

Deep Learning-Powered Crop Disease Diagnosis and Fertilizer Guidance System

S.V.V.D. Jagadeesh¹, Kandula Mounika², Komati Lohith Kumar³ and Channamsetti Navaneeth Venkat⁴

¹⁻⁴ Laki Reddy Bali Reddy College of Engineering, Mylavaram, Andhra Pradesh, India

Email: jagadeesh.s@lbrce.ac.in, mounikakandula63@gmail.com, lohithkomati@gmail.com, navaneethvenkat5@gmail.com

Abstract—Predicting leaf diseases is vital for precision agriculture, enabling early detection, reducing losses, and improving yields. Traditional models often lacked adaptability across multiple crops and failed to provide actionable recommendations, limiting their practical use. This project overcomes these challenges by integrating disease detection and tailored treatment advice into a unified system for crops like paddy, tomato, potato, blackgram, and mirchi. Utilizing advanced deep learning models such as VGG16, ResNet50, and Deep CNN, the system delivers robust multi-class disease classification. VGG16 excelled with 97% accuracy in detecting and classifying diseases. The inclusion of a recommendation system adds significant value, offering effective disease management strategies and empowering farmers to make informed decisions, enhancing productivity and sustainability in agriculture.

Index Terms— Leaf disease prediction, Plant disease classification, Deep learning in agriculture Disease recommendation system, Multi-crop disease detection, Convolutional neural network (CNN), VGG16 model.

I. INTRODUCTION

Leaf diseases pose a significant risk to agriculture by reducing crop yields, compromising quality, and causing economic losses. Caused by various pathogens, including fungi, bacteria, and viruses, these diseases affect leaf health and hinder photosynthesis, nutrient distribution, and plant growth. Fungal diseases like rust, blight, and powdery mildew are especially prevalent in warm, humid climates, while bacterial diseases such as leaf spot and bacterial blight cause visible symptoms like yellowing and wilting. Viral infections like the tomato yellow leaf curl virus also lead to leaf deformation. To manage these diseases, early detection and accurate diagnosis are crucial, with modern technologies like image processing, machine learning, and sensors complementing traditional methods. Integrated pest management (IPM) techniques, such as crop rotation, resistant varieties, and biological controls, are gaining popularity to reduce pesticide reliance and promote sustainable farming practices.

II. LITERATURE SURVEY

“HELONG YU1, JIAWEN LIU1, CHENGCHENG CHEN, ALI ASGHAR HEIDARI, QIAN ZHANG, HUILING CHEN, (Associate Member, IEEE), MAJDI MAFARJA, AND HAMZA TURABIEH”, “Corn Leaf Diseases Diagnosis Based On K-Means Clustering and Deep Learning, 2021” The study need for a more diverse dataset, improved generalization to other crops, and optimized K-means clustering for better corn leaf disease[1].

“SunilS. Harakannanavar , JayashriM. Rudagi , VeenaI Puranikmath, Ayesha Siddiqua, R Pramodhini, “Plant leaf disease detection using computer vision and machine learning algorithms,2022”The model can be improved using fusion techniques for extraction of significant features and examined for other leaf samples of datasets[2]. “EMMANUELMOUPOJOU, APPOLINAIRE TAGNE, FLORENT RETRAINT, ANICET TADONKEMWA, DONGMO WILFRIED, HYPPOLITE TAPAMO, AND MARCELLIN NKENLIFACK: “FieldPlant : A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning,2023”,This study presents FieldPlant, a dataset of 5,170 annotated field images for plant disease research, including unique cassava images, evaluated with state-of-the-art classification and object detection models[3].

Abebech , Jenber Belay , Ayodeji , Olalekan Salau , Minale Ashagire , Melaku , Bitew Haile (2021) “A chickpea disease identification model for detecting chickpea diseases using deep learning,2022”, This study proposes a chickpea disease identification model using CNN-LSTM and a hybrid GF-MF filtering technique, achieving 92.55% accuracy in classifying chickpea diseases[4].

“Construction of deep learning based disease detection model in plants,2023”,To develop a broadly applicable disease classification model, the studies should include a range of data on crops with and without diseases[5].

“Tomato plant disease detection using transfer learning with C-GAN synthetic images,2021”We intended to apply this disease classification and identification technique to different plant parts, such as fruits, stems, and branches.

Additionally, we sought to determine the various stages of the plant disease [6]. “Plant Disease Detection Using Deep Learning,2020”, We aim to address real-time data challenges by developing a multi-object deep learning model to detect plant diseases in clusters of leaves, rather than just individual leaves[7].

“Using Deep Learning for Image-Based Plant Disease Detection,2020”, In this current results indicate that more (and more variable) data alone will be sufficient to substantially increase the accuracy, and corresponding data[8]. Andrew J, Jennifer Eunice , Daniela Elena Popescu , M. Kalpana Chowdary , Jude Hemanth “Deep LearningBased Leaf Disease Detection in Crops Using Images for Agricultural Applications”,2022”, In this it can be tackle realtime data collection challenges and develop a multi-object deep learning model to detect plant diseases from clusters of leaves, not just individual ones[9].

A Multiclass Plant Leaf Disease Detection using Image Processing and Machine Learning Techniques], Nilay Ganatara and Atul Patel, 2020With more classes and images, machine learning algorithms perform worse; however, this limitation can be overcome by employing more efficient algorithms.[10].

"Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques," by Muhammad E. H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Mohamed Arselene Ayari, Aftab Ullah Khan, Muhammad Salman Khan, Nasser Al-Emadi, Mamun Bin Ibne Reaz, Muhammad Tariqul Islam, and Sawal Hamid Md Ali, 2021 For portable solutions, it may be helpful to look into the lighter architecture of CNN models with non-linearity in the feature extraction layers. [11].

Deep Kothari, Harsh Mishra, Mihir Gharat, Vishal Pandey, Rashmi Thakur “Potato Leaf Disease Detection using Deep Learning” ,2022”,Using GAN for data creation and Transfer Learning can enhance our model's robustness and accuracy by accommodating variations in object orientation[12].

“Ebrahim Hirani; Varun Magotra; Jainam Jain; Pramod Bide” The study uses CNN and DNN models along with OpenCV for image processing, employing techniques like segmentation and feature extraction. The approach depends heavily on clear image quality, lacks generalization to all crops, and may not detect diseases before visible symptoms appear[13].

“Pranesh Kulkarni¹, Atharva Karwande¹, Tejas Kolhe¹” Employs image processing techniques and a random forest classifier for disease detection based on shape, texture, and color features.

Limited adaptability to new diseases and potential performance issues in real-world field conditions [14].

“Bahaa S. Hamed, Mahmoud Hussein, Afaf M. Mousa” EfficientNetV2S model was employed, showing high performance in plant disease classification tasks.

Comparative analysis was conducted with other models such as DenseNet121, VGG16, and MobileNet V3.

The model currently focuses on single-leaf disease detection, with plans for future work to expand its capabilities to multi-leaf disease identification, enhancing its real-world applicability [15].

III. METHODOLOGY

A. Model Representation

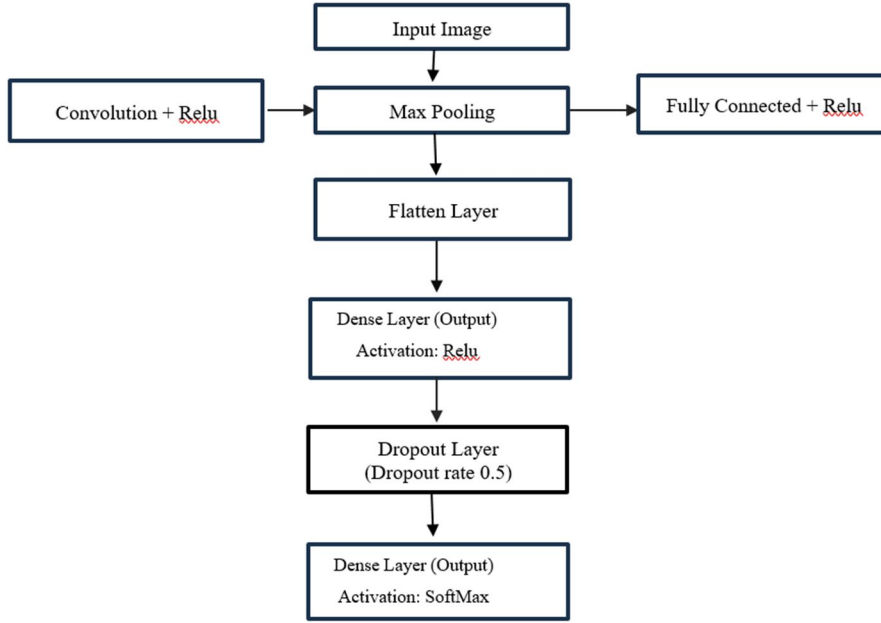


Fig. 1: Model Representation of VGG16 Model

B. Architecture

The VGG16 model has a sequential architecture with 16 weight layers, including convolutional and fully connected layers. Here's a simplified structure:

- Input Layer: Expects 224×224×3 RGB images.
- Convolutional Blocks:
 - Block 1: 2 Convolutional layers (64 filters, 3×3), followed by MaxPooling.
 - Block 2: 2 Convolutional layers (128 filters, 3×3), followed by MaxPooling.
 - Block 3: 3 Convolutional layers (256 filters, 3×3), followed by MaxPooling.
 - Block 4: 3 Convolutional layers (512 filters, 3×3), followed by MaxPooling.
 - Block 5: 3 Convolutional layers (512 filters, 3×3), followed by MaxPooling.
- Fully Connected Layers:
 - FC1: Dense layer with 4096 units. FC2: Dense layer with 4096 units.
- Output Layer: Softmax layer for classification.

C. Parameters Used

Input Size: Images are resized to 128×128 pixels, reducing computational load compared to the default size of 224×224 pixels

Batch Size: Set as 32, meaning 32 images are processed in one forward and backward pass.

Dropout: A dropout rate of 0.5 is used to prevent overfitting. The probability of retaining a neuron is:

$$p=1-\text{Dropout Rate} \quad (1)$$

Learning Rate: The Adam optimizer uses a learning rate $\alpha=0.001$, controlling the step size for weight updates. The weight update formula is:

$$w:=w-\alpha \cdot \nabla L(w) \quad (2)$$

Metrics:

- Precision: Measures the accuracy of positive predictions:

$$Precision = \frac{TP}{TP + FP}$$

➤ Recall: Measures the model's ability to identify all positive instances:

$$Recall = \frac{TP}{TP + FN}$$

Loss Function: Sparse categorical cross-entropy calculates the error for multi-class classification:

$$H(y) = - \sum_i^n y_i \log(y_i)$$

Activation Function: ReLU introduces non-linearity in hidden layers:

$$ReLU(x) = \max(0, x) \quad (6)$$

D. Fine Tuning

In the initial phase, the MobileNetV2 model is loaded without the top layer, base layers are frozen, and a custom classification head is trained for 555 epochs with a learning rate $\alpha=0.001$ $\alpha=0.001$:

$$W := W - \alpha \cdot \nabla L(W) \quad (7)$$

A batch size of 32, prefetching, and a 20% validation split improve efficiency. Final accuracy is calculated as:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \quad (8)$$

IV. DATASET INFORMATION

This dataset is a composite of several specialized collections: BPLD Dataset (Blackgram diseases), Chili Plant Disease Dataset, Potato Dataset, Tomato Dataset, and Rice Leaf AUG Dataset. Each dataset contributes images of disease symptoms specific to its respective crop, providing a comprehensive variety of plant health conditions. This combined dataset enhances the model's ability to accurately diagnose multiple crop diseases in diverse conditions.

TABLE I: DATASET SPECIFICATIONS

S.NO	LEAF NAMES	No.of Leaves
1	Chili_Plant_Diseases	400
1.1	Yellowish	80
1.2	Whitefly	80
1.3	Leaf spot	80
1.4	Leaf curl	80
1.5	Healthy leaf	80
2	Potato Plant Diseases	356
2.1	Potato_____Late_blight	144
2.2	Potato_____Early_blight	87
2.3	Healthy leaf	125
3	Rice Plant Diseases	399
3.1	Bacterial Leaf Blight	97
3.2	Sheath Blight	71
3.3	Leaf Blast	111
3.4	Brown Spot	70
3.5	Healthy leaf	50
4	Black Gram Plant Diseases	689
4.1	Powdery Mildew 180	180

4.2	Yellow Mosaic 220	222
4.3	Anthracoese 230	71
4.4	Leaf Crinckle 150	152
4.5	Healthy Leaf	64
5	Tomato	396
5.1	Tomato Bacterial_spot	64
5.2	Tomato Late_blight	71
5.3	Tomato Early_blight	78
5.4	Tomato Target_Spot	84
5.5	Healthy Leaf	99

V. RESULTS

The accuracy, precision, recall, and F1-score were the main performance metrics used to assess the disease classification model on a validation dataset. These metrics, which were computed for every model, shed light on how well the model could identify cases of each disease type. Below is a detailed analysis of the results.

Here, we see a detailed comparative analysis of all the models used in this project

	Model	Accuracy	Precision	Recall	F1-Score
0	VGG16	0.962798	0.963373	0.962798	0.962608
1	MobileNetV2	0.770833	0.794367	0.770833	0.770020
2	ResNet50	0.958333	0.959691	0.958333	0.958085
3	CNN	0.611607	0.626683	0.611607	0.608553
4	Deep CNN	0.297619	0.259793	0.297619	0.139416
5	Vanilla CNN	0.678571	0.699258	0.678571	0.682001

Fig. 2: Classification Report for all Models

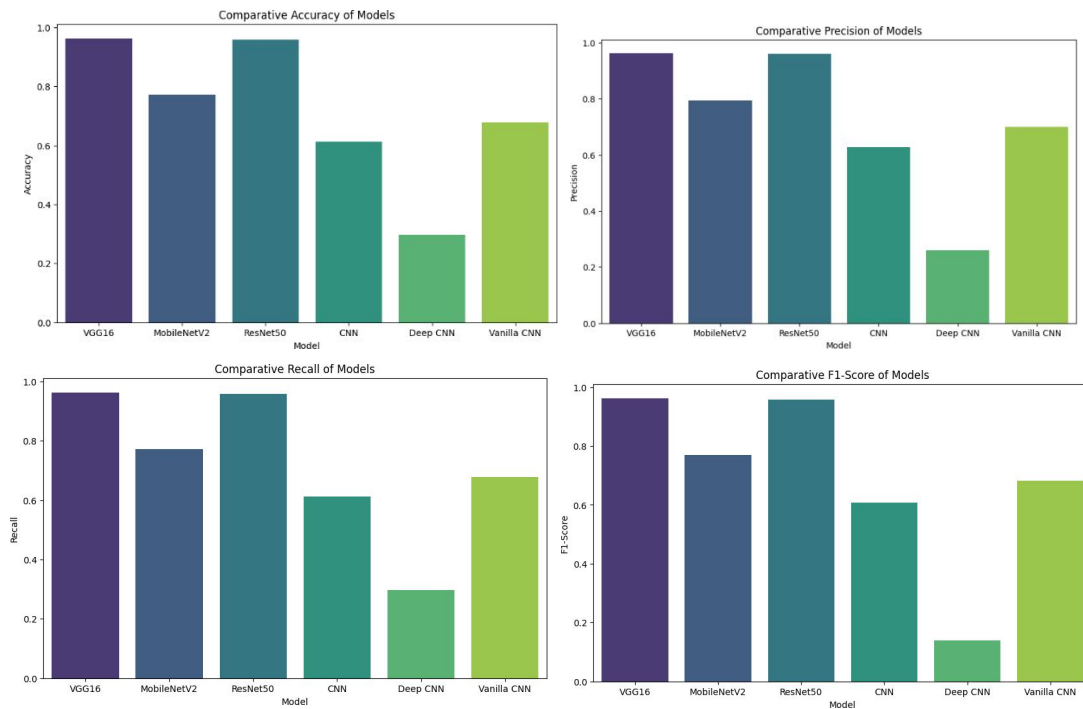


Fig. 3: Bar Graph for all Models

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