IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

Smart Farming System Using Machine Learning for Crop Disease Detection and Precision Spraying

Payal C. Patil[1], Vinit S. Bari[2], Bhavesh D. Chaudhari[3], Sumit B. Khedwan[4]

Prof. Priyanka D. Lanjewar[5]

Student, Department of Artificial Intelligence and Machine Learning, R. C. Patel Institute of Technology, Shirpur, Maharashtra, India[1-4]

Assistant Professor, Department of Artificial Intelligence and Machine Learning, R. C. Patel Institute of Technology, Shirpur, Maharashtra, India[5]

Abstract: Crop diseases cause serious yield losses, and many farmers cannot reach an expert quickly enough to identify them. This paper presents a Smart Farming System that uses machine learning for crop disease detection and precision spraying. A farmer uploads a photograph of a crop leaf through a web interface, and a multimodal vision model classifies the leaf as healthy or diseased and reports the disease name with a confidence score. The system then produces treatment and preventive advice and, after the farmer approves, sends a command to a spraying unit that treats only the affected area. The platform also provides soil and weather information, crop management, market price trends and a chatbot to support everyday farm decisions. The proposed approach aims to reduce unnecessary pesticide use, lower cost and encourage timely action. Quantitative performance results will be reported after field testing.

Keywords: Smart farming, crop disease detection, machine learning, precision spraying, precision agriculture, Gemini Vision, decision support system.

I. INTRODUCTION

Agriculture is the main source of livelihood for a large share of the population in many countries, and the quality of a harvest depends strongly on how well crops are protected from disease. Plant diseases reduce both the quantity and the quality of produce. When a disease is not identified early, it spreads from a few leaves to the whole field. Farmers normally identify diseases by looking at the plant or by asking a local expert. This method is slow, depends on personal experience, and is often wrong when symptoms of different diseases look alike.

Pesticide application is another major concern. In most farms the chemical is sprayed uniformly over the whole field, even when only a small part of the crop is affected. This wastes money, harms beneficial insects and soil, pollutes water and exposes the farmer to health risks. Precision spraying tries to solve this problem by applying the right chemical, at the right place and in the right amount.

Machine learning and computer vision have achieved very good results in recognising plant diseases from leaf images [1]-[4]. Reviews of smart farming and machine learning in agriculture also show that data-driven tools can support better farm decisions [6]-[8]. In addition, recent multimodal AI models can understand an image and a text instruction together and can explain what they see in natural language [10]. This makes it possible to build a single tool that diagnoses a disease, explains it and suggests a treatment.

This paper presents a Smart Farming System, named AgriWise, that combines machine learning based crop disease detection with a precision spraying mechanism. The farmer uploads a leaf photograph; the system identifies the condition, gives treatment and preventive advice, and, after the farmer's approval, instructs a spraying unit to treat only the affected area. The same platform also provides soil and weather information, crop management, market price trends, supply chain support and a chatbot. The rest of the paper is organised as follows: Section II reviews related work, Sections III and IV state the problem and objectives, Sections V to IX describe the methodology, architecture, requirements, machine learning model and spraying mechanism, Section X discusses the results, and Sections XI to XIII give the advantages, conclusion and future scope.

 This work is licensed under a Creative Commons Attribution 4.0 International License



International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026
DOI: 10.17148/IJARCCE.2026.151155

II. LITERATURE REVIEW

Many researchers have applied deep learning to plant disease recognition. Mohanty et al. [1] trained a deep convolutional neural network (CNN) on 54,306 leaf images of 14 crop species and 26 diseases from the PlantVillage collection and reported 99.35% accuracy on a held-out test set. They also noted that the images were collected under controlled conditions, so performance on real field images needs further study. Ferentinos [2] compared several CNN architectures on a database of 87,848 images covering 25 plants, and the best model (VGG) achieved a 99.53% success rate. Sladojevic et al. [3] used a CaffeNet-based CNN to recognise 13 types of plant disease, healthy leaves and background images, with an average precision of about 96.3%. Too et al. [4] compared fine-tuned VGG16, Inception-V4, ResNet and DenseNet models on PlantVillage and found that DenseNets gave the highest accuracy with fewer parameters and shorter training time.

Datasets that suit our crop of interest are also available. Thapa et al. [5] released the Plant Pathology 2020 data set of real-life apple leaf images that includes healthy, scab, rust and multiple-disease classes, which is closer to field conditions than laboratory images. Broader studies place these methods in context: Kamilaris and Prenafeta-Boldu [6] surveyed 40 research efforts that used deep learning in agriculture and concluded that it generally gave higher accuracy than commonly used image processing techniques, Liakos et al. [7] reviewed machine learning in crop, livestock, water and soil management, and Wolfert et al. [8] discussed the role of big data in smart farming together with its organisational and socio-economic challenges.

For the spraying side, Berenstein and Edan [9] developed an automatic adjustable spraying device with a single nozzle whose spray angle changes with the size of the detected target. In an outdoor test with artificial targets it reduced pesticide use, and their economic analysis estimated savings of up to 45%. Finally, large multimodal models such as Gemini [10] can accept images and text together, which allows disease explanation and advice to be generated along with the classification. Table I summarises the reviewed work.

TABLE I SUMMARY OF REVIEWED WORK

Ref.	Focus of the work	Main observation
[1]	Deep CNN on PlantVillage (54,306 images)	99.35% test accuracy; images taken under controlled conditions
[2]	CNN comparison on 87,848 images, 25 plants	Best model (VGG) reached 99.53% success rate
[3]	CaffeNet-based leaf disease recognition	About 96.3% average precision, 13 diseases
[4]	Fine-tuning of popular CNN models	DenseNets gave best accuracy with fewer parameters
[5]	Apple leaf data set (Plant Pathology 2020)	Real-life images: healthy, scab, rust, multiple diseases
[6]	Survey of deep learning in agriculture	Deep learning outperformed common image processing
[7]	Review of machine learning in agriculture	Covers crop, livestock, water and soil management
[8]	Review of big data in smart farming	Role of data and socio-economic challenges
[9]	Adjustable-angle precision sprayer	Reduced pesticide use; savings up to 45% estimated
[10]	Multimodal AI models (Gemini)	Joint understanding of images and text

Research gap: Most of the above studies deal with classification alone and stop at the predicted label. Very few connect diagnosis, treatment advice, farm information and a spraying unit into one tool that a farmer can use directly. The proposed system tries to fill this gap.

III. PROBLEM STATEMENT

Small and medium farmers face three linked problems. First, diseases are often identified late or wrongly because expert help is not always available. Second, pesticides are sprayed over the entire field instead of only the affected area, which increases cost and environmental damage. Third, information such as soil condition, weather alerts, market prices and crop schedules is scattered across different sources, so the farmer cannot take timely decisions. There is a need for a low-cost, easy-to-use system that detects crop disease from a leaf image, recommends treatment and controls spraying in a targeted manner.

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

IV. OBJECTIVES

The main objectives of the proposed Smart Farming System are:

1) To detect crop leaf diseases from an uploaded photograph using a machine learning (vision) model.
2) To display the disease name with a confidence score and to generate treatment and preventive recommendations.
3) To design a precision spraying mechanism that applies pesticide only where it is needed and only after the farmer approves.
4) To reduce unnecessary pesticide use and, in turn, cost and environmental impact.
5) To provide a single dashboard with soil health, weather, alerts, crop growth tracking and market price information.
6) To support farmers with a chatbot and supply chain information for better decisions.
7) To build a simple, free-to-use interface that does not need sign-up for a basic scan.

V. PROPOSED METHODOLOGY

A. Overview

The proposed system follows a sensing, analysis, decision and action approach. The farmer provides a leaf image; the analysis module classifies it; the decision module prepares advice and a spray instruction; and the action module (spraying unit) carries out the instruction after approval. All results are stored and shown on a dashboard so that the farmer can follow the history of each crop.

B. Working of the Smart Farming System

The complete working of the system, shown in Fig. 1, is explained in the following steps.

Step 1 - Image capture: The farmer opens the web application and uses the Scan option on the home page to take or upload a photograph of a crop leaf.

Step 2 - Image check and pre-processing: The system checks the file type and size and whether the leaf is clearly visible. A poor image is rejected and the farmer is asked to retake it. A valid image is resized and prepared for analysis.

Step 3 - Disease analysis: The image is sent to the multimodal vision model (Gemini Vision) together with a structured instruction. The model returns the probable condition (for example healthy, scab or rust), a confidence value and a short description of visible symptoms.

Step 4 - Result and recommendation: The interface shows the diagnosis and the confidence for each class. The recommendation module then gives treatment options and preventive care such as field hygiene, pruning and monitoring.

Step 5 - Context check: Soil, weather and alert information from the dashboard is considered before any spraying. For example, a heavy rain alert should delay spraying because rain washes the chemical away.

Step 6 - Farmer approval: If a disease is detected with sufficient confidence, the farmer is asked to approve spraying. If the farmer declines, the result remains an advisory.

Step 7 - Spray command: After approval, a spray command carrying the zone and duration is sent to the microcontroller of the spraying unit.

Step 8 - Targeted spraying: The microcontroller switches the relay, which runs the pump and opens the valve for the set time, so that only the affected area is treated.

Step 9 - Logging and monitoring: The event is recorded, the crop health status is updated in the Crop Management module and the farmer can review the history and market prices for planning harvest and sale.

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

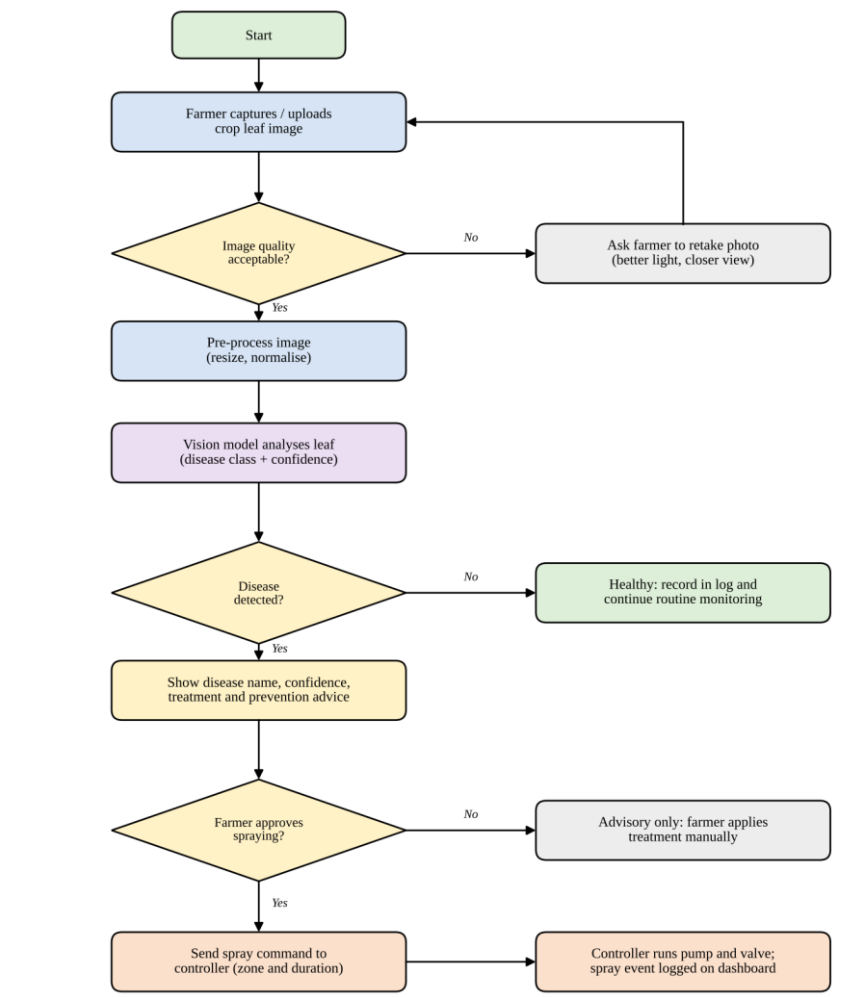


Fig. 1 Flowchart of the working of the proposed Smart Farming System

C. Functional Modules

The web application is divided into the modules listed in Table II, which are accessible from the navigation bar of the interface.

TABLE II MODULES OF THE WEB APPLICATION

Module	Function
Home	Introduction and quick access to the leaf scan
Dashboard	Soil health, weather, live market prices, yield analytics and alerts
Diagnosis	Leaf image upload and AI based disease diagnosis
Crop Management	Current, planned and past crops with growth progress and health status
Recommendations	Treatment, preventive care and farm advice
Market Trends	Price gainers and decliners, trading volume and annual price trends
Supply Chain	Support for movement and sale of produce
Chatbot	Question and answer help for farmers
Settings	User and notification preferences

VI. SYSTEM ARCHITECTURE AND BLOCK DIAGRAM

The architecture of the system, shown in Fig. 2, has four layers. The **input layer** collects the leaf image, soil, weather and location data, and crop details or queries typed by the farmer. The **presentation layer** is the web application through which the farmer interacts with all modules. The **intelligence layer** contains image pre-processing, the multimodal vision

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

model for disease classification, the recommendation engine, and the chatbot and market services. The **action layer** converts an approved decision into a physical spray operation through a microcontroller, relay, pump, valve and nozzle.

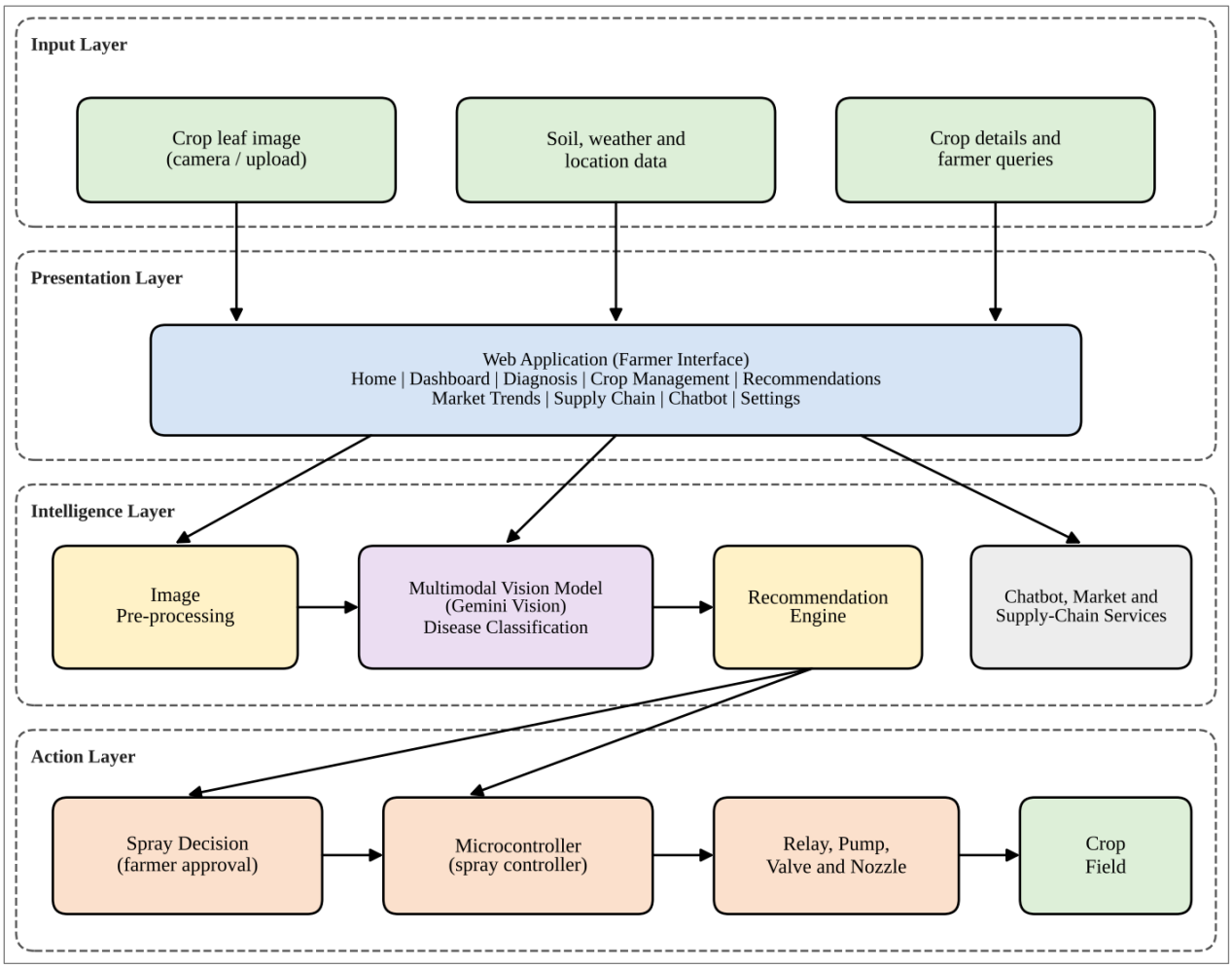


Fig. 2 System architecture and block diagram of the Smart Farming System

The layers are loosely coupled. The disease analysis and the spraying unit communicate only through a simple command (spray or do not spray, zone and duration), so the spraying hardware can be changed without changing the software, and the software can be improved without changing the hardware.

VII. HARDWARE AND SOFTWARE REQUIREMENTS

The hardware proposed for the precision spraying unit is given in Table III and the software requirements are given in Table IV.

TABLE III HARDWARE REQUIREMENTS

Component	Purpose
Smartphone or camera	Capture leaf images
Computer / server with internet	Run the web application and call the AI model
Wi-Fi enabled microcontroller board	Receive spray command and control outputs
Relay / driver module	Switch the pump and valve on and off
DC pump and solenoid valve	Move the liquid and control its flow
Spray nozzle / boom	Apply the liquid on the affected area
Pesticide tank and tubing	Store and carry the liquid
Battery or power adapter	Power the spraying unit

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

TABLE IV SOFTWARE REQUIREMENTS

Software	Purpose
Web browser	Access the farmer interface on phone or computer
Web front end	User interface, dashboard and charts
Backend service	Handle requests, call AI model, store data
Google Gemini Vision AI	Leaf image analysis and disease classification
Weather and market data sources	Weather, alerts and price information
Microcontroller firmware	Control of relay, pump and valve

VIII. MACHINE LEARNING MODEL FOR CROP DISEASE DETECTION

A. Choice of Model

Conventional approaches train a CNN on a labelled data set [1]-[4]. Such models give high accuracy on images similar to their training data but need a large labelled collection and re-training for every new crop or disease. In this work a pre-trained multimodal vision model (Gemini Vision) [10] is used for diagnosis. Such a model can read a leaf image and an instruction together, classify the visible condition and describe the symptoms in simple language, so one model can support several crops and can also explain its result to the farmer.

B. Input and Pre-processing

The uploaded image is checked for format (JPEG or PNG) and size, resized when it is too large, and sent with a structured instruction that asks the model to return the crop, the most likely condition, a confidence value for each class, the visible symptoms and suitable treatment.

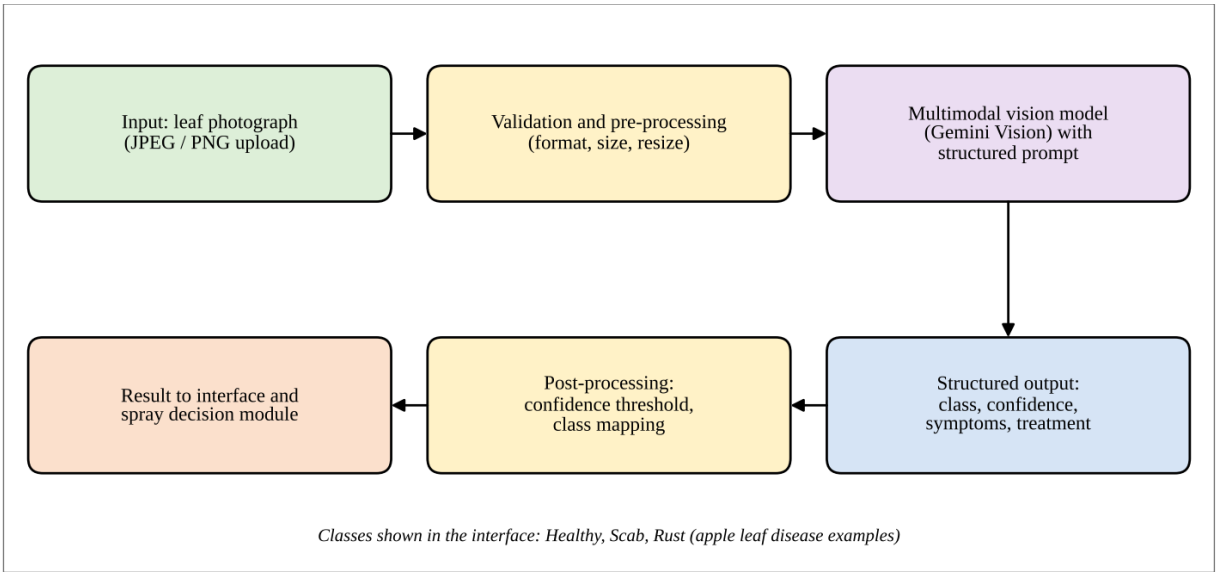


Fig. 3 Machine learning pipeline for crop disease detection

C. Classification and Output

The output is a set of class confidence values, for example Healthy, Scab and Rust for apple leaves, which are mapped to a final label. A confidence threshold is applied: results below the threshold are shown only as advisory and do not trigger a spray request. The label and advice are then shown on the interface and passed to the spraying decision module.

D. Evaluation Metrics

The model will be evaluated on a set of labelled leaf images that were not used for tuning the prompt. The following standard measures are used, where TP, TN, FP and FN are the true positives, true negatives, false positives and false negatives:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$Precision = TP / (TP + FP) \qquad Recall = TP / (TP + FN)$$

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

F1-score = 2 x Precision x Recall / (Precision + Recall)

Labelled apple leaf images such as the public Plant Pathology 2020 data set [5], which contains healthy, scab and rust classes, are suitable for this evaluation.

IX. PRECISION SPRAYING MECHANISM

A. Principle

In precision spraying, the chemical is applied only to the diseased plants or zone and in a controlled quantity, instead of covering the whole field. The idea is similar to the site-specific sprayer in [9], where the spray is adjusted to the target. In the proposed system the target is identified by the disease detection module and the spray is released by a low-cost microcontroller based unit, shown in Fig. 4.

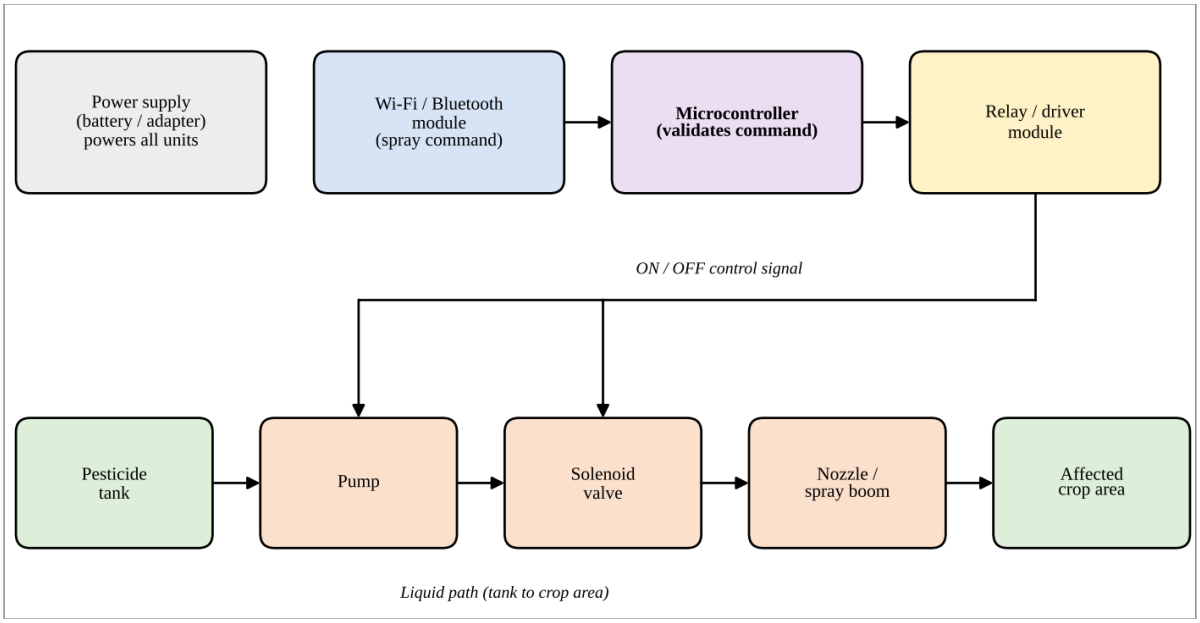


Fig. 4 Block diagram of the precision spraying unit

B. Decision Logic

A spray command is generated only when all conditions in Table V are satisfied. These rules keep the farmer in control and prevent unnecessary spraying.

TABLE V SPRAY DECISION LOGIC

Condition	Action
Image rejected or quality is poor	Ask the farmer to retake the photo; no spray
Leaf classified as healthy	Log result and continue monitoring; no spray
Disease detected, confidence below the set threshold	Show advice only; ask for a clearer image
Disease detected, confidence above threshold	Show treatment advice and ask for farmer approval
Heavy rain alert active	Advise delay of spraying
Farmer approves and conditions are safe	Send command (zone, duration) to controller
Farmer declines or presses stop	No spray; manual override always available

C. Control Operation and Safety

The microcontroller receives the command through its Wi-Fi or Bluetooth link, checks that it is valid, and switches the relay for the requested duration. The relay powers the pump and the solenoid valve, and the liquid flows from the tank through the nozzle to the affected area. When the time is over, the relay turns off and the event is reported back to the dashboard. The dose and chemical must follow the product label and local agricultural guidelines, and the farmer should use protective equipment. The spray quantity per zone and the spray duration are set by calibration.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

X. RESULTS AND DISCUSSION

A. Implemented Web Platform

The web application of the Smart Farming System has been implemented, and its main screens are shown in Fig. 5 to Fig. 8. These screenshots show the working user interface; they are not used as a measure of model accuracy, which will be measured as planned in Table VI.

Home page (Fig. 5): The home page introduces the system and provides the Scan Your Crop button for free leaf analysis without sign-up. A live scan card shows the class-wise confidence for the analysed leaf (Scab, Rust and Healthy) and a card shows the active farmers using the platform.

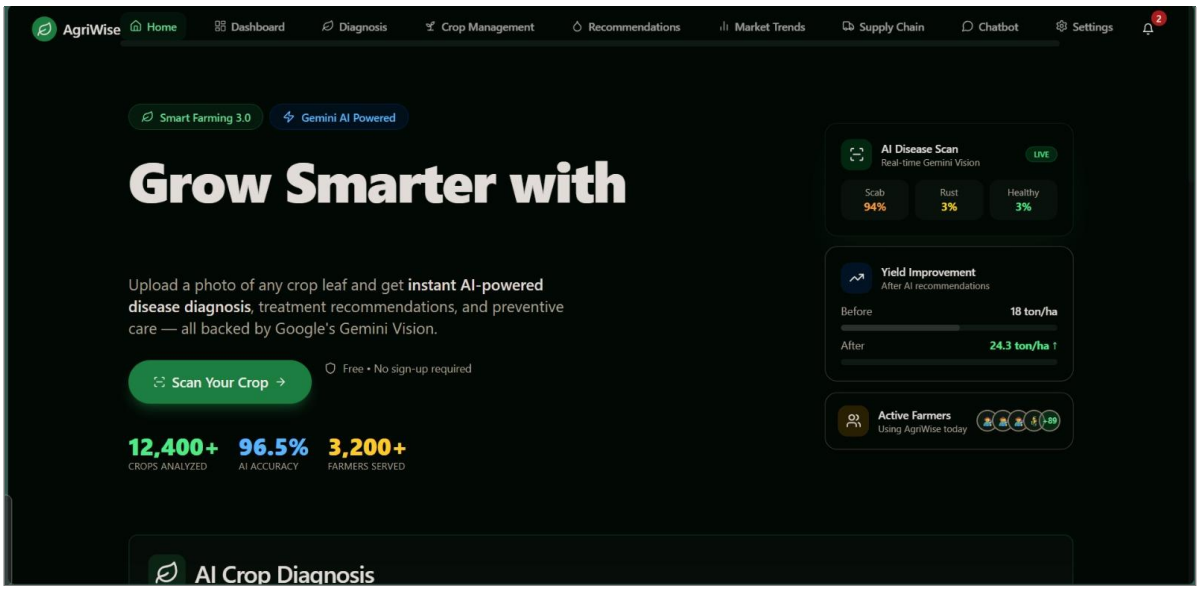


Fig. 5 Home page of the AgriWise system with the AI disease scan card

Dashboard (Fig. 6): The dashboard gathers the soil health status (overall score, pH level and moisture), the current weather (temperature, humidity, wind and rain chance), live market prices of major crops, apple yield and revenue analytics, and alerts such as a heavy rain alert and a pest detection warning.

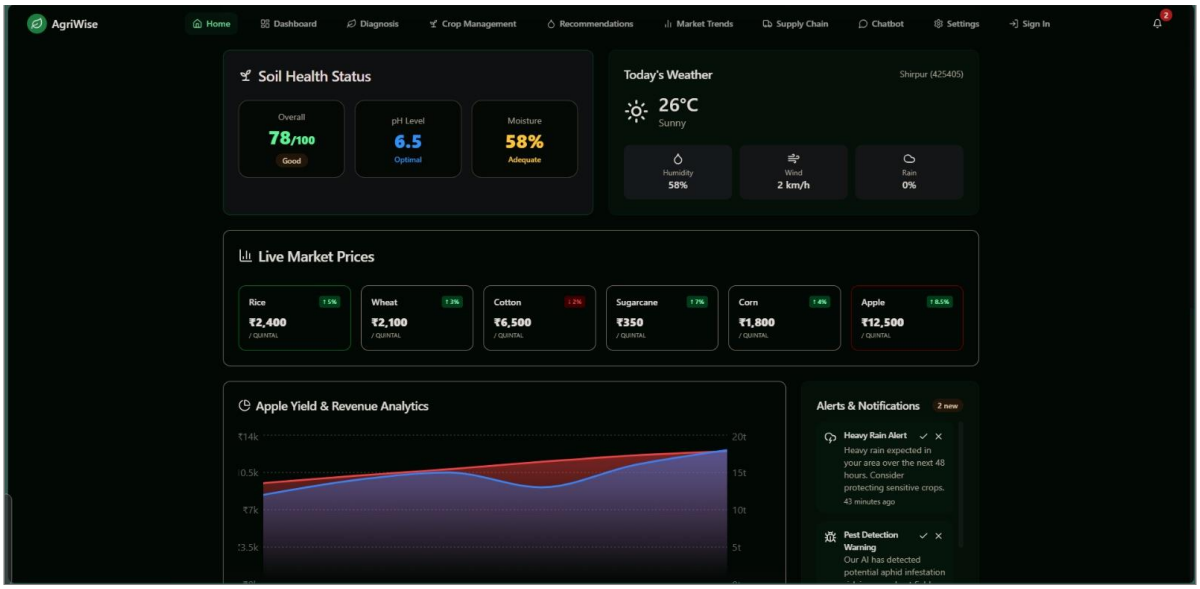


Fig. 6 Dashboard showing soil health, weather, market prices, analytics and alerts

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

Crop Management (Fig. 7): This module lists the current crops (apple, wheat, rice and sugarcane) with variety, area in acres, sowing and expected harvest dates, growth progress bar and health status. Separate tabs are available for planned crops and crop history.

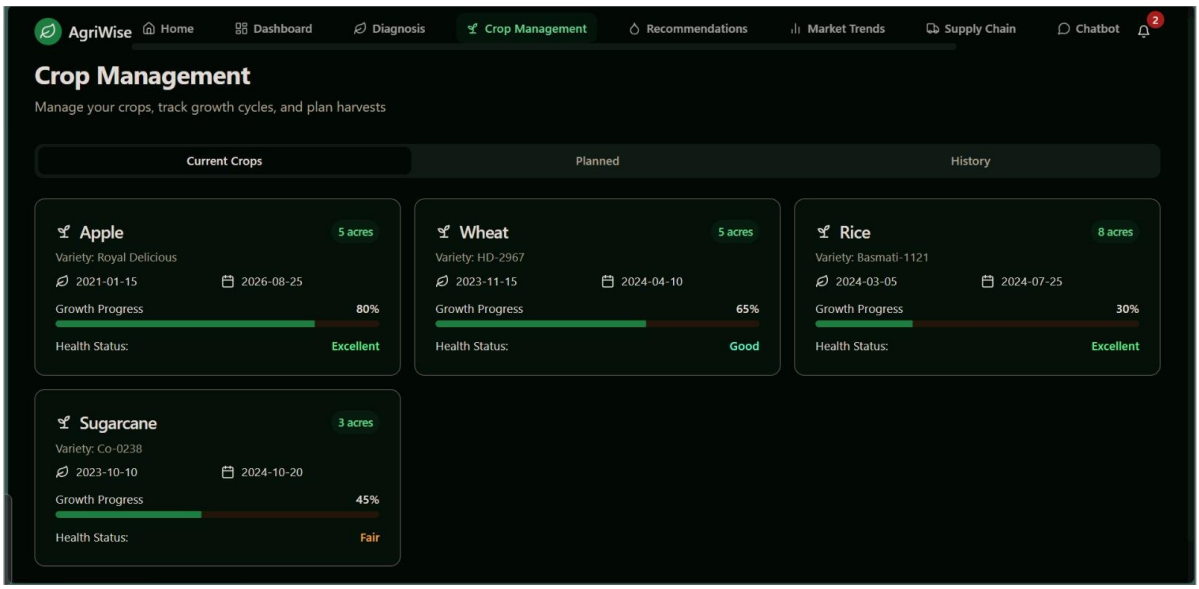


Fig. 7 Crop Management module showing growth progress and health status of each crop

Market Trends (Fig. 8): This module shows the crops with the highest price increase and decrease, the trading volume by crop, annual price trends and the commodity distribution, with refresh and export options to help the farmer decide when to sell.

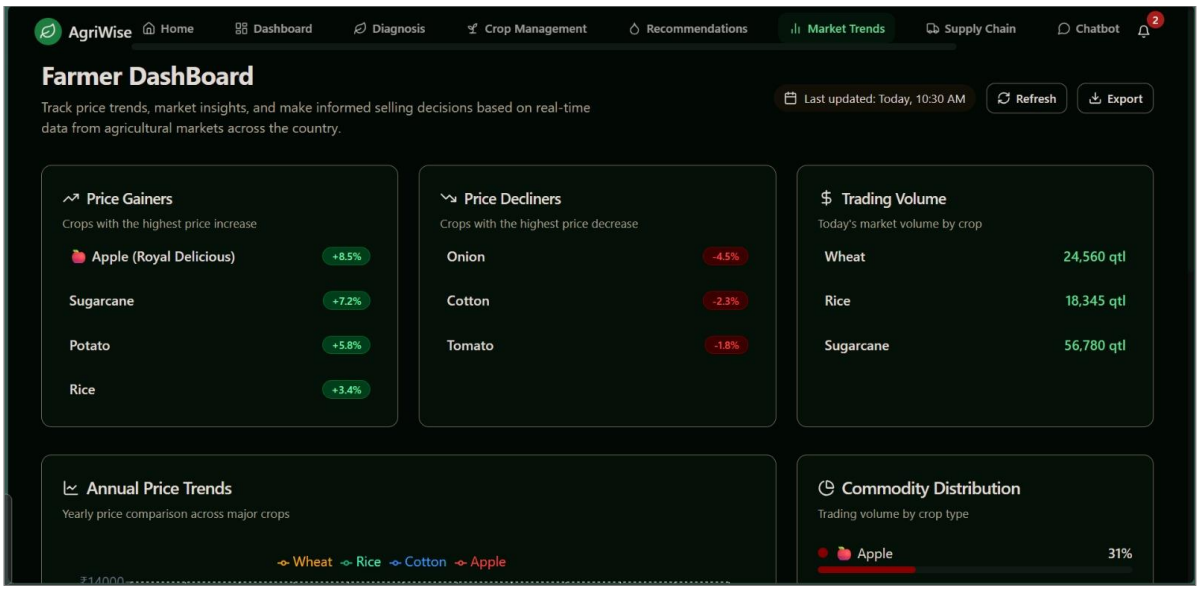


Fig. 8 Market Trends module showing price gainers, decliners and trading volume

B. Evaluation Plan

The performance of the disease detection model and of the spraying unit will be measured as planned in Table VI. The detection model will be tested on labelled leaf images that were not used for tuning, using the measures given in Section VIII. The spraying unit will be compared with conventional uniform spraying over the same area. The measured values will be reported in the extended version of this work.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.151155

TABLE VI PLANNED EVALUATION OF THE SYSTEM

Aspect	Method	Measure
Disease detection	Test on labelled leaf images (healthy, scab, rust)	Accuracy, precision, recall, F1-score, confusion matrix
Response time	Time from image upload to displayed result	Average seconds per image
Spraying unit	Compare precision spraying with uniform spraying on the same area	Liquid used, area covered, spray uniformity
Command delay	Time from spray approval to pump start	Average delay in seconds

C. Discussion

The implemented platform shows that diagnosis, farm information and decision support can be brought together in one interface that a farmer can open on a phone. Using a multimodal model removes the need to train a separate network for each crop, and the explanation of symptoms makes the result easier to understand than a label alone. The confidence threshold and the farmer approval step add safety before any chemical is released. The limitations are that the accuracy of any vision model depends on image quality, lighting and the stage of the disease; that cloud-based analysis needs an internet connection; that similar-looking diseases may be confused; and that the results must be validated on field images before they are relied upon. These points will be addressed in the final evaluation.

XI. ADVANTAGES AND APPLICATIONS

A. Advantages

1) Early and quick disease identification from a single photograph.
2) Targeted spraying that can reduce chemical use, cost and environmental harm.
3) Treatment and preventive advice in simple language, which also helps farmers with limited technical knowledge.
4) One platform for soil, weather, alerts, crop tracking, market prices and chatbot support.
5) Low-cost hardware and a browser-based interface that works on ordinary phones.
6) Farmer approval and manual override keep the human in control of spraying.

B. Applications

1) Disease monitoring and spraying support in orchards and field crops such as apple, wheat, rice and sugarcane.
2) Advisory service for small and medium farmers, farmer groups and agricultural extension workers.
3) Crop record keeping and harvest planning.
4) Selling decisions based on market price trends and supply chain information.
5) Teaching and demonstration of precision agriculture in agricultural and engineering colleges.

XII. CONCLUSION

This paper presented a Smart Farming System that uses machine learning for crop disease detection and a precision spraying mechanism. A farmer can upload a leaf image, receive a diagnosis with a confidence score and treatment advice, and, after approval, trigger targeted spraying through a microcontroller based unit. The web platform also brings together soil health, weather, alerts, crop management, market trends, supply chain support and a chatbot. The system is designed to help farmers act earlier, spray only where needed and make better use of information. The detection model and the spraying unit will be evaluated as planned in Table VI to show how much the system improves on conventional practice.

XIII. FUTURE SCOPE

The work can be extended in several directions. A lightweight model that runs on the device can allow diagnosis without internet. A custom model trained on local field images can be compared with the current approach to improve accuracy. Drones or robotic vehicles with cameras can scan the field automatically and spray at the exact location of each infected plant. Soil moisture, temperature and humidity sensors can be linked to the dashboard for automatic alerts. Support for regional languages and voice input will make the system easier for more farmers, and large-scale field trials over complete crop seasons will help to measure the effect on yield and pesticide saving.

ACKNOWLEDGMENT

The authors thank their project guide, Prof. Priyanka D. Lanjewar, and the Department of Artificial Intelligence and Machine Learning, R. C. Patel Institute of Technology, Shirpur, for their guidance and support during this work.



International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026
DOI: 10.17148/IJARCCE.2026.151155

REFERENCES

[1]. S. P. Mohanty, D. P. Hughes and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection", *Frontiers in Plant Science*, vol. 7, Art. no. 1419, 2016.
[2]. K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis", *Computers and Electronics in Agriculture*, vol. 145, pp. 311-318, 2018.
[3]. S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification", *Computational Intelligence and Neuroscience*, vol. 2016, Art. no. 3289801, 2016.
[4]. E. C. Too, L. Yujian, S. Njuki and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification", *Computers and Electronics in Agriculture*, vol. 161, pp. 272-279, 2019.
[5]. R. Thapa, N. Snavely, S. Belongie and A. Khan, "The Plant Pathology Challenge 2020 data set to classify foliar disease of apples", *Applications in Plant Sciences*, vol. 8, no. 9, e11390, 2020.
[6]. A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey", *Computers and Electronics in Agriculture*, vol. 147, pp. 70-90, 2018.
[7]. K. G. Liakos, P. Busato, D. Moshou, S. Pearson and D. Bochtis, "Machine Learning in Agriculture: A Review", *Sensors*, vol. 18, no. 8, Art. no. 2674, 2018.
[8]. S. Wolfert, L. Ge, C. Verdouw and M.-J. Bogaardt, "Big Data in Smart Farming - A review", *Agricultural Systems*, vol. 153, pp. 69-80, 2017.
[9]. R. Berenstein and Y. Edan, "Automatic Adjustable Spraying Device for Site-Specific Agricultural Application", *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 2, pp. 641-650, 2018.
[10]. Gemini Team, Google, "Gemini: A Family of Highly Capable Multimodal Models", *arXiv preprint arXiv:2312.11805*, 2023.

 This work is licensed under a Creative Commons Attribution 4.0 International License