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"Detection Of Weeds And Diseases In Crops Using Deep Neural Network"

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ABSTRACT

Plant diseases pose a significant threat to global food security, causing substantial crop losses and financial setbacks for farmers. This study explores the current landscape of plant disease detection, emphasizing the importance of timely identification for effective control measures. Traditional methods rely on visual recognition by agricultural technicians, demanding high levels of expertise and substantial manpower. Alternatively, molecular biological techniques offer more accurate pathogen diagnosis but necessitate specialized laboratory conditions.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promising results in automating crop disease detection. This study delves into the application of these deep learning architectures, including ResNet and InceptionV3, in analyzing crop images and sensor data. Annotated datasets play a crucial role in training these models, and transfer learning proves essential in overcoming data limitations.

The study concludes by summarizing key findings, discussing potential future trends, and encouraging interdisciplinary collaborations among researchers, agronomists, and technologists. The ultimate goal is to collectively address the complex challenges in crop disease detection and leverage the power of deep learning to enhance the accuracy of detection systems. Plant diseases are responsible for substantial yield losses, as high lighted by statistics from the Food and Agriculture Organization (FAO).Understanding the factors contributing to plant diseases is crucial for developing effective mitigation strategies and ensuring

the sustainability of national and global food production systems.

INTRODUCATION

Plant diseases pose a significant threat to global food production, causing substantial yield losses and economic setbacks. Detecting and diagnosing these diseases promptly is crucial for implementing effective control measures. Traditional methods rely on visual recognition by agricultural technicians in the field, demanding expertise and manpower. Molecular biological techniques have enabled quicker pathogen diagnosis, but challenges persist.

Recent progress in deep learning, notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), holds potential for the detection of crop diseases. This study explores their application, emphasizing the role of an notated datasets and the relevance of transfer learning to address data limitations.

This study aims to enhance the accuracy of crop disease detection systems. Plant diseases contribute significantly to global food production losses, ranging from 20% to 40%, according to the Food and Agriculture Organization. Recognizing the importance of identifying plant diseases for mitigating yield losses, the study addresses factors responsible for these diseases, concluding by summarizing key findings and encouraging inter disciplinary collaboration to address complex challenges in crop disease detection.

MOTIVATION

The motivation behind the identification and recognition of leaf diseases stems from the critical need to address challenges associated with crop diseases, particularly in the context of agriculture farms.

According to the Census of India 2011, about 58% of the country's total workforce was engaged in agriculture and allied activities. This includes both cultivators (farmers) and agricultural laborers. Agriculture contributes to a substantial portion of India's Gross Domestic Product (GDP).

India is predominantly an agrarian economy, with a substantial portion of its population engaged in agriculture. Leaf diseases pose a direct threat to the livelihoods of millions of farmers who rely on crop yields for sustenance and income. With a growing population, ensuring food security is a major challenge for India. Leaf diseases can lead to reduced crop yields, impacting the availability and affordability of food. Efficient disease detection can contribute to mitigating these challenges.

RATIONALE

The rationale behind identifying and recognizing leaf diseases lies in the critical role it plays in safe guarding large farms from significant crop losses. This proactive approach not only preserves farm productivity and profitability but also extends its impact to agricultural institutes and biological research, fostering advancements that contribute to global food security goals.

Profit ability in Agriculture

Crop diseases directly contribute to economic losses for farmers, affecting overall profitability. The ability to detect and recognize leaf diseases provides farmers with the means to implement targeted disease control measures. This, in turn, safeguards crop yield and contributes to increased profitability in agricultural practices.

Contribution to Biological Research

Biological research endeavors to deepen our understanding of plant-pathogen interactions and disease mechanisms. Leaf disease identification provides biological researchers with valuable data to study the molecular and genetic aspects of plant diseases. This contributes to advancements in molecular biology techniques, contributing to the creation of new and inventive solutions as well as diagnostic instruments.

Overall Impact on Food Security

The global need for sustainable food production is essential for ensuring food security. Recognizing and managing leaf diseases is pivotal in achieving food security goals. By safeguarding crop yields and enhancing agricultural practices, the identification of diseases directly contributes to the overall stability of food production.

In summary, the motivation behind the identification and recognition of leaf diseases extends beyond individual farms to encompass broader agricultural and biological research contexts. The aim is to address challenges related to crop diseases, ultimately leading to increased productivity, profitability, and advancements in agricultural and biological sciences. The importance of this motivation is underlined by its potential to positively impact food security and sustainability.

OBJECTIVE

ACCURATE IDENTIFICATION

Accurate identification of crop diseases is important for several reasons. First, it allows farmers to choose the correct treatment for the disease, which can improve the chances of a successful outcome. Second, accurate identification can help farmers to save time and money, as they will not have to waste resources on treatments that are not effective. Third, accurate identification can help farmers to track the spread of diseases and to take steps to prevent them from spreading further. There are a number of ways to accurately identify crop diseases. One way is to visually inspect the plants and compare the symptoms to known diseases. This can be done by farmers themselves, or by trained professionals.

METHODOLOGY

IMPLEMENTATION WORK

In our proposed work, we meticulously curetted a diverse dataset encompassing images of both healthy and diseased crop leaves, spanning various crop species and disease types. The leaves were meticulously labeled and categorized into distinct disease lasses. The dataset is divided in to two parts: the first comprises195 images across four classes, while the second includes 48 images divided into four classes. To evaluate the model's performance, we employed various metrics such as Training Accuracy, Validation Accuracy with respect to Epochs. To mitigate over fitting, we partitioned the dataset into training and validation sets.

Upon achieving satisfactory performance on the validation set ,the final model underwent testing on a separate set that the model had not encountered during training, ensuring an unbiased assessment of its generalization ability. Our exploration involved advanced optimization techniques, including different network architectures such as attention mechanisms and residual networks, as well as advanced training algorithms like adaptive learning rate methods. We also experimented with hyper parameter settings such as learning rate, batch size, optimizer, and network architecture to optimize the model's performance for our specific dataset.

To further enhance the model's capabilities, we expanded the diversity and size of the dataset by collecting additional images of healthy and diseased crop leaves. These new images encompassed varied disease types, plant species, lighting conditions, and backgrounds. Post-satisfactory performance on the testing set, we deployed the trained hybrid model for real-world crop disease detection applications, rigorously testing it on new, unseen images to gauge its accuracy and reliability.

In the training process, the model utilized the labeled dataset with pre-trained weights initialized to their original values. To prevent overwriting valuable knowledge in the pre- trained layers, we froze their weights during training. Only the newly added layers were made train able. The model parameters were optimized using the Adam optimizer and the categorical cross-entropy loss function. After training the new layers, a strategic approach was taken to gradually unfreeze some of the earlier layers in the pre-trained model. This fine-tuning involved using a lower learning rate to ensure adaptation to the specific task of crop disease detection.

DATASET

We gathered a diverse dataset comprising images of healthy and diseased crop leaves. The dataset covers a wide range of crop species and disease types. The leaves were meticulously labeled and categorized into appropriate disease classes. Dataset is collected from Plant Village[23].It contains 250 images of 224x224 px of Apple Leaves. Dataset split into valid and Train folder which contains four classes of apple leaves. Four classes area follow:

- **Healthy Leaf**

  Healthy apple leaves exhibit vibrant green color, indicating optimal growth and photosynthesis.

- **Black rot**

  Black rot canker affects leaves during early spring, as they begin to unfold. Initially, small purple specks appear on the upper leaf surface, enlarging into circular lesions measuring1/8to1/4inch(3-6mm)in diameter. The lesions feature a purple margin and a tan to brown center. Over time, these leaf spots undergo secondary enlargement, worsening the condition.

- **Cedar Rust**

  Leaf spots initially appear yellow before transitioning to bright orange-red, often with a vivid red border. As the spots mature, small raised black dots develop at their center on the upper leaf surface. Beneath the leaf, very short finger-like fungal tubes emerge directly below the spots, indicative of cedar apple rust. These tubes, when open, release yellow to orange powdery spores, contributing to the spread of the disease.

- **Apple Scab**

  Apple scab is commonly found on apple trees, affecting both leaves and fruits. Symptoms include twisted or puckered leaves with black, circular spots on the upper surface, while the underside may exhibit velvety spots that can merge to cover the entire leaf surface. Severe cases may result in yellowing and premature leaf drop.

1. Healthy Leaf

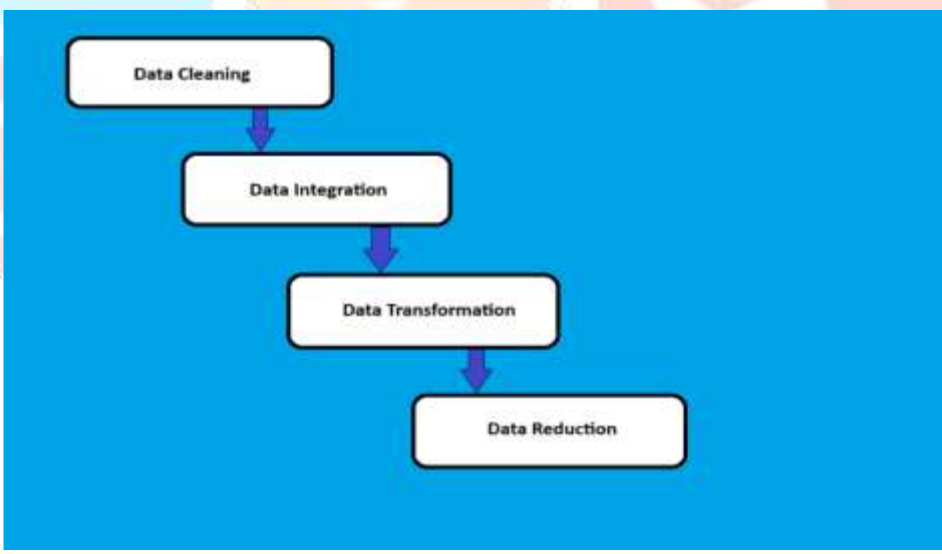
2. Apple_Black_rot

3.Cedar_rust

4. Apple_scab

PREPROCESSING

Pre-processed the images by resizing them to a consistent size, normalizing the pixel values, and converting them to a suitable color space (e.g., RGB). Split the dataset into training and testing sets.



Data Cleaning

The first step in data preprocessing involves identifying and correcting errors and inconsistencies within the dataset. This process is crucial to ensure the accuracy and reliability of the data.

Data Integration

After cleaning, the next step is data integration, where the cleaned data from various sources is combined into a unified dataset. This is essential when dealing with multiple data sources to create a comprehensive and cohesive dataset.

Data Transformation

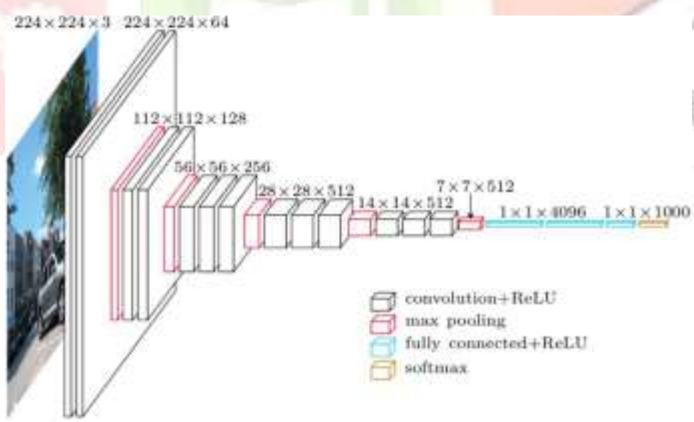
After integration, the data under goes transformation to adapt it into a suitable format for analysis. Standardization and normalization are common techniques employed in this phase, aimed at ensuring consistency and enabling meaningful comparisons across different features or datasets.

Data Reduction

In the final stage of data preprocessing, data reduction is undertaken. This step focuses on reducing the size of the dataset while retaining crucial information. It is especially crucial for optimizing computational resources, as large datasets may demand significant hardware resources. Data reduction techniques facilitate size reduction while safeguarding essential information.

DEEP LEARNING MODEL SELECTION

Choose a pre-trained deep learning model such as VGG16, ResNet, or InceptionV3. These models have been trained on large-scale datasets like ImageNet and are capable of extracting meaningful features from images. We choose VGG16 for our study.



The VGG16 architecture, as the name suggests, is a specific variant of the VGG architecture with 16 weight layers. Here is a detailed explanation of VGG 16 architecture-

Input Layer

The input layer takes images of size 224x224pixels.

Convolutional Blocks

These blocks consist of multiple convolutional layers stacked together. Convolutional layers apply filters to the input data to extract features. In each block, multiple convolutional layers are used to capture increasingly complex patterns and features from the input images. The ReLU (Rectified Linear Unit) activation function is applied after each convolutional layer to introduce non-linearity into the network, enabling it to learn more complex relationships within the data.

Block 1: Two convolutional layers with 64 filters, each followed by a ReLU activation function.
Block2:Two convolutional layerswith128 filters ,each followed by a ReLU activation function.
Block3:Three convolutional layers with 256filters, each followed by a ReLU activation function.
Block4:Three convolutional layers with 512filters, each followed by a ReLU activation function.
Block5:Three convolutional layers with 512filters, each followed by a ReLU activation function.

Max Pooling Layers

Max pooling layers are inserted after each pair of convolutional layers in Blocks 1-5. Max pooling reduces the spatial dimensions of the feature maps, helping to make the network more computationally efficient and reducing the risk of over fitting by summarizing the most important information in each region of the feature maps. A2x2 window with a stride of2 is used for max pooling, which means the window moves across the feature map in steps of 2 pixels.

Fully Connected Layers

After the convolutional and pooling layers, the feature maps are flattened into a single vector and passed through fully connected layers. These layers are densely connected, meaning each neuron in one layer is connected to every neuron in the next layer. In this architecture, two hidden layers with 4096 neurons each are used.The ReLU activation function is applied to the output of each hidden neuron, introducing non-linearity and enabling the network to learn complex relationships in the data.

Output Layer

The output layer of the network produces the final predictions or classifications. The number of neurons in this layer is equal to the number of classes in the classification task. In this case, a SoftMax activation function is used, which converts the raw output values of the network into probabilities, representing the likelihood of each class. The class with the highest probability is then chosen as the predicted class for the input image.

TRANSFER LEARNING

We employed transfer learning by utilized a pre-trained deep learning model that had been trained on a large dataset, such as ImageNet. Specifically, we chose the VGG16 model as our base architecture. The original classification layer of the pre-trained model was removed, as it was not suitable for crop disease detection.

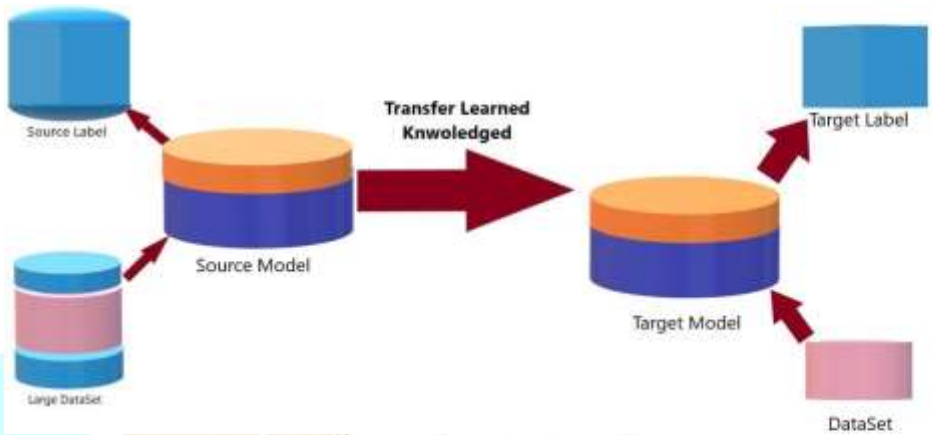


Figure Concept of Transfer Learning

Remove Last Layers

Remove the last few layers of the pre-trained model, typically the ones responsible for the specific task it was originally trained on. Retain the layers that capture more general features.

Freeze Pre-trained Layers

Freeze the weights of the remaining layers from the pre-trained model. This ensures that the already learned features are not modified during the initial training on the new dataset.

Add New Layers

Add new layers to the model to match the requirements of the new task. These layers are then trained on the new dataset.

Training on New Data

Train the modified model on the new dataset. This involves updating the weights of the added layers while keeping the pre-trained layers frozen.

RELATED TO THE DATA

Source Data (e.g.-ImageNet)

ImageNet is a large-scale dataset with millions of labeled images across thousands of categories. It is commonly used as a source for pre-training models because it covers a wide range of visual features.

Source Data Labels

In the case of ImageNet, each image is labeled with one of the thousands of categories it belongs to. These labels are used to train the model on the initial task, like image recognition.

New Dataset

The new dataset is specific to the target task. It might be a smaller dataset related to a different set of categories.

New Dataset Labels

These are the labels associated with the new dataset. For example, if you are training a model to recognize different diseases of leaves, each image in the new dataset would be labeled with the corresponding leaves diseases.

FEATURE EXTRACTION

Feeded the pre-processed images into the deep learning model to extract high-level features. Extract features either by removing the final fully connected layers and using the output of the last convolutional layer as feature vectors or by employing techniques like global average pooling.

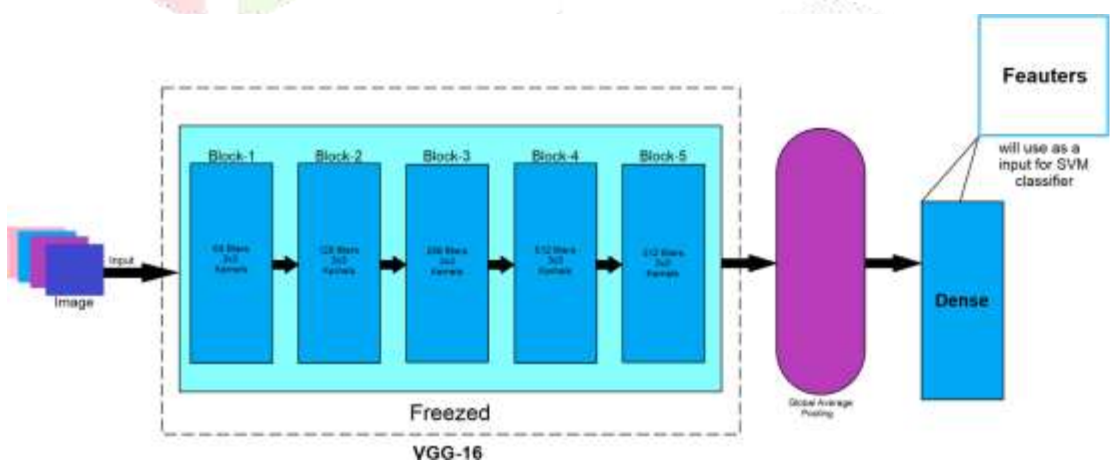


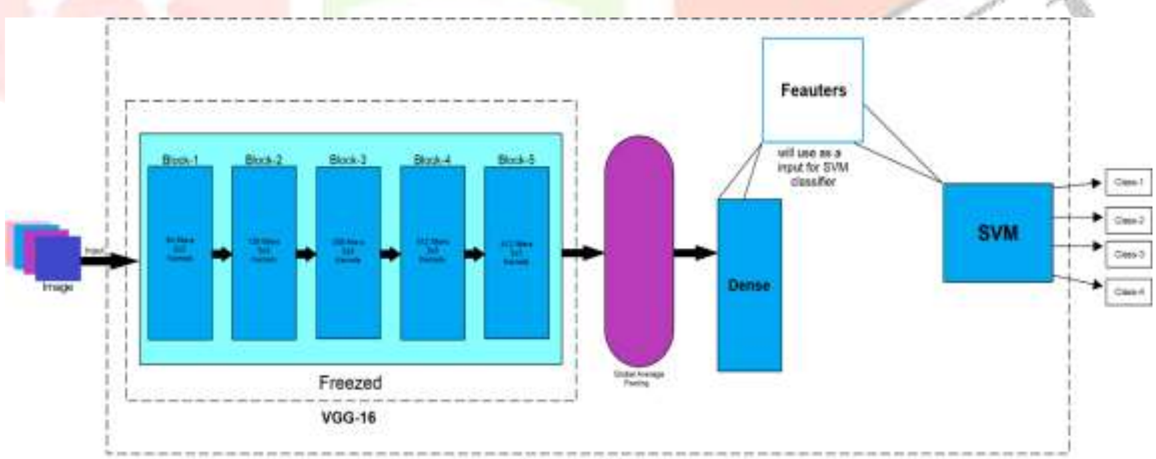
Fig. Feature Extraction

TRADITIONAL MACHINE LEARNING

Using extracted features as input for traditional machine learning ,such as Support Vector Machines(SVM),offers a robust approach to plant leaf classification. By selecting SVM, we leverage its ability to construct optimal decision boundaries in high-dimensional feature spaces. Through training on a labeled dataset, the SVM model learns to differentiate between healthy and diseased plant leaves based on the extracted features. This process enables accurate classification of plant leaves into their respective classes, facilitating early detection and intervention in case of disease outbreaks. Additionally, hyper parameter tuning ensures the SVM model's optimal performance by fine-tuning parameters such as the choice of kernel function and regularization strength. Overall, employing SVM for plant leaf classification based on extracted features represents a reliable and effective method for disease diagnosis in agricultural settings.

HYBRID APPROACH

This hybrid approach combines the feature extraction capability of a pre-trained deep learning model(VGG16) with a traditional machine learning classifier (SVM). This can be beneficial when limited labeled data is available, allowing the model to leverage the knowledge learned from a large-scale pre-trained model while adapting to the specific characteristics of the target dataset using a simpler and faster machine learning algorithm.



Proposed Model

RESULT AND DISSCUSSION

MODEL EVALUATION AND TESTING

The performance of the trained model was evaluated using Training Accuracy and Validation Accuracy with respect to epochs. To prevent over fitting, the dataset was split into training and validation sets. After achieving satisfactory performance on the validation set, the final model was tested on a separate testing set that the model had not encountered during training, providing an unbiased assessment of its generalization ability. The results of our proposed model are given below in **Table No. 1**

IMPROVING ACCURACY

To enhance the accuracy of the crop disease detection system, we explored several techniques:

AUGMENT THE DATASET

Increasing the diversity and size of the dataset by collecting more images of healthy and diseased crop leaves with varied disease types, plant species, lighting conditions, and backgrounds.

FINE-TUNING HYPER PARAMETERS

Experimenting with different hyper parameter settings, such as learning rate, batch size, optimizer, and network architecture, to optimize the model's performance for the specific dataset.

DATA AUGMENTATION

Applying data augmentation techniques, such as rotation, scaling, flipping, and adding noise, to artificially increase the dataset's size and improve the model's robustness.

TableNo.1 Accuracy of Proposed Hybrid Model

Training Accuracy	Validation Accuracy	Epochs
0.65	0.79	1
0.84	0.88	2
0.90	0.93	3
0.92	0.93	4
0.94	0.94	5
0.95	0.94	6
0.95	0.94	7
0.95	0.95	8
0.96	0.95	9
0.96	0.95	10

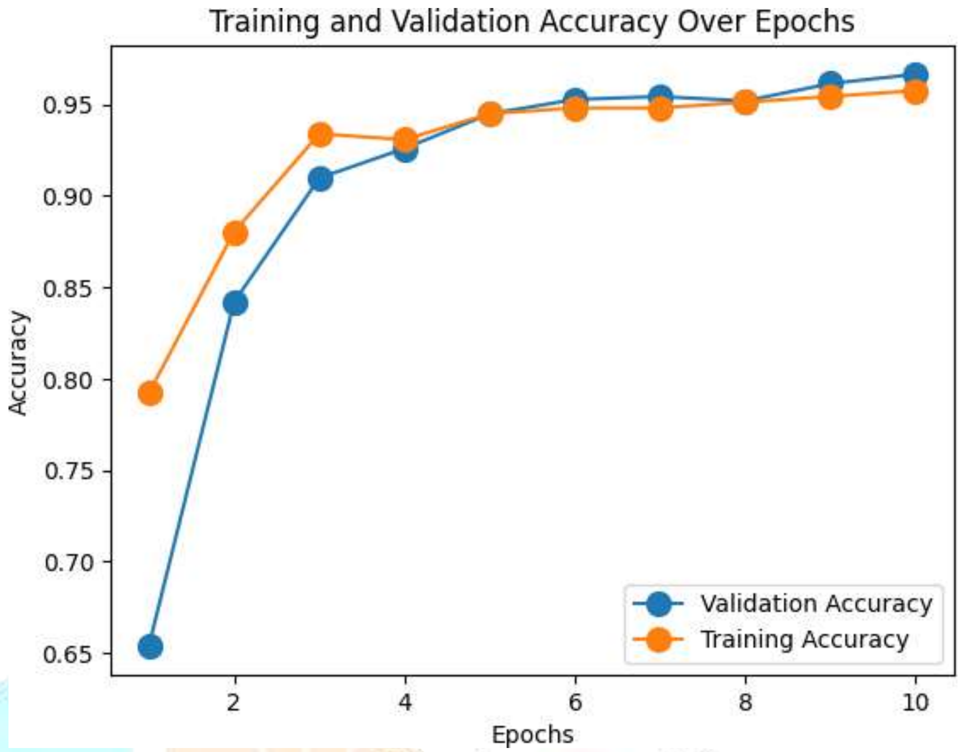


Fig. Graph of Hybrid Model

Observation

1. The model commences with a mean accuracy of 0.72 and progressively enhances with each epoch.
2. Both training and validation accuracies consistently ascend, indicating positive learning trends.
3. The model demonstrates a strong alignment with the training data, as training accuracy remains consistently high.
4. Validation accuracy also shows an upward trend, suggesting effective generalization to novel data.
5. The overall performance estabilizes around the 8th epoch, showing marginal improvement thereafter.

In summary, your model appears to be learning effectively and demonstrating robust generalization capabilities. It's crucial to monitor for signs of over fitting or under fitting. Nonetheless, based on the provided information, the model seems to be performing reasonably well.

TableNo.2 Accuracy of existing CNN Model

Training Accuracy	Validation Accuracy	Epochs
0.48	0.66	1
0.65	0.57	2
0.73	0.80	3
0.73	0.76	4
0.71	0.80	5
0.79	0.87	6
0.65	0.77	7
0.75	0.68	8
0.76	0.88	9
0.77	0.80	10

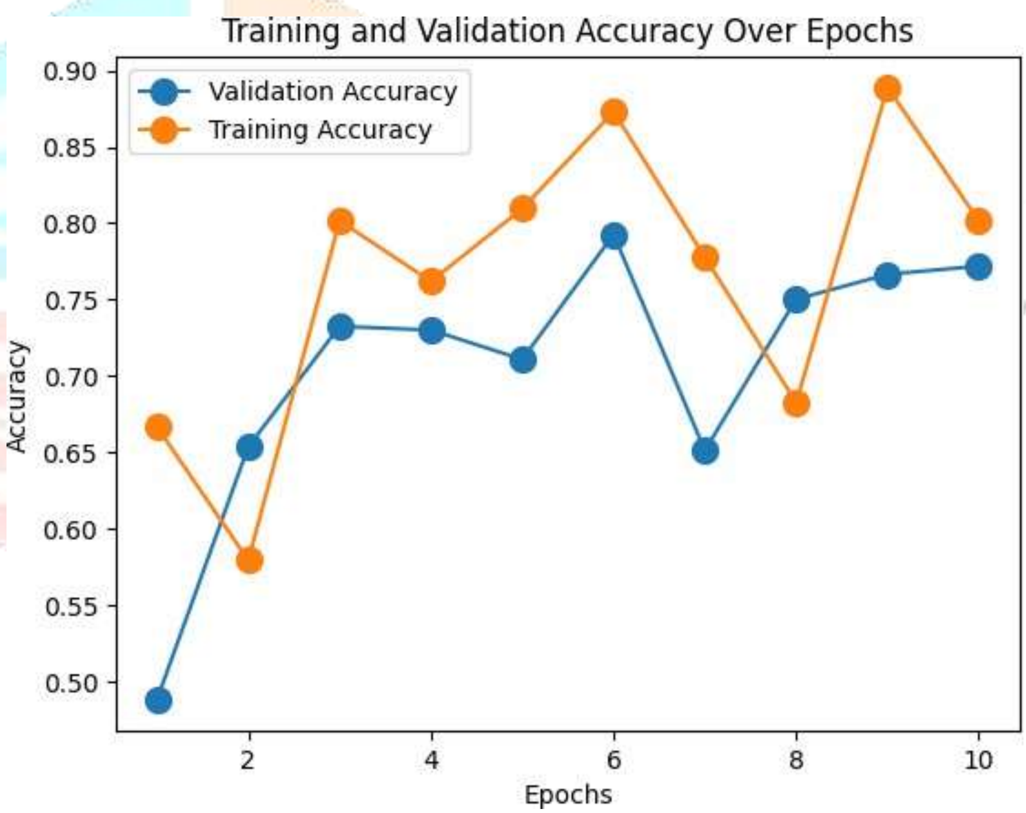


Fig. Graph of existing CNN Model

Observations

1. The model starts with are latively low average accuracy of 0.57in the first epoch.
2. Training accuracy is lower than validation accuracy in the early epochs (e.g., epoch 1 and 2), which might indicate under fitting.
3. The model's performance improves in terms of both training and validation accuracy until around

the 6th epoch.

4. There is some fluctuation in accuracy in the later epochs, which could indicate that the model is not converging to a stable solution.
5. The highest validation accuracy is achieved in the 9thepoch,but it drops slightly in the 10th epoch.

In summary, your model's performance is somewhat inconsistent. Training accuracy remains relatively low, suggesting an inadequate fit to the training data. While there are moments of improvement in validation accuracy, there is also notable fluctuation, indicating an unstable ability to generalize to new data. with the highest validation accuracy achieved in the 9th epoch followed by a slight drop in the 10th epoch. Overall, the model's performance raises concerns about its effectiveness and reliability.

Table No. 3 Comparison Table between Hybrid Model and Existing CNN Model

Epochs	Average Accuracy of Hybrid Model	Average Accuracy of CNN Model
1	0.72	0.57
2	0.86	0.61
3	0.91	0.76
4	0.92	0.74
5	0.94	0.75
6	0.94	0.83
7	0.94	0.71
8	0.95	0.72
9	0.95	0.82
10	0.95	0.78

Observations

1. The new model starts with a higher average accuracy (0.72) compared to the old model (0.57) in the first epoch.
2. The new model consistently out performs the old model in terms of average accuracy throughout the training process.
3. Both models show improvement in accuracy over the first few epochs, but the new model's accuracy increases at a faster rate.
4. In the 6th epoch, the new model achieves not ably higher accuracy(0.94) compared to the old model (0.83).

5. The new model maintains a consistently higher average accuracy across all epochs compared to the old model.

In summary, the new model demonstrates superior performance, consistently achieving higher average accuracy compared to the old model across all training epochs.

CONCLUSION

We gathered a diverse dataset comprising images of healthy and diseased crop leaves. The dataset covers a wide range of crop species and disease types. The leaves were meticulously labeled and categorized into appropriate disease classes. The dataset consists of two parts, the first containing 195 images divided into four classes, and the second containing 48 images divided into four classes.

FUTURE SCOPE

The future scope for the crop disease detection system outlined above could involve the following areas of development and improvement:

EXPANSION OF DATASET

Continuously expand and diversify the dataset to include more crop species, disease variations, and environmental conditions. This would enhance the model's ability to generalize across a broader range of scenarios.

REAL-TIME MONITORING

Integrate the system with real-time monitoring capabilities, allowing farmers to receive instant alerts about potential crop diseases. This could involve the use of Io T devices or drone technology for on-the-fly data collection.

MOBILE APPLICATION INTEGRATION

Create a user-friendly mobile application that enables farmers to easily interact with the system, view disease predictions, and access relevant information and recommendations for disease management.

LOCALIZED LANGUAGE SUPPORT

Incorporate support for localized languages and user interfaces to ensure accessibility and usability for farmers in diverse regions.

By addressing these future aspects, the crop disease detection system can evolve into a more robust, adaptive, and user-friendly tool for supporting sustainable agriculture practices.

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