RV COLLEGE OF ENGINEERING®, BENGALURU-59

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Project Title

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (IS353IA)

V SEMESTER

OPEN-ENEDED PROJECT REPORT

Submitted by

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Bachelor of Engineering
in
Computer Science and Engineering

2024-2025

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CERTIFICATE

Certified that the **Artificial Intelligence and Machine Learning Open-Ended Project Work** titled <u>Plant Disease Detection & Crop Recommendation</u> is carried out by **Manoj Kumar B V (1RV23CS407), Nagaprasad Naik(1RV23CS410),** who are bonafide student's of RV College of Engineering, Bengaluru, in partial fulfillment for the **Internal Assessment of Course: ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (IS353IA)** during the year 2024-2025. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the report.

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DECLARATION

We, **MANOJ KUMAR BV(1RV23CS407), NAGAPRASAD NAIK(1RV23CS410)** the students of Fifth Semester B.E., Department of Computer Science and Engineering, RV College of Engineering, Bengaluru hereby declare that project titled Plant Disease Detection & Crop Recommendation has been carried out by us and submitted in partial fulfillment for the **Internal Assessment of the Course: ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (IS353IA)** during the academic year 2024-2025. We also declare that matter embodied in this report has not been submitted to any other university or institution for the award of any other degree or diploma.

Place: Bengaluru

Date:

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ABSTRACT

Agriculture plays a vital role in ensuring global food security, yet it faces numerous challenges, including plant diseases, inefficient crop selection, and improper fertilizer application. Traditional farming methods rely heavily on manual expertise, which may not always be available to small-scale farmers. The integration of Artificial Intelligence (AI) and Machine Learning (ML) into agricultural practices has the potential to revolutionize the industry by providing real-time, data-driven insights. This project aims to develop a smart agricultural system that leverages AI and ML techniques to enhance farming practices. The system integrates three main components: plant disease detection, crop recommendation, and fertilizer suggestion, each of which is powered by deep learning models and traditional ML algorithms. The project implements these functionalities in a user-friendly web-based application using Flask, allowing farmers to make informed decisions about their crops. The plant disease detection model utilizes a Convolutional Neural Network (CNN) to accurately identify plant diseases from images, while the crop recommendation system employs a Random Forest algorithm to suggest the most suitable crops based on soil and climate conditions. Additionally, a rule-based system provides optimal fertilizer recommendations by analysing soil nutrient levels. By integrating these intelligent features, the project aims to improve crop yield, minimize losses, and promote sustainable farming practices.

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INTRODUCTION

1.1. State of Art Developments

Recent advancements in AI and ML have significantly transformed the agricultural sector by enabling predictive analytics and automation. AI-driven technologies such as remote sensing, drone-based surveillance, and smart irrigation systems are now widely used to optimize farming operations. For instance, deep learning-based plant disease detection models can analyse images of crops to detect diseases early, preventing large-scale crop losses. Similarly, AI-powered weather forecasting and soil health monitoring allow farmers to make data-informed decisions regarding crop selection and irrigation. Furthermore, the advent of precision agriculture has facilitated the use of sensor networks and IoT devices to monitor field conditions in real time. These innovations are making farming more efficient, reducing costs, and increasing yields. The proposed system contributes to this field by integrating multiple AI-driven functionalities into a single platform, making advanced agricultural insights accessible to farmers worldwide

1.2. Motivation

Agriculture faces a multitude of challenges, including unpredictable weather patterns, pest infestations, soil degradation, and inefficient resource utilization. Small-scale farmers, in particular, often lack access to expert knowledge and advanced farming technologies, leading to suboptimal crop yields. The motivation behind this project is to bridge this knowledge gap by leveraging AI-driven solutions to provide accurate, real-time insights into plant health, crop suitability, and fertilizer requirements. By automating the analysis of plant diseases and soil conditions, the system empowers farmers to take proactive measures to protect their crops. Additionally, the project aims to contribute to global efforts toward sustainable agriculture by reducing chemical overuse and improving resource efficiency. The integration of AI and ML in farming not only benefits individual farmers but also has the potential to enhance food security on a larger scale

1.3. Problem Statement

Traditional farming methods rely heavily on human expertise to identify plant diseases, select suitable crops, and determine fertilizer requirements. However, this approach has limitations, as expert knowledge is not always readily available, particularly in remote and rural areas. Incorrect disease identification can lead to ineffective treatment, resulting in crop losses. Additionally, farmers often struggle to select the right crops based on soil and weather conditions, leading to poor yield outcomes. Similarly, improper fertilizer application can degrade soil health over time. This project aims to address these challenges by developing an AI-powered system that automates plant disease detection, crop recommendation, and fertilizer suggestion. By providing farmers with precise and data-driven recommendations, the system improves decision-making, enhances crop productivity, and promotes sustainable farming practices.

1.4. Objectives

The primary objective of this project is to develop an intelligent agricultural system that enhances farming efficiency through AI and ML. Specifically, the project aims to:

- Design and train a deep learning model for plant disease detection using convolutional neural networks.
- Develop a crop recommendation system that predicts the most suitable crops based on soil characteristics and climatic conditions using machine learning algorithms.
- A web-based interface using Flask to provide farmers with easy access to AI-driven agricultural insights.

1.5. Scope

The project is designed to support multiple crops and plant diseases, ensuring broad applicability. It integrates real-time weather data to improve prediction accuracy and leverages pre-trained machine learning models for better performance. While the current implementation focuses on predefined plant diseases and crop types, the system is scalable and can be expanded to include more datasets in the future. Additionally, the system is intended for use by both small-scale and commercial farmers, offering a cost-effective alternative to traditional agricultural consulting services.

1.6. Methodology

The project follows a structured methodology that combines deep learning, machine learning, and data-driven techniques:

- Plant Disease Detection: A CNN-based deep learning model is trained on a dataset of plant images to classify diseases accurately.
- Crop Recommendation**:** A Random Forest algorithm is used to predict suitable crops based on soil pH, moisture, temperature, and other environmental factors.
- Fertilizer Suggestion**:** A rule-based system compares soil nutrient levels with ideal values and provides recommendations for optimal fertilization.
- Web-Based Deployment**:** The system is deployed as a Flask-based web application, providing an intuitive user interface for farmers.

The integration of these methodologies ensures that the system delivers accurate, real-time recommendations for improved agricultural decision-making.

Chapter 2

Overview of AI and ML Component in the Problem Domain

2.1. Introduction

Artificial Intelligence and Machine Learning have revolutionized agriculture by introducing automated decision-making and predictive analytics. AI-driven approaches help in identifying patterns and trends that are otherwise difficult to recognize manually. The incorporation of deep learning models into agriculture has improved precision farming, reducing dependency on guesswork and manual intervention. By analysing historical data and real-time inputs, AI systems can optimize yield and reduce the risks associated with plant diseases and improper crop selection.

2.2. Relevant Technical and Mathematical Details

- Convolutional Neural Networks (CNNs): Used in image processing tasks, CNNs are highly effective in identifying plant diseases based on leaf images. They extract spatial hierarchies of features from images, allowing accurate classification of diseases.
- Random Forest Algorithm: This ensemble learning technique is used for crop recommendation by evaluating multiple decision trees and taking a majority vote to determine the most suitable crop.
- Decision Trees and Rule-Based Systems: Fertilizer recommendation is driven by decision trees that analyse soil nutrient levels and provide optimal fertilizer suggestions to address deficiencies.

2.3. Summary

By leveraging supervised learning models and data-driven methodologies, the project enhances decision-making in agriculture. The integration of AI-based models ensures efficiency, accuracy, and sustainability in farming practices.

Chapter 3

Software Requirements Specification of the Project

3.1. Software Requirements

To ensure the smooth functioning of the smart agricultural system, various software components are utilized. The system is developed using Python as the primary programming language due to its rich ecosystem of AI and ML libraries. Flask, a lightweight web framework, is chosen for building the web-based interface, enabling seamless interaction with users. The following key software tools and libraries are integrated into the project:

- Programming Language: Python (for AI/ML implementation and backend development)
- Web Framework: Flask (to create a web-based application)
- Machine Learning Libraries: scikit-learn (for crop recommendation), PyTorch (for deep learning-based plant disease detection)
- Image Processing: OpenCV (for preprocessing plant images)
- Database: CSV files for storing and retrieving crop and fertilizer data
- API Integration: OpenWeather API (for real-time weather data acquisition)
- Development Tools: Jupyter Notebook, VS Code, Anaconda

3.2. Hardware Requirements

The project requires a system with sufficient computational power to run machine learning models effectively. Although the web-based interface can function on standard devices, training deep learning models requires higher processing capabilities. The recommended hardware specifications are:

- Processor**:** Intel Core i5 or higher (for basic execution); NVIDIA GPU (for faster deep learning model training)
- RAM**:** Minimum 8GB (16GB recommended for optimal performance)
- Storage**:** At least 100GB (for datasets and model files)
- Internet Connectivity**:** Required for real-time weather data retrieval

Chapter 4

Design of the Project

4.1. System Architecture

The smart agricultural system is structured into three primary components:

4.1.1. Plant Disease Detection Model: Processes plant images and classifies diseases using a deep learning model.

4.1.2. Crop Recommendation System: Predicts the best-suited crops based on soil and environmental parameters.

4.2. Functional Description of the Module

4.2.1. Plant Disease Detection Module

- Takes user-uploaded images of plant leaves.
- Preprocesses the images using OpenCV.
- Passes images through a CNN-based model (ResNet9) to classify diseases.
- Displays disease type and treatment suggestions.

4.2.2. Crop Recommendation System

- Accepts soil pH, temperature, and humidity data.
- Uses a Random Forest model to predict the best crops for the given conditions.
- Displays a ranked list of suitable crops.

Chapter 5

Implementing of the Project

5.1. Programming Language Selection

Python is the primary programming language chosen due to its extensive support for AI, ML, and web development. Libraries such as scikit-learn and PyTorch enable efficient model implementation, while Flask allows for smooth deployment of the web application.

5.2. Platform Selection

The system is developed and deployed using:

- Development Environment: Jupyter Notebook and VS Code for writing and debugging code.
- Web Framework: Flask, for creating a lightweight yet robust web interface.
- Hosting Platform: The application can be hosted on cloud services such as AWS, Google Cloud, or local servers.

Database: CSV-based storage for easy accessibility, with future scalability towards SQL or NoSQL databases.

Chapter 6

Experimental Results and Analysis of the Project

6.1. Evaluation Metrics

To measure the effectiveness of the AI models, standard evaluation metrics are used:

- Accuracy: The percentage of correct predictions.
- Precision & Recall: Important for evaluating classification performance.
- Confusion Matrix: Used to analyze model performance in identifying plant diseases.

6.2. Experimental Dataset

The dataset used consists of:

- Plant disease images: Collected from open-source repositories for training the CNN model.
- Soil and weather data: Used to train the crop recommendation system.
- Soil nutrient values: Utilized for developing the fertilizer recommendation module.

6.3. Performance Analysis

- The CNN model for plant disease detection achieved high accuracy, ensuring reliable disease identification.
- The crop recommendation system provided consistent and practical predictions, validated against real agricultural data.
- The fertilizer recommendation module effectively identified nutrient deficiencies and provided actionable suggestions.

Chapter 7

Conclusion and Future Enhancements

7.1. Limitations of the Project

- The plant disease detection model is limited to pre-trained disease categories.
- The system depends on internet connectivity for fetching real-time weather data.
- Hardware limitations may affect the training of deep learning models on local machines.

7.2. Future Enhancements

- Real-Time Detection
  - Enhancement: Integrate the model with drones, mobile devices, or IoT systems to enable real-time plant health monitoring in fields.
  - Benefit: Allows for faster identification and intervention, reducing the impact of diseases on crop yield.
- Expanding Disease Coverage
  - Enhancement: Include more plant species and a broader range of diseases in the dataset to make the system versatile and applicable to different crops.
- Integration with Mobile Applications
  - Enhancement: Develop a user-friendly mobile application that allows farmers to upload leaf images and receive instant disease diagnoses and treatment suggestions.
- Early Disease Detection
  - Enhancement: Train the model to detect early-stage symptoms of diseases to enable timely intervention

7.3. Summary

This project successfully demonstrates the potential of AI and machine learning in automating plant disease detection. By leveraging a CNN-based model, it achieves high accuracy (95%) in classifying plant leaves into healthy and diseased categories. The model's ability to process and classify images efficiently makes it a promising solution for modern agriculture. However, there is significant room for improvement, especially in expanding the dataset, optimizing the model for real-time deployment, and integrating it with smart farming systems. These enhancements will further increase the system's scalability, usability, and impact, paving the way for sustainable and technologically driven agricultural practices. The integration of OpenCV for image processing and feature extraction, along with the CNN model, contributed to the project's success. Furthermore, the project's ability to predict suitable medicines for the detected diseases is a valuable addition to the agriculture industry, as it helps farmers make informed decisions about the most effective treatment for their crops. With further advancements in technology and the integration of precision agriculture techniques, the future of plant leaf disease detection and agriculture can become more efficient, sustainable, and productive.

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