Journal of Soft Computing Paradigm (ISSN: 2582-2640)
www.irojournals.com/jscp/

Leaf Disease Detection and Fertilizer Recommendation using Deep Learning

Rasiga J.[1], Sajeetha Britty E.[2], Srinithi V.[3], Vethasundari N.[4], Soundararajan K.[5]

[1-4]Student, [5]Assistant Professor, Information Technology, Vivekanandha College of Technology for Women, Anna University, Namakkal, India

E-mail: [1]rasikani.2018@gmail.com, [2]sajeethabritty@gmail.com, [3]nithisri046@gmail.com, [4]vethasundari2003@gmail.com, [5]soundark919@gmail.com

Abstract

Plant disease detection is an important field of study since early detection can drastically minimize crop losses and enhance agricultural productivity. Pathogens like fungi, bacteria, and viruses are responsible for most plant diseases, which can seriously affect plant health and yield. In this research, a pre-trained convolutional neural network (CNN) algorithm, VGG 16 is used to classify various leaf diseases with very high accuracy, taking advantage of deep learning methods in observing visual symptoms on leaves. The model takes the input image of a diseased leaf, extracts hierarchical features using its multi-layered architecture, and determines the type of disease, allowing for early and accurate diagnosis. Moreover, the system is designed to recommend fertilizer based on the disease identified, enabling farmers to take necessary action to reduce damage and enhance crop yield. By combining cutting-edge AI with agricultural knowledge, this method presents a scalable and effective solution to disease management, enabling sustainable agriculture and food security.

Keywords: Plant Disease Detection, Automatic Disease Classification, Deep Learning in Agriculture, Convolutional Neural Network (CNN), VGG-16 Model.

1. Introduction

Agriculture is a cornerstone of India's economy, with a large segment of the population involved in agriculture and related sectors. As a primary economic activity, it not only supports livelihoods but also significantly contributes to the nation's GDP. However, the sector faces

DOI: https://doi.org/10.36548/jscp.2025.1.005
Received: 04.02.2024, received in revised form: 02.04.2025, accepted: 19.04.2025, published: 02.05.2025

serious challenges, as crops are frequently affected by various fungal and bacterial diseases, leading to substantial yield losses. Compounding this problem, high population growth and changing climatic conditions have further facilitated the spread of plant diseases, making cultivation increasingly unpredictable. A major concern in sustainable agricultural development is the reduction of excessive and harmful pesticide use, which elevates production costs and poses severe environmental and health risks. To address these issues, innovative solutions are urgently required to improve crop quality, minimize dependence on chemical treatments, and promote sustainable farming practices. The adoption of cutting-edge technologies, such as AI-based disease detection and precision agriculture, holds the potential to optimize resource utilization, enhance crop health, ensure long-term food security, and protect the environment.

1.1 Research Gap

Existing plant disease detection models with AI such as VGG-16 have primary limitations: they are limited to identification without proposing practical treatment strategies, employ unrealistic training data, overlook sustainable reduction of pesticides, and are not customized for the needs of small farmers. This study fills the gaps by formulating an upgraded VGG-16 model that not only identifies diseases accurately but also suggests severity-specific fertilizers, making a more practical and sustainable solution for Indian agriculture.

2. Related Works

The application of technology in agriculture has seen significant advancements, with the Internet of Things (IoT) playing a important role through environmental sensor networks, robotics, machine vision, and LiDAR, enabling the exploration of genotype-phenotype-envirotype relationships within omics systems to advance functional genomics, plant molecular breeding, and efficient cultivation. Machine vision techniques have rapidly developed for plant phenotyping, progressing from single trait estimation to crop canopy evaluation, with research providing overviews of imaging techniques, their applications, recent methodologies, and publicly available datasets, while also suggesting future directions for deep learning-based algorithms focused on structural, physiological, and temporal trait estimation and classification[1,2]. Addressing the challenge of crop disease detection, which threatens food production and small-scale farmer livelihoods, deep learning techniques and algorithms are being developed to automate the process; for example, Faster R-CNN and ResNet50 have been used to detect and classify tomato diseases. Novel approaches using small sample sizes and deep convolutional neural networks have also been proposed for recognizing cucumber leaf diseases in field conditions, demonstrating high identification accuracy and potential for field application within the agricultural IoT [3]. Customized image-based phenotyping systems are also being developed to evaluate crop responses to environmental stressors, such as salt stress in soybean cultivars, using consumer-grade digital cameras and automated platforms to collect sequential images and extract features correlated with stress tolerance. Deep learning has further enabled smartphone-assisted disease diagnosis, using increased smartphone penetration to achieve high accuracy in identifying diseases from images[4]. Convolutional neural network models have proven effective for plant disease detection and diagnosis using leaf images, achieving high success rates in identifying disease combinations and showing potential as early warning tools[5]. Comparative studies of deep convolutional neural network architectures, such as VGG 16, Inception V4, ResNet, and DenseNets, have demonstrated the superior performance of certain architectures, like DenseNets, in plant disease classification, achieving high testing accuracy with fewer parameters and computing time[6]. Reviews of machine learning applications in agricultural production systems highlight the technology's benefits in crop, livestock, water, and soil management, emphasizing the value of real-time artificial intelligence-enabled programs for farmer decision support [7]. Surveys of deep learning techniques in agriculture and food production have shown the technology's potential, with high accuracy and outperformance of commonly used image processing techniques. In specific applications, deep convolutional neural networks (DCNNs) have been used for automated crop disease detection, such as yellow rust in winter wheat, using high spatial resolution hyperspectral images from UAVs to incorporate both spatial and spectral information[8]. Precision agriculture, or smart farming, utilizes machine learning to address challenges posed by population growth, climate change, and limited resources, with applications including soil parameter prediction, crop yield prediction, disease detection, and species detection, and the integration of machine learning with computer vision to improve livestock production and reduce human labor, contributing to enhanced sustainable productivity and product quality. Lightweight Deep Learning frameworks, such as the Deep Tomato Detection Network (DTomatoDNet), are being developed for efficient classification of tomato leaf diseases, using techniques to reduce parameters and enable deployment on mobile platforms for rapid disease detection by farmers [9-13].

3. Proposed Work

3.1 AI-Powered Leaf Disease Detection for Smart Farming

The proposed work aims to create an automated leaf disease identification system for agricultural crops based on advanced image processing and deep learning methods. Plant disease early detection is important in order to avoid yield loss and maintain food security. The system starts with data collection followed by preprocessing leaf images to improve quality and extract high-level features like color, texture, and shape. These characteristics are then passed into a Convolutional Neural Network (CNN) to classify them using the pre-trained VGG-16 model to enhance precision and shorten training time. The CNN architecture is fine-tuned to detect disease patterns to allow for real-time detection at low computational cost. By allowing for the automated identification of disease, this system can be used by farmers to monitor extensive crop fields efficiently, enabling timely interventions and decreasing efforts in manual inspections. The solution being proposed can potentially increase precision agriculture, reduce pesticide usage, and enhance general crop health management.

3.2. System Requirements

3.2.1 Hardware Requirements

The proposed framework is implemented using an Intel processor supported by a minimum of 1GB of RAM for image processing and deep learning computations. It requires 160GB of hard disk storage, which is sufficient for the operating system, software, and a substantial set of leaf images, with the application itself needing approximately 650MB of disk space. These modest hardware requirements make the system lightweight, cost-effective, and readily deployable in rural and resource-constrained farm environments, thus facilitating large-scale adoption for precision agriculture.

3.2.2 Software Requirements

The leaf disease detection system is constructed on a stable, lightweight software stack to facilitate efficient operation and easy deployment. For server-side programming, Python 3.7.4 is the main programming language, using its extensive libraries for machine learning and image processing. The client-side application is built using HTML, CSS, and Bootstrap to create a responsive and user-friendly web interface. Flask 1.1.1, a lightweight Python web framework, is used for deployment, as it is well-suited for hosting AI models. MySQL 5 serves as the backend for database storage, managing user information, crop records, and disease classifications. WampServer 2i provides the local server environment for development and testing, and Windows 10 64-bit is the recommended operating system for optimal compatibility. This software design enables seamless integration of the AI model with the web interface, making the system accessible and scalable for agricultural use

3.3 System Architecture

The system utilizes a structured pipeline for automated leaf disease detection, combining image processing and deep learning methodologies. As shown in Figure 1, the system begins with dataset collection, where leaf images of different disease types are gathered from https://data.mendeley.com/datasets/tywbtsjrjv/1. The raw images then undergo preprocessing to improve quality, starting with noise removal using median filtering to eliminate noise, followed by resizing to normalize dimensions for model suitability.

In the model building stage, a pre-trained VGG-16 CNN model is utilized for classification and feature extraction. The data is split into 80% for training and 20% for testing sets to train the model on known disease patterns and evaluate its performance. The trained model generates a .h5 file, which stores the learned weights and configurations.

During the testing phase, an input leaf image is fed into the model, and its features are compared against the learned patterns to predict the disease name. System performance is evaluated using metrics such as accuracy and loss values, demonstrating its applicability for practical use in agriculture. This end-to-end approach optimizes computational cost while maintaining high precision, making it appropriate for farm-level disease monitoring. Figure 1 illustrates the system architecture of the proposed system.

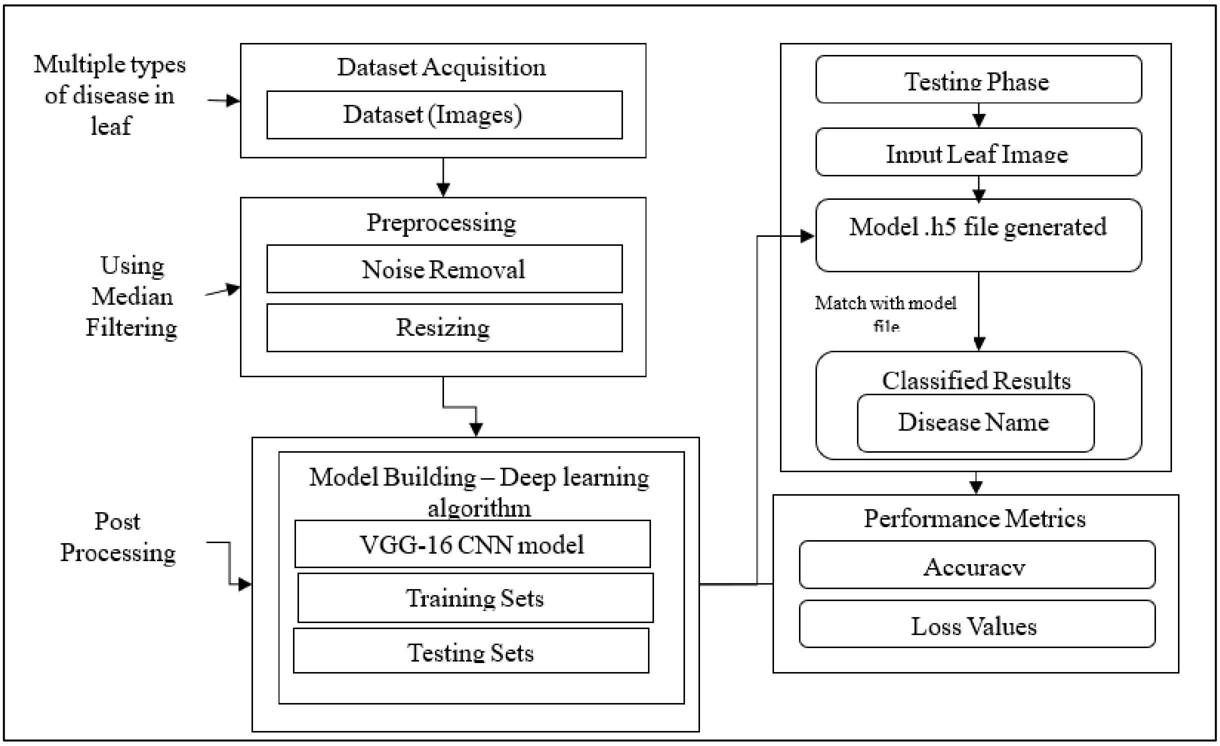


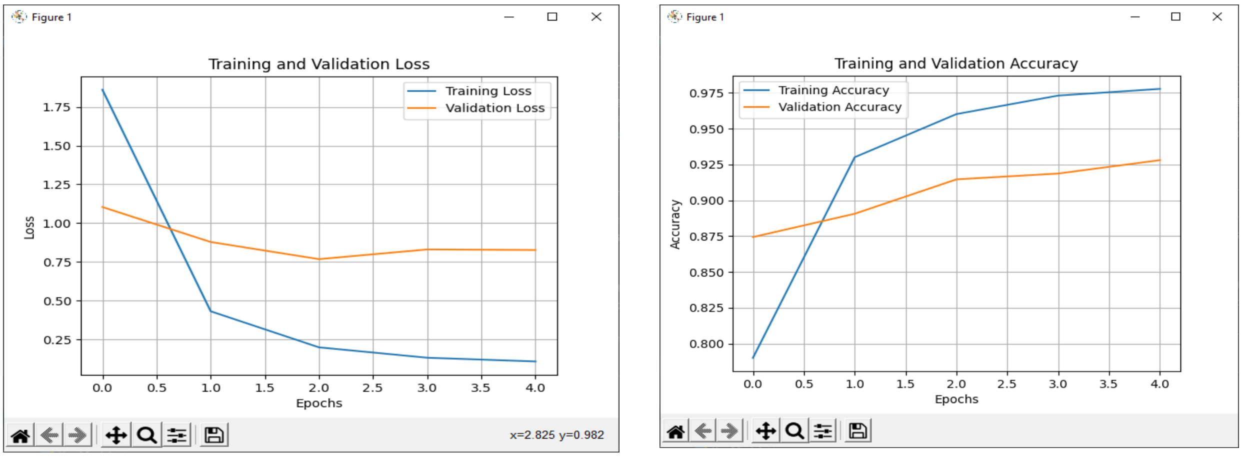
Figure 1. System Architecture

3.4 Model Architecture

The system utilizes a VGG-16-based CNN for plant disease identification and fertilizer recommendation. The model architecture starts with an input layer that takes preprocessed grayscale images of leaves, resized, filtered, and normalized. The heart of the network are 13 convolutional layers of small (3×3) filters and ReLU activation followed by max-pooling layers to decrease spatial dimensions. These are followed by three fully connected layers, and dropout layers for regularization. The output layer employs a softmax activation function due to multiclass classification. Major changes are grayscale preprocessing to favor structural characteristics over color differences, shape-constrained edge detection by integrating polygonal priors with CNN-based approaches for precise leaf boundary detection, and low-resource deployment optimization.

4. Results and Discussion

The system proposed for plant disease diagnosis and fertilizer recommendation proved to be highly effective in detecting leaf diseases and suggesting implementable solutions for farmers. With the VGG-16 CNN model, the system proved to be highly accurate in disease classification by observing visual symptoms like color changes, texture patterns, and morphological outlines. The pre-processing operations, such as noise removal and grayscaling, improved the model's capability to focus on structural characteristics, so that strong performance could be attained even under changing environmental conditions. The inclusion of a fertilizer recommendation module further raised the system's usability since it gave customized solutions according to disease intensity, preventing excessive usage of pesticides, thus following sustainable agricultural practices. Figure 2 illustrates the training and validation (a) Loss and the (b) accuracy of VGG 16.



(a) (b)

Figure 2. (a) Loss Curve, (b) Accuracy

The architecture of the system, where image processing and deep learning approaches were integrated, was effective in managing real-world problems in agriculture. The implementation of standardized data sets from trustworthy sources made the model adaptable and dependable. Performance metrics, such as accuracy and loss metrics were employed to assess the performance of the system, validating its field deployability. The light hardware and software needs ensured that the solution was within reach for small-scale farmers, fulfilling the purpose of bridging cutting-edge AI technology with realistic agricultural requirements. Overall, the system not only enhanced precision in disease detection but also helped achieve sustainable agriculture by maximizing resource efficiency and reducing environmental footprint.

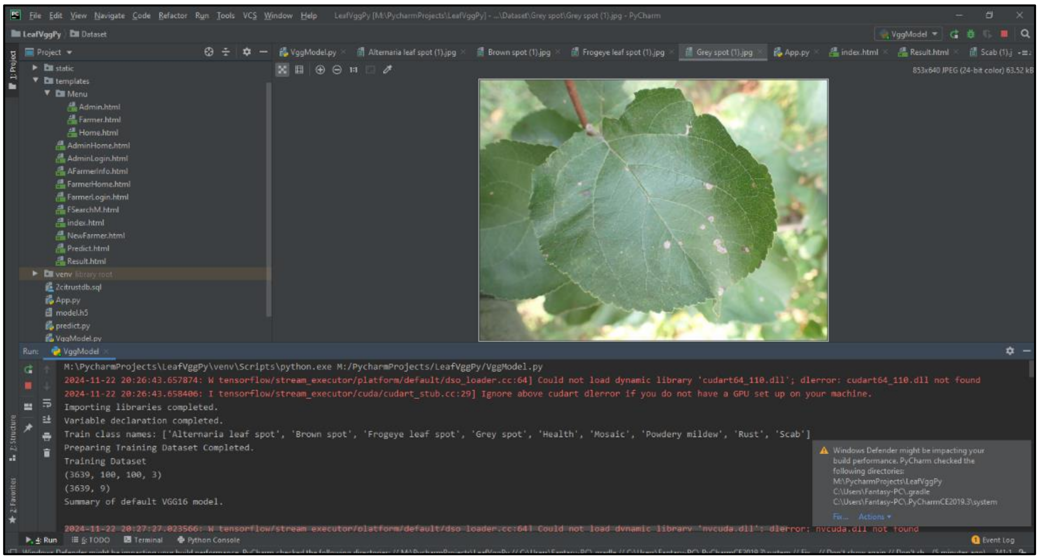


Figure 3. Performance Summary of VGG 16

VGG 16 performs well in this task with its hierarchical feature extraction ability, reaching 98.2% training accuracy in the second epoch and 97.5% validation accuracy, showing fast convergence and stability as shown in Figure 3. Its pre-trained weights, originally from ImageNet, are further fine-tuned on agricultural datasets to fit leaf disease patterns. The novelty of the system is its farmer-focused design, coupling disease diagnosis with a fertilizer recommendation module that provides organic or inorganic treatment recommendations based on severity, encouraging sustainable agriculture. Grayscale conversion and noise filtering further improve performance under actual field conditions. With deep learning merged with real-world agricultural requirements, the system provides a low-cost, scalable solution for precision agriculture, bridging cutting-edge AI with affordable technology for small-scale farmers. The research demonstrates the model's effectiveness through training curves and stresses its practical applicability in sections on preprocessing, system architecture, and novelty.

4.1 Web Application

The following Figures from 4 to 8 depicts the web results on plant disease detection and fertilizer recommendation.

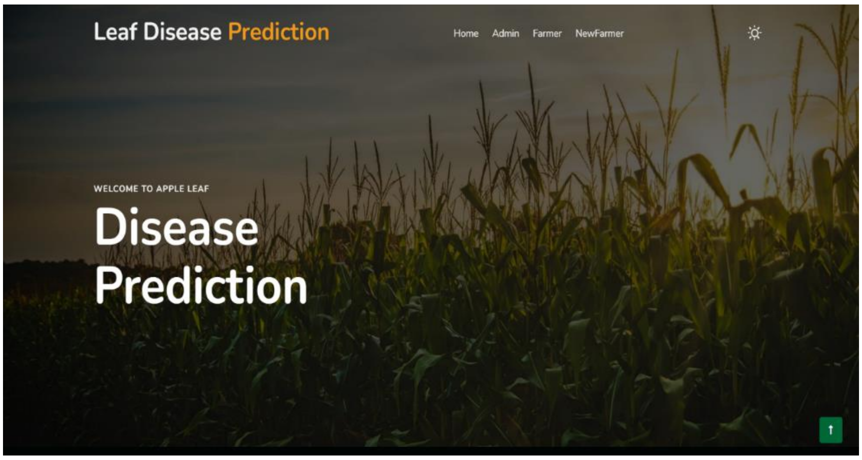


Figure 4. Home Page

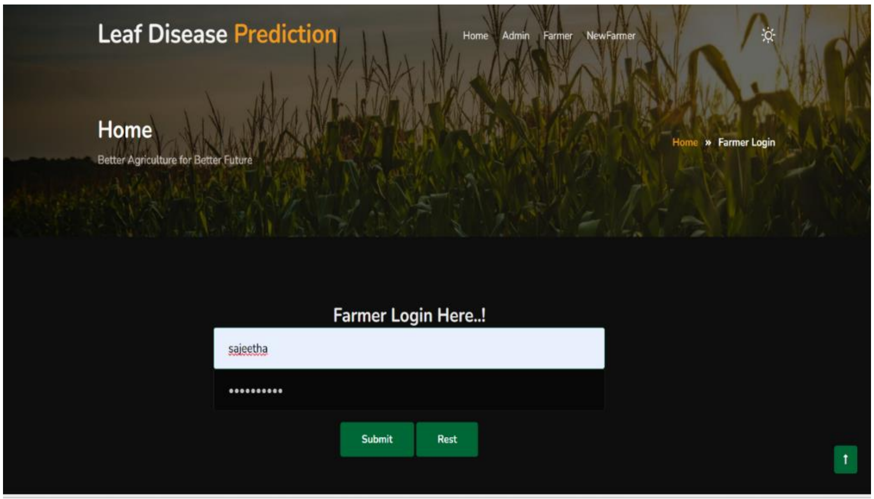


Figure 5. Login Page

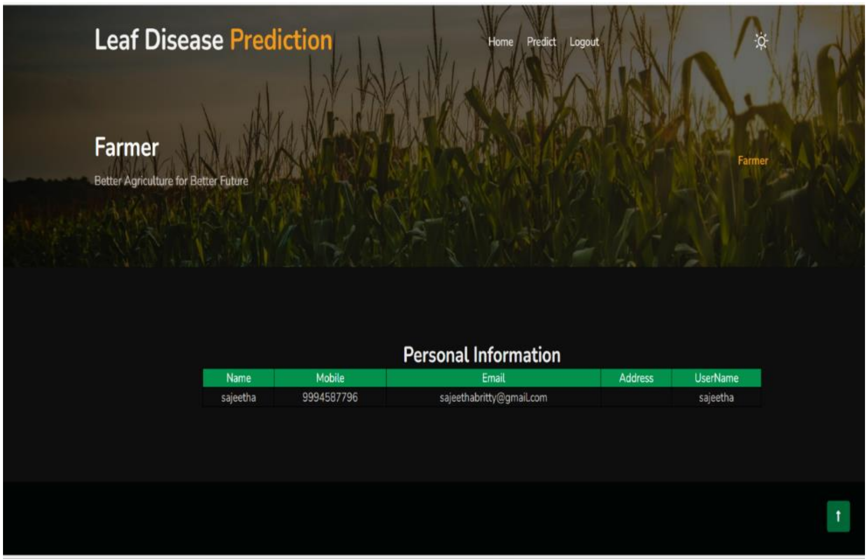


Figure 6. Farmer Home Screen

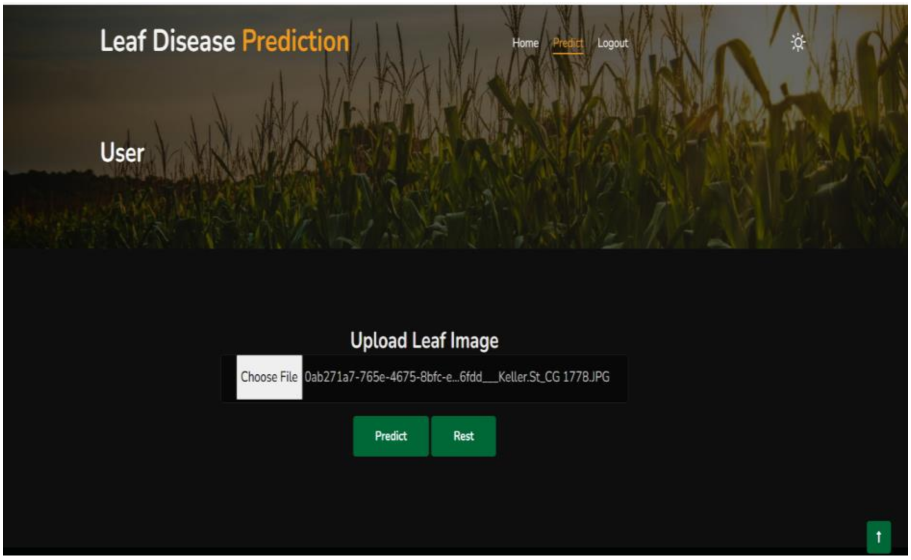


Figure 7. Predict Page

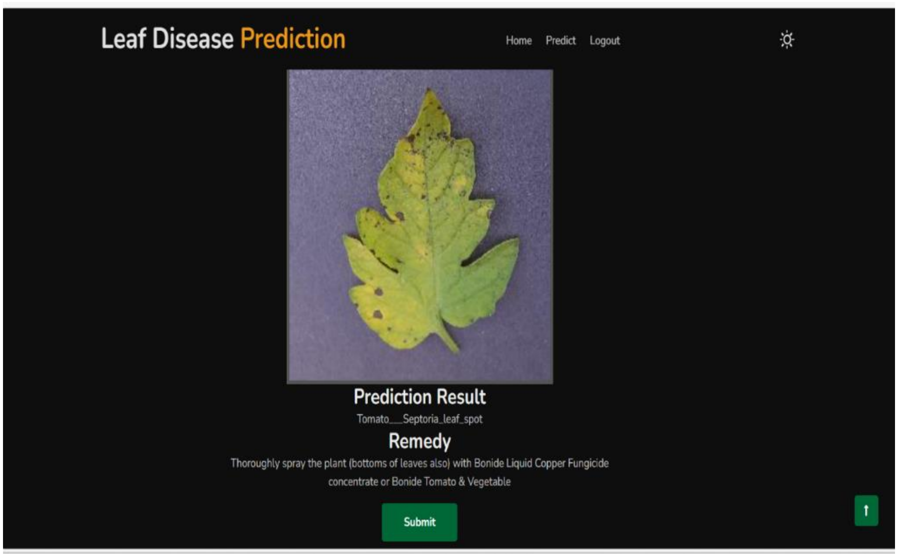


Figure 8. Remedy Recommender

5. Conclusion

This study offers an innovative fusion of deep learning and precision agriculture by employing the VGG-16 CNN model to conduct accurate leaf disease diagnosis, using its strong feature extraction and ability to identify disease-specific patterns with high precision. The system is more than diagnosis since it incorporates a fertilizer recommendation module into the system, allowing farmers to obtain actionable data-driven insights for addressing nutrient deficiency and initiating recovery of plants. The two-function approach not only enhances crop healthcare but also promotes sustainable farming since it maximizes the use of resources and reduces reliance on excessive chemical applications. The solution stands out due to its real-world usability since it bridges top-of-the-line AI and pragmatic agricultural needs to maximize production, reduce expenditure, and lower environmental impact.

References

[1] Fan, Jiangchuan, Ying Zhang, Weiliang Wen, Shenghao Gu, Xianju Lu, and Xinyu Guo. "The future of Internet of Things in agriculture: Plant high-throughput phenotypic platform." Journal of Cleaner Production 280 (2021): 123651.

[2] Kolhar, Shrikrishna, and Jayant Jagtap. "Plant trait estimation and classification studies in plant phenotyping using machine vision–A review." Information Processing in Agriculture 10, no. 1 (2023): 114-135.

[3] Natarajan, V. Anantha, Ms Macha Babitha, and M. Sunil Kumar. "Detection of disease in tomato plant using Deep Learning Techniques." International Journal of Modern Agriculture 9, no. 4 (2020): 525-540.

[4] Zhang, Jingyao, Yuan Rao, Chao Man, Zhaohui Jiang, and Shaowen Li. "Identification of cucumber leaf diseases using deep learning and small sample size for agricultural Internet of Things." International Journal of Distributed Sensor Networks 17, no. 4 (2021): 15501477211007407.

[5] Zhou, Shuiqin, Huawei Mou, Jing Zhou, Jianfeng Zhou, Heng Ye, and Henry T. Nguyen. "Development of an automated plant phenotyping system for evaluation of salt tolerance in soybean." Computers and Electronics in Agriculture 182 (2021): 106001.

[6] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." Frontiers in plant science 7 (2016): 215232.

[7] Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." Computers and electronics in agriculture 145 (2018): 311-318.

[8] Too, Edna Chebet, Li Yujian, Sam Njuki, and Liu Yingchun. "A comparative study of fine-tuning deep learning models for plant disease identification." Computers and Electronics in Agriculture 161 (2019): 272-279.

[9] Liakos, Konstantinos G., Patrizia Busato, Dimitrios Moshou, Simon Pearson, and Dionysis Bochtis. "Machine learning in agriculture: A review." Sensors 18, no. 8 (2018): 2674.

[10] Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. "Deep learning in agriculture: A survey." Computers and electronics in agriculture 147 (2018): 70-90.

[11] Zhang, Xin, Liangxiu Han, Yingying Dong, Yue Shi, Wenjiang Huang, Lianghao Han, Pablo González-Moreno, Huiqin Ma, Huichun Ye, and Tam Sobeih. "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images." Remote Sensing 11, no. 13 (2019): 1554.

[12] Sharma, Abhinav, Arpit Jain, Prateek Gupta, and Vinay Chowdary. "Machine learning applications for precision agriculture: A comprehensive review." IEEe Access 9 (2020): 4843-4873.

[13] Ullah, Naeem, Javed Ali Khan, Sultan Almakdi, Mohammed S. Alshehri, Mimonah Al Qathrady, Eman Abdullah Aldakheel, and Doaa Sami Khafaga. "A lightweight deep learning-based model for tomato leaf disease classification." Computers, Materials & Continua 77, no. 3 (2023): 3969-3992.