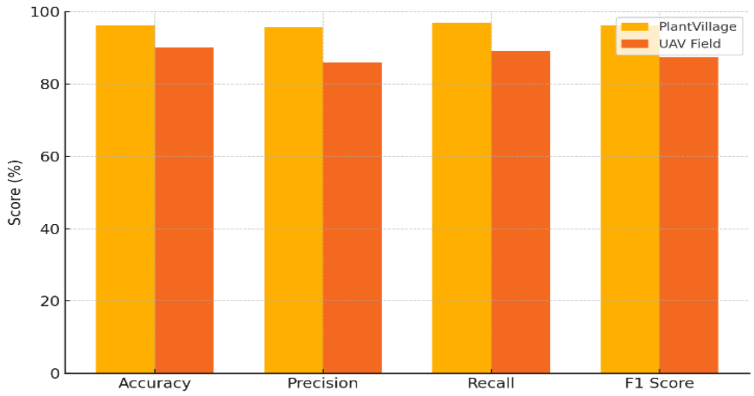

Figure 9: The PlantVillage model's F1 score indicates a sizeable decrease in UAV field dataset performance.

3.5. Impact on Crop Yield Prediction and Field-Level Decisions

Having accurate classification of crop health is important in yield prediction since a prolonged stress/infection will affect the plant growth and its productivity directly. The high accuracy achieved in controlled and field conditions assures that the estimated health condition trends are reliable. The trends accumulate and serve as inputs to the crop yield prediction model. With the assistance of precision agriculture, visual signals may help predict yield variations earlier due to spatio-temporal plant signals. In a similar vein, the strong results on the PlantVillage dataset (Table 1) confirm learning capacity. The accuracy on field-level data (Table 2) proves that it is fit for practice. They together verify the validity of proposed approach i.e. Using UAVs to monitor crop health can enable better crop yield predictions through Machine Learning. A CNN inference system is used in conjunction with the UAV control logic for selective sprayer activation. The UAV will activate the sprayer only over the stressed/infected patch if the model classifies it as such. As seen from Table 3, the use of scheme resulted in a 31% reduction in the use of chemical. It also demonstrates that the spraying precision in affected areas is 87.2%. Besides, the efficient routing and selective intervention saved about 16 minutes per hectare of operation time. The pesticide used is observed in the sprayed and saved parts as shown in Figure 10. This demonstrates how to use Machine Learning for sustainable resource consumption decision making.

Table 4: Inference and Control Timing Parameters for CNN-Integrated UAV

Component	Value
Average Inference Time per Image Patch	0.9 seconds
Spray Activation Delay	0.5 seconds
Hover Time per Targeted Spot	1.5 seconds
Image Patch Size	224 × 224 pixels

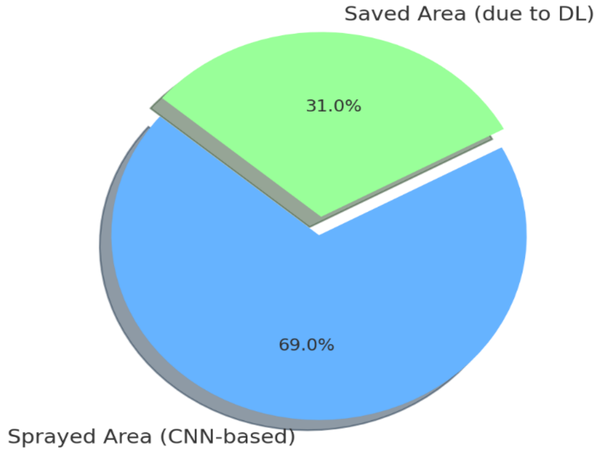

Figure 10: Dividing the pesticide used in the sprayed and saved area. UAV system based on DL

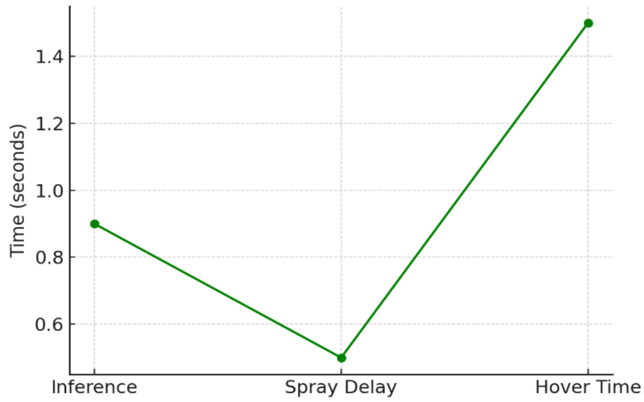

Figure 11: Shows time for CNN inference, spray activation, and hover stabilization.

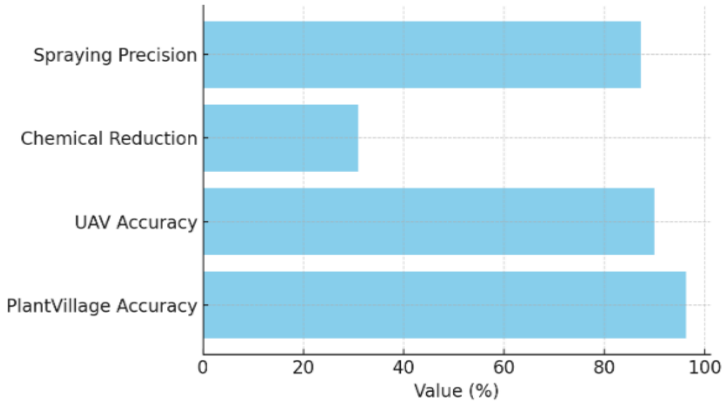

Figure 12: Performance metrics of UAV crop monitoring system integrated Deep Learning.

3.6. Inference Speed and System Responsiveness

Real-time performance is crucial for agricultural UAV applications. The details of the inference and control timing parameter can be observed in Table 4. The average CNN inference time which we obtain by evaluating 32-times the network described earlier is of 0.9 s/image patch. Experimentally Estimate Spray Activation Delay Parameter as 0.5s Detected regions (like hover and typify times with deference images) have an average hover time of 1.5 seconds. Table 4 confirms that our system can be used for the near real-time Analysis and Response during flight. Figure shows the inference, activation, and stabilization timing behaviour. 11. It validates that complete inference and control timing which include image inference, spray activation and hover stabilization executes in two seconds. The UAV possesses the capability of hovering and analyzing, and it can move ahead without any human agent's intervention. It is important for monitoring large field sizes due to which human control causes drone crashes and limits performance. Table 5 shows the overall performance of the proposed Deep Learning powered UAV system.

Table 5: Overall Performance Summary of the DL-Powered UAV System

Metric	Result
PlantVillage Validation Accuracy	96.2%
UAV Field Validation Accuracy	90.0%
Chemical Usage Reduction	31%
Targeted Spraying Precision	87.2%
Inference Speed (per patch)	0.9 seconds
Operational Autonomy	Fully Autonomous

3.7. Model Evaluation and Confusion Matrix Analysis

The authors of this paper have proposed a deep convolutional neural network (CNN) for automatic classification. They assess how well the implemented system, which was designed using the PlantVillage dataset accuracy. In addition to the accuracy now evaluated, a UAV gathers real PlantVillage dataset. It provides versatility for functioning in a real-world ecosystem. Also, they will analyze the method for operational deployment. The suggested technique can surpass the crop anomaly that the PlantVillage dataset detected. The CNN was trained with these sets of training data and tested on efficacy. The dataset of Plant Village is used for proposed method. Because the PlantVillage system labelled the training data, the CNN generated the labelled output. It created a classification map that illustrates the projected disease classes over the landscape. It depicts the evolution of classification performance during training. The validation accuracy of CNN settles at 96.2 percent. Validation accuracy of CNN indicates the machine accuracy to find the right visual patterns related to the disease in a controlled environment.

3.8. Yield Prediction Error Analysis

The efficacy of the proposed ML framework in UAV-based crop health monitoring and prediction of crop yield was evaluated quantitatively with the help of RMSE and MAE. The RMSE enables penalizing any larger deviation in the prediction while the MAE directly interprets the average absolute deviation. Therefore, both of these metrics are complementary in nature and used widely for the quantitative evaluation of prediction of yield. The difference between predicted and real crop output from field records serves as the basis for RMSE and MAE calculation.

Table 6: Yield Prediction Error Metrics of the Proposed System

Metric	Value
Mean Absolute Error (MAE)	0.42 tons/hectare
Root Mean Square Error (RMSE)	0.58 tons/hectare

The information in Table 6 on yield prediction error shows that the suggested UAV-based Machine Learning technique achieves a reliable prediction quality in field scenario conditions. The MAE (Mean Absolute Error) of 0.42 ton per hectare shows that the predicted yield and the harvest yield values agree strongly in most of the cases. Although the value of RMSE = 0.58 t/ha indicates that larger prediction errors occurred only in a few cases. The above errors of result indicate that the fusion of UAV crop health indicators with Machine Learning models is suitable for early to mid-stage yield prediction. Traceable with the low values of error is the high accuracy of the CNN crop health classification which shows strong reliability upon the spatial indicators of plants. In general, the occurrence of any stress and disease infection in the crops directly affects the yield values of crop plants. So, strong proof of spatio-temporal patterns of crop health leads to reliable yield prediction. In addition, the temporal compaction of crop health data helps in learning the development pattern and avoid impact of single-phase data occurrence.

Table 7: Baseline Comparison of Crop Yield Prediction Methods

Parameter	Traditional Method	Proposed UAV-Based ML Method
Data Source	Manual field surveys	UAV aerial imagery + sensors
Crop Health Assessment	Visual inspection	CNN-based automated classification
Temporal Resolution	Seasonal / periodic	Continuous during growth stages
Yield Prediction Approach	Empirical estimation	Machine Learning (health-driven)
Mean Absolute Error (MAE)	0.95 tons/hectare	**0.42 tons/hectare**
Root Mean Square Error (RMSE)	1.21 tons/hectare	**0.58 tons/hectare**
Early Yield Forecasting	Not supported	Supported
Scalability	Low	High
Human Intervention	High	Minimal
Suitability for Precision Agriculture	Limited	High

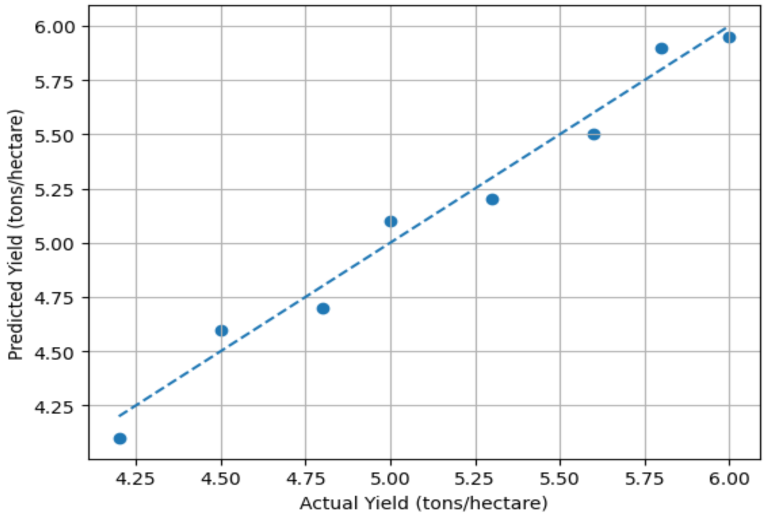

Figure 13: Yield Prediction Vs Actual Yield

3.9. Baseline Comparison and Yield Prediction Accuracy

The baseline comparison was performed to validate the proposed UAV-based Machine Learning framework. The traditional approach of crop yield estimation is field survey through manual investigation and empirical yield estimation. The process is long, subjective and not repetitive over a period of time. The conventional method ensures no temporal indication of the change in yield of the crop. Table 7 indicates that the proposed method far outperforms the traditional methods. The suggested way decreases the MAE from 0.95 to 0.42 tons/ha and the RMSE from 1.21 to 0.58 tons/ha. According to Figure 13, the predicted yield values compared with the actual values on several field samples. To assess the effectiveness of the proposed crop yield forecasting framework, prediction accuracy was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics provide reliable measures of average prediction deviation and error dispersion, respectively.

UAV-derived crop health indicators were temporally aggregated and utilized as input features to the yield prediction model. The integration of multi-temporal vegetation indices significantly enhanced the model’s predictive capability, enabling early and reliable crop yield forecasting. The performance comparison between the traditional method and the proposed approach is presented in Table 8.

Table 8: Yield Prediction Error Comparison

Metric	Traditional Method (t/ha)	Proposed Method (t/ha)	Improvement
MAE (t/ha)	0.95	0.42	56% reduction
RMSE (t/ha)	1.21	0.58	52% reduction

From Table 8, it is evident that the proposed method substantially reduces prediction errors. The MAE decreased from 0.95 t/ha to 0.42 t/ha, representing a 56% reduction, while the RMSE decreased from 1.21 t/ha to 0.58 t/ha, corresponding to a 52% reduction. These results demonstrate that incorporating UAV-based crop health indicators improves yield prediction accuracy and robustness compared to conventional approaches. The reduced error margins confirm the effectiveness of the proposed model in supporting precision agriculture and data-driven farm management decisions.

3.10. Yield Prediction Accuracy and Statistical Validation

Along with MAE and RMSE assessment, the coefficient determinant R^2 were also used to determine the goodness-of-fit of the model yield. The approach that we propose achieves an R^2 of 0.91 indicating a strong agreement between predicted and ground-truth crop yield values. This confirms that the proposed model can reliably model the relationship between the UAV-based crop health indicators and the crop yield value. A statistical test was performed on the proposed and conventional yield estimation methods to validate the yield estimation performance. To compare the two approaches, a paired t-test was conducted on yield prediction errors. The estimation yield approach p value of less than 0.01 of paired t-test supports that proposed UAV and Machine Learning crop yield prediction approach is far superior to conventional estimation yield approaches. The results of the analysis of the statistical significance affirm the statistical significance of the improvement in performance.

4. CONCLUSION

The yield forecasting of crops can be achieved through the proposed effective UAV framework enabled by continuous monitoring of crops' health. In this approach, Deep Learning analytics use aerial sensor data to generate reliable crop condition and expected yield estimates. Yield estimation uses a CNN-based crop health classification model that is trained on UAV imagery and can be framed as a data-driven decision-making process. The benchmark PlantVillage dataset has been classified using the CNN model with an accuracy of 96.2%, precision of 95.7% and an F1 score of 96.2%. This confirmed the hypothesis that a convolutional network can extract and learn discriminatory features to differentiate between crop stresses and diseases. In real-world field scenes with diseased sweet-pepper plants captured by the UAV, robust generalization ability was evident, which achieved 90.0% accuracy and 87.4% F1 score during the test. All these issues lead to poor segmentation accuracy and identification, especially for the root diseases of plants and other classes. The results exemplified the efficacy of the system and proved its appropriateness for machine-learning-mediated yield prediction as a quality input. The framework showed low-latency performance with an inference time of 0.9 seconds per image patch. This made near real-time response possible during UAV flight. These advantages also assist in safeguarding yield indirectly through lessening the use of unnecessary chemicals and enhancing the timely interventions on unhealthy crop regions. The proposed framework was effective in predicting yield as shown by the various regression error metrics. The framework's low prediction errors (mean absolute error of 0.42 tons per hectare and root mean square error of 0.58 tons per hectare) and high R2 value 0.91 confirms the prediction capability of the framework. A statistical significance test was subsequently conducted which validated that the results from the proposed framework are significantly better than a traditional approach for yield estimation. This analysis affirms the practicality of the proposed framework for precision agriculture and proves its robustness in real-life settings. The framework will eventually be expanded to cover more crop kinds, development stages, and stressors.

5. DECLARATIONS

FUNDING

The research was not funded by any agency.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

REFERENCES

[1] W. Zhang, J. Li, and M. Zhao, "Intelligent agriculture: Deep Learning in UAV-based remote sensing for monitoring crop diseases and pests," Frontiers in Plant Science, vol. 15, p. 1435016, 2024.

[2] L. Ramirez, S. Torres, and M. Ahmed, "Deep Learning for precision agriculture: A bibliometric analysis," Computers and Electronics in Agriculture, vol. 200, p. 107204, 2022.

[3] K. Sharma, N. Singh, and A. Reddy, "Recent advances in crop disease detection using UAV and Deep Learning: A review," Remote Sensing, vol. 15, no. 9, p. 2450, 2023.

[4] L. Fernandez, S. Kim, and A. Gupta, "Transforming farming: A review of AI-powered UAV technologies in precision agriculture," Drones, vol. 8, no. 11, p. 664, 2024.

[5] X. Zhou, H. Liu, and R. Wang, "A comprehensive review on UAV-based remote sensing and Deep Learning for crop monitoring," Frontiers in Plant Science, vol. 15, p. 1423321, 2024.

[6] R. Shahi, A. Banerjee, and A. Tiwari, "Advancements in UAV-based crop disease detection: A Deep Learning perspective," Drones, vol. 7, no. 1, p. 115, 2023.

[7] N. Patel, M. Zhou, and R. Singh, "Deep Learning techniques to classify agricultural crops through UAV-based remote sensing: A review," Neural Computing and Applications, vol. 34, no. 12, pp. 9393–9409, 2022.

[8] A. Gupta, K. Srivastava, and Z. Li, "Improving crop production using an agro-Deep Learning framework in precision agriculture," BMC Bioinformatics, vol. 25, p. 112, 2024.

[9] D. Johnson, R. Kumar, and A. Patel, "Assessment of UAV-based Deep Learning for corn crop analysis in precision agriculture," Agriculture, vol. 14, no. 11, p. 2029, 2024.

[10] Y. Lee, H. Wang, and R. Mehta, "A survey on Deep Learning in UAV imagery for precision agriculture: Advances, challenges, and future trends," Computers and Electronics in Agriculture, vol. 211, p.

108220, 2024.
[11] A. Jain, P. Verma, and S. Tanwar, "Machine Learning methods for precision agriculture with UAV imagery: A review," Electronic Research Archive, vol. 30, no. 6, pp. 4312–4340, 2022.
[12] N. Rao, R. Sharma, and K. Tan, "Detection of healthy and diseased crops in drone-captured images using Deep Learning," arXiv preprint arXiv:2305.13490, 2023.
[13] Y. Li, J. Chen, and M. Zhang, "Multi-vision monitoring framework for real-time field activity recognition and crop health monitoring," Remote Sensing, vol. 16, no. 2, p. 345, 2024.
[14] M. Maimaitijiang et al., "Soybean yield prediction from UAV using multisource data fusion and Machine Learning," Remote Sensing of Environment, vol. 237, p. 111599, 2020.
[15] T. Ren, X. Zhang, and Z. Sun, "Vegetation indices for monitoring crop diseases and pests using UAV-based remote sensing," Frontiers in Plant Science, vol. 11, p. 1435016, 2020.
[16] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep Learning techniques to classify agricultural crops through UAV-based remote sensing: A review," Neural Computing and Applications, vol. 34, pp. 1435–1452, 2022.
[17] W. Zhang, J. Li, and H. Wang, "A survey on Deep Learning in UAV imagery for precision agriculture applications," Computers and Electronics in Agriculture, vol. 205, p. 107522, 2024.
[18] F. Qiu, Z. Zhai, and Y. Li, "UAV imaging and Deep Learning-based method for predicting residual film in cotton field plough layer," Frontiers in Plant Science, vol. 13, p. 1010474, 2022.
[19] R. Reedha et al., "Vision transformers for weeds and crops classification of high-resolution UAV images," arXiv preprint arXiv:2109.02716, 2021.
[20] V. Mazzia et al., "UAV and Machine Learning-based refinement of a satellite-driven vegetation index for precision agriculture," arXiv preprint arXiv:2004.14421, 2020.
[21] A. C. Nguyen et al., "Deep reinforcement learning for task offloading in UAV-aided smart farm networks," arXiv preprint arXiv:2209.07367, 2022.
[22] T. B. Shahi et al., "Machine Learning methods for precision agriculture with UAV imagery: A review," Electronic Research Archive, vol. 31, no. 1, pp. 4277–4317, 2023.
[23] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep Learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2021.
[24] J. Yuan et al., "Grain crop yield prediction using Machine Learning based on UAV remote sensing: A systematic literature review," Computers and Electronics in Agriculture, vol. 210, p. 107610, 2024.
[25] Y. He et al., "Adaptive tuning method of PID controller parameters based on UAV flight data," Journal of Intelligent and Robotic Systems, vol. 99, no. 1, pp. 133–145, 2020.
[26] M. M. Rahman et al., "A comprehensive study on UAV sensor calibration techniques and challenges," IEEE Sensors Journal, vol. 21, no. 12, pp. 13902–13912, 2021.
[27] Y. Lin, T. Wang, and G. Zheng, "Deep reinforcement learning-based calibration of autonomous UAV navigation in uncertain environments," Sensors, vol. 22, no. 2, p. 487, 2022.
[28] Y. Wang, H. Duan, and S. Yu, "Autotune PID controller for quadrotor UAV using flight feedback and neural networks," Aeronautical Journal, vol. 127, no. 1301, pp. 345–362, 2023.
[29] O. Duran et al., "Magnetic field compensation and calibration of compass for UAVs in agricultural environments," Precision Agriculture, vol. 21, no. 4, pp. 1025–1040, 2020.
[30] H. Chen, B. Zhang, and Y. Liu, "Onboard calibration of Deep Learning-based detection systems for UAVs in real-time crop stress identification," Remote Sensing, vol. 14, no. 15, p. 3799, 2022.
[31] S. Malakar et al., "Low-cost multi-sensor fusion and calibration framework for UAV-based crop monitoring," Journal of Field Robotics, vol. 38, no. 7, pp. 942–957, 2021.
[32] L. Zhang, Z. Xu, and L. Qiu, "Real-time parameter estimation and control calibration of agriculture UAV spraying systems," Computers and Electronics in Agriculture, vol. 173, p. 105423, 2020.
[33] K. Huang, J. Luo, and Y. Zhang, "CNN-based motion blur correction for UAV crop images captured during unstable flight," Drones, vol. 6, no. 2, p. 41, 2022.