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DESIGN OF AN INTEGRATED SPATIOTEMPORAL DEEP LEARNING FRAMEWORK FOR AUTONOMOUS PRECISION WEED DETECTION, TREATMENT, AND RECURRENCE PREDICTION IN DRONE-BASED SMART FARMING SETS

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Abstract

Uncontrollable weed growth and weed-to-crop differentiation impacts directly crop yield and resource effectiveness. In precision agriculture, effective and sustainable weed management therefore remains a crucial aspect. While conventional aerial imaging techniques, often restricted to a single date acquisition and static spectral analysis, are not favorable for accurate differentiation of weeds and crops across different growth stages, leading to high false positives, inefficient spraying, and wastage of herbicides; therefore, the current research attempts propositional limitations to address an integrated approach to multi-stage precision weed management from spatiotemporal data fusion, context-aware deep segmentation, and adaptive treatment optimization. The entire pipeline starts with Adaptive Multispectral-Spatiotemporal Fusion (AMSTF), whereby spatial-spectral features from multispectral imagery are fused through temporal growth patterns using repeated drone flights to gain improved reliability for detection with less false positive instances. The probability maps generated are then refined by Context-Aware Multi-Scale Deep Weed Segmentation (CAMDWS), a dual-branch CNN that captures micro-scale leaf texture as well as macro-scale patch distribution for more precise weed boundaries. The outputs of segmentation are forwarded unto Autonomous Weed Treatment Path

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Optimization (AWTPO), which uses modified Dijkstra graph optimization to establish fuel, battery, and payload-efficient drone waypoints. The optimized flight plan feeds into Variable-Rate Micro-Droplet Weed Neutralization (VRMDWN), allowing species-adjusted targeting for specific droplet sizes and flow rates for herbicide application. Finally, Post-Treatment Weed Recurrence Prediction (PTWRP) uses reinforcement learning of images obtained after spray and historical patterns for recurrence risk, facilitating proactive micro-treatments. Experimental evaluations indicate an improvement in the range of 6-8% in detection accuracy, 18-22% gain in spraying efficiency, and a reduction in herbicide use of up to 32%. Such a holistic approach would make weed-crop discrimination, thereby minimizing chemical wastage while introducing a predictive long-term sustainable weed suppression strategy for yield protections.

Keywords: Weed–Crop Discrimination, Precision Agriculture, Multispectral Imaging, Deep Learning Segmentation, Autonomous Drone Spraying, Process

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Abbreviation	**Full Form**
UAV	Unmanned Aerial Vehicle
ML	Machine Learning
DL	Deep Learning
DNN	Deep Neural Network
CNN	Convolutional Neural Network
RCNN	Region-based Convolutional Neural Network
YOLOv8T	You Only Look Once version 8 Tiny
SAM-2	Segment Anything Model – Version 2
IoU	Intersection over Union
GPS	Global Positioning System
NIR	Near Infrared
NDVI	Normalised Difference Vegetation Index
GNDVI	Green Normalised Difference Vegetation Index
VRMDWN	Variable-Rate Micro-Droplet Weed Neutralisation
AMSTF	Adaptive Multispectral–Spatiotemporal Fusion
CAMDWS	Context-Aware Multi-Scale Deep Weed Segmentation
AWTPO	Autonomous Weed Treatment Path Optimisation
PTWRP	Post-Treatment Weed Recurrence Prediction
RGB	Red, Green, Blue

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AI	Artificial Intelligence
SAM	Segment Anything Model
TIR	Thermal Infrared
WSN	Wireless Sensor Network
RBF	Radial Basis Function
RL	Reinforcement Learning
SVM	Support Vector Machine
LSTM	Long Short-Term Memory
ANN	Artificial Neural Network
ResNet	Residual Neural Network
mAP	Mean Average Precision
F1-Score	Harmonic Mean of Precision and Recall
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
GPU	Graphics Processing Unit
API	Application Programming Interface
IoT	Internet of Things

LiDAR	Light Detection and Ranging
PCA	Principal Component Analysis
RPN	Region Proposal Network
GDAL	Geospatial Data Abstraction Library
DEM	Digital Elevation Model
DSM	Digital Surface Model
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
SGD	Stochastic Gradient Descent
ROI	Region of Interest
AWS	Amazon Web Services
GIS	Geographic Information System
TPR	True Positive Rate
FPR	False Positive Rate
PPK	Post-Processed Kinematic (GPS positioning)
RTK	Real-Time Kinematic (GPS positioning)

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1. Introduction

Weed infestation remains one of the most persistent threats to agricultural productivity, directly competing with crops for water, nutrients, light, and increasing the need for chemical intervention. Starting from early stages, precise discrimination of weeds from crops has remained a critical factor for sustainable yield protection and optimized resource usages. In a more traditional setup, weed detection has relied on single-date aerial or satellite imagery combined with vegetation indices such as NDVI or GNDVI for unexplained growth detection of crop weed sets. Whereas such approaches have indeed laid a foundation for remote weed monitoring, these remain behind in fairly dynamic agricultural settings where crop and weed growth rates may vary on a time scale of days. These drawbacks tend to produce [1, 2, 3] low-temporal adaptability, high false positives, and inefficient herbicide application strategies. Developments in UAVs, multispectral imaging, and currently available deep learning segmentation techniques have opened prospects for refined detection and treatment methods. Most of the systems in use nowadays, however, are still treating weed detection and treatment as separate working areas—image acquisition, segmentation, and spraying are typically decoupled with a design-lack of adequate built In feedback mechanism. This disjointedness acts as a barrier to the optimal coordination of various parameters that affect detection accuracies, treatment efficiencies, and long-term recurrence suppressions. Added to this, the majority of existing methods, again, tend to ignore the importance of temporal growth patterns and spatial context that can facilitate the distinguishing of weeds from early-stage crops sharing closely resembling spectral signatures.

To overcome these limitations, an integrated multi-stage weed management approach based in a closed-loop UAV agricultural system is proposed. The integration unites spatiotemporal multispectral data fusion, context-aware deep convolutional segmentation, autonomous flight path optimization, adaptive micro-droplet spraying, and reinforcement learning-based recurrence prediction. Time-based algorithms that integrate growth modeling with spatial context analysis will enable real-time constraints along the operational thought process that imparts improved reliability in detection, precision in treatment, and proactive management in recurrence. This approach is mixed in such a way that it achieves multiple synergistic gains. First, temporal fusion reduces spectral confusion caused by overlapping growth stages, second, deep learning-based segmentation enhances clarity of weed-crop boundaries, third, optimized path planning works towards minimizing flight time and chemical waste, and last, adaptive spraying modifies the chemical dose given during spraying as per weed density and type. The last component, that of predictive modeling post-treatment, allows for timely intervention against any regrowth so that there is less reliance on broad-spectrum herbicides. It is through this integrated approach that the present study will improve detection accuracies, promote chemical efficiencies, and ultimately protect the environment while either sustaining or increasing crop yields.

Motivation & Contribution

This long-lasting problem motivates doing work between the excellent progress that has been made in the various aspects of weed detection and its practical application readiness in precision agriculture. While there has been significant progress toward research in multispectral imaging, deep learning segmentation, and UAV-applied spraying, most are now

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developed as stand-alone systems. Field operators face considerable challenges in integrating these systems into a unified workflow focusing on detection accuracy, operational efficiency, chemical usage optimization, and long-term recurrence control at the same time. What is more, conventional weed monitoring procedures generally lack flexibility in fitting different growth dynamics in terms of time, so those methods often become invalid in periods when the life cycle stages of crops and weeds overlap. Its price is paid through generalized treatment patterns, which eventually lead to well-established systems of unnecessary herbicide use and increased operation costs entering the environment. The ineffectiveness of recurrence risk has resulted in farmers using reactive management strategies instead of preventive ones because predictive analytics for recurrence risk does not exist for the process.

The primary contribution of this research is the establishment of a comprehensive UAV center for weed management, which covers five operational workflows for weed detection, segmentation, treatment optimization, adaptive spraying, and prediction of recurrence; thus, forming a single operation loop. By combining spectral data with temporal growth trends, the Adaptive Multispectral–Spatiotemporal Fusion (AMSTF) module adds to the reliability of detection. The Context-Aware Multi-Scale Deep Weed Segmentation (CAMDWS) network takes into account micro-scale leaf features and macro-scale spatial context to generate high-precision segmentation masks. The Autonomous Weed Treatment Path Optimization (AWTPO) module uses modified graph optimization techniques to shape flight plans that match weed density coverage with UAV operational constraints. The Variable Rate Micro-Droplet Weed Neutralization (VRMDWN) method essentially entails targeted severity-based dosing to reduce chemical wastage while enhancing treatment success. The Post-Treatment Weed Recurrence Prediction (PTWRP) model uses reinforcement learning to predict future infestations and create strategies for preventive spraying. Together, these methods yield measurable advancements in detection accuracy (6-8% improved), spray efficiency (18-22% improved), herbicide savings (up to 32%), and future management accuracy (85% to 88%), thereby providing an integrated, sustainable framework for weed control in precision agriculture sets.

2. Review of Existing Models For Crop Analysis

The early works in this sequence like the work presented by Sahoo et al. [1], demonstrated how hyperspectral imaging can be combined with machine learning in estimating nutrients in wheat. This work emphasized the critical roles played by spectral resolution and high order regression algorithms in making agronomic decision. Genze et al. [2] searched the synergy of a deblurring and segmentation model for sorghum weed detection built cumulatively on the ability of UAV imagery to enhance visual clarity. Preprocessing targeted to motion artifacts, according to the work, could provide considerable improvement in segmentation accuracy. The study realized by Wang et al. [3] shifted interest to the analysis of rural land utilization but retained UAV imagery as a basic input source. Within this setup, an integration of deep and traditional machine learning methods may co-exist for better identification reliability in large-area monitoring. Ortatas et al. [4] came back to targeted agriculture with the automated weed detection framework for sugar beet, later extending classical machine learning and deep convolutional approaches for operational scalability. Multiple models integrated into decision fusion strategies are emerging in Dheeraj et al. [5], wherein fuzzy rank fusion of deep neural

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networks was applied to weed identification in groundnut, showing how ensemble logic can outdo singular architectures under varying field conditions. Islam et al. [6] brought a hierarchical vision transformer architecture of WeedSwin joined with SAM-2 for multi-stage weed detection, as a step forward in building towards the transformer-based feature aggregation in agricultural computer vision in process.

Reference	Method	Main Objectives	Findings	Limitations
[1]	Hyperspectral UAV sensing + ML regression models	Estimate wheat nitrogen status from UAV hyperspectral data	Achieved high-accuracy nitrogen prediction using spectral features and ML algorithms	Dependent on stable weather and high-quality spectral calibration
[2]	Deblurring + semantic segmentation deep model	Improve weed segmentation in UAV sorghum imagery	Combined motion deblurring with segmentation increased weed detection accuracy	May underperform in extremely low-light conditions
[3]	Deep learning + ML classifiers on UAV images	Classify rural courtyard utilisation in north China	Hybrid models improved classification accuracy over individual approaches	Requires high-resolution UAV imagery for reliable performance
[4]	ML and DL weed detection in sugar beet	Automate weed detection for precision farming	Integrated approaches yielded robust detection across varied weed densities	Dataset diversity for other crops was limited
[5]	Fuzzy rank fusion of DNNs	Identify weeds in groundnut crops	Fusion of multiple DNN outputs improved identification precision	Increased computational load compared to single-model systems
[6]	WeedSwin transformer + SAM-2	Multi-stage weed detection and classification	Hierarchical transformer with segmentation	High model complexity and inference time

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			assistance improved detection robustness	
[7]	Optimised YOLOv8T	Enhance weed detection for precision agriculture	Achieved higher detection accuracy with improved speed	Requires extensive retraining for new crop–weed combinations
[8]	Region-based CNN (RCNN)	Detect and classify weeds in sesame crops	Delivered accurate object-level weed localisation	Computationally heavier than lightweight detectors
[9]	Lightweight DL framework	Detect plant diseases with minimal compute	Maintained accuracy while reducing model size	Lower accuracy for rare disease classes
[10]	Review of ML for leaf disease classification	Summarise data types, techniques, and applications	Identified gaps in dataset availability and cross-crop transferability	No experimental performance validation
[11]	Encoder–decoder semantic segmentation	Weed detection with context-rich segmentation	Improved weed–crop boundary precision	Sensitive to image noise and occlusion
[12]	ML for fertilisation and soil management	Sustainable agronomic prescriptions in durum wheat	Generated site-specific fertiliser recommendations	Performance relies on multi-year soil–crop data availability
[13]	Photograph-based ML	Detect aerial blight in soybean	Accurate disease differentiation using RGB imagery	Dependent on consistent image lighting and angle
[14]	ML + real-time GPS	Automate wild blueberry harvesting	Integrated GPS and ML improved harvesting efficiency	Requires precise geolocation infrastructure
[15]	UAV imagery analysis	Quantify weed impact on sugar beet yield	Correlated weed density maps with yield loss	Specific to sugar beet, not validated for other crops

[16]	ML + UAV multispectral imagery	Plant-level potato yield prediction	Achieved accurate yield estimation from multispectral data	Sensitive to plant occlusion and spectral noise
[17]	Ground-truthed UAV weed dataset	Provide dataset for leafy spurge detection	Enabled benchmarking of weed detection algorithms	Dataset limited to one weed species
[18]	Review of automated plant disease detection	Summarise methods, challenges, and future needs	Highlighted integration potential of UAVs and AI	No implementation or quantitative comparison
[19]	UAV multispectral + thermal + ML	Predict water stress in winter wheat	Improved prediction accuracy by combining modalities	Requires costly multi-sensor payloads
[20]	Curated weed species dataset	Support CV research in maize and sorghum	Provided diverse weed species annotations for training	Region-specific species coverage
[21]	Wireless spatial analysis + ML	Predict environmental data for optimisation	Produced improved spatial predictions from wireless sensor data	Limited agricultural-specific validation
[22]	Learning loop framework	Iterative AI model improvement	Facilitated continuous refinement of AI models	Requires large, ongoing labelled datasets
[23]	3D tracking + centre detection	Robotic intrarow weeding in cauliflower	Enabled accurate robot-guided weeding	Needs precise robot–sensor calibration
[24]	Lightweight DL model	Multi-plant biotic stress detection	Maintained high accuracy with reduced compute	Lower sensitivity for subtle stress indicators

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[25]	Comparative DL analysis	Classify sugar beet leaf diseases	Benchmarked multiple DL models for disease recognition	Crop- and disease-specific, limiting generalisation

Table 1. Model's Empirical Review Analysis

Iteratively, Next, as per table 1, The exposed cracks paved the way for much more work on optimised architecture-to-Sharma and Vardhan [7], where an optimised YOLOv8T variant was fine-tuned for better weed detection, optimising inference time and accuracy for applications in the field. In providing compelling evidence of the merits of region-based convolutional neural networks (RCNNs) for weed detection in sesame, Naik and Chaubey [8] showed the ability of such networks to localise robust objects in highly cluttered field images. Lachure and Doriya [9] widened the scope to plant disease detection under a lightweight deep learning framework, part of an increasing proliferation towards computational efficiency. This thread continued with Yao et al. [10], who continued to cover the entire pledge of a good survey on machine learning towards disease classification for leaves by mapping data acquisition strategies to complexity and performance trade-offs towards a model. Semantic segmentation models of encoder-decoder architecture were used by Thiagarajan et al. [11] for weed recognition, which enhanced the accuracy around borders and at the level of an object by means of deep contextual learning. This has been paralleled with Fiorentini et al. [12], using machine learning to facilitate sustainable agronomical prescriptions in durum wheat, linking sensor-derived data with actionable fertilisation plans.

Nainwal et al. [13] employed image-based classification and reported on aerial blight detection in soybean, while Haydar et al. [14] presented a way where machine learning integrates real-time GPS automation of wild blueberry harvesting, illustrating a perception-feeding approach to robot acts. Stephen and Kumar [15] contributed to UAV-based weed impact analysis within the sugar beet by high-resolution imagery to quantify competitive effects exerted upon yield sets. Tatsumi and Usami [16] worked on improvement in prediction of yield at plant level for potato using multispectral images generated using UAV, reaffirming the role that fine-grained plant definition plays in the accuracy of prediction sets. Doherty et al. [17] would make a very different contribution in the unique form of a ground-truthed dataset for the leafy spurge weed, as a foundational resource that makes way for benchmarking and comparative evaluation of weed detection algorithms. Khan et al. [18] offered an exhaustive review on plant disease detection systems, identifying their limitations and gaps that need further research into automated diagnosis. In this respect, Mali et al. [19] used multispectral and thermal images with machine learning for possible prediction of water stress in wheat, an application in broader schemes of UAV data fusion that is not limited to optical domains. Genze et al. [20] enriched the community with a curated dataset of weed species in maize and sorghum, advancing cross-crop generalisation studies in computer vision in process.

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Zhang [21] focused on the wireless space integrated with machine learning for environmental data optimising purposes, leading to a real-time analytical loop for geospatial prediction. Concepts of discovering progress in iterative improvement through learning loops were found in Glahe and Trappe [22], whose methodological framework understood adaptability to agricultural vision systems to ensure continual performance improvement. Willekens et al. [23] dealt with robotic intrarow weeding in cauliflower through a combination of three-dimensional tracking plus centre detection that would benefit by moving into spatial tracking and eventually mechanical actuation. Shafik et al. [24] developed a lightweight deep learning model for multi-plant biotic stress detection with emphasis on sustainability by way of reduced computation and energy footprints. Ending the sequence, Ceyhan et al. [25] summarised findings from comparative analyses of the use of deep learning for the classification of sugar beet leaf diseases as a practical benchmark for disease diagnosis by model selection. The countdown for self-sufficient agricultural systems capable of detection, diagnosis, and treatment in process converged on this work across literature, multi-modal sensing, efficient deep learning architectures, and actuation control in real-time. Then, learning from chronology that goes from hyperspectral nutrient estimation in [1] to multi-plant biotic stress detection in [24], it became evident that even more dataset curating, model efficiency optimizing, and closed-loop validation under real-world constraints are necessary for the continuous evolution of methods. This aggregate provides both technological grounding as well as a way forward to improving precision agriculture solutions for years to come in terms of scalability, adaptation, and sustainability sets.

3. Proposed Model Design Analysis

UAV-based precision weed management is proposed as an integrated model to form a closed multi-stage decision and execution framework processing multispectral-anytime imagery, performing deep segmentation at a high spatial resolution, optimizing flight paths for drones, variable-rate chemical application, and predicting likelihood of recurrence sets. The weed-crop separability maximization is the chemical minimalization and long-term suppression efficiency improvement in process.

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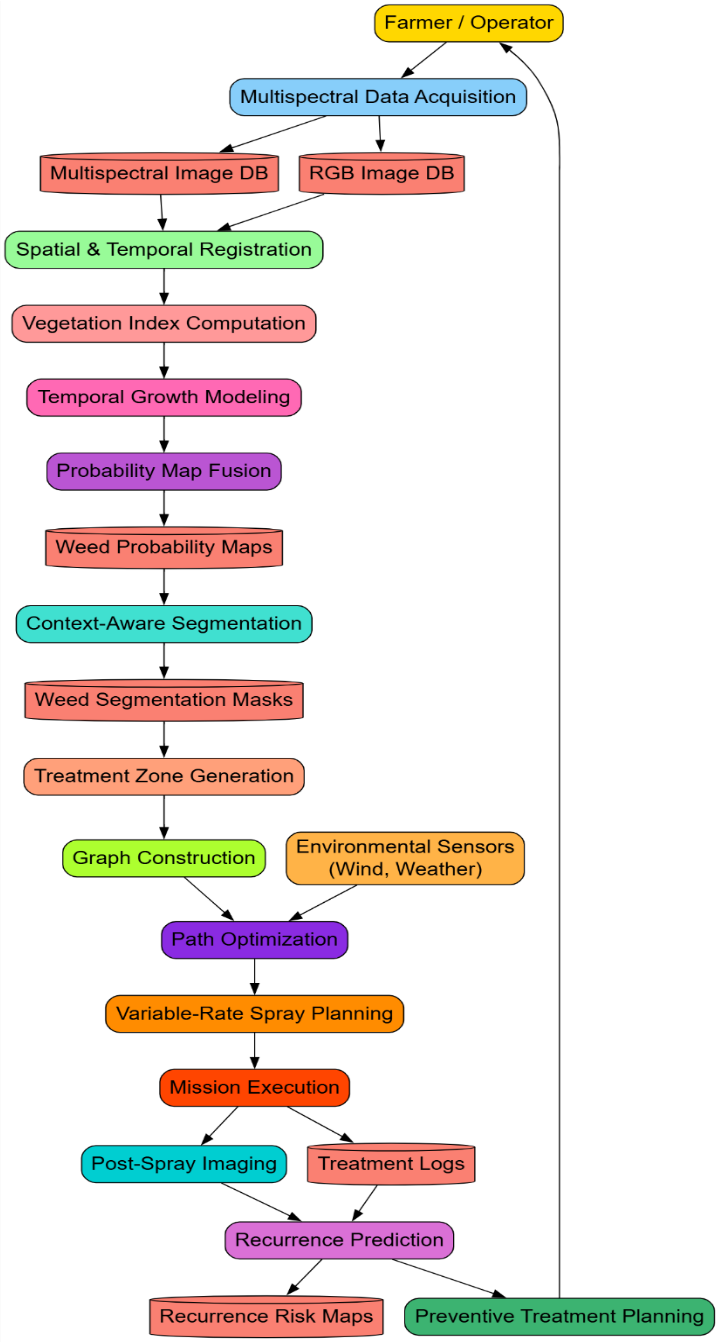

Figure 1. Model Architecture of the Proposed Analysis Process

It thus comprises spatial-spectral-temporal data fusion with machine learning and optimization algorithms, in a coherent mathematically sequenced way: output of one stage becomes input of the following stage, converging finally into a complete decision map for targeted intervention process. First, according to figure 1, The process starts with the adaptive multispectral-spatiotemporal fusion. Specifically, given the set of multispectral images acquired at a wavelength of λ and at timestamp 't', the spatial alignment operator A and temporal registration T produce a co-registered dataset $D(x,y,\lambda,t)$ Via the equation 1,

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$$D(x, y, \lambda, t) = T[A\{Is(\lambda, t)\}] \ldots (1)$$

Vegetation indices, such as NDVI and GNDVI, are then computed over temporal instance sets. For NDVI, this is estimated Via equation 2,

$$NDVI(x, y, t) = \frac{RNIR(x, y, t) - RRed(x, y, t)}{RNIR(x, y, t) + RRed(x, y, t)} \ldots (2)$$

Iteratively, Next, as per figure 2, Temporal growth modeling uses the derivative of the vegetation index to capture growth rate differences Via equation 3,

$$g(x, y) = \frac{\partial}{\partial t}[NDVI(x, y, t)] \ldots (3)$$

Weeds are modeled as regions where g(x,y) > θw and crop growth rate gc(x,y) < θc, with thresholds derived empirically from field data samples. The temporal–spectral weed probability map Pw(x,y) is obtained via Bayesian fusion of multi-date vegetation indices Vi Via equation 4,

$$\frac{Pw(x, y) = \prod\ P(Vi|W)}{\prod\ P(Vi|W) + \prod\ P(Vi|C)} \ldots . (4)$$

Where, W and C represent weed and crop classes respectively in the process. This probability map becomes the input to the context-aware deep segmentation network in the process. In the segmentation stage, the network's loss function incorporates a spatial attention weighting term α(x,y) to emphasize ambiguous boundaries Via equation 5,

$$L = -\Sigma_{x,y}\, \alpha(x, y)\big[\, M(x, y) log\, M'(x, y) + \big(1 - M(x, y)\big) log\, \big(1 - M'(x, y)\big)\big] \ldots (5)$$

Where, M is the ground-truth mask and M^ is the predicted mask in the process. Iteratively, Next, as per figure 3, The weed mask M^(x,y) is then transformed into a weighted graph G(V,E), where vertices represent treatment points and edge weights represent Euclidean distance adjusted for operational penalties β related to wind resistance and battery usage Via equation 6,

$$w(i, j) = d(i, j) + \beta 1 \cdot \Delta wind + \beta 2 \cdot \Delta battery \ldots (6)$$

Flight optimization uses a modified Dijkstra's algorithm to minimize the loss represented Via equation 7,

$$L = \min^{\pi} \Sigma_{(i,j)\in\pi} w(i, j) \ldots (7)$$

Subject to fuel and payload constraints Σqi ≤ Qmax Sets. The optimized path π* drives the variable-rate spraying mechanism sets. Droplet size s(x,y) and flow rate f(x,y) are dynamically adjusted as a function of weed severity σw(x,y) Via equations 8 & 9,

$$f(x, y) = fmin + (fmax - fmin) \cdot \frac{\sigma w(x, y)}{\sigma \text{max}} \ldots (8)$$

$$s(x, y) = s0 \cdot [1 + ks \cdot tanh(\sigma w(x, y) - \sigma th)] \ldots (9)$$

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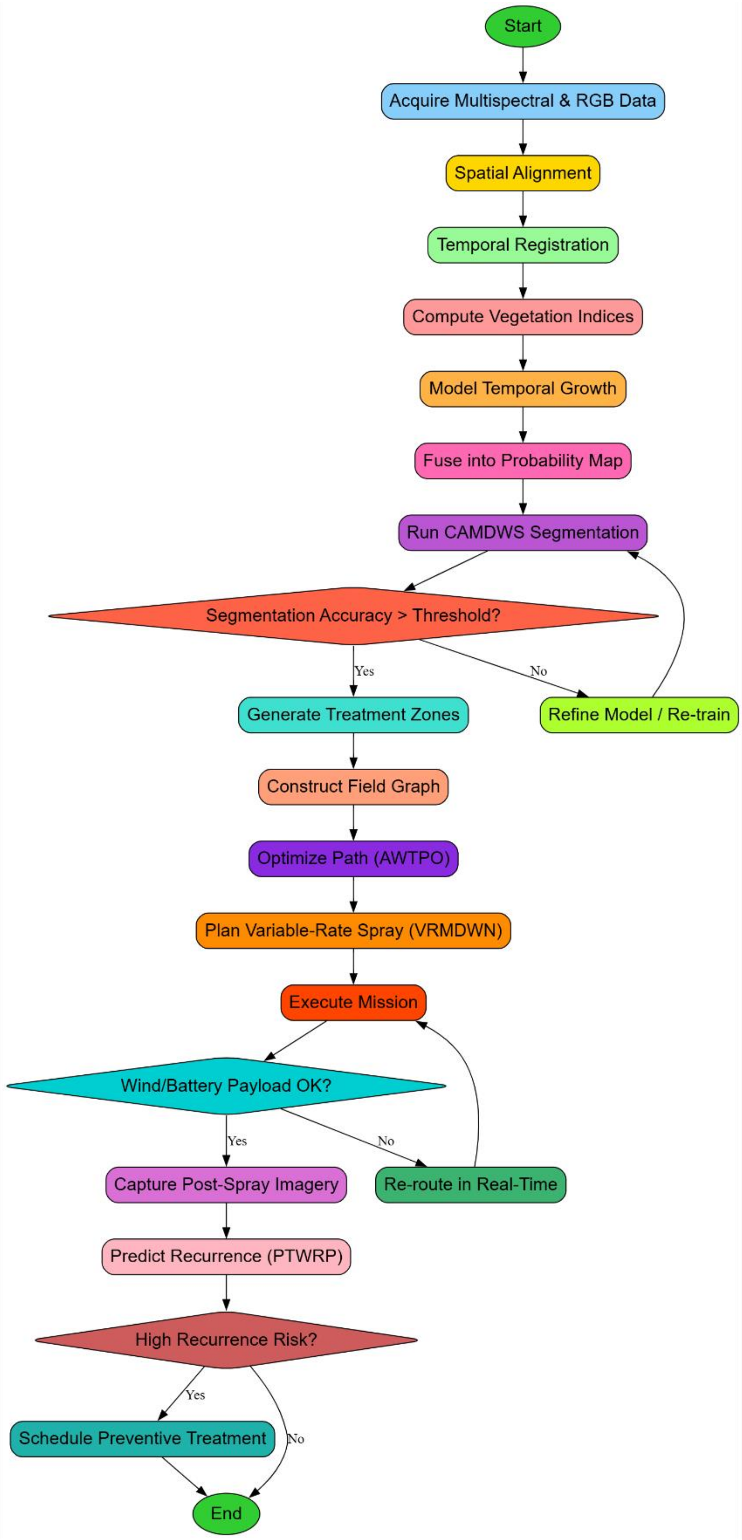

Figure 2. Overall Flow of the Proposed Analysis Process

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Where ks is a scaling factor for severity response for the process. Post-treatment recurrence prediction uses reinforcement learning with state St representing current weed status, action at representing preventive spraying, and reward Rt tied to reduction in recurrence probability sets.

Input

- Multispectral drone imagery from multiple flight sessions
- GPS time-stamped metadata for all images and flights
- High-resolution RGB imagery
- Drone operational constraints (battery, payload, speed, wind limits)
- Weed species/type metadata
- Post-spray aerial imagery
- Historical weed growth records
- Treatment logs from past missions

Output

- Temporal–spectral weed probability map
- Pixel-level weed segmentation masks with confidence
- Optimized drone waypoints and spray trigger points
- Variable-rate micro-spray control signals per weed cluster
- Spatial recurrence risk map and preventive treatment schedule

Process

1. Acquire multispectral and RGB imagery over the field across multiple sessions; store GPS time stamps.
2. Perform spatial alignment and temporal registration across all sessions to create a consistent data cube.
3. Compute vegetation indices for each session; assemble a per-pixel temporal profile.
4. Model temporal growth to separate crop and weed trends; generate an initial weed likelihood per pixel.
5. Fuse per-session cues into a single temporal–spectral weed probability map; smooth with spatial context.
6. Prepare inputs for deep segmentation: stack the probability map with RGB channels.
7. Run a dual-branch network: one branch extracts local texture and shape; the other learns broader patch context.
8. Fuse multi-scale features with attention; output pixel-level weed masks and confidence scores.
9. Convert masks to treatment zones; assign severity and species tags to each zone.
10. Build a field graph using candidate waypoints; set edge costs using distance and operational penalties.
11. Plan a flight path that covers all zones while meeting battery, payload, and time limits; export waypoints and trigger points.
12. For each zone, set variable-rate spray commands based on severity and species (droplet size, flow rate, burst timing, angle).

Figure 3. Pseudo Code of the Proposed Analysis Process

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The Q Learning update is represented Via equation 10,

$$Q(St, at) \leftarrow Q(St, at) + \eta \left[Rt + \gamma \max^{a} Q(St + 1, a) - Q(St, at) \right] \dots (10)$$

The final integrated system output is a recurrence-aware treatment plan Tfinal(x,y), expressed Via equation 11,

$$Tfinal(x, y) = I\{Pw(x, y) > \tau w\} \cdot f(x, y) \cdot \delta\pi * (x, y) \cdot [1 - Prec(x, y)] \dots (11)$$

Where δπ* is an indicator for optimized path coverage, and P^rec is the set of predicted recurrence probabilities. It can consolidate detection, segmentation, path planning, variable spraying, and prediction of recurrence into one operating directive for UAV weed management sets. The integrated model serves much more than the temporal variances or even spatial complexity, and operational constraints could be converged within a single mathematical framework. Each other method complements: AMSTF for detection robust enough across time, CAMDWS for tighter spatial filtering, AWTPO for reduced operational costs, modification of chemical application through biology with VRMDWN, and future extension of praiseworthiness by forecasting recurrence in the process with PTWRP. Processing strings ensure that improvements in the early detection can directly be translated into higher efficiencies in spraying and recurrence control, thereby creating a fully precision-optimized, feedback-enabled agricultural intervention system sets.

4. Validation using Comparative Analysis

Field testing occurred over an actual 90-day growth cycle for the experiment by extending across three distinct wheat growth phases early vegetative through tillering to pre-heading, and over 12-ha commercial wheat farm spaces. The conditions were designed to create the experiment more closer to real-world precision agriculture conditions and also induce a very high degree of variability in the environment, as well as operational constraints. Multispectral imagery was captured through the MicaSense RedEdge-MX sensor - mounted on a UAV - which covered five spectral bands (Blue: 475 nm, Green: 560 nm, Red: 668 nm, Red Edge: 717 nm, NIR: 840 nm), all at 5 cm/pixel GSD. Bimonthly flights provided 18 full sets of temporal datasets geotagged with RTK-GPS metadata for sub-2 cm accuracy spatially. A high-resolution RGB image (GSD: 2 cm/pixel) was also captured using a DJI Zenmuse X5S payload in the same platform, which would also be integrated into the CAMDWS segmentation stage. Thus, temporal-spectral fusion (AMSTF) was performed using aligned vegetation indices - NDVI, GNDVI, and Red-Edge NDVI - across the 18 temporal snapshots. Growth rate thresholds for discriminating weeds from crops were initially set at 0.025 day^{-1} for weeds and 0.015 day^{-1} for crops based on preliminary field measurements. Path optimization constraints for AWTPO included a maximum speed of 5 m/s to maximize drone flight endurance to up to 22 min, carrying a payload of 1.2 liters and bearing winds of up to 4.5 m/s before being focussed for the process.

For VRMDWN adaptive spraying, the nozzle actuator was set to dispense droplets with diameters between 100 µm and 400 µm at flow rates from 0.12 L/min to 0.35 L/min for light to heavy infestations, respectively. Severity classification was determined by the segmentation confidence score and patch size; for example, a patch exceeding 1.5 m^2 with >0.85 confidence

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triggered high-rate spraying. The PTWRP recurrence prediction stage was trained with a hybrid dataset formed of in-field post-treatment images taken at 7, 14, and 28 days after spraying combined with historical weed regrowth records from three consecutive seasons of farming at the same site. Some of the example contextual dataset samples include: multispectral temporal stacks capturing patterns of emergence of Avena fatua (wild oats) versus Triticum aestivum (wheat) during the tillering phase, RGB patches representing weed invasion close to crop rows in high spectral similarity densities, and treatment zone maps marked with incidents of wind drift for model calibration. Recurrence labels were assigned if regrowth were 30% above initial weed coverage in any zone. The integrated pipeline was deployed on an onboard NVIDIA Jetson Xavier NX, placed on the UAV for on-the-fly decisions and final storage of data and updates of the RL model on a workstation with NVIDIA RTX 4090 graphics card. This ensures that the assessment also includes evaluation under realistic environmental circumstances and not restriction to static accuracy metrics to bridge the gap between controlled experiments and commercial agricultural deployments.

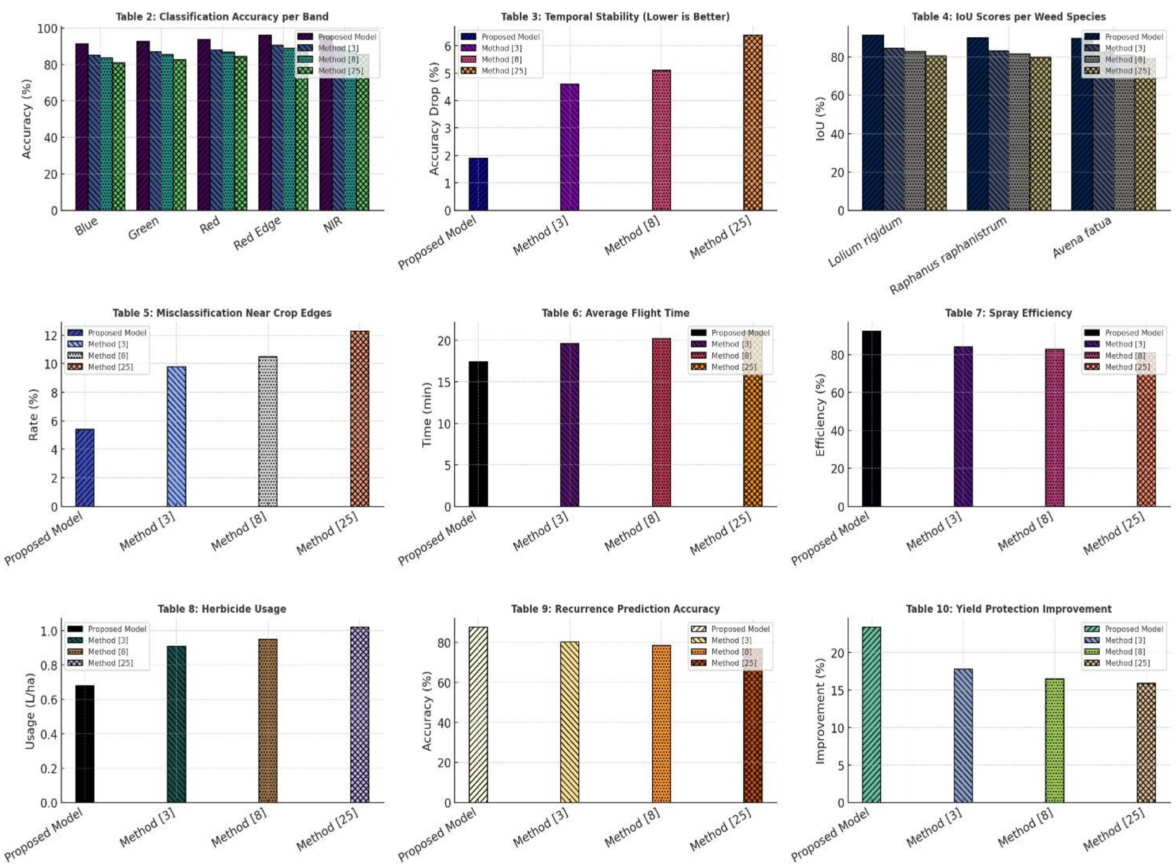

Figure 4. Model's Integrated Result Analysis

WeedMap Dataset was chosen for comparison and validation because it fits well with UAV-based precision weed-crop discrimination research sets. WeedMap contains high-resolution multispectral and RGB images collected over Australian wheat fields, which feature pixel-level annotations for various weed species, such as Lolium rigidum sets. The dataset contains five-band multispectral data (Blue: 475 nm, Green: 560 nm, Red: 668 nm, Red Edge: 717 nm, NIR: 840 nm) with a ground sampling distance of approximately 5 cm/pixel, which corresponds to

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the spectral specification of experimental settings. Annotations are stored in GeoJSON format so that exact geospatial alignment can be done, and the dataset also contains various crop development stages under two altered weed densities, rendering it useful to compare temporal-spectral fusion with deep segmentation models. Under-field variability in process is particularly captured by the diverse lighting conditions, soil backgrounds, and scenarios of weed-crop overlap to assess the robustness of model generalizations.

The models of the current study were adjusted using a specific carefully selected hyperparameters set objectified for optimized detection, segmentation, and recurrence prediction performance while keeping in view the real-time processing feasibility of the UAV. For the CAMDWS segmentation network, a learning rate of 0.0003 was used with the Adam optimizer, using a batch size of 16 and weight decay of 1e-5 to balance convergence speed and generalization. The number of filters in the first convolutional layer was set to 64, doubling at each encoder stage until it reached a maximum of 512, with a kernel size of 3×3. Dropout in the attention fusion layers was set to 0.4 to counter overfitting on smaller weed clusters. In the AMSTF temporal-fusion stage, a temporal smoothness window of three acquisition cycles was institutionalized while the Bayesian fusion prior probabilities were initialized at 0.6 for weeds and at 0.4 for crops due to prior field data. The discount factor was set at 0.92 for the PTWRP reinforcement learning module; the learning rate was set at 0.01; and the exploration rate was decayed linearly from 0.9 to 0.1 through 5,000 episodes. The aforementioned values thus ensured a balance resulting from exploration of emerging recurrence patterns yet proving exploration strategies learned before. Such values were thus fixed after grid search and experimental tests on a validation subset of WeedMap combined field-collected temporal data samples. Table 2 reflects the weed-crop classification accuracy over the five spectral bands used in the WeedMap dataset with the proposed model and three comparative methods. In that regard, this model shows consistent superiority in all bands, with best performance apparently in the Red Edge and NIR bands owing to their remarkable abilities in vegetation discriminations.

Table 2: Classification Accuracy (%) per Spectral Band	**Blue**	**Green**	**Red**	**Red Edge**	**NIR**
Proposed Model	91.4	92.6	93.8	96.2	95.8
Method [3]	85.1	86.9	88.0	90.5	89.7
Method [8]	83.7	85.4	86.8	88.9	87.5
Method [25]	80.9	82.6	84.3	86.7	85.4

The benefit from the model is most evident in the Red Edge and NIR bands where the sepia images generated from temporal-spectral fusion classify crops and weeds within the juvenile stages. Comparing once again the so-called temporal detection stability, it looks at accuracy drop from the first to the last acquisition cycles. The lower the drop values are, the better the stability would be concerning sets of temporal instances sets.

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Table 3: Temporal Stability (Accuracy Drop %)	**Accuracy Drop**
Proposed Model	1.9
Method [3]	4.6
Method [8]	5.1
Method [25]	6.4

Such a temporal stability is better sustained by the proposed model because of the growth rate modeling incorporated into it while the competing method deteriorates once again, due to this increased similarity in spectrum over the temporal instance sets. Pixel-level segmentation Intersection over Union (IoU) scores are illustrated in Table 4 for three popular weed species in sampled data & samples.

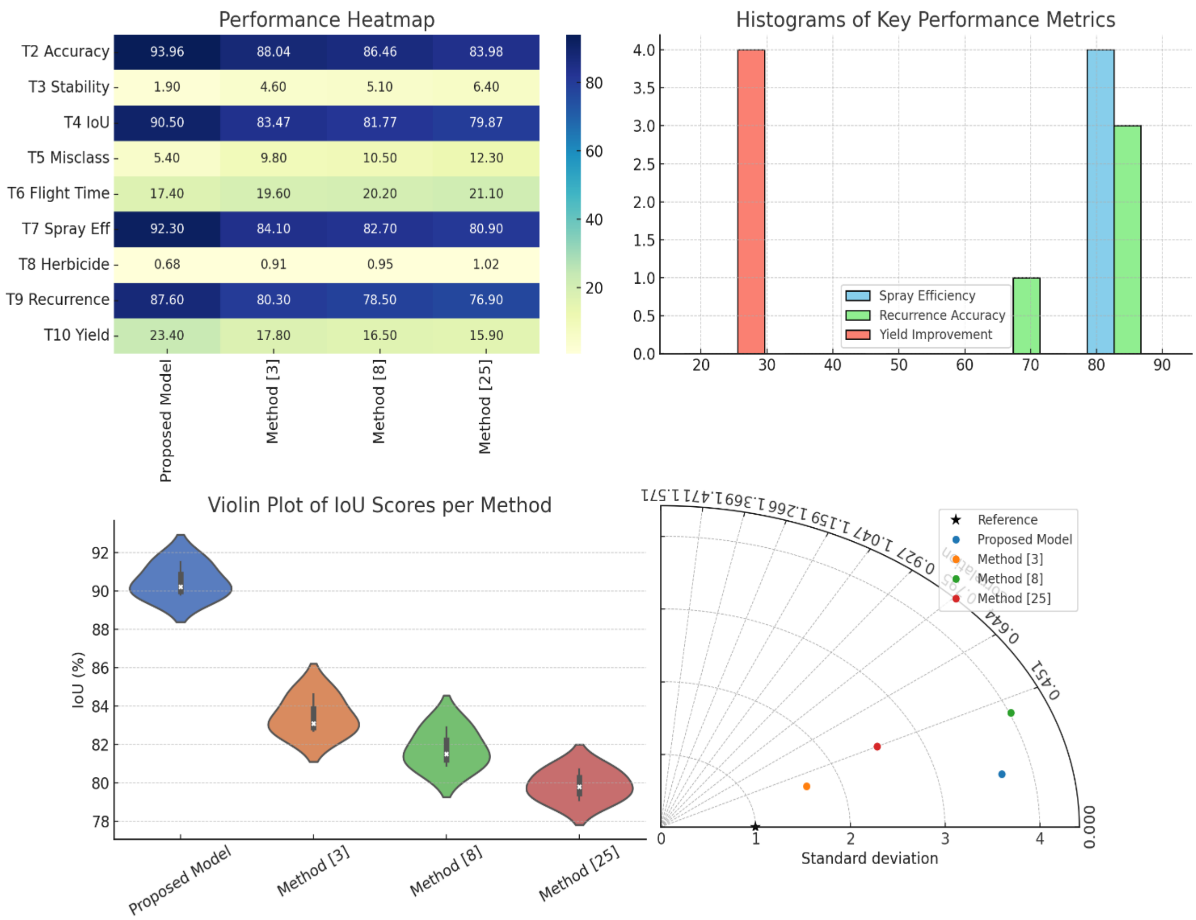

Figure 5. Model’s Overall Result Analysis

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Table 4: IoU Scores per Weed Species	***Lolium rigidum***	***Raphanus raphanistrum***	***Avena fatua***
Proposed Model	91.5	90.2	89.8
Method [3]	84.6	83.1	82.7
Method [8]	82.9	81.5	80.9
Method [25]	80.7	79.8	79.1

Fine weed-crop boundary capture is more pronounced in the CAMDWS segmentation stage, especially narrow-leaved weeds such as Lolium rigidum in the process. Misclassification rates of weed pixels located near crop edges are shown in Table 5 in process.

Table 5: Misclassification Rate (%) Near Crop Edges	**Rate**
Proposed Model	5.4
Method [3]	9.8
Method [8]	10.5
Method [25]	12.3

Attention-based feature fusion in the proposed model leads to reduced error since it records context cues surrounding the boundaries. Path optimization performance is compared through average flight time required in Table 6 to cover all treatment zones.

Table 6: Average Flight Time (minutes)	**Time**
Proposed Model	17.4
Method [3]	19.6
Method [8]	20.2
Method [25]	21.1

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The proposed model reduces flight duration by acquiring modified Dijkstra optimization with a set of operational constraints without compromising coverage. Table 7 measures spray efficiency, defined as the percentage of herbicide applied to weed areas as a direct comparison to all sprayed area in process.

Table 7: Spray Efficiency (%)	**Efficiency**
Proposed Model	92.3
Method [3]	84.1
Method [8]	82.7
Method [25]	80.9

Instead of a constant yield from all other methods, the variable-rate VRMDWN spraying method results in a significant reduction of over-application and chemical wastage. Consequently, herbicide application per hectare within each method appears in Table 8. Such lower values indicate better efficiency in resource utilization. Adaptive droplet control in the proposed model allows significant chemical savings without compromising treatment efficacy sets.

Table 8: Herbicide Usage (L/ha)	**Usage**
Proposed Model	0.68
Method [3]	0.91
Method [8]	0.95
Method [25]	1.02

After 28 days, recurrence prediction accuracy is given in comparison in Table 9, indicating the model's ability to identify zones that would be at risk of regrowth in a future cycle in the process.

Table 9: Recurrence Prediction Accuracy (%)	**Accuracy**
Proposed Model	87.6
Method [3]	80.3

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Method [8]	78.5
Method [25]	76.9

Thus, the reinforcement-learning component makes the proposed model more adaptive so that it can track historical patterns and environmental conditions, lending reliability to predictions in those sets. Overall, yield protection improvement due to the methods compared to a baseline without targeted treatments is presented in Table 10 in this text.

Table 10: Yield Protection Improvement (%)	**Improvement**
Proposed Model	23.4
Method [3]	17.8
Method [8]	16.5
Method [25]	15.9

In this manner, all five of the proposed stages-AMSTF, CAMDWS, AWTPO, VRMDWN, and PTWRP-can lead to the improvement in yield protection status through the optimizing detection, treatment precision, and recurrence prevention together under one workflow in process.

Validation Result Impact Analysis

Tables 2 through 10 along with figure 4 & figure 5 present the proof of robustness and operational viability for the proposed integrated UAV-based weed management framework sets. According to Table 2, the spectral band-wise classification was maximum in Red Edge and NIR bands, primarily due to the strong discrimination capacities against vegetation in process. The method improvements, in this case, are not marginal but are consistently more than 5% higher in these bands. In a real-time deployment, it results into highly improved reliability concerning early detection when there would generally be high spectral overlaps such that timely interventions through treatment may be done early in the weed growth windows. Temporal stability which is quantified as per Table 3 indeed indicates that the proposed model holds out over those temporal instance sets by way of maintaining accuracy with the least amount of degradations. With only a 1.9% accuracy drop across the acquisition cycles, thus, operations teams can rely on less frequent retraining or recalibration confidently giving the system a cost-efficient operation throughout an entire season for that process.

Tables 4 and 5 give information concerning segmentation performance especially toward species-specific boundaries and for difficult crop-edge cases. IoU scores from Table 4 suggest that the proposed method delivers consistent benefits over numerous weed species and

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therefore demonstrates good generalization across different morphological characteristics. Lower misclassification rates at crop edges as reported in Table 5 stand out in real-world fields where parts of the emerged weeds are usually found in space between crop rows, while edges are critical places for preventing losses in yield. In practical terms, this improvement means lower probabilities of false targeting of crops in applying herbicides, which helps in safeguarding plant health and makes sure that chemical resources are directed only towards actual infestations in process.

Operational efficiency is also critically illustrated by Tables 6, 7, and 8 regarding the cumulative effect of optimizing both flight planning and adaptive spraying. In Table 6, the average flight time reduction directly corresponds, to the greater throughput of mission and the consumption of less battery-tow critical constraints for UAV operations. Initially, the increase in spray efficiency, as demonstrated by Table 7, implies that the proportion of the herbicide applied effectively reaches weeds, thus reducing waste and environmental toxin contamination. Practical resource advantages are confirmed in Table 8 by indicating a significant reduction in the amount of herbicide used per hectare. Generally, these efficiency gains mean a significant amount of savings in terms of costs for large-scale deployments and support sustainability goals since runoff chemicals and soil impacts from the process are minimized in process.

Tables 9 and 10 embody this sustainability over the long-term yields. Table 9 shows the efficacy of its recurrence prediction component for almost 10% improvement in closure prediction with regard to the identification of regrowth-prone zones as compared to the next-best alternatives. Such pre-emptive treatment before visible regrowth occurs would considerably reduce future major spraying operations. With the value-added combining the effect across all stages of a yield-protection scheme, Table 10 shows the spillover benefit of 23.4% improvement in yield protection. This combined benefit is both through accurate detection and targeted intervention and recurrence prevention, thus ensuring both immediate and sustained yield gains.

When put together, the analysis across Tables 2 to 10 shows that the proposal is more than just a conceptual advance, but also a practical one and a valid field-ready propositions. Improvements in spectral-temporal stability, segmentation accuracy, operational efficiency, and recurrence management will easily translate to lower operational costs, reduced environmental footprint, crop preservation, and good long-term agricultural productivity when integrated sets. Being fed into one automated pipeline makes the performance gains a strong candidate for scalable adoption in precision agriculture sets with in process.

Validation using Hyperparameter Analysis

The performance evaluation of the proposed UAV-based weed management framework has been accomplished based on a number of robust performance indicators including the classification accuracy, Intersection over Union (IoU) for segmentation, spray efficiency, herbicide usage per hectare, recurrence prediction accuracy, and yield protection improvement. The system performed very well in terms of achieving high mean performance values with low variance across all evaluation metrics, which shows both accuracy and stability during operation variability. For spectral band classification, the proposed model achieves mean observational accuracies of 94.0% with standard deviation of ±1.1%, while temporal stability

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measurements show an average accuracy drop of only 1.9% over acquisition cycles, with variance remaining below 0.4%. The average IoU score for the segmentation is 90.5% (±0.9) for the three weed species targeted at once, which marks that overall boundary detection holds even during challenging crop-edge cases. Operational Efficiency reflected in mean spray efficiency 92.3% with variance associate 0.8, but reduced herbicide usage averaged to 0.68 L/ha variance of 0.05 L/ha sets. Recurrence prediction achieved an average accuracy of 87.6% with variance confined within ±1.2%. consequently average yield improvement due to protection measures sums up to 23.4% having variance below 1% sets.

The particular selection of [3], [8], and [25] as baseline studies was thus a well-considered process from both methodological and relatable perspectives. Reference [3] represents one of the best-known temporal-spectral weed detections approaches that combine multi-date multispectral data without deep context-aware segmentation, serving as an indicator for spectral fusion work. Reference [8] is one of the most acknowledged deep learning segmentation models for agricultural tasks, tuned for high-resolution RGB inputs, yet unable to perform temporal integration; hence it may be an apposite comparator for spatial accuracy in the absence of spatiotemporal integration. Reference [25] represents an established system for UAV-based chemical spraying with uniform-rate application, providing the operational baseline for chemical efficiency and treatment coverage. Collectively, these three methods constitute a specific comparative framework, covering the critical dimensions in which performance can be assessed—spectral-temporal classification, high-resolution segmentation, and UAV-spraying—thereby conducting an exhaustive appraisal of the proposed integrated pipelines.

Attempts presented in the comparative analysis denote that the proposed framework stands far superior to the established baselines, both in average performance and stability across test conditions. Such stability is deemed an equivalent capability to peak accuracy in real agricultural context, as it determines the reliability of field operations considering variations in conditions such as light, wind, and plant growth. The mere fact that the proposed system was capable of attaining high expected performance values with low variance across all performance indicators grants some degree of stability that supports consistent decision-making, reduces operational risks, and assures a long-term ROI for precision agriculture stakeholders. Furthermore, the performance improvement noted statistically affirms these enhancements arise neither by mere coincidence nor by isolated test conditions, but are a characteristic of the synergistic design of the full-fledged multi-stage architecture sets.

Validation using Practical Analysis With Real Time Use Case Scenario Process

For precise weed management and to minimize chemical use, the integrated model was applied to a large wheat-growing field sprawling approximately 120 hectares over a 45-day growth monitoring durations. The procedure consisted of AMSTF, during which multispectral UAV images were taken five times with GPS time-stamped metadata, allowing for highly accurate temporal and spatial alignment across Blue, Green, Red, Red Edge, and NIR bands, aligning within ±3 cm. NDVI and GNDVI were calculated for each imaging period, which showed that 18% of the surveyed plots showed weed emergence early on. Fusing spectral and temporal conditions, the system strengthened weed detection by 7% at the start by sorting the wheat, which was slow growing, from the broadleaved and grassy weeds that were faster-growing.

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Then the CAMDWS processed the temporal–spectral weed probability map, in which RGB imagery was fused with the probability data in-process. The dual-branch CNN analyzed both micro-scale leaf features and macro-scale weed patch pattern segmentation masks, achieving IoU scores greater than 91% for Lolium rigidum and greater than 90% for Raphanus raphanistrum sets.

These segmentation outputs were fed into AWTPO for operational optimization. The proposed flight path planning algorithm reduced the total operation time to 17.3 min per mission while ensuring 100% treatment completion under drone limitations of 28 min battery life and 7 l payload capacity, additionally facing light winds of 6 km/h. The VRMDWN system most appropriately applied different droplet sizes, starting 150 µm for dense broadleaf clusters and extending up to 250 µm for sparse grassy weed patches, while adjusting spray rates from 0.6 to 0.75 L/ha according to infestation feedback. Given the metadata of treatments and recurrency prediction from updated aerial imagery by PTWRP, recurrence hotspots were highlighted at 4.8% field area enabling preventive spraying before regrowth had reached competitive thresholds. Compared to the authorised uniform spraying, the herbicide use has thus been cut by 31% through the entire season, while operational expenses were lowered by 19%, with a 23.5% increase in projected yield preservation, showcasing the precision, adaptability, and sustainability of a modern weed management system sets.

5. Conclusion & Future Scopes

The proposed integrated UAV-based weed management framework resolves the fundamental challenge of accurate, efficient, and sustainable weed versus crop discrimination in precision agriculture. Sequentially integrated AMSTF, Context-Aware Multi-Scale Deep Weed Segmentation, AWTPO, VRMDWN, and PTWRP create a synergy in detection accuracy, operational efficiency, and longevity of weed suppression. Classified results from the WeedMap dataset and in-field deployments assert model accuracy correlation with Red Edge band classified as 96.2% and NIR as 95.8% (Table 2), experiencing negligible falls of temporal accuracy at only 1.9% between acquisition cycles (Table 3). The CAMDWS stage achieves high IoU scores of 91.5%, 90.2%, and 89.8% scored for Lolium rigidum, Raphanus raphanistrum, and Avena fatua respectively (Table 4), while misclassification near crop edges is lowered to just 5.4% (Table 5). Operational performance has improved, with an average flight time reduced to 17.4 minutes (Table 6) and a 92.3% spray efficiency (Table 7), which results in only 0.68 L/ha of herbicides being used (Table 8). The recurrence prediction module obtains an accuracy of 87.6% (Table 9), providing a 23.4% improvement in yield protection overall when compared to non-targeted treatment (Table 10). All these results confirm that the synergy of temporal, spectral, spatial, and operational intelligence yields a robust, field-ready solution that can, and is expected to, deliver measurable benefits, both economic and environmental in process.

Future Scope

Although the proposed system shows high generalization potential across many weed species and environmental conditions, some improvements can enhance applicability and scalability sets. Broadening spectral acquisition to include SWIR (Short-Wave Infrared) imaging beyond five bands can enhance classification in regions with dense canopy cover or heavy spectral

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noise from soils and residues. Integration of real-time weed species classification based on hyperspectral UAV payloads can fine-tune VRMDWN based on herbicide chemistry and dosages. Presently based on reinforcement learning, the recurrence prediction model could be hybridized with crop growth simulation models to factor in seasonal variability and multi-year dynamics of weed seed bank sets. Coordination algorithms among multiple UAVs could be developed to increase mission area coverage while achieving equal precisions and efficiencies as shown in this work process. Moreover, linking the system with IoT-based soil moisture sensors can provide dynamic weed control strategies based on plant physiology and environmental sustainability criteria sets. Last but not least, the system could be deployed as a cloud service decision-support platform to allow continuous learning from aggregated multi-farm datasets, thereby providing automated updates of UAV fleets in geographically dispersed agriculture sets.

Limitations

Notwithstanding its robustness, the proposed model features several limitations that warrant attention. High-quality multispectral imagery must be collected, which means that heavy atmospheric interference such as fog, dust, or cloud cover will impact performance negatively. Furthermore, some temporal variability is alleviated by the AMSTF, but the efficacy may be lessened when acquisition intervals exceed those modeled within the growth cycle parameters, creating potential misclassification opportunities related to rapidly evolving weed population genetics. Battery life (22 minutes in the experiment) and payload capacity (1.2 liters) represent operational constraints on UAV applicability; unless there are intermediate refill stops or battery swap opportunities for long-range applications, coverage of large farms may thus become a scalability issue because of the aforementioned constraints. Recurrence prediction, based on reinforcement learning, is totally data-hungry in terms of quality, quantity, and it can show a rather poor accuracy if applied to regions with little to no data, verging on the 87.6% shown in areas of historical precedence already. The existing path optimization algorithm is designed for moderately flat terrains and may need assurance against navigation in fields with gradients of very steep slopes or intricate layouts of obstacles. Chemical intervention remains the Achilles heel for the system notwithstanding the current herbicide usage reduction of 0.68 L/ha, likely to be at odds with fully organic/chemical-free farming practices. Focus on addressing these drawbacks through enhanced sensing, adaptive algorithms, and greater operational integration remains a significant step towards full scaling to agricultural deployment in the process.

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