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AI BASED PLANT DISEASE PREDICTION AND DIAGNOSIS

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Abstract : Plant health plays crucial role in assessing crop productivity levels in India often leading to significant losses in yield when adversely affected this study explores the use of a pre-trained VGG16 model to identify plant diseases and their symptoms by conducting simulations and experiments on sample datasets the CNN-based systems the model's effectiveness was assessed across various levels of complexity and regions impacted by plant diseases the system was improved iteratively to enhance both its accuracy and reliability the research focuses on 37 different types of diseased plant leaves including issues such as apple scab corn maize common rust and tomato yellow leaf curl infections assessing the impact of these diseases on diverse crops the proposed model achieved an impressive testing accuracy of 9647 several performance metrics were calculated such as CNN accuracy image processing indicators and evaluations across training and validation datasets this work demonstrates the powerful potential of pre- trained deep learning architectures such as VGG16 for detecting plant diseases leveraging artificial intelligence offers a practical solution to minimize the damaging effects of crop diseases helping secure agricultural output strengthen food security integrating such advanced technologies is critical promoting sustainable farming practices ensuring continuous growth and stability of India’s agriculture sector a vital contributor to the nations economy.

I. INTRODUCTION

India's agricultural industry is consistently jeopardized by various plant diseases that can lead to considerable declines in crop production and food security. With the rising demand for sustainable farming practices, artificial intelligence, particularly deep learning technologies, has gained prominence in tackling these issues. This research focuses on the implementation of the VGG16 model, a pre-trained convolutional neural network designed for identifying plant diseases through the visual assessment of leaf symptoms.

The study leverages a dataset featuring images from 37 different categories of affected leaves, including those with ailments like apple scab, common rust in maize, and tomato yellow leaf curl disease. The model's performance was scrutinized across various conditions, simulating diverse geographical regions impacted by plant diseases, through numerous training and optimization iterations. The system demonstrated impressive accuracy, achieving a success rate of 96.47% on test data.

To thoroughly evaluate the model's effectiveness, various metrics were utilized, such as image processing accuracy and consistency of results across training and validation datasets. The results highlight the considerable promise that advanced models like VGG16 hold for enhancing modern agriculture. By facilitating early and accurate disease detection, these technologies can play a crucial role in reducing crop losses, improving yields, and fostering the long-term sustainability and advancement of India's agricultural sector.

II. LITERATURE SURVEY

Plant conditions continue to hang agrarian productivity worldwide, leading to major declines in harvest outputs. Timely and precise identification of conditions is essential for effective operation strategies. recent research has demonstrated success through the development of pre-trained deep learning frameworks, particularly VGG16, a well- known Convolutional Neural Network(CNN) armature, for factory complaint discovery and bracket tasks

1. Ferentinos (2018) uses convolutional neural networks to recognize plant diseases, achieving an impressive accuracy rate of over 99% across various crop datasets. His research highlighted the crucial role of large and high-quality image datasets in effectively training deep learning models.

2. Narejo et al.(2023) enforced the VGG16 frame to design a bracket system to identify conditions affecting tomato and potato foliage. Their model displayed strong delicacy, pressing the capability of VGG16 to differentiate healthy leaves from diseased ones.

3. Shijie et al.(2020) assessed the use of VGG16 for relating eggplant conditions. Their system involved using VGG16 for rooting features, which were also classified using a Support Vector Machine(SVM), performing in notable bracket performance

4. Aqeel et al.(2024) conducted a relative analysis between pre-trained models like VGG16 and exception and a custom-erected CNN for tomato splint complaint recognition. Their findings indicated that pre-trained models not only achieved analogous or superior delicacy but also needed lower training time, emphasizing their practical effectiveness

5. Patil et al.(2022) applied the VGG16 model to classify 19 different factory conditions across multiple crop types. Their results demonstrated high delicacy situations, attesting VGG16's effectiveness in handling multi-class factory complaint discovery problems.

6. Wang et al.(2021) delved the use of colorful pre-trained models, including VGG16, for diagnosing conditions in sludge and apple leaves. Their study further validated the versatility and strong individual capabilities of pre-trained CNNs across different factory complaint scripts.

III. METHODOLOGY

The study on "Plant Disease Detection and Diagnosis using Pre-trained CNN Model" follows a structured and organized methodology to build an efficient and accurate disease identification system. Each phase is carefully designed to progressively enhance the detection process through deep learning techniques. The overall workflow is detailed as follows:

1. Image Collection

The first step involves capturing images of plant leaves using cameras or smartphones. These images serve as the foundational input for the entire detection process.

2. Image Preprocessing

To prepare the images for analysis, preprocessing techniques are applied. Thes step includes nose removal and enhancement of significant features, ensuring that the input content is clean and suitable for further processing.

3. Color Space Transformation

Taken images are converted from the standard RGB color models to the HSV (Hue, Saturation, Value) color space. This transformation helps to differentiate color information from brightness, making it easier to isolate relevant patterns and improve image segmentation.

4. Edge Identification

Edge detection algorithms are used to find the boundaries within leaf images. Identifying edges is essential for recognizing shapes and textures that are indicative of disease symptoms.

5. Channel Division and Noise Filtering

The image is separated into individual HSV channels, and noise components are extracted. Although this step is not typically standard in CNN pipelines, it can enhance system performance in specific disease detection applications.

6. Preparation of Training Dataset

A comprehensive dataset of leaf images is prepared, cover a wide range of crop types and disease categories. A diverse and balanced dataset ensures the model can generalize existing to new, unseen input.

7. Feature Extraction

Critical features, such as color variations, texture patterns, and structural differences, are extracted from the images. These features guide the learning process and help the model differentiate between various diseases.

8. HSV Model Development

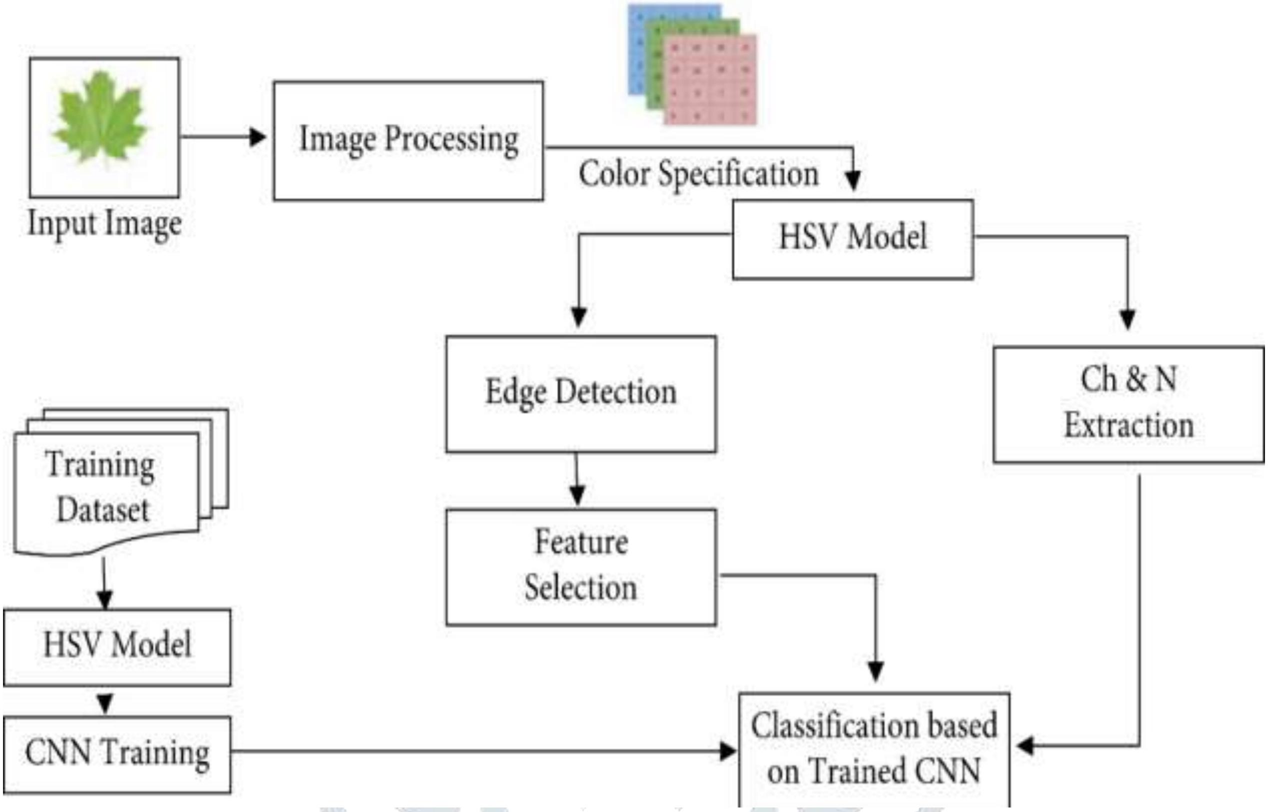
An additional model based on HSV features may be created to highlight color-related disease patterns. This step, while optional, can further improve classification accuracy in certain scenarios.

9. CNN Model Training

The VGG16 pre-trained CNN is fine-tuned on the curated dataset. During training, the network learns to map the extracted features to the corresponding disease classes, continuously optimizing its performance.

10. Disease Classification

After training, the model is deployed for classification tasks. When a new image is inserted into the system, the CNN analyzes the features and accurately predicts the associated disease or identifies a healthy leaf.



IV.DESIGN AND ARCHITECTURE OF THE SYSTEM

Convolutional Neural Networks (CNNs) are highly used in machine learning, especially for processing images. They offer a more straightforward solution compared to traditional methods by automatically learning important features. A CNN is typically structured into three main types of layers, each serve a unique purpose

A. Input Layer

The input layer is where data, such as plant leaf images, is inserted into the network. This dataset is usually divided into two parts: one for training the model and the other for testing its performance. In image processing, each neuron in this layer represents a pixel from the image. As an example, Figure 2 shows two images of tomato leaves. A major part of the data is use for train, while a smaller share is set aside for testing.

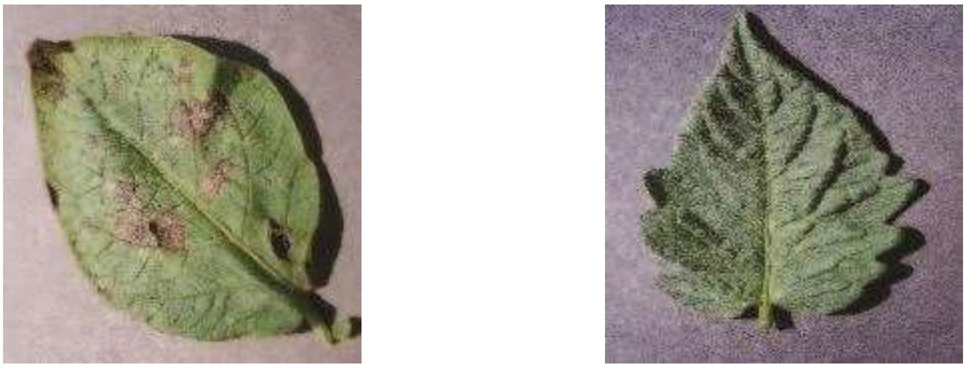


Fig 2: Displayed are sample images from the database, featuring Potato Early Blight followed by a healthy Tomato

B. Hidden Layers

Following the input subcaste, retired layers play a critical part in recycling the data. They prize meaningful features through operations like complication and pooling. The number of neurons in these layers varies depending on how complex the problem is. By learning important patterns and characteristics, retired layers help the model directly descry conditions in factory leaves.

C. Affair Subcaste

The affair subcaste is responsible for producing the model's final decision. It interprets the features learned by the retired layers and applies an activation function similar as softmax or sigmoid to affair probability values. These chances determine which specific class, like a particular factory complaint, the input belongs to.

V. RESULT OF THE SYSTEM

Fig 3: *Main Dashboard*

Fig 4: AI Engine

Fig 5: Results Dashboard

Fig 6: Supplements/Fertilizer Store

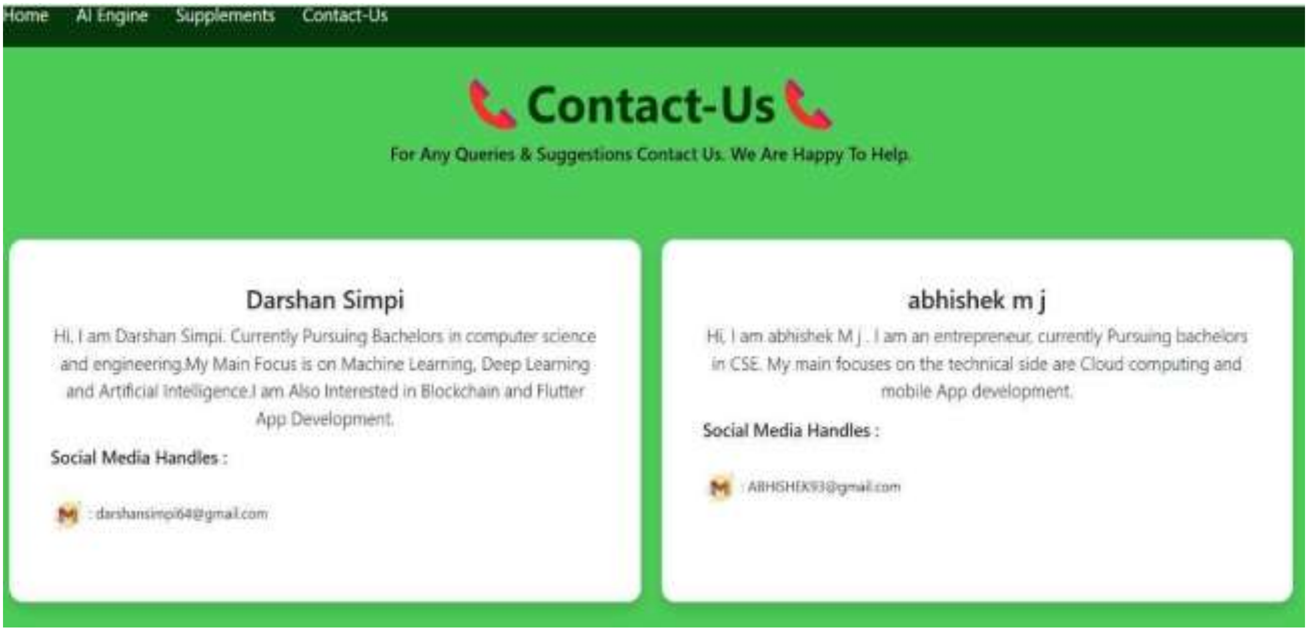


Fig 7: *Contact Us*

VI. CONCLUSION

The perpetration of a pre-trained CNN model for factory complaint discovery has demonstrated great eventuality in perfecting agrarian practices. By directly relating conditions at an early stage, this system can help growers take timely action to cover crops, reduce losses, and increase overall yield. The use of deep literacy, particularly the VGG16 model, has proven to be largely effective in feting various types of factory conditions with high delicacy. It not only enhance productivity but also supports sustainable husbandry by minimizing gratuitous chemical operation. Overall, the design highlights the transformative part of artificial intelligence in addressing critical challenges in husbandry and icing food security for the future.

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