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Leaf Disease Detection Using VGG16-Based CNN Model in a Web Application

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Abstract: Nowadays, plant diseases (mainly leaf diseases) have seriously affected agricultural production. Early identification and control are crucial for minimizing crop loss and maximizing yield potential. Manual observation by experts is a common approach to detecting leaf disease; however, this method is typically time-consuming and prone to errors. With the emergence of machine learning and deep learning technologies, automated systems for detecting leaf diseases have become more effective and more robust. This article describes a web-based solution that automates leaf disease detection and identification using the VGG-16 deep learning model, trained on images sent by users. The VGG16 model is known for its deep CNN architecture, which has been pre-trained on the ImageNet dataset. After transfer learning was performed, it was used to learn various plant diseases from leaf images. Moreover, the web application presents actionable feedback to farmers by recommending identified supplements and treatments for the diagnosed diseases. This is achieved by associating each detected disease with a corresponding set of agricultural supplements. The app, built using the Flask framework, features a user-friendly interface that enables users to upload leaf pictures and receive disease predictions, as well as treatment suggestions. By embedding deep learning as one component in the decision-making chain of agriculture, the proposed technique aims to help farmers diagnose crops accurately and in a timely manner, ensuring that crop management is well-maintained, which will ultimately lead to sustainable agriculture. The system's real-time usability in the fields is a revolutionary shift in plant disease management, which will have major implications for increasing agricultural yield and crop protection.
Keywords: VGG16 model, Web app, Python, leaf disease

I. INTRODUCTION

The worldwide agricultural industry is struggling with mounting challenges such as pest attacks, uncertain weather and most critically plant diseases. All these diseases, and especially disease of leaves, are very harmful to crops. These diseases can cause crop yields to drop dramatically, both in quality and volume of products produced. It is estimated that about 20% of the world's food supply goes waste each year before it can be harvested due to various plant diseases, suffering a damage worth billions of dollars. Conventional methods of disease detection include visual inspection by professionals, who diagnose symptoms on leaves. Although successful in a certain extent, these approaches need more time, labour and artificiality and can have errors, particularly for those who are at the early stage of disease.

1. Apple scab 2. Grape Esc 3. Corn leaf spot 4. Potato Early Blight 5. Tomato Bacterial Spot

Fig. 1 Leaves with Disease part

The deep learning algorithms, especially the Convolutional Neural Networks (CNNs) have shown excellent performance in image Classification [2], [5]. VGG16 is one of the most popular CNNs and has achieved state-of-the-art results in various image classification problems.

The VGG16 model, trained on ImageNet originally, has been successfully employed in various domains such as medical image analysis, face recognition and plant disease detection. In this paper, we fine-tune the VGG16 architecture for the task of leaf disease identification. In this paper, by using transfer learning technique we customize VGG16 model to classify multiple leaf diseases and bring about an effective yet efficient solution.

Apart from disease diagnosis, a supplemental recommender system has also been integrated in this research work via the means of a web application. Once the disease has been identified, the system advises plant enhancement based on the nature and severity of such disease. By combining disease detection and a recommendation for an intervention, the goal is to deliver actionable insights, so that farmers can take action to protect their crops at the right time. The web based application is user-friendly - even for non-technical users.

II. LITERATURE REVIEW

The field of Plant Disease Detection (PDD) is attracting remark-able attention in recent years and Deep Learning (DL) are playing a crucial role in solving the problem, with Convolutional Neural Networks (CNNs) being used as its state-of-the-art technique. Many papers have investigated the performance of pre-trained CNN models such as VGG16, ResNet, Inception to detect different types of leaf diseases. Recently, a critical analysis of the related literature about plant disease detection using deep learning models particularly VGG16 is detailed below as 10 relevant related research papers.

Tariq, M. (2024) - "Corn Leaf Disease: Intuitive Diagnosis via VGG16" In this work, we used VGG16 for corn leaf disease classification. The dataset comprised of normal, disease classes and the model obtained 92% accuracy. The research demonstrated the success of transfer learning in which the model was first pre-trained with ImageNet and subsequently fine-tuned with the targeted task i.e. corn leaf disease classification. This work proved that VGG16 has the capabilities to identify common corn diseases such as blight and rust, which is practical for farmers.

Chakraborty, A. et al. (2024) Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG16 Model

In this study, the VGG16 model was used to detect three types of diseases on tomato leaves: early blight, late blight and leaf mold. An impressive accuracy of 99.2% was achieved in the study. The authors also stressed the significance of data augmentations like rotation, flipping and zooming to make their models more robust. The authors stated that deep learning models (e.g. VGG16) had the potential to play a significant role in early detection and prediction of disease fate, reduce the overall demand for pesticides by ensuring healthier crops.

Alatawi, A. et al. (2022) "Plant Disease Detection Using AI based VGG16 Model" In this work, we experimented VGG16 for disease detection across several plants such as apple, tomato and potato. At high accuracy (95% correct classification was obtained by the model), 90%. The data pre-processing and augmentation of deep learning models were exploited to achieve good accuracy. The authors suggested to implement of VGG16 in IoT based disease detection systems for live detection of diseases in field of agricultural fields.

Alatawi, A. et al. (2023) - ”AI based Models for Leaf Disease Detection” In this work VGG16 is compared with other integrated models such as ResNet, AlexNet for the detection of leaf diseases. Results demonstrated that the VGG16 model was the best, with respect to accuracy and speed. Our study also proposed using VGG16 in large-scale agricultural image processing application due to its superior results and simple architecture.

Bidwe, R. (2024) - "Web-Based Plant Leaf Disease Detection 'Using VGG16." In this paper, a website was designed to detect cotton plant diseases using VGG16 model. The system was also incorporated with a supplement recommendation that proposed organic treatment for the identified disease. We showed how deep learning model could be applied in a real-world agricultural practise, offering farmers with an instrument that enables them to detect diseases and manage crops.

Tariq, M. et al. (2023) - "VGG16 Based Crop Leaf Disease Detection" In this work, the authors employed the VGG16 model to recognize leaf disease in various types of crops commodity including bean, corn and rice. The model had an average accuracy of 93%, with highest performance on corn and beans. The study underlined the modelfor its utility to farmers indiagnosing diseases at early-stage that will help deploy rapid response system and manage crops better.

Zhang, Y. et al. (2024) - "Deep Learning for Agricultural Applications: VGG16 in Plant Disease Diagnosis" This article focused on the use of VGG16 in diagnosing diseases of various crops including wheat, maize and soybean. The accuracy of the model was 94.5%, precision was 90%. The authors also reported that the availability of large annotated datasets and ground truth were crucial for training deep learning models, and called for more research on better data collection in agricultural domain.

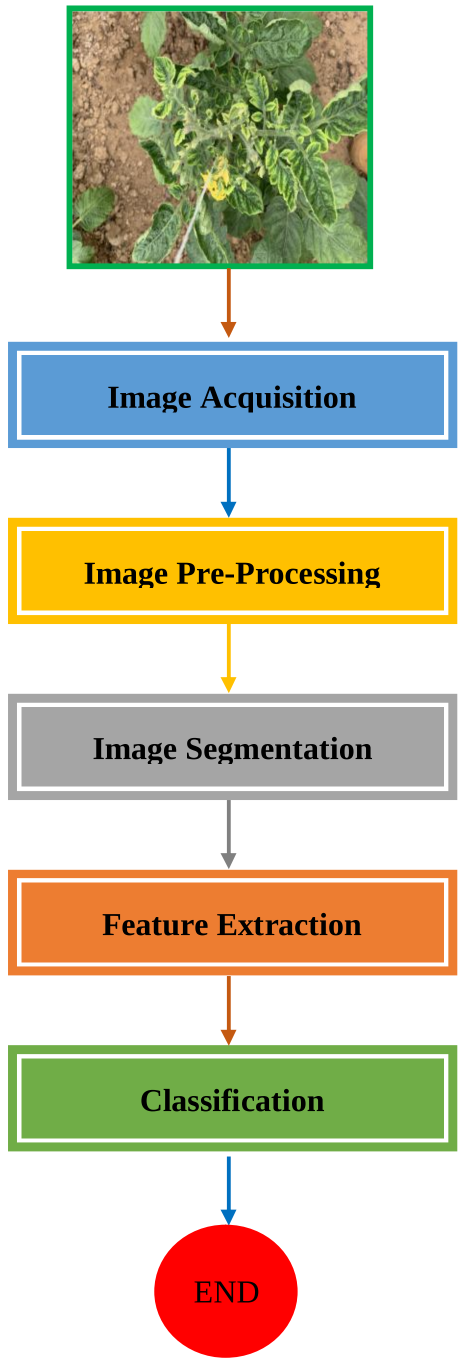

Fig. 2 Leaves Disease General Flow Chart

Kumar, S. et al. (2023) - "Real-time plant disease detection with VGG16 on mobile devices" In this work, we deployed the VGG16 model on mobile platforms for real-time field-based detection of plant disease. The accuracy of the mobile app for discriminating bacterial, fungal diseases and others was 91%. The study highlighted how mobile technology could be used to facilitate disease detection among farmers, especially in rural places.

Mohanty, S.P. et al. (2022) **-** Classification of Plant Diseases Based on VGG16 and Transfer learning the authors conducted a study on the application of VGG16 for disease detection of multiple crops, and obtained 92% accuracy. In the work, transfer learning has been applied by adapting the VGG16 model with a reduced domain specific dataset. The study implied that transfer learning might be especially useful in agriculture where big datasets and labels are scarce.
Chen, L. et al. (2024) **-** "Enhanced Performance of Plant Disease Detection Using VGG16 and Data Augmentation"
In this study, the VGG16 was combined with highly advanced data augmentation (e.g. color jittering, cropping and scaling). The model performance was substantially increased in the detection accuracy with a maximum of 95.5%. The research also proved that by multiple augmentation techniques were combined together to avoid overfitting and improve the performance of model in plant disease detection.

III.METHODOLOGY

A. Dataset

The PlantVillage dataset was used, containing images of healthy and diseased leaves from various plant species.Images were preprocessed by resizing to 224x224 pixels and normalizing pixel values. Plant leaf diseases with an augmentation data set. The authors have proposed a new dataset of 39 different classes of plant leaf and background images. The dataset contains 61,486 images. For the augmentation of the dataset size, we employed six different methods. These techniques are 1) Vertically flipped image, 2) Gamma correction, 3) noise injection, 4) rotation and 5) scaling [13].
We apply the Plant leaf diseases dataset with augmentation datasets, with only 30,052 pictures with 24 labels. The apple labels are: Apple scab, Black rot, apple rust and healthy. Corn caption, i.e. is: Corn Cercopora spot, Grey spot, Corn rust, Healthy corn, Northern blight of corn13. Grape label to wit: Black rot, Esca (Black Measles), healthy, and Leaf blight. Labels of potato as: Early blight, healthy and Late blight. Tomato label to include: bacterial spot, early blight, healthy leaf, late blight, leaf mould, septoria leaf spot, spider mite, target spot and white fly, including other general plant diseases.

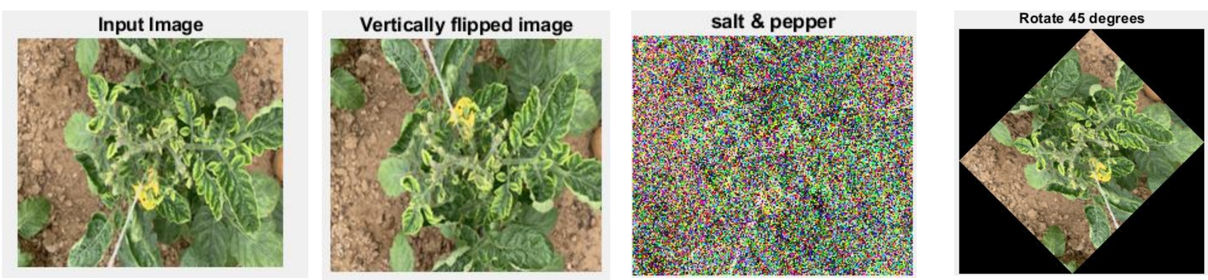

Fig. 3 Leaves Augmentation

B. Model Architecture

VGG16, known for its deep architecture and small receptive fields, was employed for feature extraction.The model was fine-tuned on the dataset using transfer learning to adapt it to the specific task of leaf disease classification.
The automatic system which can detect diseases that occur inadequately supplementation using image processing and machine learning is proposed in a flowchart. Procedure starts with image acquisition; a camera or smartphone is used to take plant or leaf-image. This image is then preprocessed for the purpose of noise reduction, contrasting, and brightness, and rescaled. In the next step, one will segment the image: partitioning it to regions that make sense—usually separating between the leaf or infected area from its uninfected surroundings.
Then image extraction to generate attributes such as color, shape and texture that are indispensable in the identification of disease symptoms is carried out. The processed features are passed to the classification stage, and a trained machine learning model makes its decision as to whether the plant is healthy or being affected by a certain disease. According to the result of classification, or MDII) then we will recommend a supplement for this, which may include fertilizers, pesticides and compounds industrially prepared (Humic acid etc.). Meanwhile, last step is end stage and this cycle of automatic diagnosis recommendation finishes, which is very helpful for modern precision agriculture.

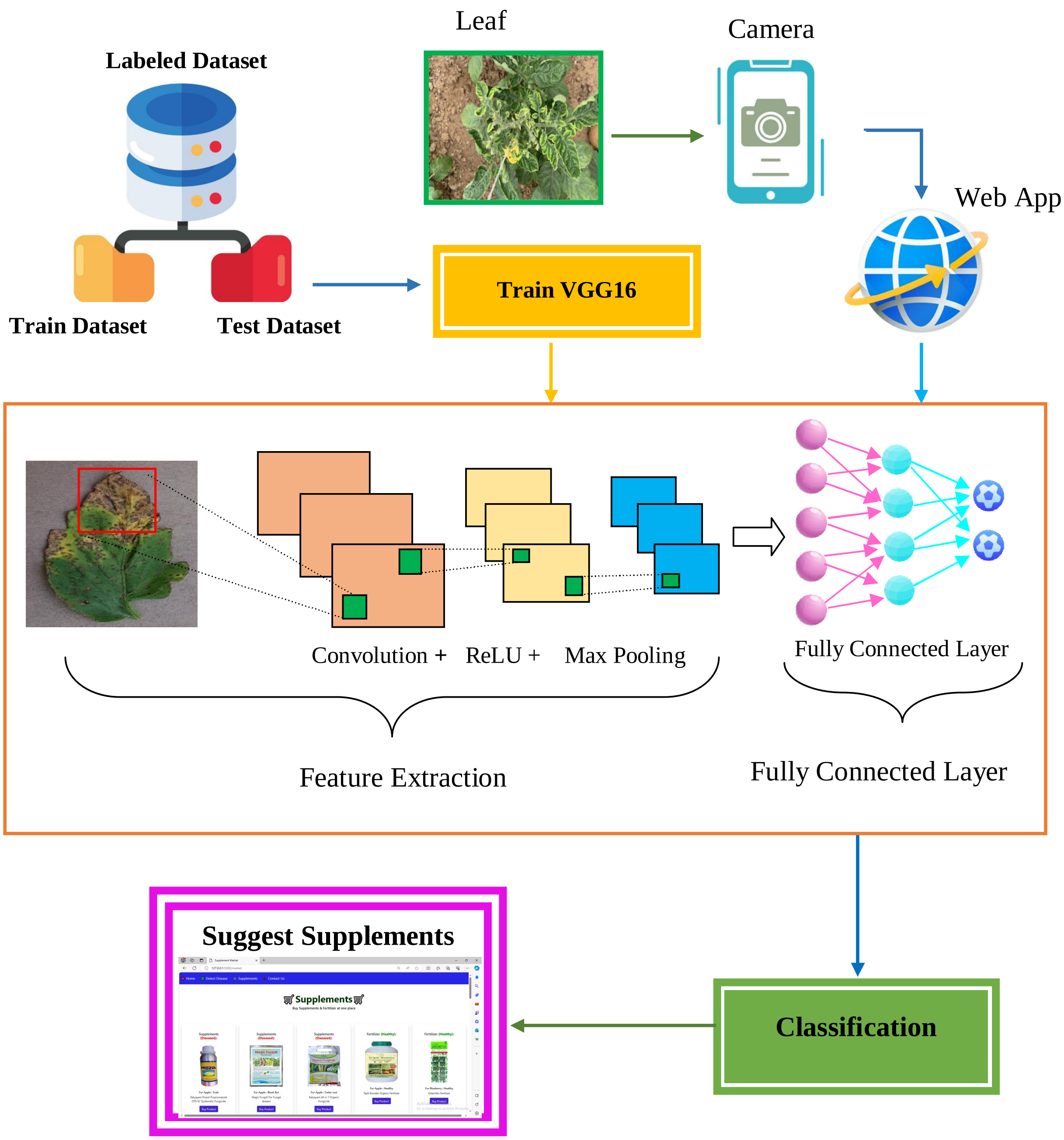

Fig. 4 Proposed Flow chart

C. Web Application Development

The proposed system is a web-based application designed to assist users—primarily farmers—in identifying plant leaf diseases using deep learning techniques. The system begins with the user uploading a leaf image through a web interface. This interface, accessible via a web browser, allows users to interact with the application by submitting an image of an affected or healthy leaf. Once the image is uploaded, it is sent as a request to the Flask server, which acts as the backend of the application. The Flask server then processes this request and forwards the image to a pre-trained Convolutional Neural Network (CNN) model, specifically the VGG16 architecture, which has been optimized for image classification tasks.

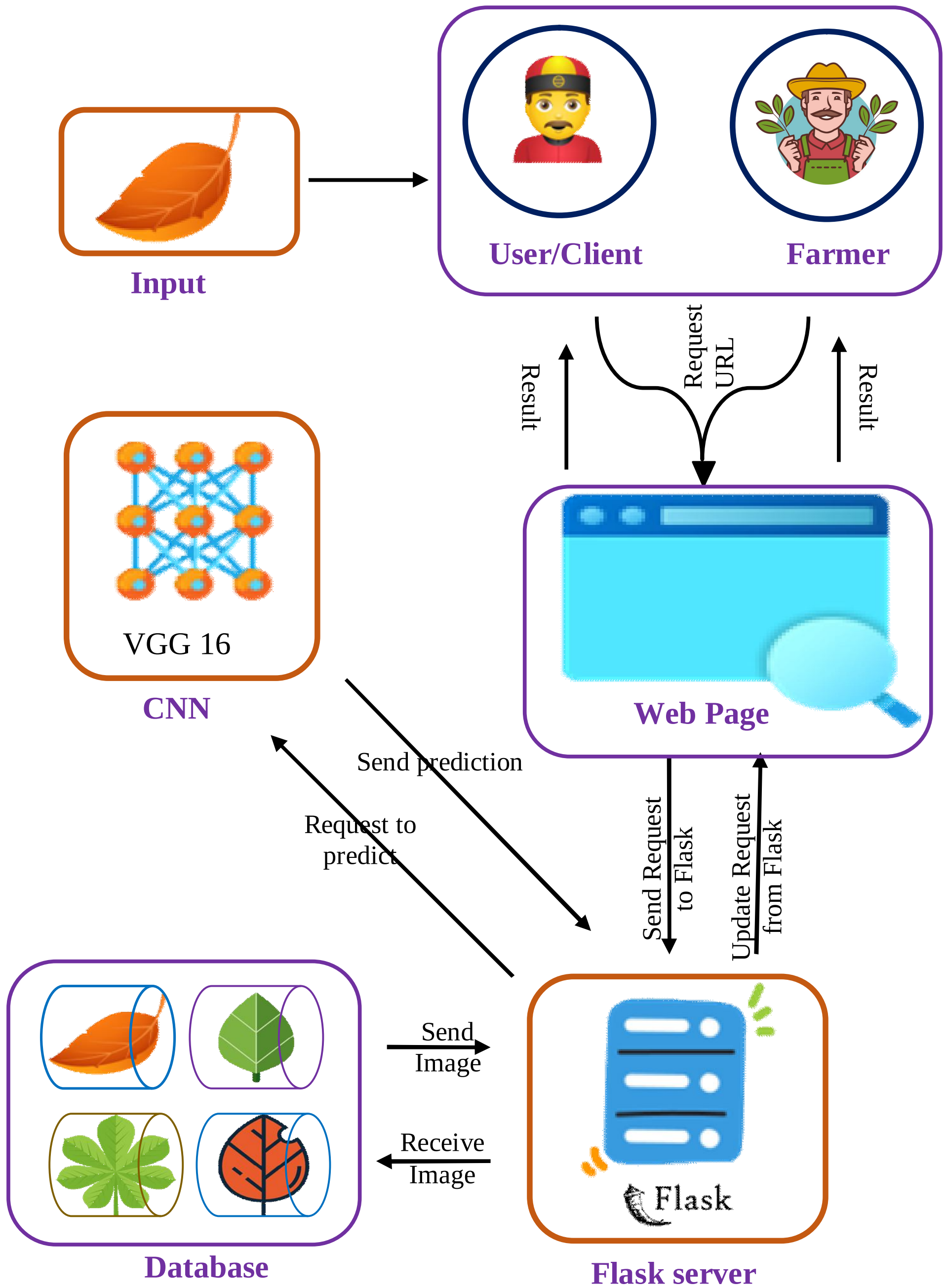

Fig. 5 Proposed Web Application

The VGG16 model analyzes the image and generates a prediction indicating whether the leaf is healthy or affected by a specific disease. This prediction is then returned to the Flask server, which prepares the response and sends it back to the web interface. The result is subsequently displayed to the user. Additionally, the system interacts with a database that stores reference images, classification categories, and possibly historical user queries. This enables efficient management of data and supports the model's performance by allowing access to relevant training or comparison data. The overall architecture ensures real-time interaction between the user and the prediction model, delivering fast and accurate results through a simple and intuitive web interface.

D. Results

The web application for plant leaf disease detection provides a user-friendly interface that enables end-users, particularly farmers, to easily interact with the system. As illustrated in Fig 6, the user begins by accessing a webpage that allows them to upload a leaf image for disease testing. This input page includes helpful information about the importance of early disease detection and how the system operates, thus enhancing user engagement and understanding. Upon submitting the leaf image, the system processes it through the backend model and generates a disease prediction. The outcome is displayed on a result page, as shown in Fig 7, where the system has correctly identified the disease as “Tomato: Yellow Leaf Curl Virus.” This screen also displays the uploaded leaf image along with the diagnosed condition, providing a clear and immediate result to the user.

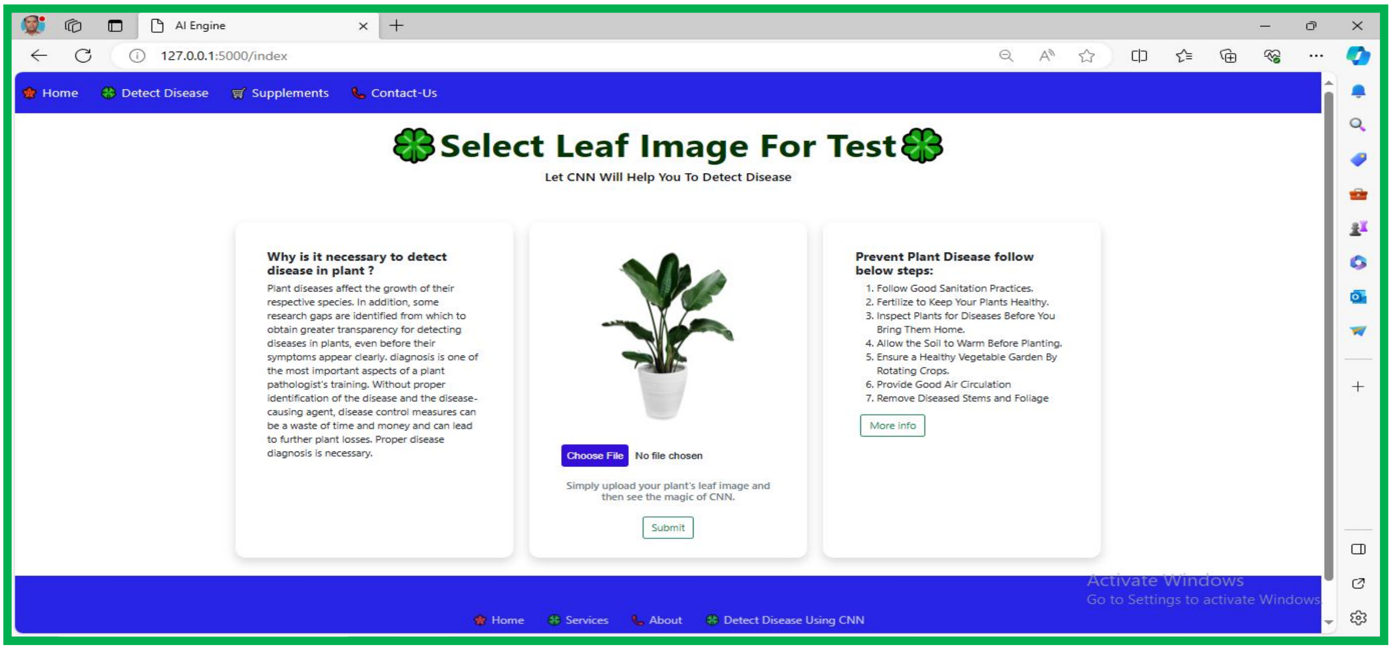

Fig. 6 User Input Leaf for online testing

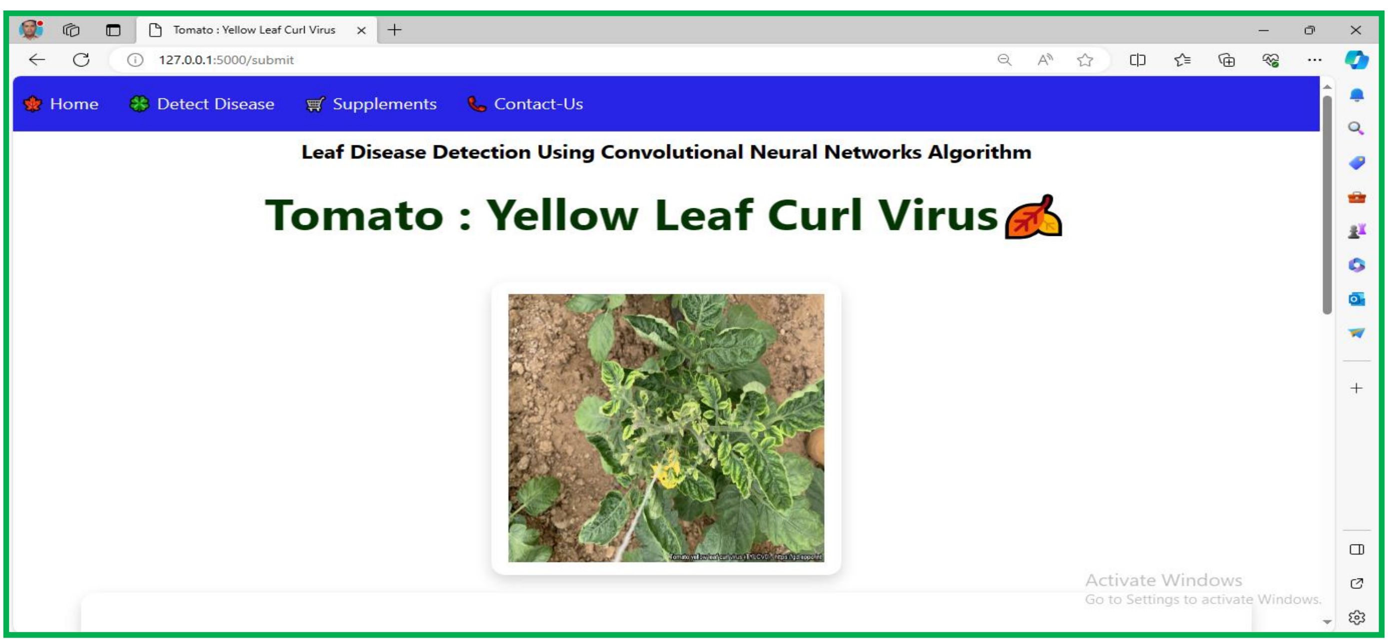

Fig. 7 Online Leaf Disease Detection Result

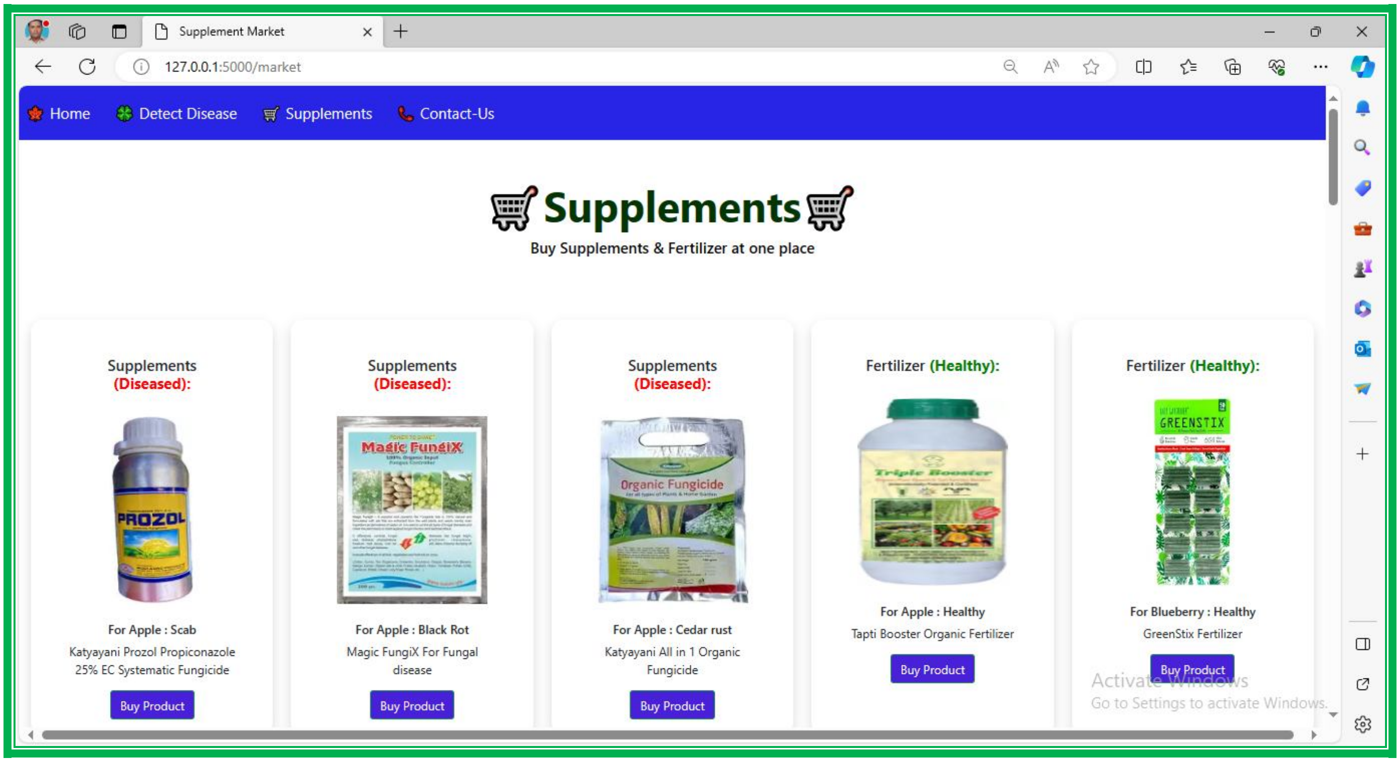

Fig. 8 Suggested Supplements for Leaf Disease

Additionally, the system enhances its utility by recommending actionable solutions. As shown in Fig 8, after identifying the disease, the application redirects users to a supplements page that suggests various agricultural products such as pesticides, fertilizers, and plant growth enhancers specifically suited for the detected condition. This integration of disease diagnosis with product recommendation makes the platform not only diagnostic but also prescriptive, offering practical guidance for disease treatment. Overall, the result interface of the system is designed to be intuitive, informative, and actionable, empowering users to make timely and informed decisions for crop health management.

IV. CONCLUSIONS

The developed web application demonstrates the feasibility of using the VGG16 model for leaf disease detection and supplement recommendation. This approach can aid farmers in early disease detection and informed decision-making, contributing to sustainable agricultural practices. Image processing offers an efficient method for improving agricultural yield through plant disease detection.

The primary objective of this project was to evaluate the capability of image processing tools in accurately identifying plant diseases and supporting farmers in increasing crop yields. The project successfully introduced image processing techniques for plant disease detection. Developing a standalone application will enhance the accessibility and utility of this technology for farmers. A dedicated system can be developed to distinguish between diseased and healthy plants. Future work will focus on creating a mobile application to further assist farmers and employing drones to expand the training image dataset, with the goal of improving the system's accuracy and generalization.

The current system utilizes a feature-based approach achieved through image processing techniques. The process involves several steps: image acquisition, preprocessing, segmentation, feature extraction, and classification. The proposed system employs a convolutional neural network (CNN), which achieved an accuracy of 96.23 percent. The VGG16 model was also applied for leaf disease prediction, but it demonstrated lower accuracy than the CNN. Future work may include expanding the number of leaf and disease type classes.

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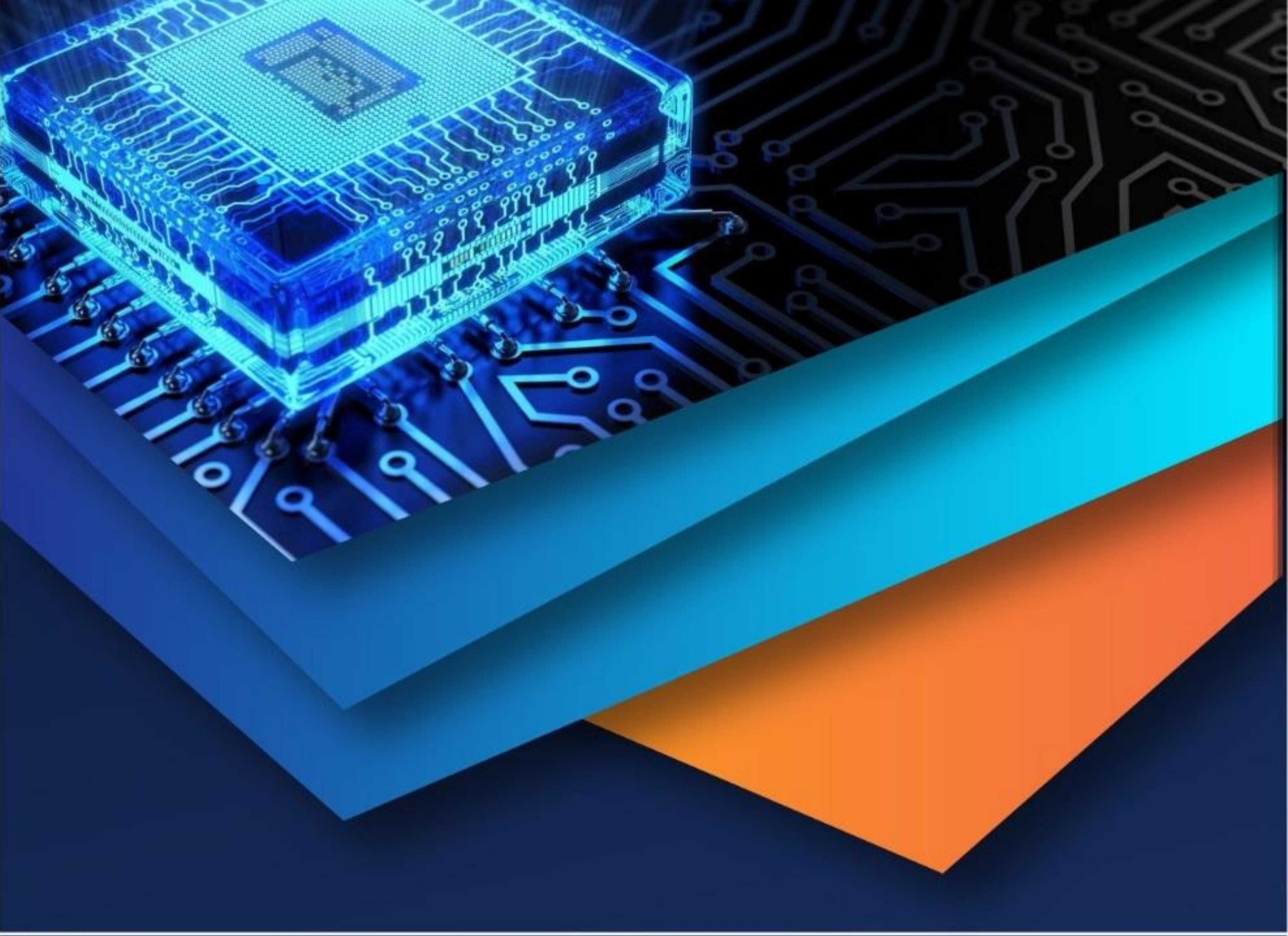

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