

Design of a Precision Pesticide Spraying System for Smart Agriculture

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Abstract—The design of a precision pesticide spraying system that combines explainable artificial intelligence, computer vision, and Internet of Things (IoT)-based robotic control for smart agriculture is presented in this study. A NASNetMobile-based convolutional neural network (CNN) for disease classification, Gradient-weighted Class Activation Mapping (Grad-CAM) for interpretability, a severity estimation stage, and a regression model that forecasts the necessary pesticide quantity are used to analyze crop images obtained by an onboard camera. Robot movement is remotely controlled through an ESP32-based IoT layer via a web/mobile interface, while dosage is administered using a three-nozzle mechanism that exclusively activates the nozzle or nozzles corresponding to the localized infected region. Presented are the hardware architecture, mechanical platform, and full operational process. The AI pipeline and three-nozzle actuation are detailed as the suggested approach for further implementation; dataset preparation, model training, and field validation are scheduled for later phases. This paper presents the results of the first project review phase. The technology is designed to increase crop treatment efficiency and precision while lowering pesticide waste, environmental pollution, and farmer exposure to dangerous chemicals.

Keywords— Precision Agriculture; NASNetMobile; Convolutional Neural Network; Grad-CAM; Explainable AI; Disease Severity Estimation; Regression; Internet of Things; Precision Spraying.

I. INTRODUCTION

Uniform pesticide spraying, still the predominant practice in field cultivation, applies chemicals across an entire crop row irrespective of the health status of individual plants. The consequence is substantial pesticide wastage, elevated input cost, soil and water contamination, harm to beneficial organisms, and increased exposure risk to farm labor [1]-[4]. Manual scouting and spot-treatment, the conventional alternative, are labor-intensive and prone to inconsistency across large field areas.

A system capable of identifying diseased plants, localizing the extent of infection, and dispensing only the pesticide quantity required at the precise site of infection addresses these limitations directly. This paper reports the design of such a system: a mobile robotic platform that couples NASNetMobile-based disease detection with Grad-CAM explainability, severity-aware dosage regression, and independently actuated multi-nozzle spraying, coordinated with a remotely controlled IoT navigation layer.

Section 2 reviews related work and identifies the gap motivating this design. Section 3 presents the proposed system overview. Section 4 describes the hardware components. Section 5 details the mechanical design. Section 6 presents the AI-based detection and dosage methodology. Section 7 describes IoT-based navigation. Section 8 presents the system architecture, and Section 9 the operational workflow. Sections 10-12 discuss comparison, advantages, and limitations, Sections 13-14 the timeline and budget, and Sections 15-16 present future scope and the conclusion.

II. RELATED WORK

Pesticide-spraying automation has been approached along three broadly distinct lines in the literature reviewed for this project: mechanized/IoT-controlled spraying platforms, CNN-based disease detection, and explainable-AI localization methods.

Jiwtode et al. [1], Kale et al. [2], Babu et al. [3], and Vishnu et al. [4] each developed pesticide-spraying robots automating chemical dispersal through sensor-triggered or IoT-controlled actuation; together they establish the feasibility of replacing manual spraying with a mechanized, remotely supervised platform, though none of the four incorporates disease-specific image-based targeting, relying instead on fixed or manually-issued spray commands. Baltazar et al. [5] extended this direction by studying perception and control strategies for variable-rate precision spraying in woody crops, reporting improved adoption of non-uniform spray mechanisms relative

to fixed-rate systems — a finding consistent with the variable, severity-dependent dosage approach adopted in this work. More recent IEEE-published work reinforces this direction: Danton et al. [15] demonstrated an edge-following, Lidar-guided control scheme for independently-actuated multi-nozzle spraying in orchard rows, Dhumale and Bhaskar [16] coupled an image-processing-based disease classifier directly to pesticide-controller actuation, and BV et al. [17] reported an efficiency-optimized robotic sprayer platform — together confirming mechanized, sensor-driven spraying as an active IEEE research area, though still without the severity-proportional dosage regression pursued here.

A second group of studies establishes CNN-based classification as the standard approach for plant disease recognition. Upadhyay et al. [6] and Liu et al. [13] both report that CNN and deep-learning architectures consistently achieve high classification accuracy across diverse crop-disease datasets, while Rehana et al. [11] and Shafik et al. [10] specifically highlight the need for lightweight, field-deployable CNN variants, with Shafik et al. [10] additionally noting persistent gaps in combining detection with IoT deployment. Dhaka et al. [12] and Junaidi et al. [8] address this deployment gap directly, demonstrating IoT-integrated and edge-computing-based disease detection respectively, and Tahir et al. [7] further show that combining IoT-based data acquisition with federated learning and multimodal feature analysis improves the transparency and interpretability of the resulting agricultural decision, a conclusion that motivates the explainability stage adopted in this work. Recent IEEE Access studies extend this evidence base: Khattak et al. [18] and Shovon et al. [19] each report high-accuracy CNN-based disease and fruit classification using deep neural network and multi-model ensemble architectures respectively, while Shrotriya et al. [20] combine YOLOv5 with Grad-CAM-based explainability for automated plant-disease detection — a pairing of CNN classification with gradient-based interpretability that directly parallels the detection-to-explainability pipeline adopted in this work. Lochan et al. [9], used as the base reference for the hardware architecture of this project, similarly identify intelligent, severity-aware spraying as a key direction for advancing precision spraying robots.

Selvaraju et al. [14] introduced Grad-CAM as a gradient-based class-discriminative localization technique, which has since been widely adopted for visualizing the image regions responsible for a CNN's prediction; this technique is common to the explainability component of AI-driven agricultural systems referenced above [7] and is adopted directly in this work for disease-region localization.

Taken together, the reviewed works individually establish mechanized/IoT spraying [1]-[4], [15]-[17], CNN-based detection [6], [8], [10]-[13], [18]-[20], and explainable localization [7], [14] as mature, separately-demonstrated components. None of the reviewed spraying platforms [1]-[4], [15]-[17] combines image-based severity estimation with a regression-driven dosage prediction and independently-actuated multi-nozzle output. This gap — an integrated pipeline linking explainable disease detection to severity-proportional, multi-nozzle dosage control — motivates the system proposed in this paper.

III. PROPOSED SYSTEM OVERVIEW

The proposed system follows the sequence Plant Scanning → NASNetMobile-Based Disease Detection → Grad-CAM → Disease Severity Estimation → Machine Learning-Based Pesticide Prediction → Three-Nozzle Precision Spraying →

IoT-Controlled Robot Movement, maintained consistently across the detection, dosage, and actuation stages described in Sections 6-9. The robotic platform traverses the field under remote IoT control while the onboard camera continuously monitors crop rows; on capturing a plant image, the AI pipeline determines whether treatment is required and, if so, the quantity and nozzle(s) to activate.

The principal distinction from the existing smart sprayers reviewed in Section 2 [1]-[4] is the combination of severity-aware dosage regression with explainable, region-specific multi-nozzle actuation, in place of a binary detection outcome coupled to a fixed spray rate.

IV. MECHANICAL DESIGN

Before manufacture, the mechanical structure was modeled in CAD software to confirm structural clearance and component placement. Sections A to Section D cover each of the four main points of view separately.

A. Isometric View

The isometric view (Fig. 1) shows the overall arrangement of the pesticide tank at the chassis center, with the camera stand and spray stand rising vertically from the rear and front of the frame respectively. This arrangement keeps the heaviest component (the filled tank) close to the wheel axis, improving stability during motion.

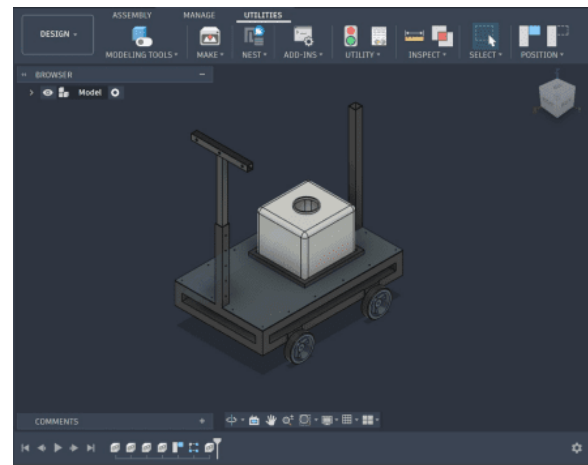


Fig. 1. CAD model — isometric view.

B. Front View

The front view (Fig. 2) illustrates the vertical camera stand positioned to provide an unobstructed forward field of view for plant scanning, clear of the tank and chassis structure.

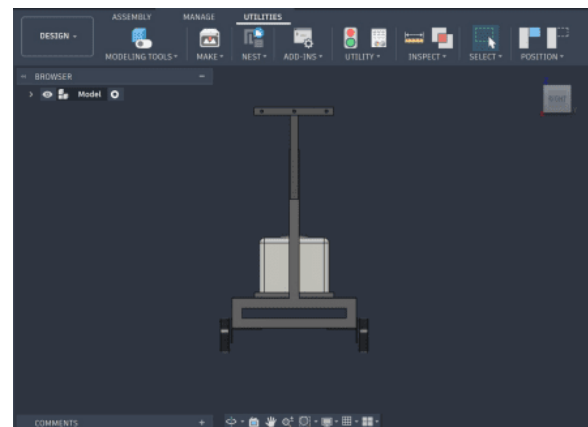


Fig. 2. CAD model — front view.

C. Top View

The top view (Fig. 3) shows the wheel placement at the four corners of the chassis and the central positioning of the tank, which centers the load and simplifies weight distribution across all four wheels.

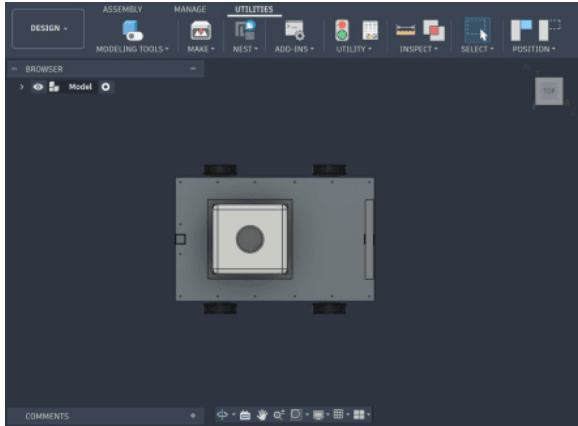


Fig. 3. CAD model — top view.

D. Side View

The side view (Fig. 4) shows the relative height of the camera stand and spray stand above the chassis deck, and confirms accessibility of the tank for refilling without obstruction from the stands.

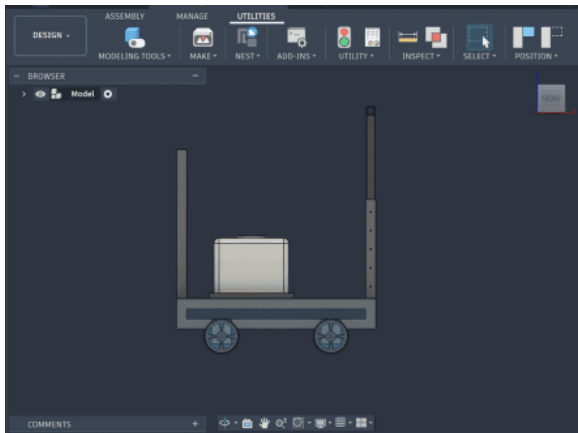


Fig. 4. CAD model — side view.

E. Mechanical Specification Summary

TABLE I. MECHANICAL DESIGN SPECIFICATIONS

Component	Dimension
Chassis	40 cm (L) x 25 cm (W), 2 mm sheet
Square Support Pipe	2 cm x 2 cm, 1 mm thick
Pesticide Tank	15 x 14 x 12 cm
Wheel Diameter	7 cm
Camera Stand	30 cm height
Spray Stand	40 cm, extensible

^a Note: The dimensions above are the proposed design targets for this platform and remain to be verified against the fabricated prototype in the next project phase.

V. AI-BASED DISEASE DETECTION AND PESTICIDE PREDICTION

This section presents the proposed AI pipeline governing disease identification and dosage decisions. As noted in the Abstract, this pipeline constitutes the proposed methodology for the system; model training and quantitative validation are planned for the subsequent project phase.

A. Image Acquisition

The camera described in Section IV-B captures plant images as the robot advances along the crop row, under ambient field lighting, at intervals coordinated with the IoT navigation cycle described in Section G.

B. NASNetMobile-Based Disease Detection

A NASNetMobile-based convolutional neural network is proposed as the classifier for identifying the disease class of the scanned plant. The network is intended to extract hierarchical spatial features through successive convolution and pooling operations and to output a predicted disease class together with a confidence score, consistent with the CNN-dominant approach reported across the reviewed literature [6], [8], [10]–[13].

C. Explainable AI Using Grad-CAM

Grad-CAM [14] is proposed to generate a class-discriminative heatmap over the input image, highlighting the region most responsible for the CNN's predicted class. This serves two purposes in the proposed system: it localizes the infected region for the severity and nozzle-selection stages described below, and it renders the AI decision visually inspectable to the farmer, addressing the interpretability gap noted in Tahir et al. [7]. Fig. 6 illustrates this on a sample capture, pairing the Grad-CAM heatmap with the resulting disease classification and predicted dosage.

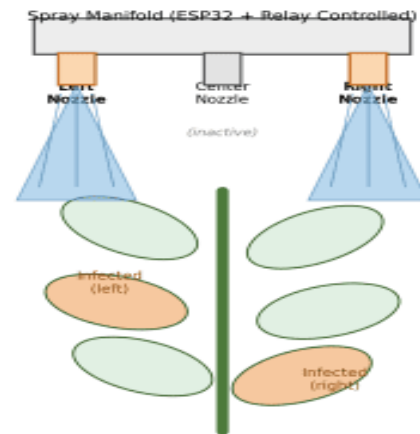


Fig. 5. Conceptual illustration of localized infection regions informing nozzle selection (see Section F).

TABLE II. DISEASE SEVERITY SCALE

Severity Class	Affected Leaf Area
Healthy	0%
Mild	0-25%
Moderate	25-50%
High	50-75%
Severe	75-100%

D. Disease Severity Estimation

The Grad-CAM activation map is proposed to be thresholded and expressed as a proportion of total leaf area, yielding a severity percentage mapped to the discrete classes in Table III.

Fig. 7 presents the overall system architecture, showing the interconnection of the perception/AI pipeline (camera, preprocessing, NASNetMobile-based CNN, Grad-CAM, severity estimation, and regression), the ESP32 control unit, the actuation chain (relay, pump, tank, three nozzles), the locomotion subsystem (motor driver, motors, chassis,

ultrasonic sensors), and the IoT connectivity layer (Wi-Fi, cloud link, and mobile/web application).



Fig. 6(a)

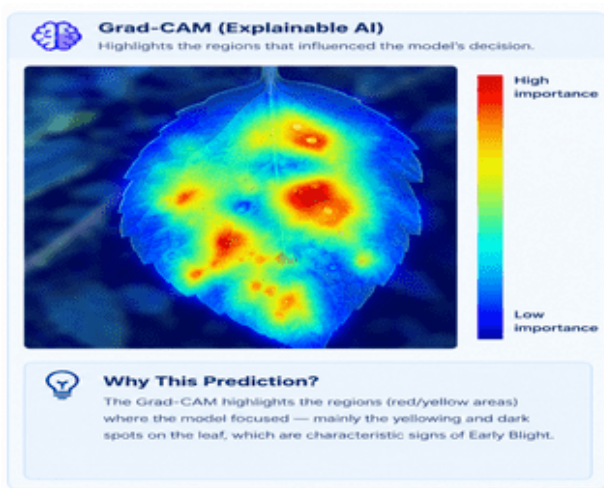


Fig 6 (b)

Fig. 6. (a) and (b). Example system output: original leaf image, Grad-CAM heatmap overlay, and the resulting disease classification and predicted pesticide dosage.

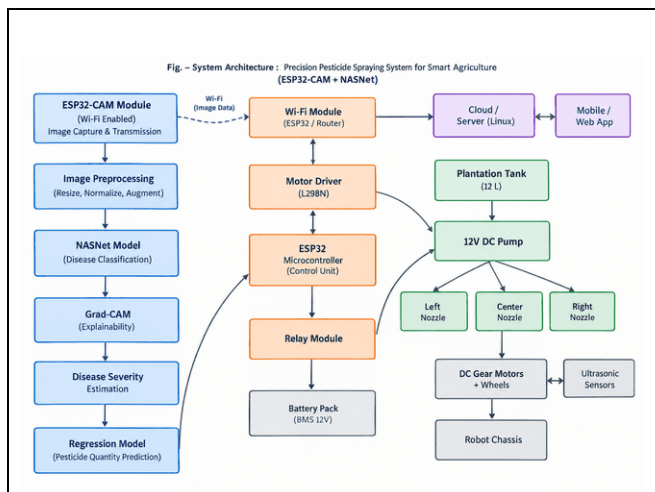


Fig. 7. Overall system architecture.

E. Machine Learning-Based Pesticide Quantity Prediction

A regression model is proposed to predict the required pesticide quantity (mL), using disease class, severity

percentage, estimated leaf area, and crop type as input features. Regression, rather than classification, is adopted because the target output is a continuous quantity that scales with infection extent, allowing the model to interpolate dosage across intermediate severity levels rather than restricting output to discrete quantities.

F. Three-Nozzle Precision Spraying Mechanism

The predicted quantity is proposed to be dispensed through the three-nozzle configuration introduced in Section IV-G: a center nozzle addressing infection at the main plant region, and independently-actuated left and right nozzles activated only when the Grad-CAM localization indicates lateral disease spread. Only the nozzle(s) aligned with the detected region are activated, which is expected to reduce pesticide consumption relative to the single fixed-position nozzle in the original hardware layout (shown in Fig. 5).

G. Preliminary Model Comparison: Baseline CNN and NASNetMobile Architectures

As an initial step toward finalizing the classifier architecture referenced in Section V-B, preliminary training experiments were carried out comparing a baseline convolutional neural network against a NASNetMobile-based convolutional neural network, trained under identical conditions over ten epochs on the disease-classification dataset assembled at this stage of the project. Fig. 7 and Fig. 8 present the resulting training and validation accuracy and loss curves for the baseline CNN and the NASNetMobile model, respectively.

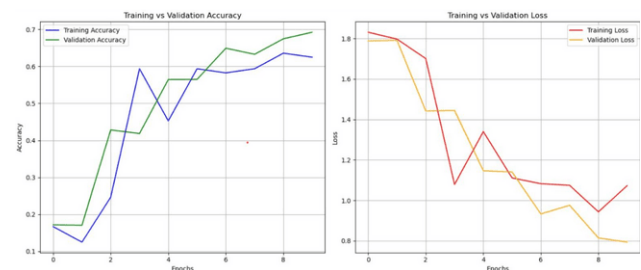


Fig. 8. Baseline CNN model — training vs. validation accuracy and loss.

The baseline CNN (Fig. 7) shows training and validation accuracy rising together across epochs, reaching approximately 0.63 and 0.69, respectively, by epoch 10, with training and validation loss tracking one another closely throughout. This close tracking indicates limited overfitting but comparatively modest overall accuracy.

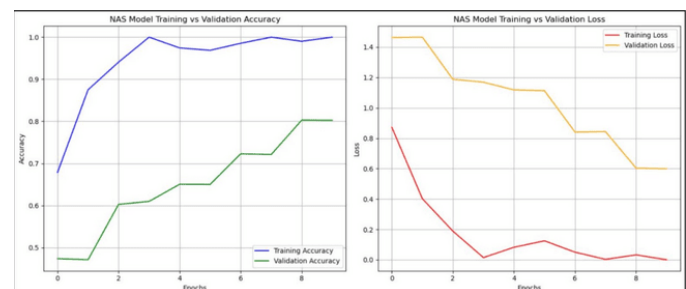


Fig. 9. NASNetMobile model — training vs. validation accuracy and loss.

The NASNetMobile model (Fig. 8) converges considerably faster, with training accuracy approaching 1.0 within the first three epochs, while validation accuracy rises more gradually to reach 0.80 by epoch 10. The wider separation between the training and validation curves relative to the baseline CNN indicates a degree of overfitting, to be

addressed through dataset expansion and regularization in the subsequent training phase.

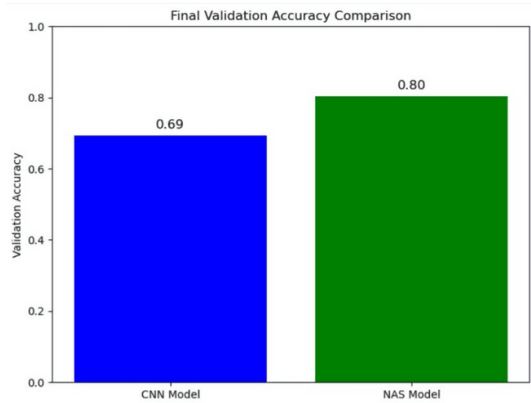


Fig. 10. Final validation accuracy comparison — baseline CNN vs. NASNetMobile model.

Fig. 9 summarizes the final validation accuracy achieved by each architecture: 0.69 for the baseline CNN against 0.80 for the NASNetMobile model. On the basis of this comparison, the NASNetMobile-based architecture was selected as the classifier to be carried forward into the disease-detection stage described in Section V-B. This preliminary comparison serves to guide architecture selection at the current project stage; full-dataset training and field-level validation, as noted in the Abstract and Section V, remain part of the subsequent project phase.

VI. IOT-BASED ROBOT NAVIGATION

Robot movement is remotely controlled through the ESP32-based IoT layer, independently of the AI spraying pipeline. The ESP32's Wi-Fi interface communicates with a web/mobile application through which forward, reverse, left, right, and stop commands are issued in real time. Navigation and spray-activation commands are handled as independent control routines on the ESP32, so that platform movement continues uninterrupted while the AI pipeline (Section F) completes detection and dosage computation for the current plant. The ultrasonic sensors of Section IV.X supplement operator commands with obstacle-triggered halting.

For reference, Fig. 11 reproduces the block-level hardware layout originally developed for the platform, from which the architecture in Fig. 10 was elaborated.

VII. SYSTEM ARCHITECTURE

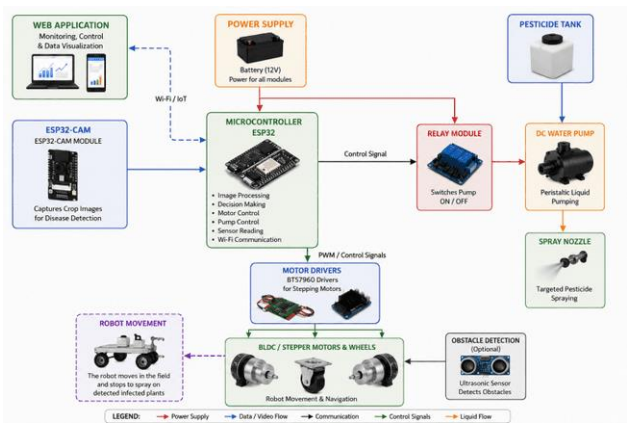


Fig. 11. Original hardware block diagram (from project design documentation).

VIII. SYSTEM WORKFLOW

Fig. 12 presents the complete operational flowchart, integrating IoT-controlled navigation with the AI-driven detection and spraying pipeline into a single repeating field-traversal cycle.

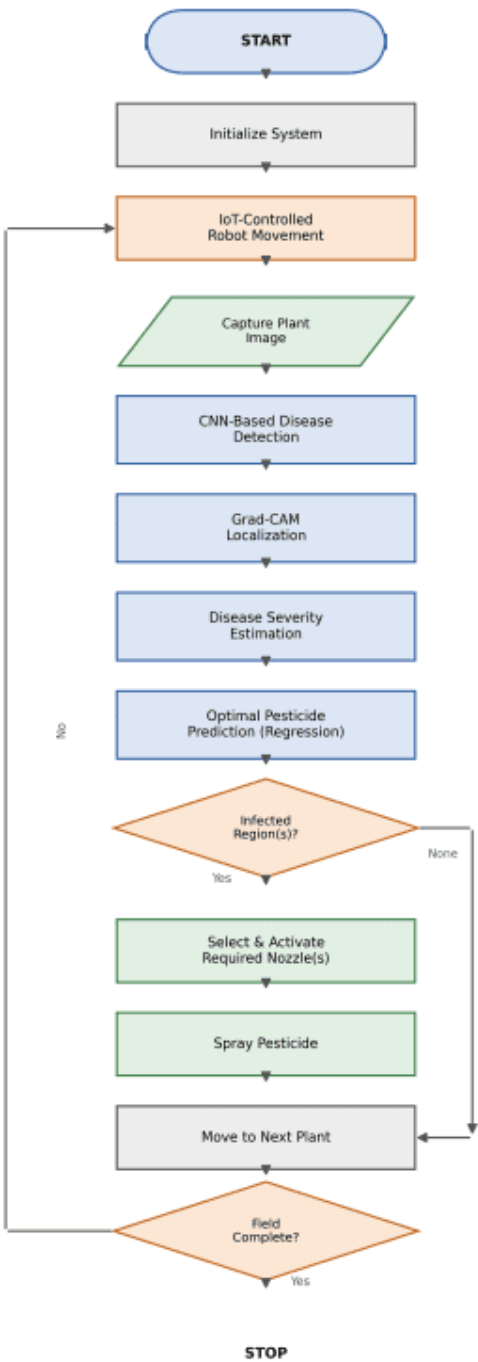


Fig. 12. Operational flowchart of the complete system cycle.

IX. COMPARISON WITH EXISTING METHODS

Table IV compares the proposed system against the traditional and existing approaches reviewed in Section B [1]-[4].

TABLE IV. COMPARISON OF SPRAYING APPROACHES

Parameter	Traditional	Manual	Existing Smart Sprayers [1]-[4]	Proposed System

Accuracy	Low	Operator-dependent	Moderate	High (NASNetMobile-based)
Chemical Saving	None	Low	Moderate	High
Automation	None	None	Partial	AI assisted
Explainability	N/A	N/A	Absent	Grad-CAM based
IoT Connectivity	No	No	Partial	Yes
Precision	None	Low	Moderate	High (multi-nozzle)

X. CONCLUSION AND FURTHER WORK

This paper presented the proposed design of a precision pesticide spraying system combining NASNetMobile-based disease detection, Grad-CAM explainability, severity-aware regression-based dosage prediction, and three-nozzle spraying on an IoT-controlled mobile platform. The hardware architecture, mechanical design, and complete operational workflow were described and compared against existing spraying approaches identified in the literature. As the outcome of the first project review phase, this paper establishes the proposed methodology and hardware framework; the next phase will focus on dataset preparation, model training, hardware fabrication, and field-level experimental validation.

Future work includes deployment of the NASNetMobile / Grad-CAM inference pipeline on dedicated edge-AI hardware to reduce latency, evaluation of lightweight real-time detectors, integration of autonomous navigation and SLAM for GPS-denied operation, incorporation of multi-spectral imaging for nutrient/water-stress detection alongside disease, cloud-based analytics for farm-level trend monitoring, and development of a digital twin of the field for spraying-schedule optimization.

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