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UNMANNED AERIAL VEHICLES FOR SMART AGRICULTURE USING MACHINE LEARNING

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ABSTRACT :

Rising food demand and climate variability are accelerating the adoption of smart agriculture (SA), where unmanned aerial vehicles (UAV), commonly known as drones, combined with Machine Learning (ML), are transforming modern agriculture by enabling precision farming. UAVs collect high-resolution images and environmental data, while ML algorithms analyse this data to detect crop diseases, estimate soil moisture, monitor plant health, predict crop yield, and optimize irrigation. This technology helps farmers improve productivity, reduce costs, and use resources efficiently. However, challenges such as limited battery life, high costs, large data processing, and environmental conditions still affect widespread adoption. Conventional farming methods that apply water, fertilizers, and pesticides uniformly across a field are ecologically and economically unsustainable. This report details a comprehensive cyber-physical framework combining Unmanned Aerial Vehicles (UAVs) and classical Machine Learning (ML) algorithms to enable precision agriculture. UAVs bridge the operational gap between coarse satellite imagery and labor-intensive ground scouting by capturing ultra-high spatial resolution, multi-sensor data beneath cloud layers. Advanced machine learning models (such as Random Forest, XGBoost, SVR, and PLSR) act as the analytical engines to transform unstructured spatial-spectral aerial data into actionable agronomic intelligence. This integrated framework supports site-specific management fields including soil moisture tracking, crop water stress estimation, nutrient mapping, selective weed classification, disease monitoring, and highly accurate in-season yield forecasting.

Keywords: Unmanned Aerial Vehicles (UAVs)**,** Smart agriculture, Machine learning, Sensors, IOT & AI based analysis.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that operate without an onboard pilot and can be controlled remotely or fly autonomously. In recent years, UAVs have become an important technology in many fields, especially agriculture, environmental monitoring, disaster management, surveillance, and mapping.

In agriculture, UAVs play a key role in precision farming by capturing high-resolution images and collecting real-time data using advanced sensors. When combined with emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), Blockchain, and 5G, drones help farmers monitor crop health, detect diseases and pests, assess soil moisture, identify water stress, and estimate crop yield. These technologies improve productivity while reducing the use of water, fertilizers, pesticides, time, and labor costs recent developments in additive manufacturing (3D printing) have further enhanced UAV technology by enabling the production of lightweight, durable, and customized drone components. This improves flight performance, manufacturing speed, and design flexibility, making UAVs more efficient for different applications.

Although UAV technology offers significant advantages, challenges such as limited battery life, data accuracy, communication security, manufacturing standards, and system reliability still need to be addressed. With continuous advancements in AI, sensor technology, and advanced manufacturing, UAVs are expected to play an even greater role in the future of smart and sustainable agriculture.

1.1 Global context and rise of smart agriculture (SA)

Smart Agriculture is an advanced farming concept that uses modern technology to increase the quantity and quality of agricultural products while optimizing human labour and resource use. The foundation of global food security is facing severe challenges due to rapid population growth and climate volatility. With the human population projected to reach 8.5 billion by 2030 and 10 billion by 2050, global food production must increase dramatically. Crucially, this output must scale under zero-growth constraints on arable land and water resources, while fighting issues like soil degradation and pest outbreaks.

1.2 Overview of UAV technology

Unmanned Aerial Vehicles (UAVs) serve as a critical sensing layer in modern Smart Agriculture, bridging the structural scale gap between labour intensive ground scouting and coarse satellite remote sensing. Operating at low altitudes allows UAV platforms to acquire ultra-high-resolution imagery that

completely bypasses the fixed revisit cycles and heavy cloud-cover interference typical of orbital satellite constellations.
A Unmanned Aerial Vehicle (UAV) is an aircraft that operates without a human pilot onboard. It may be controlled remotely or may follow a pre-programmed autonomous flight path.An agricultural UAV generally consists of several interconnected systems:

- Air frame
- Propulsion system
- Battery/power system
- Flight controller
- GPS/GNSS
- Inertial sensors
- Communication system
- Cameras and other sensors
- Payload system
- Data-processing system

The UAV first receives a flight mission. The mission includes the field boundary, flight altitude, speed, direction and image overlap. During flight, sensors collect information from the crop. GPS/GNSS provides the location of the collected information.
The UAV system is not limited to the aircraft itself. The research review treats UAV agriculture as a system-level architecture, in which platform selection, payload, calibration, mission planning, communication and computing all influence the final quality of agricultural information.
Modern systems are also moving towards edge computing, where some processing is performed close to the UAV rather than sending all raw data to a remote server. Lightweight ML and Tiny ML approaches are being investigated because conventional deep-learning models can require considerable computing power.

1.3 UAVs in Smart Agriculture

UAVs are used in smart agriculture mainly as a data-collection platform. They provide information about the field at a much higher spatial resolution than many conventional remote-sensing methods.
A typical UAV smart-agriculture system works as follows:
Agricultural Field → UAV Flight → Sensor Data → Image Processing → Feature Extraction → Machine Learning → Agricultural Decision
For example, a UAV equipped with a multi spectral camera can collect images of a crop field. The images can be processed to calculate vegetation indices. Machine-learning algorithms can then use these features to estimate crop health or identify stressed areas.
The references in the review cover applications including:

- Soil-moisture estimation
- Irrigation management
- Fertilizer optimization
- Weed detection
- Crop disease detection
- Pest monitoring
- Pesticide/herbicide application
- Crop classification
- Biomass estimation
- Nutrient estimation
- Yield prediction

The important point is that the UAV does not directly solve the agricultural problem. It collects information, while image processing and ML convert that information into useful decisions.

1.3.1 Components of an agricultural UAV

Figure illustrates the major components of an Agricultural Unmanned Aerial Vehicle (UAV) and their functions. The air frame provides the main structure and supports all other components, while the propulsion system, consisting of motors and propellers, generates the thrust required for flight. The battery supplies electrical power to the UAV, and the flight controller maintains flight stability and controls its movements. The GPS/GNSS system determines the UAV's geographical position, helping to create accurate agricultural maps. Cameras and sensors, such as RGB, multi spectral, hyper spectral, thermal, and LiDAR sensors, collect images and information about crop health, weeds, and field conditions. The communication system enables data exchange between the UAV and the ground station. Finally, the payload includes the equipment required for specific agricultural tasks, such as crop monitoring, weed detection, and spraying. All these components work together to improve agricultural monitoring, precision farming, and crop management.



Fig. 1.1 Components of UAV

1. **Airframe**

The airframe is the main structural body of the UAV. It supports the motors, propellers, battery, flight controller, GPS and sensors. The airframe

must be lightweight but strong enough to carry the required payload.The design of the airframe affects flight endurance, stability, payload capacity and field coverage.

2. Propulsion system

The propulsion system consists mainly of motors, propellers and electronic speed controllers. It produces the thrust required to lift and move the UAV.Multi rotor UAVs use several motors to control movement and maintain stability. The propulsion system directly affects energy consumption and flight time.

3. Battery

The battery supplies electrical energy to the motors, flight controller, sensors and communication equipment. Battery capacity influences how long the UAV can remain in the air.Higher payload and power requirements generally increase energy consumption. Therefore, battery management is important for agricultural missions.

4. Flight controller

The flight controller acts as the control unit of the UAV. It receives information from sensors such as the IMU and GPS and controls the motors to maintain stable flight.It can also execute programmed flight paths and support autonomous missions.

5. GPS/GNSS

GPS or GNSS provides the geographical position of the UAV. Accurate positioning is important because agricultural images must be associated with their correct locations.This allows the processed images to be converted into Geo-referenced maps.

6. Cameras and Sensors

Sensors are among the most important components of an agricultural UAV. Depending on the application, UAVs can carry RGB, multispectral, hyperspectral, thermal and LiDAR sensors.The choice of sensor determines what type of agricultural information can be obtained.

7. Communication System

The communication system provides interaction between the UAV and the ground station. It can be used for flight commands, telemetry, monitoring and data transmission.Research is also examining 5G and future 6G communication for low-latency UAV operations.

8. Payload

The payload includes the equipment carried by the UAV for a specific application. In agriculture, payloads may include cameras, multispectral sensors, thermal sensors, LiDAR systems or spraying equipment.

1.3.2 Types of UAVs used in agriculture

1. Multirotor UAV

Multirotor UAV contain multiple motors and propellers. Common configurations include quadcopters, hexacopters and octocopters.Their main advantage is the ability to take off vertically, land vertically and hover over a particular area. This makes them suitable for:

- Crop inspection
- Disease monitoring
- Weed detection
- Plant counting
- Small-area mapping
- Precision spraying

Their main limitation is relatively high energy consumption during hovering, which can reduce flight endurance.

2. Fixed-wing UAV

Fixed-wing UAVs use wings to generate lift during forward movement. They generally have better endurance and can cover larger areas than multirotor UAV.They are useful for:

- Large-field mapping
- Crop monitoring
- Large-area surveys
- Vegetation analysis

However, they cannot normally hover like multirotor UAVs and may require suitable launch and landing arrangements.

3. Hybrid VTOL UAVs

Hybrid VTOL UAVs combine vertical take-off and landing with fixed-wing flight.They can:

- Take off vertically
- Transition to efficient forward flight
- Cover large areas
- Land vertically

They are useful when both maneuverability and longer-range operation are required.

1.3.3 Working principle

The working principle of UAV-based smart agriculture can be divided into several stages.

Step 1: Mission Planning

The agricultural field is selected and its boundary is defined. Flight altitude, speed, direction, image overlap and sensor type are selected according to the application.

Step 2: Sensor Selection

The appropriate sensor is selected according to the required information. For example, RGB may be sufficient for visual crop monitoring, while multispectral or thermal sensing may be more suitable for stress-related applications.

Step 3: UAV Flight

The UAV follows the planned flight path and collects images or sensor measurements.

Step 4: Data Processing

The collected images are calibrated and corrected. Images may then be aligned, orthorectified, mosaicked and georeferenced.

Step 5: Feature Extraction

Important information is extracted from the processed data. This may include:

- Vegetation indices
- Spectral characteristics
- Texture
- Plant height
- Canopy structure
- Temperature
- Object-level information

Step 6: Machine Learning
An appropriate ML model is trained using the extracted information. The model may perform classification, regression or grouping.
Step 7: Validation
The model's performance is evaluated using suitable validation data. The review emphasizes that spatial and temporal data leakage should be avoided during validation.
Step 8: Agricultural Decision
The final result can be presented as a map or recommendation for irrigation, fertilizer application, weed control, disease management or yield estimation

1.3.4 Advantages of UAVS in agriculture

commonly known as drones, provide a fundamental shift in precision agriculture by bridging the operational gap between low-resolution satellite data and labor-intensive manual ground scouting.The primary advantages of integrating UAVs into modern agricultural workflows include,

Ultra-High spatial resolution

- Millimeter-to-Centimeter Scales: UAVs fly at low altitudes, allowing them to capture image pixel sizes under 2 cm per pixel.
- Early Problem Detection: This extreme detail makes it possible to isolate localized weed clusters from target crop rows during early seedling growth stages, long before visible damage occurs across the wider field.

Temporal flexibility

- User-Configured Timelines: Unlike satellite systems tied to fixed orbital paths (which take days or weeks to return), drones offer complete scheduling freedom.
- Critical Phenological Windows: Flights can be quickly deployed on short notice during highly critical crop growth windows, such as the booting and grain-filling stages.

Cloud Cover Immunity

- Below the Weather: Satellite data is frequently obscured or ruined by heavy cloud layers during crucial weather events.
- Consistent Data Streams: Because UAVs operate entirely underneath the cloud layer, they consistently collect high-fidelity spatial data without atmospheric distortions.

1.3.5 Applications of UAVs

An Unmanned Aerial Vehicle (UAV) is an aircraft that operates without a human pilot onboard. These aircraft can be controlled remotely by an operator on the ground or fly autonomously using pre-programmed flight paths, advanced artificial intelligence, and onboard sensor networks.

- Crop Monitoring: Flying over fields to check plant growth and health.
- Irrigation Management: Finding dry or over-watered soil areas using thermal cameras.
- Pest & Disease Detection: Spotting sick plants early to stop bugs and sickness from spreading.
- Yield Prediction: Using data to estimate how much food will be harvested.
- Weed Detection: Mapping out weed locations to spray chemicals only where needed.

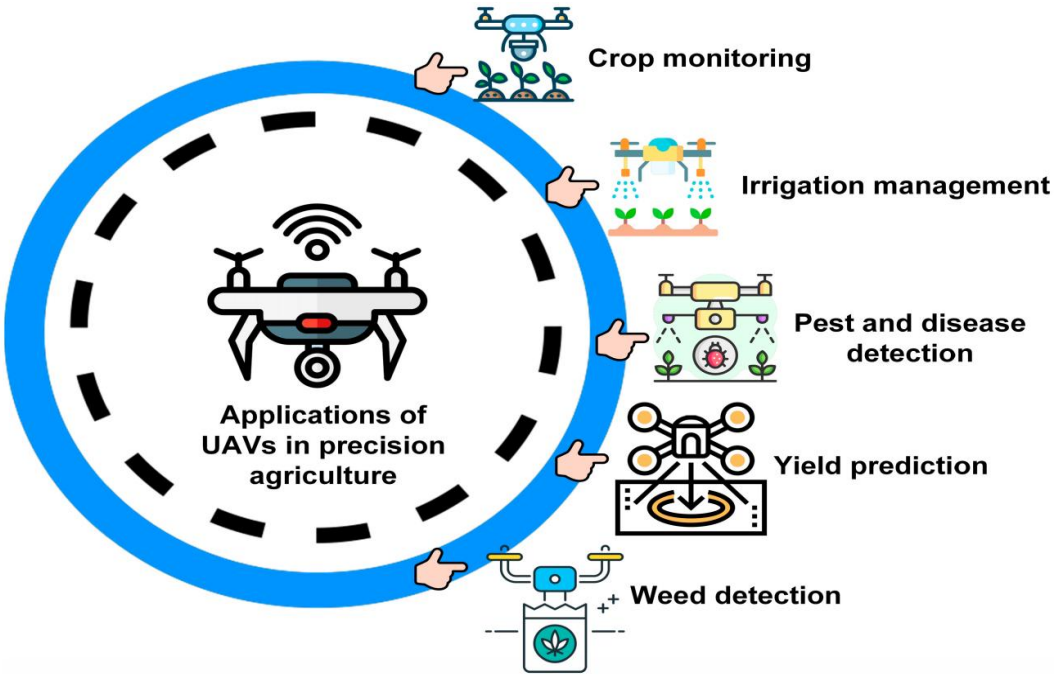


Fig. 1.2 Applications of UAVs in precision agriculture

1.4 The core analytical layer – Machine Learning (ML)

Machine learning (ML) is a branch of artificial intelligence (AI) that focuses on building systems that learn from data, identify patterns, and make decisions with minimal human intervention.

Within the architecture of UAV enabled smart agriculture, machine learning (ML) serves as the core analytics engine. While unmanned aerial vehicles, Internet of Things (IoT) sensors, and wireless sensor networks function as the physical perception layers that collect raw data, it is the machine learning pipeline that transforms these massive, unstructured aerial measurements into agronomically actionable information. By modelling highly complex, non-linear relationships among multi-sensor spectral bands, spatial textures, morphological traits, and historical weather data, ML algorithms extract real-time insights that surpass traditional manual field scouting and uniform application practices.

1.5 Operational Application Domains UAVs and ML

The figure below illustrates that the system-level deployment of integrated UAV-ML models drives predictive and prescriptive capabilities across the entire crop management life cycle. In water management, fused multispectral and thermal imagery track localized crop water stress index (CWSI) values to schedule precision irrigation zones. Soil and nutrient tracking pipelines leverage red-edge reflection sensitivities and regularized machine learning regressors to continuously monitor leaf nitrogen concentration (LNC) and map organic matter distributions without lab delays. For crop protection, automated image segmentation generate early-stage weed density maps and flag localized pathogen hotspots, converting aerial perception directly into target coordinates. These diagnostic layers ultimately fuel smart actuation by feeding prescription maps directly into variable-rate UAV sprayers, closing the automation loop to optimize droplet deposition profiles, prevent environmental pesticide drift, and secure stable crop yields.

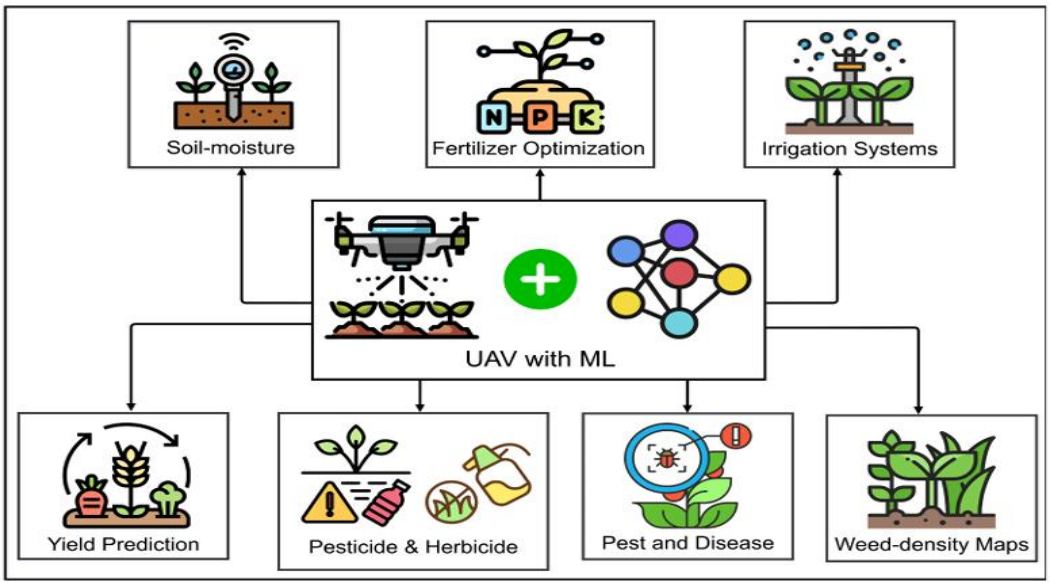


Fig.1.3: Representative application domains of UAV–ML systems in SA, spanning soil-moisture monitoring, irrigation management, nutrient mapping, weed and disease detection, precision spraying, and yield prediction. [1]

1.6 Sensors used in agricultural UAVs

1.6.1 RGB Camers

RGB cameras capture visible red, green and blue wavelengths.They are relatively inexpensive and useful for:

- Crop monitoring
- Plant counting
- Weed detection

1.6.2 Multispectral Sensors

Multispectral sensors capture selected wavelength bands beyond normal RGB.They can be used to identify differences in vegetation condition, crop stress and nutrient-related characteristics.

1.6.3 Hyperspectral Sensors

Hyperspectral sensors capture information across many narrow wavelength bands.They provide detailed spectral information and can help identify subtle changes related to plant biochemical and physiological conditions.However, they generally produce larger datasets and require more processing.

1.6.4 Thermal Sensors

Thermal sensors measure infrared radiation related to surface temperature.They can help identify differences in crop temperature and water-stress conditions.

1.6.5 LiDAR

LiDAR uses laser measurements to obtain three-dimensional information.It can provide information about Plant height and Crop structure.

1.6.6 GPS/GNSS

GPS/GNSS is not normally considered an imaging sensor, but it is essential for accurate positioning and georeferencing of agricultural UAV data.

2. LITERATURE REVIEW

2.1 Soil moisture and soil property estimation

Soil moisture and soil organic properties represent foundational variables dictating cropvigor, seed germination, and nutrient availability. Remote sensing of soil via UAVs leverages combinations of multispectral, thermal, and microwave signals [6], [16].

Recent studies have established that surface soil moisture content (SMC) can be mapped effectively using high-resolution multispectral imagery transformed via machine learning algorithms [16], [17]. Khose and Mailapalli demonstrated that combining multispectral reflectance indices (such as the Normalized Difference Water Index, NDWI) with surface temperature data significantly enhances Random Forest regression accuracy for sub-field SMC mapping [17]. Wang et.al. developed an upscaling framework converting high-resolution UAV multispectral data to match field-scale moisture dynamics,demonstrating that spatial upscaling reduces noise in bare-soil reflection [16].

Beyond optical techniques, passive and active microwave methods—such as Global Navigation Satellite System Reflectometry (GNSS-R) integrated onto UAV payloads—allow direct sensitivity to soil dielectric constants [6]. Senyurek et al. proved that fusing reflectometry signals (direct and reflected L-band GPS signals) with optical UAV multispectral imagery improves sub-surface moisture estimation, overcoming the shallow surface penetration limit (top 1–2 cm) inherent to purely optical systems [6].

2.2 Irrigation management and water stress

Water availability directly governs stomatal conductance, leaf temperature, and biomass accumulation. Plant stress induced by deficit irrigation can be intercepted thermally long before visible foliar symptoms occur [21].

The Crop Water Stress Index (CWSI), derived from thermal infrared (TIR) crop temperature measurements normalized by ambient air temperature and vapor pressure deficit, serves as a standard metric for water deficit [21]. However, non-water-stressed baselines vary dynamically with atmospheric conditions. Machine learning models overcome empirical baseline limitations by directly learning the non-linear relationship between raw thermal emissions, atmospheric metrics, and stomatal conductance.

When water intake drops, plants close stomata to conserve moisture, suppressing evaporative cooling and causing canopy temperatures to rise relative to ambient air. UAV thermal imaging captures this canopy temperature elevation [21]. Fusing thermal data withed-edge and NIR vegetation indices allows ML algorithms (such as SVR and Gradient Boosting) to decouple structural canopy sparsity from genuine thermal stress, enabling highly accurate variable-rate irrigation scheduling that reduces water consumption while maintaining crop productivity.

2.3 Nutrient mapping and fertilizer optimization

Optimizing nitrogen (N), phosphorus (P), and potassium (K) application is critical to preventing crop yield penalties and minimizing fertilizer runoff into ground ecosystems.Precision nutrient mapping leverages spectral absorption dynamics—particularly the sharp reflectance gradient across the Red-Edge region (690–740 nm) driven by chlorophyll concentration [14], [34].

Singhal et al. evaluated enhanced chlorophyll estimation models in maize by integrating canopy structural traits extracted from UAV multi-view photogrammetry with multispectral indices [14]. Their findings demonstrated that incorporating canopy volume metrics into a machine learning model along with the Red-Edge Normalized Difference Vegetation Index(NDRE) improved Chlorophyll Meter (SPAD) value predictions, counteracting the saturation effects observed in dense crop canopies.

At the field level, establishing the Nitrogen Nutrition Index (NNI) via UAV spectral data allows variable-rate fertilizer applicators to adjust prescriptions dynamically [4], [33]. Allu and Mesapam demonstrated that combining machine learning regression (RF and SVR) with UAV derived spectral indices enabled real-time estimation of above-ground biomass (AGB) and NPK accumulation, generating variable-rate fertilizer prescription maps that optimized nitrogen application efficiency across localized spatial management zones [33].

2.4 Weed detection, classification and mapping

Weed management requires early-season discrimination between emerging crop seedlings and weed species to enable localized herbicide application [7], [30], [35].Traditional uniform spraying leads to high chemical waste, increased operational costs,

and herbicide resistance development. Early-season discrimination is challenged by small plant sizes and spectral similarities between young crop shoots and adjacent weeds. Object-Based Image Analysis (OBIA) combined with machine learning pipelines has addressed these hurdles [7]. Gašparović et.al. introduced an automated method for weed mapping in oat fields using UAV imagery,where spectral features, texture metrics (GLCM), and spatial morphometrics were grouped at the object level [7]. Their machine learning classification pipeline achieved over 90% overall accuracy in separating emerging weeds from target crops.Further advancing this domain, De Villiers et al. evaluated weed detection in rainfed maize crops by comparing high-resolution UAV imagery against satellite platforms [30]. They confirmed that while satellites detect gross field anomalies, ultra-high-resolution UAV imagery (pixel size < 2 cm) processed with Random Forest classifiers is required to discriminate localized weed clusters from crop rows during early phenological growth stages.

2.5 Crop disease and pest monitoring

Pathogens, fungal infections, and pest infestations alter leaf biochemical properties,cellular structure, and canopy transpiration, resulting in distinct spectral anomalies [12],[13], [28], [29], [30].

Early warning systems rely on detecting per-symptomatic spectral shifts. Narmilan et al.applied machine learning techniques to UAV multispectral imagery to detect White Leaf Disease in sugarcane, demonstrating that changes in the red-edge and shortwave infrared regions preceded visible chlorosis [29]. Zhu et al. provided a comprehensive analysis of UAV-based remote sensing imagery for crop disease and pest detection, noting that traditional ML models like Random Forest and SVM, when provided with optimized spectral vegetation indices and texture features, offer rapid and computationally efficient disease classification [28].Complementing disease monitoring, Ma et al. demonstrated data-driven precision pest management by modeling the spatial distribution of beneficial or target biological agents(such as vermiculite-carried predatory mites) released from UAVs, using machine learning regression to match deployment density with micro-climatic pest infestation maps [30].

2.6 Variable rate actuation, pesticide and herbicide application

Integrating aerial sensing with aerial application represents a closed-loop precision management workflow [10], [18], [35], [33]. Spraying UAVs equipped with variable-rate pulse-width modulation (PWM) nozzles use real-time or per-planned ML prescription maps to adjust flow rates dynamically based on flight speed and localized target density[18], [33].

Prabhu et al. validated an integrated adoption framework for precision agriculture where UAV weed detection maps were translated directly into variable-rate herbicide spraying missions, achieving significant chemical volume reductions [18]. However, aerial application efficacy depends heavily on droplet deposition, canopy penetration, and drift minimization.
To optimize application parameters, Ni et al. designed a variable spray system for plant protection UAVs using Computational Fluid Dynamics (CFD) combined with regression analysis [10]. Their ML regression models predicted droplet distribution patterns as a function of multirotor down wash velocity, flight altitude, wind speed, and nozzle pressure. Similarly, Wang et al. developed an autonomous drone spraying control system that evaluates the coefficient of variation (CV) of spray distribution in real-time, leveraging operational feedback models to maintain uniform droplet coverage across dynamic field topographies [33].

2.7 Yield prediction and pre-harvest forecasting

Accurate, in-season yield forecasting allows growers to optimize storage, logistics,marketing, and supply chain commitments prior to harvest [9], [19], [20], [27], [31], [33],[34], [28].Traditional yield models relied on simple late-season single-date vegetation index correlations. Recent research demonstrates that multi-temporal, multi-sensor data fusion paired with advanced machine learning substantially improves yield prediction accuracy [27], [31], [28]. Fei et al. demonstrated that fusing UAV multispectral data, thermal metrics, and 3D structural canopy height models (CHMs) into ensemble machine learning algorithms (Random Forest and Gradient Boosting) generated highly accurate wheat yield predictions weeks prior to maturity, vastly outperforming single-sensor baselines [27].

2.8 Gaps in the literature

Despite significant progress across these domains, several critical gaps remain:

- Lack of End-to-End System Coupling: A disjoint persists between raw flight parameter planning, radiometric calibration pipelines, machine learning model generation, and the down-stream execution on variable-rate hardware [12], [26].
- Spatial Auto correlation and Over-Optimistic Validation: Many published studies rely on random train-test splits on contiguous spatial pixels or adjacent plot units. Due to spatial auto correlation, this practice results in severe data leakage and artificially inflated performance metrics (R^2, F1-score) that fail to generalize to independent fields [11], [34].
- Spectral Saturation in Dense Canopies: Traditional two-band vegetation indices (e.g., NDVI) saturate during high canopy closure phases (LAI > 3), degrading ML model sensitivity to biomass and nutrient variations in late growth stages [8], [14],[35].
- Domain Shift Across Seasons and Cultivars: ML models trained on a single field, single cultivar, or specific phenological window exhibit substantial performance degradation when applied to different seasons or soil types due to variable background reflectances and illumination geometries [31], [34].
- Compute and Edge Processing Constraints: Modern high-density sensor payloads generate massive datasets that require prolonged offline processing, creating a latency bottleneck between aerial sensing and real-time field actuation [28].

3. METHODOLOGY

3.1 UAV based weed detection and precision herbicide spraying

The figure illustrates the sequential workflow consisting of seven stages: UAV image acquisition, image preprocessing, feature extraction and weed detection, AI analysis and decision-making, weed mapping and path planning, precision herbicide spraying, and performance evaluation. The downward arrows indicate the order of operations, from collecting field images to evaluating the final system performance. The flowchart represents a synthesis of stages reported across the reviewed studies; it does not imply that all seven stages were experimentally implemented together in a single field trial.

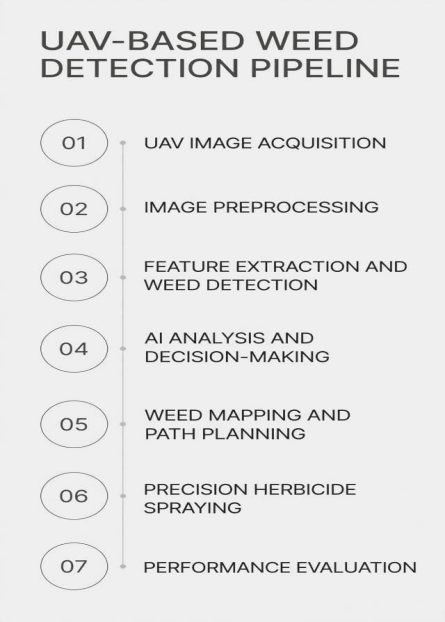


Fig. 3.1 UAV based weed detection& precision herbicide spraying

UAV image acquisition
UAVs equipped with suitable cameras and sensors capture high-resolution aerial images of agricultural fields. Images are collected at appropriate flight heights and crop growth stages to monitor crop conditions and identify weed-infested areas.
Image preprocessing
The collected images are processed to improve their quality and suitability for analysis. Preprocessing includes image correction, noise removal, image stitching where required, segmentation and preparation of image datasets.
Feature extraction and weed detection
Spectral, textural, structural and vegetation-index features are extracted from the processed images. Machine-learning and deep-learning algorithms are used to distinguish weeds from crops and identify areas requiring treatment.
AI-based analysis and decision-making
The extracted features are analyzed using trained ML models to classify vegetation, estimate crop health and determine weed locations. Model performance can be assessed using accuracy, precision, recall, F1-score and other suitable evaluation metrics.
Weed mapping and path planning
The detected weeds are represented on spatial maps to identify the locations requiring herbicide application. These maps can be used to plan UAV flight paths and targeted spraying operations. Precision herbicide spraying a UAV equipped with a spraying mechanism applies herbicides to identified weed-infested locations. Targeted spraying is intended to reduce unnecessary chemical application while maintaining effective weed control.

3.2 Major Components

The major technologies and components discussed in the reviewed studies include:

- Unmanned Aerial Vehicles (UAVs): Used to capture aerial images and collect spatial information from agricultural fields.
- Sensors and cameras: RGB, multispectral, hyperspectral, thermal and LiDAR sensors used to monitor crop and soil conditions.
- Image-processing systems: Used to preprocess aerial images, extract useful features and identify weeds, crops and stressed vegetation.
- Machine-learning algorithms: Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Decision Trees and XG-Boost for classification and prediction.
- Deep-learning algorithms: Convolutional Neural Networks (CNNs), artificial neural networks and other deep-learning architectures for image classification and crop analysis.
- IoT sensors: Soil-moisture and environmental sensors used to collect field data, including soil moisture, temperature and humidity.
- Precision spraying systems: UAV mounted spraying mechanisms designed to apply herbicides selectively to identified weed locations.
- Computing systems: Cloud, edge and embedded computing platforms used for image analysis, model execution and agricultural decision-making.

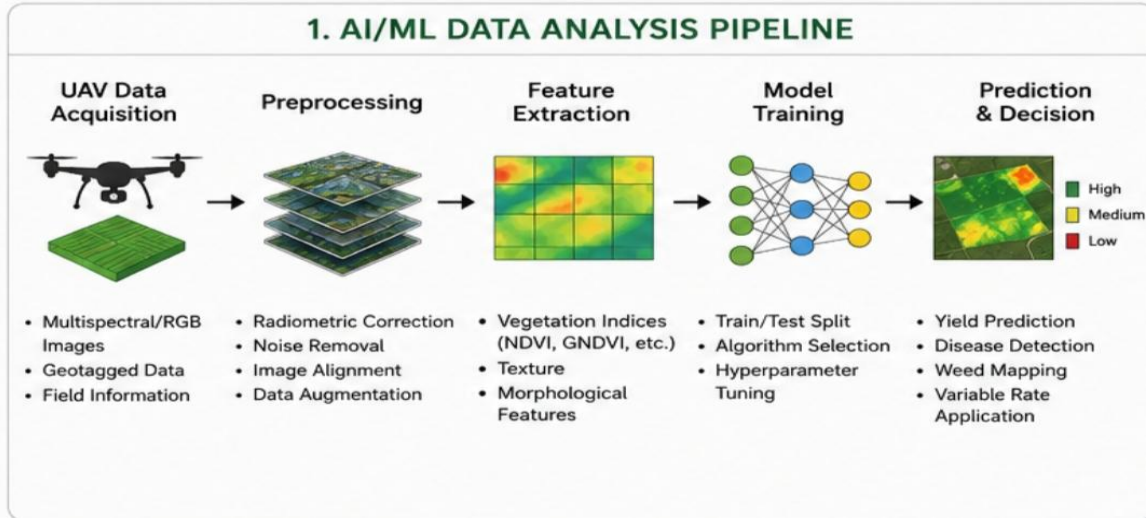
UAVs are used as aerial data-collection platforms to capture images and sensor measurements over agricultural fields. Multirotor drones provide flexibility and manoeuvre ability for detailed field surveys, while fixed-wing UAVs can cover larger areas. The choice of platform depends on the field size, sensor payload, flight duration, and monitoring requirements

3.3 Data Analysis Using AI/ML

The reviewed studies assess model performance, prediction errors, detection accuracy, resource efficiency and the potential benefits and limitations of UAV-based precision agriculture.
This workflow represents an integrated system derived from the reviewed research. It is a proposed synthesis of different approaches, not a claim that all these stages were experimentally implemented together in one field trial.
The supplied agricultural studies use different machine learning algorithms depending on the variable being estimated and the structure of the available data.
3.3.1 AI-ML Data analysis pipeline
The figure below explains how AI/ML data analysis pipeline represents the complete process of collecting agricultural data using Unmanned Aerial Vehicles (UAVs), processing the collected images, extracting useful information, training machine learning models and generating predictions.
In smart agriculture, UAVs are equipped with cameras and sensors to collect information about crop health, soil conditions, weed growth, diseases and irrigation requirements.The collected data is analysed using AI and ML algorithms to support accurate and efficient agricultural decision-making.

Fig. 3.2 AI &ML Data analysis pipeline

Step 1: UAV Data Acquisition
Data acquisition is the first stage of the pipeline. UAVs fly over agricultural fields and collect images using different types of cameras and sensors.



Step 2: Preprocessing
The collected images may contain noise, distortions, lighting variations and unwanted information. Preprocessing improves the quality of the data before applying ML algorithms.
Step 3: Feature Extraction
Feature extraction means identifying useful characteristics from agricultural images.
Step 4: Model Training
In this stage, the extracted features are provided to machine learning algorithms.The model learns patterns from the training data and uses them to predict results for new data.
Model training process:
1. Collect the dataset.
2. Divide data into training and testing sets.
3. Select an appropriate ML algorithm.
4. Train the model using training data.
5. Tune model parameters.
6. Evaluate performance using test data.

Step 5: Prediction and Decision
After training and testing, the model is used to analyse new agricultural images.
Expected outputs:
1. Crop yield prediction.
2. Disease detection.
3. Weed mapping.
4. Variable-rate fertilizer application.
5. Irrigation management.

Example: If a UAV captures an image of a field and the trained model identifies an area with poor vegetation health, farmers can inspect that area and take appropriate action.

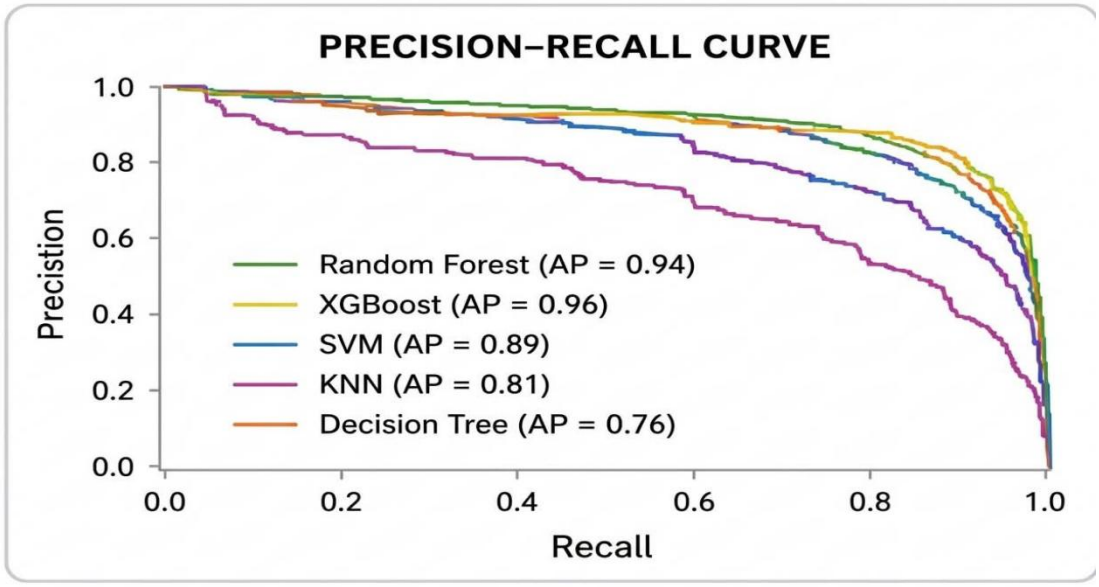


Fig.3.3 Precision Recall curve

The above figure explains Precision–Recall (PR) curve is a performance evaluation graph used to measure the effectiveness of a machine learning classification model.in agriculture, it can be used to evaluate weed detection, crop disease identification and pest detection systems.
It represents the relationship between two important performance measures Precision & Recall
The graph shows how precision changes when recall changes as the classification threshold is adjusted.Higher precision means fewer false-positive detection.Higher recall means fewer actual weeds are missed.A curve closer to the top-right corner generally indicates better performance.
Based on the illustrative graph:
1. XGBoost has the highest AP value of 0.96.
2. Random Forest has an AP value of 0.94.
3. SVM has an AP value of 0.89.
4. KNN has an AP value of 0.81.
5. Decision Tree has an AP value of 0.76.

Therefore, XGBoost shows the best illustrative Precision–Recall performance among the five models.

3.3.2 Data Analysis Using AI/ML Models
Machine learning algorithms map the relationships between high-dimensional features and ground agronomic metrics:
• Random Forest (RF): Provides exceptional robustness for mixed tabular datasets and generates clean feature importance rankings.
• Support Vector Regression (SVR): Utilizes radial basis functions to effectively process high-dimensional features on smaller sample datasets.
• Partial Least Squares Regression (PLSR): Projects predictor variables into low-dimensional latent spaces, critical for handling highly collinear continuous bands in hyperspectral datasets.

3.3.3 Random Forest (RF)
Random Forest (RF) is an ensemble machine-learning method that combines multiple decision trees to make a final prediction. In UAV-based smart agriculture, RF can process engineered features such as vegetation indices, spectral information, texture features, and object-level features obtained

from RGB or multispectral imagery. It is widely used for crop/weed classification, disease and stress detection, nutrient estimation, biomass and yield prediction, and precision agriculture applications. The paper highlights RF as a robust method for nonlinear relationships and heterogeneous UAV feature spaces, with relatively limited tuning and useful feature-importance information for agronomic interpretation.

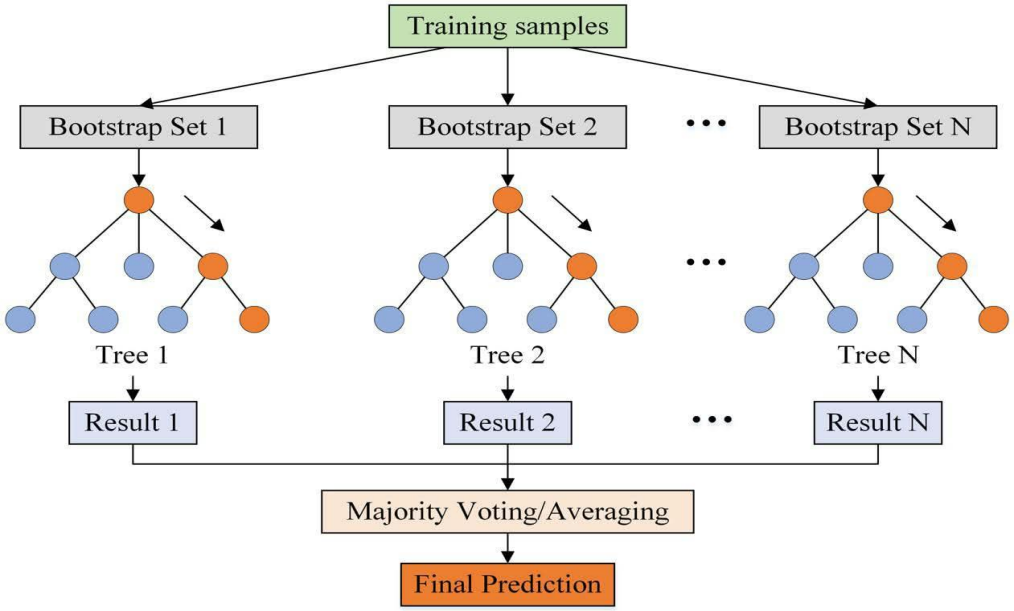


Fig. 3.4 Random Forest (RF) in UAV Agriculture

Random Forest is a Machine Learning algorithm used for classification and prediction.It works by combining multiple Decision Trees to produce one final result.

In simple words, instead of depending on one decision tree, Random Forest uses many decision trees and combines their results to improve prediction.

For example in agriculture, Random Forest can analyse UAV images and predict crop yield, identify crop diseases and estimate soil moisture.

3.3.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine-learning algorithm that separates different classes by finding an optimal decision boundary (hyperplane) with maximum margin between classes. In UAV agriculture, SVM is particularly useful when the number of features is high but labelled samples are limited, such as with multispectral or hyperspectral UAV data. The paper reports SVM applications in crop classification, weed discrimination, disease and pest detection, plant stress identification, and agricultural decision-support tasks. Kernel functions allow SVM to model nonlinear relationships, although careful selection of kernels and hyperparameters is required, and performance can decrease when datasets become very large.

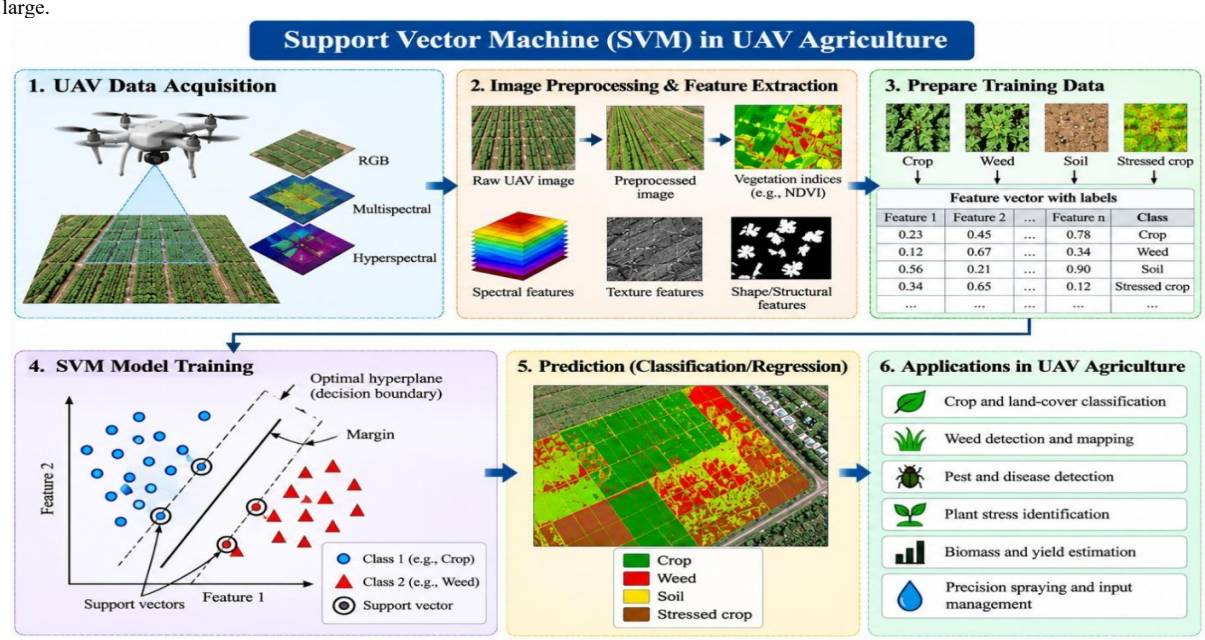


Fig. 3.5 Support Vector Machine (SVM) in UAV Agriculture

4. RESULTS AND FINDINGS

4.1 Combined Findings

- Data fusion is useful: Combining UAV imagery with satellite observations, IoT measurements or reflected-GNSS information can provide a more complete picture than relying on one data source.
- Machine learning converts observations into decisions: ML supports estimates of moisture, biomass, nitrogen-related variables, crop parameters and yield variability, and can help map weeds.
- Time and location matter: Repeated observations across crop-growth stages can improve interpretation, but models must be tested across different seasons, fields and environmental conditions.
- Automation can improve targeting: UAV mapping and variable-spray systems can support more localized weed control, crop protection and input application.
- Validation is essential: Numerical results should be interpreted in the context of the original study's dataset, validation design and field conditions. A result from one crop or location is not automatically transferable.
- Implementation requires a complete system: Sensors, UAV flight planning, positioning, data processing, ML models, communications and farm decision tools need to work together.

4.2 Key results and Limitations

Paper / focus	Aim	Results and findings	Limitations / considerations
El Alaoui et al. (2024), "Unleashing the potential of IoT, artificial intelligence, and UAVs in contemporary agriculture: a comprehensive review."	Reviews the combined role of IoT, AI and UAVs in modern agriculture.	The technologies can work together to collect field information, analyse crop conditions and support timely farm decisions. IoT provides connectivity between devices and data sources, while UAVs add flexible aerial sensing.	Review-level paper; practical adoption depends on reliable connectivity, interoperability, cost, data quality and integration with farm workflows.
Yang et al. (2025), "Precision assessment of rice grain moisture content using UAV multispectral imagery and machine learning."	Uses UAV multispectral imagery and machine learning to assess rice grain moisture.	The study illustrates how spectral information captured from a UAV can be related to a crop/product quality variable, supporting non-destructive and spatially detailed assessment.	The review excerpt does not give a specific accuracy value for this reference. Performance may depend on crop stage, calibration, field conditions and representative measurements.
Aldossary et al. (2024), "Internet of things (IoT)-enabled machine learning models for efficient monitoring of smart agriculture."	Examines IoT-enabled machine-learning approaches for agricultural monitoring.	Integrating IoT data with ML can support continuous or timely monitoring and data-driven decisions, rather than relying only on occasional manual inspection.	Deployment depends on sensor reliability, network availability, data integration, computational resources and validation in real agricultural conditions.
Singh et al. (2025), "Estimating cotton biomass and nitrogen content using high-resolution satellite and UAV data fusion with machine learning."	Combines satellite and UAV observations with ML to estimate cotton biomass and nitrogen content.	The approach uses complementary data sources: UAV imagery provides fine spatial detail and satellite data can add broader-area information. Such fusion can support crop-growth and nutrient assessment.	Data from different platforms must be aligned and calibrated. Transferability across fields, growth stages and seasons requires additional validation.
Padhiary et al. (2024), "Enhancing precision agriculture: a comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation."	Reviews ML and AI-vision uses in all-terrain vehicles for farm automation.	Ground vehicles equipped with vision and ML can complement aerial UAV surveys by carrying out close-range inspection and targeted field operations.	Ground robots and aerial UAVs have different coverage, mobility and sensing strengths. Practical performance depends on terrain, vision conditions, navigation and integration with farm systems.
Senyurek et al. (2022), "Fusion of reflected GPS signals with multispectral imagery to estimate soil moisture at sub field scale from small UAS platforms."	Combines reflected-GPS/GNSS-related measurements with UAV multispectral imagery for soil-moisture estimation.	The review reports production of 5 × 5 m soil-moisture maps, with an RMSE of about 0.013 m^3/m^3 under tenfold cross-validation. This shows the potential of combining complementary sensing sources for detailed moisture mapping.	Accuracy and transfer ability depend on local soil, vegetation cover, calibration and validation. Results should not automatically be assumed to apply to every field or crop.
Gašparović et al. (2020), "An automatic method for weed mapping in oat fields based on UAV imagery."	Develops an automatic weed-mapping method using UAV imagery in oat fields.	The work demonstrates the use of aerial imagery to identify and map weeds, creating spatial information that can support targeted weed management.	Weed/crop appearance changes with growth stage, lighting, canopy density and field background. The review does not provide a specific performance figure for this reference in the cited discussion.
Zhang et al. (2024), "Estimation of the bio-parameters of winter wheat by combining feature	Uses multi-temporal UAV multispectral images, feature	Using images from multiple growth stages can capture crop development over time. Feature selection helps focus	Results depend on the selected growth stages, image quality, chosen features and crop/field

selection with machine learning using multi-temporal unmanned aerial vehicle multispectral images."	selection and ML to estimate winter-wheat bio-parameters.	the model on useful image variables and may improve efficiency and prediction quality.	conditions. Independent validation is needed before transferring the model to other locations.
De Villiers et al. (2024), "Assessing maize yield spatiotemporal variability using unmanned aerial vehicles and machine learning."	Uses UAV observations and ML to study spatial and temporal variation in maize yield.	The work supports the use of UAV-derived crop information to map yield variability, helping identify areas within a field that perform differently and supporting site-specific management.	Yield patterns vary with weather, crop stage, soil and management. Reliable ground yield data and testing across seasons or locations are important for robust predictions.
Ni et al. (2021), "Design of variable spray system for plant protection UAV based on CFD simulation and regression analysis."	Designs a variable-rate UAV spraying system using computational fluid dynamics (CFD) and regression analysis.	The review reports a model combining CFD-based training data with a hybrid SVR–BPNN approach; predicted and measured flow rates had an RMSE of 6.50% in field validation. The work indicates that modelling can help guide spray-system settings and variable application.	Spray performance can change with nozzle type, flow rate, flight height, wind and crop structure. Field testing and calibration remain important before operational use.

5. CONCLUSIONS AND FUTURE SCOPE

5.1 Conclusions

The integration of Unmanned Aerial Vehicles (UAVs) and Machine Learning (ML) has established a scalable paradigm for precision and smart agriculture. UAVs resolve the spatial and temporal limitations of satellite platforms and the coverage constraints of ground vehicles, serving as ultra-high-resolution aerial data collectors. Machine learning algorithms transform these multi-modal, unstructured raw sensing streams into actionable agronomic intelligence. System-level integration—encompassing RTK-guided flight planning, rigorous empirical line radiometric calibration, multi-sensor feature engineering (spectral, textural, structural), and spatially safeguards-driven ML models enables site-specific management across soil moisture assessment, irrigation scheduling, variable-rate fertilization, early disease detection, selective weed management, and in-season yield forecasting. Adopting classical ML techniques (Random Forest, XGBoost, SVR, PLSR) provides high statistical accuracy, domain interpretability, and computational efficiency suitable for field-level deployments.

The combination of Unmanned Aerial Vehicles and Machine Learning presents a robust, scalable structure for modern precision farming. By transitioning the agricultural workflow away from manual evaluation or coarse satellite intervals into high-resolution, multi-sensor cyber-physical frameworks, operators can systematically execute site-specific target interventions. Utilizing statistical cross-validation safeguards alongside advanced multi-sensor data fusion sets a foundational pathway for reliable crop health tracking, sustainable input conservation, and highly accurate pre-harvest forecasting.

5.2 Future Scope

5.2.1 Edge AI and Tiny ML Integration

Onboard edge microprocessors allow lightweight, quantized machine learning models to run directly on flying drones, eliminating the latency of ground-station processing. By performing real-time inference mid-flight, these architectures can instantaneously trigger automated actions, such as activating selective spray nozzles upon detecting weeds, completely bypassing the need for slow offline mapping pipelines.

5.2.2 Wireless Sensor Networks(WSN) and IOT Synergy

Smart agricultural modeling will rely on continuous multi-layer data fusion that bridges ground-based IoT sensors with periodic aerial drone surveys. Ground networks provide high-frequency, point-scale data like soil moisture and local weather, while drones provide the broad spatial coverage needed to fill the gaps between those ground nodes for comprehensive mapping.

5.2.3 Federated learning and privacy preserving frameworks

Data privacy boundaries and bandwidth limits are resolved through Federated Learning, which trains machine learning models locally across distributed farm servers rather than a centralized database. Individual farms independently update their systems and transmit only encrypted model weights to a central server, aggregating collective agricultural knowledge while protecting proprietary management data.

5.2.4 5G/6G Networks and cloud synergy

Ultra-reliable, low-latency 5G and 6G networks will enable real-time streaming of high-abitrate raw sensor data directly from flying drones to cloud-native compute clusters. These cloud systems instantly run photogrammetry and machine learning predictions, pushing variable-rate prescription maps back to ground tractors in near-real-time for immediate field execution

5.2.5 Autonomous UAV swarms and human-AI collaboration

Scaling operations across vast landscapes requires transitioning from single-drone workflows to fully autonomous, collaborative fleets. In these heterogeneous swarms, lightweight fixed-wing mapping drones scan fields to identify target stress areas and immediately communicate targeted task assignments directly to heavy-payload multirotor spraying drones for localized spot treatment.

5.2.6 Digital twins for prescriptive farm simulation

Fusing multi-temporal drone data, high-resolution soil maps, and weather forecasts enables the creation of dynamic Digital Twins of physical agricultural fields. Integrated machine learning models allow managers to run predictive "what-if" simulations, evaluating the final yield impact of varying irrigation volumes or nitrogen application dates under changing climate scenarios before implementing them.

5.2.7 Alternative power systems for extended flight endurance

To overcome the strict 20-to-35-minute flight limitation of standard batteries, advanced alternative propulsion systems are being integrated into multirotor platforms. Utilizing solar-assisted flight frames, hybrid petrol-electric generators, and hydrogen fuel cells promises to extend drone flight endurance beyond 2 to 3 hours, making high-resolution remote sensing highly feasible over massive regional scales.

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