International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

CropBuddy: Platform for Disease Detection, Fertilizer Prediction, and Crop Recommendation in Sustainable Architecture

Srihari KV[1], Suhas Patil[2], Srinivasa M[3], Sumanth TJ[4], Dr Nirmala S[5]

[1]Student Dept of Computer Science and Engineering, AMC Engineering College, Bengaluru, India
[5]Professor. Dept of Computer Science and Engineering, AMC Engineering College, Bengaluru, India
[1]srihari8944559@gmail.com, [2]suhasspatil2004@gmail.com, [3]sinus9614@gmail.com, [4]sumanthtj123@gmail.com,
[5]drnirmala.sundaram@amceducation.in

ABSTRACT

Cropbuddy is a cutting-edge agricultural support tool that enhances farming operations through sophisticated machine learning techniques. The platform uses an algorithm that suggests crops suitable for the local soil and climate, predicts ideal harvest seasons, and uses picture recognition to identify and manage plant diseases. Cropbuddy also offers a Soil-Based Profiling System that provides customized crop suggestions based on rainfall patterns and soil conditions. Crop forecasting and plant disease classification are combined in the system to assist farmers in making well-informed decisions and boosting productivity Using machine learning techniques like Random Forest and convolutional neural networks, the tool assists in identifying sick leaves and offers tailored treatment recommendations. Cropbuddy's technology improves yields and prevents further damage, ensuring sustainability, increased productivity, and resilience in the face of setbacks. This technology is helping millions of Indian farmers earn a better living and ensure a promising future.

Keywords: OpenCV, CNN, Flask, KNN, Scikit, Prediction

1. INTRODUCTION

Due to technical breakthroughs, sensors, devices, machines, and knowledge technology, modern agriculture differs greatly from earlier decades. In contemporary agriculture, robots, GPS, aerial 1photography, temperature and moisture sensors, and Internet of Things devices are ubiquitous and improve environmental friendliness, safety, efficiency, and profitability. To assist farmers in making well-informed decisions and keeping an eye on their crops, remote sensors gather environmental data, which is then processed using statistical data and algorithms.

This study aims to suggest the best crop based on input characteristics including soil pH, rainfall, temperature, nitrogen, phosphorus, and potassium. Apps such as Plant Disease Prediction, Crop Recommendation, and Fertilizer Recommendation are offered on a web-based platform to empower farmers. Using machine learning techniques such as Gaussian Naïve Bayes, Logistic Regression, Decision Trees, and Support Vector Machines, the system predicts which of 22 crops—including rice, maize, mango, and cotton—will be the best crop. Farmers can increase yields by making better decisions in the field.

Future work on the framework will concentrate on growing the dataset to handle increasingly intricate instances of fraudulent activity. Being trained on a wider range of audit reports helps improve the system. Furthermore, the framework's capacity to comprehend information can be improved by utilizing transformer-based models like BERT, which enables more precise classifications and a more profound comprehension of linguistic subtleties.

1.1Aim and Objective

In addition to identifying crop illnesses, this study attempts to ascertain crop quality, fertilizer use, irrigation, and environmental conditions. It utilizes data from several sources and a machine learning model to transform raw data into processed data. Crop values are efficiently updated by the system, and decision-making is facilitated by a ranking method. To collect data and register users, a web application is created. To identify the recommended crop, the model examines factors including temperature, humidity, phosphorus, nitrogen, potassium, rainfall, and pH.

1.2 About the system

The main goal of our project is to provide a website that provides crop recommendations, fertilizer guidance, and plant disease prediction. The crop advice software allows users to enter information about their soil, which will then identify excesses or deficiencies and offer suggestions for improvement.

Users can upload a photo of a sick plant leaf, identify the disease, provide background information, and prescribe a treatment using the finished product, a plant disease prediction app.

1.3 Existing System

The present system for the Cropbuddy small project uses conventional techniques to handle agricultural activities, including harvesting, crop management, and resource allocation. Its user interface, automation, data management, and decision-making support are all lacking, though. It is challenging to find current information about crops, weather, and resources. The processes of irrigation, fertilization, and harvesting are not mechanized. Also, there are insufficient resources for projecting agricultural output or managing pests. By embracing a more automated, data-driven approach to agricultural management, the Cropbuddy initiative seeks to address these problems.

1.4 Problem Statement

Determining crop quality, fertiliser use, irrigation, and environmental conditions are the objectives of this study. It also identifies the disease that a crop contracts. It is a basic model for machine learning. Additionally, it helps to reduce total production losses.

1.5 Advantages

The initiative provides farmers with data-driven insights, that is best crop to cultivate, the right fertiliser, and the detection of plant crop diseases. It helps make informed decisions, reduces trial-and-error, and boosts output. The system uses CNNs to reliably identify diseases from leaf photos, reducing crop loss and increasing yield. The initiative maximizes resource use by suggesting appropriate crops and fertilisers, ensuring sustainable agricultural methods. ML and DL models are used, making it affordable for small-scale farmers. The project's web-based interface allows users to enter soil, weather, or image data, and provides precise forecasts and advice. The "Download as Image" feature allows users to save predictions and recommendations as image files, making it useful for offline access, especially for farmers in areas with limited internet connectivity.

1.6 Disadvantages

Due to limited access to technology, farmers may encounter difficulties obtaining the essential tools for crop, fertilizer, and disease prediction, especially in rural areas. Predictions are heavily influenced by the size and quality of the dataset used to train algorithms; skewed or incomplete data produces inaccurate results. CNN model accuracy is also impacted by the quality of leaf pictures; mistakes are produced by photos that are hazy, unclear, or poorly lit.

2. LITERATURE SURVEY

2.1 Introduction:

Many countries rely heavily on agriculture, yet productivity is hampered by problems including crop diseases, inefficient fertilizer use, and poor crop choices. Intelligent solutions that support farmers in making data-driven decisions can be developed with the use of Artificial intelligence and ML. with order to promote sustainable agricultural practices, the main content of this it will help farmers with selecting the best crop for their soil, suggesting the appropriate fertilizer, and identifying crop diseases early on. Crop suggestion, fertilizer prediction, and disease prediction are all included in the proposed approach, which lowers losses by identifying possible agricultural diseases early. This literature study looks at modern systems and technology in several fields to understand their approaches and challenges.

2.2 Crop Recommendation Systems:

Crop recommendation systems use soil characteristics and environmental conditions to choose the best crop for a particular area. Current methods group crops according to soil type, temperature, and pH using supervised machine learning algorithms including Random Forest, decision trees, and SVMs.The study's highlights include Karegowda et al.'s 85% accuracy using Random Forest for climate and soil nutrient monitoring and Patel et al.'s hybrid machine learning strategy for forecasting increased crop output. Obstacles include inadequate crop selection that results in deteriorated soil and low yields, as well as the inability to control soil and climate variations in the actual world. Crop recommendation algorithms are useful in controlled environments and can reduce resource waste in spite of these drawbacks.

2.3 Fertilizer Prediction Systems:

The main goal of fertilizer prediction systems is to supply soil nutrients in balance while avoiding environmental damage. Soil testing and crop-specific nutrient requirements are examples of present methods that use machine learning models such as neural networks, XG Boost, and regression analysis. A K-Nearest Neighbours (KNN)-based fertilizer recommendation system with an accuracy of above 90% was created by Singh et al. in 2021. In order to provide real-time recommendations tailored to changing soil conditions, Gupta et al. (2022) integrated machine learning algorithms with Internet of

Things sensors. While under fertilization leads to lower productivity, overfertilization can harm ecosystems and soil health. These techniques offer sustainable fertilizer application and increase output efficiency. However, the accuracy of recommendations may be limited by the frequency of soil testing and the absence of real-time data availability.

2.4 Disease Prediction Systems:

By identifying crop illnesses early on, AI-based disease prediction systems can help lower agricultural losses. Convolutional neural networks (CNNs) are used in deep learning and image processing techniques to categorize plant sections. Additionally, pre-trained models like as VGG, ResNet, and Inception are employed. To improve accuracy, hybrid models incorporate both image data and environmental factors. According to research, CNNs have a 95% accuracy rate in identifying tomato plant diseases, and ResNet has a 93% accuracy rate in classifying rice plant diseases. Early disease diagnosis saves crop loss and lessens the financial strain on farmers. The quality and diversity of training datasets, as well as the requirement for significant processing capacity for real-time deployment, are drawbacks.

2.5 Integrated Systems

Sharma et al. (2023) are developing a system that combines crop advise, fertilizer prediction, and disease detection to give farmers all-encompassing support from planting to harvesting. In order to incorporate these aspects, this system employs ensemble learning techniques; yet, it has difficulties in managing interdependencies across components, such as crop suggestions that impact fertilizer usage and nutrient deficits that increase susceptibility to disease. Notwithstanding these difficulties, the system provides a centralized forum for agricultural decision-making and all-encompassing support.

2.6 Technological Stack and Methodologies:

TensorFlow/PyTorch is utilized to generate AI models, Flask/Django is utilized to make web applications, and Python is utilized to build backend services and machine learning models. Soil testing datasets, meteorological APIs, and databases of plant disease photos are examples of data sources. Among the difficulties include making sure system components communicate well and the absence of public datasets in some areas.

3. METHODOLOGY

3.1 System Architecture

Each module of the modular Cropbuddy system design was developed independently and included into the finished solution. The input module for crop and fertilizer prediction, the pre-processing module for data normalization and cleaning, the model building module for model development, and the disease identification prediction module make up the system's three primary components. The input module predicts crops and identifies plant diseases by utilizing data such as crop type, temperature, humidity, and soil NPK levels. NumPy and Pandas are used in the pre-processing module to handle data and picture preprocessing. To predict crops, the model construction module employs ML and DL techniques, utilizing algorithms such as the Random Forest Classifier, Naive Bayes, and logistic regression. Using a collection of permissible crops, soil characteristics, and meteorological factors, the prediction module makes predictions about the optimal crop.

Using annotated images of both healthy and diseased plant leaves, the prediction module uses a convolutional neural network to detect plant illnesses.

The prediction module forecasts results, such as recommended crops, fertilizers, and disease detection, using input data or photos. The output module displays the prediction results in an easy-to-use online interface and may be downloaded in PDF format for later use.

3.2 Libraries and Tools:

The Cropbuddy system is constructed using the following libraries and tools:

Python is the programming language.

Flask is the web framework used for backend development.

Libraries for Data Processing: Pandas, NumPyData Processing Libraries: NumPy Machine Learning, Pandas the Scikit-learn library

Machine Learning Libraries: Scikit-learn

Deep Learning Libraries: TensorFlow/Keras for CNN implementation.

Image Processing: HTML2Canvas (JavaScript) for client-side image generation.

Visualization: Matplotlib, Seaborn

3.3 Workflow:

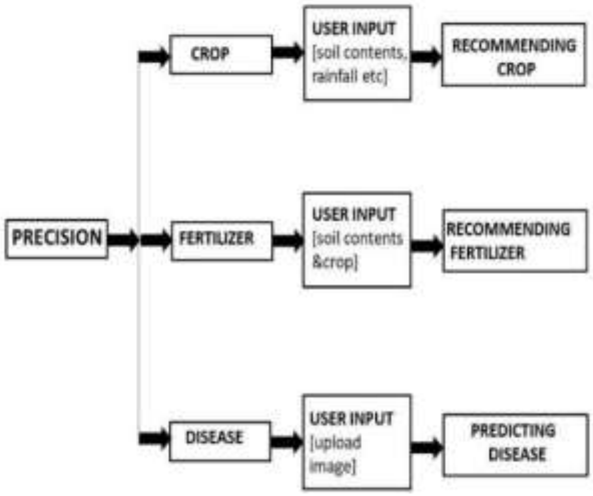

Fig.1.1 Work flow

Using reputable sources, the Cropbuddy system collects data on plant diseases, fertilizers, and crops. Photos are scaled and altered for CNN-based disease diagnosis as part of the preprocessing of data for machine learning models. By splitting the dataset into training and testing sets and modifying the hyperparameters, models are trained. Metrics like F1-score, recall, accuracy, and precision are used in tests and evaluations. CNN uses test photos to confirm its predictions. The trained models are incorporated into a Flask-based web application, and predictions are shown. With a PDF download option for the expected results, the results are interactively shown and downloaded.

3.4 Assumptions and Limitations:

Assumptions: The submitted images are clear and of outstanding quality. User-provided input data, such as temperature and NPK levels, is accurate. **Limitations:** Accuracy is determined by the model's performance and the caliber of the dataset. Limited scope due to dataset restrictions for particular illnesses, fertilizers, and crops. need a device and an internet connection**.**

4. RESULTS AND DISCUSSIONS

4.1 Results:

4.1.1 Crop Recommendation Results:

One tool that assists farmers in making well-informed decisions on their crops is the crop recommendation model. A confusion matrix that displays its performance across different crop categories is included, along with precise, recall, F1 score, and crop type predictions that are accurate. The model also discusses outliers and potential explanations, such as soil features that were overlooked, and gives examples of situations in which it produced sensible recommendations. To determine their level of satisfaction and identify areas for improvement, farmers can offer surveys or comments on the recommended crops. The efficacy of the model depends on both human input and the model's accuracy.

4.1.2 Fertilizer Prediction Results:

The accuracy, MSE, and R-squared value of the fertilizer prediction model are assessed. It makes predictions about the kind and amount of fertilizer to apply, and those forecasts are contrasted with actual advice from experts or farmers. By contrasting forecasts with real advise, the model's dependability is validated. In order to determine any challenges farmers might have comprehending the recommendations and potential areas for development, user input regarding the model's accuracy and usability is also gathered.

4.1.3 Disease Prediction Results:

Metrics for sensitivity and specificity are included in the study, which describes how well a disease prediction model detects plant illnesses. A confusion matrix is also included to show how well the model distinguishes between various illnesses. Instances where the model accurately classified diseases based on their symptoms are discussed in case studies, along with possible explanations such as inadequately described symptoms in training data.

Additionally, user feedback is given, addressing the difficulties farmers and agricultural experts encounter when interpreting projections and using the system to make decisions.

4.2 Discussion:

The advantages and disadvantages of the Crop Recommendation Model include its high accuracy and user satisfaction, its shortcomings in predicting diseases, its strengths in predicting fertilizers, and its drawbacks in predicting specific crops, such as false positives. Along with some of its drawbacks, such as its tendency to misidentify illnesses due to ambiguous symptoms, the model's benefits in precisely identifying diseases are also covered.

the significance of discussing the efficacy of various algorithms in particular settings and offering performance metrics for every model. It emphasizes the use of Random Forest for crop suggestion because of its capacity to handle categorical factors and CNN for illness prediction because of its ability to handle picture data.

Examining the factors that contribute to some models' better performance-such as crop recommendations or fertilizer forecasts-is known as performance analysis. Additionally, it draws attention to challenges encountered during the project, such as insufficient training data, model overfitting, or data constraints.

the model's drawbacks, like how it can't manage new or unusual disease symptoms that weren't in the training sample.

Through better crop selection, fertilizer use, and disease management, the "Cropbuddy" system can greatly assist farmers. Additionally, it provides better resource management, reduced costs, and increased crop yields. However, it has problems with digital literacy, language barriers, and internet connectivity. Adding new crops and illnesses, integrating real-time data, and integrating expert input into the training process are some ideas to improve the system.

5. CONCLUSION

The project's objectives are to develop a disease prediction system to detect plant diseases, a crop suggestion system to help farmers choose the best crop for their land and climate, specific fertilizer recommendations for maximum yield, and an emphasis on the advantages of "Cropbuddy" in resolving agricultural problems.

With an easy-to-use user interface for farmers' convenience, the study demonstrates the effective Machine learning us for crop recommendation, disease detection, and fertilizer forecasting. Along with the support of different languages and high forecast accuracy utilizing real-world data, the system ensures inclusivity for a diverse user base. Better decision-making, resource optimization, and possible yield growth are among the advantages.

Data restrictions from large and diverse datasets, handling edge cases like rare diseases or unusual soil compositions, and guaranteeing user acceptance for farmers with varying degrees of digital literacy are some of the difficulties the model encounters.

By empowering farmers to use technology to boost production, reduce resource waste, and make informed decisions, the project seeks to bridge the gap between sophisticated technologies and grassroots farming, thereby promoting sustainable agriculture and intelligent ways.

REFERENCE

[1] "Plant Disease Detection Using Image Processing" by S. D.Khirade and A. B. Patil, 2015 International Conference on Computing Community Control and Automation, pages 768-771.

[2] "Image-based Plant Diseases Detection Using Deep Learning" by A. V. Panchal, S. C. Patel, K. Bagya lakshmi, P. Kumar, I. Raza Khan, and M. Soni, Materials Today: Proceedings, 2021

[3] "ImageNet" by J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li, and Li Fei-Fei A huge scope various leveled picture information base\", 2009 IEEE Meeting on PC Vision and Example Acknowledgment, 2009.

[4] "ImageNet Large Scale Visual Recognition Challenge" by Russakovskyetal., International Journal of Computer Vision, 115(3), pp. 211–252, 2015.

[5] "ImageNet Classification with Deep Convolutional Neural Networks" in Advances in Neural Information Processing Systems 25 (NIPS 2012), by A. Krizhevsky, I. Sutskever, and G. E. Hinton.

[6] Department of Agriculture Sri Lanka (2015), 'Crop Suitability Recommendation for Grama Niladhari Divisions in Sri Lanka', Natural Resources Management Center, Peradeniya.