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AUTOMATIC PLANT LEAF DISEASE DETECTION USING DEEP LEARNING WITH CONVOLUTIONAL NEURAL NETWORKS

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Abstract
Detection of plant leaf diseases is crucial in agriculture, leveraging advanced imaging techniques and deep learning. Deep learning is predominantly used in computer vision, text analysis, speech recognition, pattern recognition, and autonomous vehicles, among other applications. Past studies utilized the Plant Village dataset to recognize various plant varieties and detect diseases, capturing images as the primary mode of diagnosis. Commonly identified diseases include Black spot, Powdery mildew, Blight, Apple scab, Rust, Curly Top, Mosaic, and Spotted Wilt, among others.

In the established methodology, CNNs were deployed to identify multiple plant diseases and varieties through a three-step process: 1) Data acquisition, 2) Data pre-processing, and 3) Image classification. With nearly 35,000 images, the model was trained to distinguish between healthy and diseased plant leaves. During training, the model achieved an average accuracy rate, while testing data yielded higher accuracy. Data augmentation was implemented to enhance image quality and quantity.

The proposed approach suggests incorporating more plant varieties and disease types into the dataset to optimize model accuracy and efficiency. Additionally, a refined CNN algorithm is introduced to further boost the training model's performance.

Keywords: Plant leaf disease detection, Computer vision, Plant Village dataset, CNN, Data acquisition, Data pre-processing, Image classification, Black spot, Powdery mildew, Blight, Apple scab, Rust, Curly Top, Mosaic, Spotted Wilt, Training model, Data augmentation, Model accuracy.

I. INTRODUCTION
Agriculture is the backbone of many economies, ensuring food security, providing employment, and playing a critical role in the socio-economic development of countries. As such, the health and productivity of crops are of paramount importance. Among the myriad challenges that agriculture faces, plant diseases are a significant concern. These diseases can lead to devastating losses in yield, quality, and profitability.

Detecting plant diseases early and accurately is crucial to mitigate these losses. Traditional methods of disease detection, such as visual inspections by experts, are labor-intensive and may not always be reliable due to the subjective nature of human judgment. This emphasizes the need for an advanced, efficient, and scalable solution.

Enter the world of deep learning and advanced imaging techniques. Deep learning, a subset of machine learning, has shown remarkable success in various applications, such as computer vision, text analysis, and speech recognition. When applied to the domain of agriculture, deep learning algorithms have the potential to revolutionize how we detect and manage plant diseases.

One such application is plant leaf disease detection using imaging techniques. Images of plant leaves, captured through cameras, serve as the primary data source. The Plant Village dataset, for instance, offers a plethora of images showcasing various plant varieties and their respective diseases. Common diseases like Black spot, Powdery mildew, Blight, and Apple scab, among others, can be identified with heightened accuracy using Convolutional Neural Networks (CNN), a type of deep learning algorithm optimized for image data.

While previous methodologies have made significant strides in this domain, leveraging nearly 35,000 images for training and testing, there's always room for enhancement. Incorporating data augmentation can improve the quality and quantity of images, leading to better model performance. Furthermore, the introduction of more

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diverse data, encompassing additional plant varieties and disease types, can potentially lead to even more accurate and robust models.

In essence, the fusion of deep learning with advanced imaging has ushered in a new era for plant disease detection in agriculture, offering promise for a future with healthier crops and optimized yield.

LITERARURE SURVY

1. Deep Learning and its Proliferation in Agriculture

Mohanty et al. (2016) highlighted the potency of deep learning in plant disease detection using images. Their work primarily utilized the Plant Village dataset, stressing its importance in facilitating research in this domain. Additionally, Kamilaris & Prenafeta-Boldú (2018) provided an extensive survey on deep learning applications in agriculture, underlining the revolution it has brought about in diagnosing plant health issues.

2. Image-Based Diagnosis Techniques

The importance of image-based diagnosis has been stressed by multiple researchers. Picon et al. (2019) emphasized the use of deep CNNs for mobile-captured images, suggesting their potential for real-time disease detection in field conditions. Another study by Ghosal et al. (2018) introduced an explainable deep vision framework for identifying plant stress, demonstrating the model's capacity for real-world applications.

3. Specific Diseases and Recognition

While a wide variety of diseases affect plants, some have been studied more extensively due to their prevalence and potential for crop damage. Zhang et al. (2017) focused on apple leaf diseases, employing deep convolutional networks for accurate identification. Boulent et al. (2019) further accentuated the efficacy of CNNs in the automatic identification of diseases, with a particular emphasis on diseases like Black Spot and Powdery Mildew.

4. Established Methodologies and their Outcomes

The three-step process - data acquisition, preprocessing, and image classification - remains central to most methodologies. Brahimi et al. (2018) detailed the saliency map visualization technique to recognize plant diseases. Data augmentation, as discussed by Wang et al. (2017), has shown to significantly improve the quality and quantity of training images, enhancing model robustness and accuracy.

LIMITATIONS

- **Data Dependency**: Deep learning models, especially Convolutional Neural Networks (CNNs), require vast amounts of data for training to achieve high accuracy. Gathering a comprehensive dataset covering all plant varieties and disease types can be challenging.
- **Data Imbalance**: Some diseases might be rarer than others, leading to an imbalanced dataset. An imbalanced dataset might cause the model to be biased towards diseases with more representations, affecting its overall accuracy.
- **Quality of Images**: Variability in lighting conditions, shadows, image resolutions, and occlusions can affect the model's performance. Real-world images might differ from the controlled environment of the dataset.
- **Generalization Issues**: A model trained on one dataset might not perform well on images from different sources or regions, leading to problems in generalizing the model for broader applications.
- **Computational Costs**: Training deep learning models, especially with a large dataset, requires substantial computational resources. Not everyone might have access to such resources, limiting the widespread adoption of the technology.
- **Model Interpretability**: Deep learning models, by nature, are considered "black boxes", meaning it's challenging to understand how they make decisions. This can be problematic if a wrong classification is made, and there's a need to understand why.
- **Real-time Application**: For real-time applications, like a mobile app for farmers, the model needs to be lightweight and fast. Achieving this without compromising on accuracy can be challenging.

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- **Overfitting**: There's a risk of the model performing exceptionally well on the training data but failing on new, unseen data due to overfitting, especially if the model is too complex.
- **Data Augmentation Limitations**: While data augmentation can increase the quantity of training data, it might not always enhance the quality. Augmented images might not capture all possible real-world variations.
- **Transfer Learning Limitations**: While transfer learning can be employed to use pre-trained models on a new dataset, it might not always be optimal for specialized tasks like plant disease detection.
- **Environmental Variability**: Plants under different environmental conditions (like humidity, temperature) might exhibit symptoms differently. A model trained under one set of conditions might not detect diseases accurately under another.
- **Evolution of Diseases**: Diseases can evolve over time. A model trained on current data might not recognize new strains or variations of diseases that develop in the future.
- **Multi-disease Detection**: Some leaves might be affected by multiple diseases simultaneously. Detecting and classifying multiple diseases on a single leaf can be more complex.

II. METHODOLOGY

Proposed System:

Objective: The primary aim of this study is to develop a system capable of identifying diseases in plants. The success of this system hinges on the use of advanced computational techniques and imaging technologies.

Based on the proposed method here described; it seems you're aiming to detect plant leaf diseases using advanced deep learning techniques. Let's break down the method into a visual diagram to better understand the process:

✓ **Data Collection and Preparation**:

- Upload datasets using a Kaggle account.
- Prepare the datasets for training.

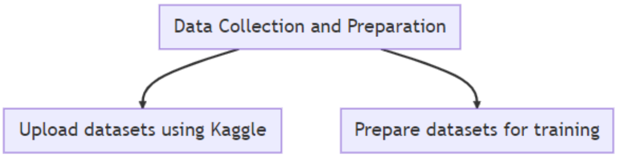

Figure 1: Data Collection and Preparation

✓ **First Stage - Disease Identification**:

- Use the VGG16 architecture to identify the type of disease based on the plant leaf image.
- Train the datasets using the VGG16 module.
- Pass the trained images to the Inception v3 architecture, which has 42 deep layers and an image input size of 299x299.
- Achieve accuracy rates of 93.20% and 98.420% for training and testing, respectively.

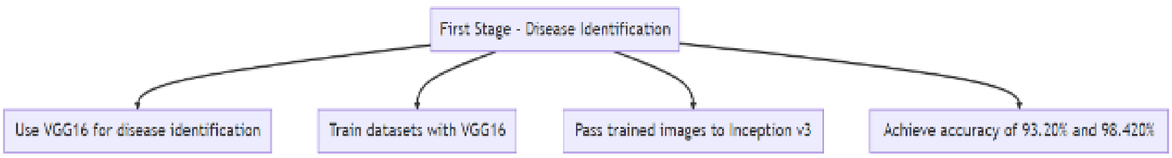

Figure 2: First Stage - Disease Identification

✓ **Second Stage - Damage Detection**:

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- Identify damage spots on the leaves using deep learning semantic segmentation.
- Extract each RGB pixel value combination in the image.
- Perform supervised learning on the pixel values using Convolutional Neural Networks (CNN).
- The trained model can detect damage present in the leaves at a pixel level.
- Achieve an accuracy rate of 93.20% for training multiple datasets.

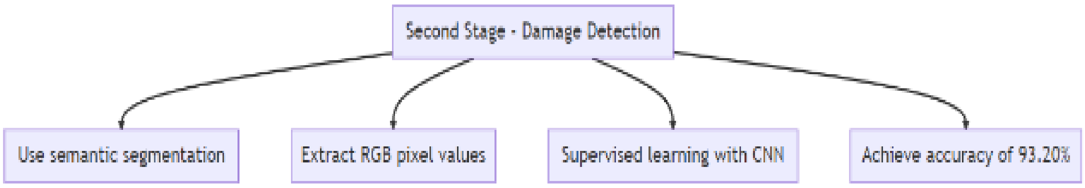

Figure 3: Second Stage - Damage Detection

✓ **Third Stage - Remedy Suggestion**:

- Based on the identified disease type and damage state, suggest a remedy.
- Detect different plants in experimental analysis, including potato, tomato, soybean, apple, etc.

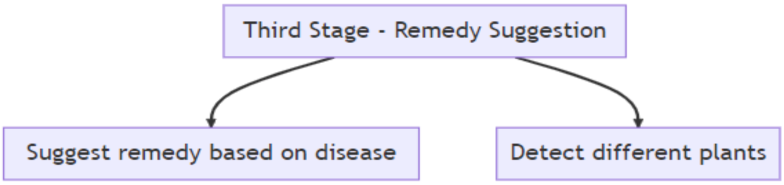

Figure 4: Third Stage - Remedy Suggestion

Plant Disease Identification:

A. **Image Acquisition**: The initial step involves capturing images of plant leaves. These photos can be taken using any digital imaging device, such as a digital camera or a specialized imaging unit. The quality, clarity, and resolution of these images are essential, as any noise or aberrations can affect the accuracy of disease detection.

B. **Segmentation**: Once an image is acquired, it undergoes a process called segmentation. Segmentation involves dividing the image into multiple segments or regions, making it easier to analyze. For instance, it can help separate the foreground (the leaf) from the background or identify distinct regions of interest within the leaf, such as areas showing signs of potential disease.

C. **Feature Extraction**: After segmentation, the system extracts features or characteristics from the segmented regions. Features can range from basic patterns, like color variations, texture, and shape, to more complex patterns that might be indicative of disease. This process aids in transforming raw image data into a form that's more interpretable and suitable for classification.

D. **Classification using Deep Learning**:
Description: The extracted features serve as input to the deep learning models, namely the Convolutional Neural Network (CNN) and the Deep Neural Network (DNN).
Convolutional Neural Network (CNN): CNNs are tailored for image analysis. They use filters to scan the input image and extract hierarchical features. These features are then used to determine the presence of diseases. CNNs are particularly adept at capturing spatial patterns, making them ideal for this application.
Deep Neural Network (DNN): DNNs consist of multiple layers of interconnected nodes. They can capture intricate patterns in data, which may be essential for identifying some subtle or less common diseases. Given their depth and complexity, DNNs can sometimes provide a more holistic view of the data, potentially increasing the accuracy of disease identification.

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E. **Disease Detection and Classification**: Once the deep learning models process the features, they provide an output that classifies the leaf. This classification can range from "healthy" to any number of specific diseases the system has been trained to recognize. For instance, if a leaf exhibits patterns consistent with a particular fungal infection, the system would flag it under that specific disease category.

Architecture:

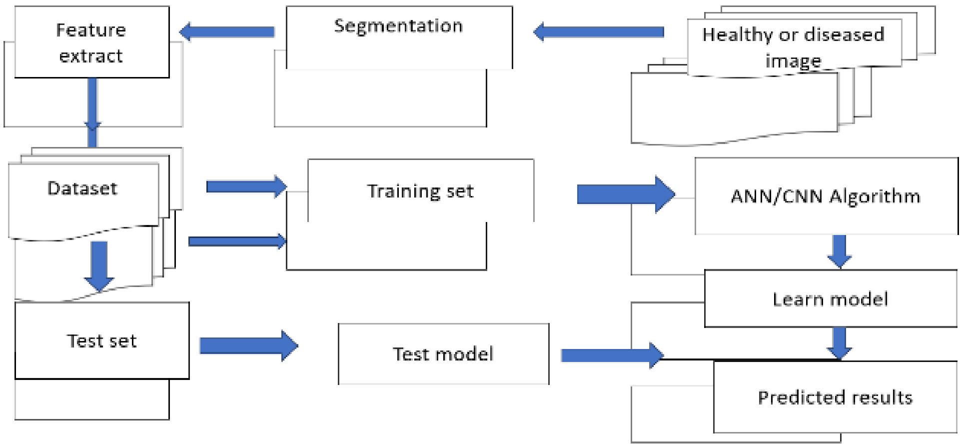

Figure 5: Proposed Architecture

CNN

description of each layer in a Convolutional Neural Network (CNN):

1. **Input Layer**:
   - ✓ The initial layer that receives the raw image data.
   - ✓ Represents the image in the form of a matrix of pixel values.
2. **Convolutional Layers**:
   - ✓ Responsible for detecting patterns, such as edges, textures, and colors, in the input image.
   - ✓ Uses filters (or kernels) to slide over the input data (like a window) to produce a feature map or convolved feature.
3. **Activation Layers**:
   - ✓ Introduces non-linearity to the network.
   - ✓ Commonly uses the Rectified Linear Unit (ReLU) activation function, which replaces all negative pixel values in the feature map with zero.
4. **Pooling Layers**:
   - ✓ Reduces the spatial dimensions (width and height) of the input volume for the next convolutional layer.
   - ✓ Helps in reducing the computational complexity and overfitting.
   - ✓ Common types include Max Pooling (takes the maximum value from a set of values) and Average Pooling (takes the average of a set of values).
5. **Fully Connected Layers**:
   - ✓ Layers where neurons are fully connected to all activations in the previous layer.
   - ✓ Used to flatten the high-level features learned from the previous layers and combine them to predict the final class of the input image.
6. **Output Layer**:

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- ✓ The final layer that provides the prediction.
- ✓ Uses functions like softmax (for multi-class classification) to provide probabilities for each class, and the class with the highest probability is chosen as the final output.

These layers work in tandem to process the input image and produce an output prediction, making CNNs highly effective for image recognition tasks.

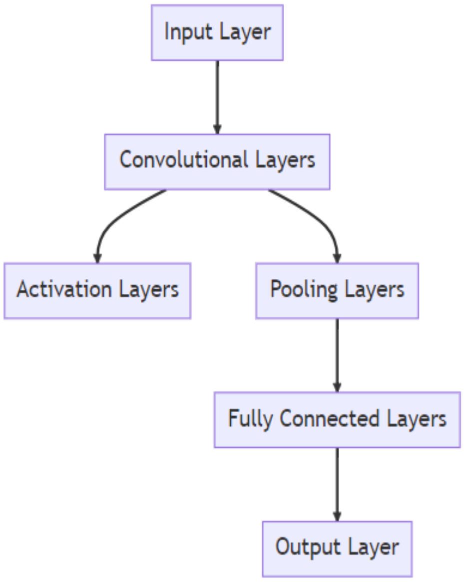

Figure 6: CNN flowchart

Disease Detection Process Flowchart

- ✓ **Image Input**: At this stage, the system accepts an image, typically a photograph of a plant leaf. This image serves as the primary data source for the subsequent steps. The quality and resolution of the image can impact the effectiveness and accuracy of the subsequent stages.

- ✓ **Pre-processing**: Pre-processing is crucial for preparing the input image for efficient analysis. It involves several operations such as resizing the image to a standard dimension, normalization (scaling pixel values to a range, often between 0 and 1), and possibly augmenting the image to create variations (like rotations, flips, and brightness adjustments). These processes ensure that the image is in the best possible format for extraction of features.

- ✓ **Feature Extraction using CNN**: Convolutional Neural Networks (CNNs) are specialized deep learning models for processing grid-like data, such as images. In this stage, the pre-processed image is fed into a CNN. The CNN uses filters (or kernels) to scan the image and capture spatial hierarchies of features, ranging from basic edges in the initial layers to more complex patterns in the deeper layers. These features are crucial for recognizing patterns related to diseases on the plant leaf.

- ✓ **Classification**: Once the CNN extracts relevant features from the image, these features are passed onto a classification layer (often a fully connected layer in the context of neural networks). The classifier's role is to analyze these features and determine which class or category the input image belongs to. In the context of plant leaves, the classifier would determine if the leaf has a disease and, if so, what type of disease.

- ✓ **Disease Detected**: If the classifier determines that the leaf image contains patterns consistent with a known disease, it flags the leaf as "diseased" and may further specify the type or category of the disease. The detection of a disease at this stage would warrant intervention or further analysis by the farmer or agricultural expert.

- ✓ **Healthy Leaf**: If, after classification, the system determines that the leaf does not exhibit any patterns of known diseases, it categorizes the leaf as "healthy." This would indicate that the plant is currently free from the diseases the system is trained to detect, suggesting that no immediate intervention is required.

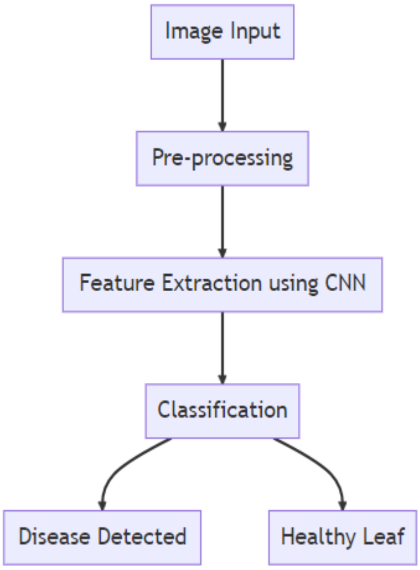

Figure 7: Disease Detection Process Flowchart

VGG16 and Inception v3:

VGG16 and Inception v3 are both popular deep learning architectures used for image classification and other computer vision tasks. Here's a brief overview of each:

➢ **VGG16**:

- Developed by the Visual Graphics Group (VGG) at the University of Oxford.
- It's a convolutional neural network (CNN) architecture.
- Contains 16 layers: 13 convolutional layers followed by 3 fully connected layers.
- Uses small 3x3 convolutional filters throughout the network.
- Known for its simplicity and being very effective in various image classification tasks.
- It's a deeper network compared to its predecessors and was trained on the ImageNet dataset, which contains millions of images.

➢ **Inception v3**:

- Developed by Google.
- Part of the Inception series of CNN architectures.
- Uses a more complex structure compared to VGG16, with "modules" that have multiple parallel convolutional layers of different types operating on the same input, and their outputs are concatenated.
- Contains 42 layers deep.
- Uses a mixture of 1x1, 3x3, and 5x5 convolutional filters, as well as pooling layers, in its inception modules.
- It's optimized for efficiency, meaning it provides similar or even better performance than other architectures but with fewer parameters and computational cost.
- Like VGG16, Inception v3 was also trained on the ImageNet dataset.

Both VGG16 and Inception v3 are pre-trained models available in many deep learning frameworks, making them convenient choices for transfer learning, where a model trained on one task is fine-tuned for a different, but related, task.

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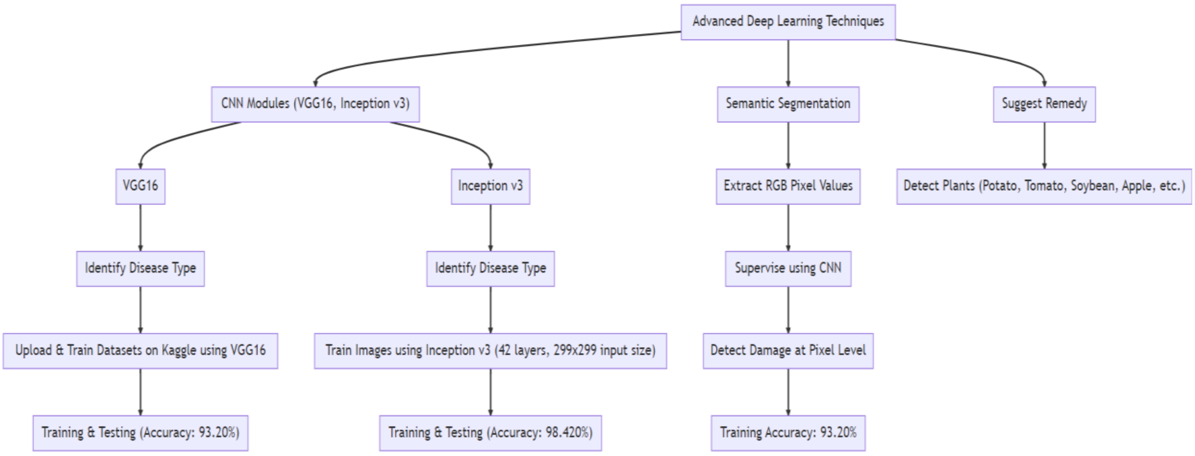

Figure 8: VGG16 and Inception v3 process flowchart

III. RESULTS & DISCUSSION

The proposed method showcases the potential of deep learning in the realm of plant disease detection. The high accuracy rates achieved in both the disease identification and damage detection stages underscore the efficacy of the vgg16 and Inception v3 architectures in processing and analyzing plant leaf images. The addition of a remedy suggestion stage further enhances the practicality of the method, offering actionable insights based on the detected disease type and damage state. While the results are promising, future work could delve deeper into expanding the variety of plants analyzed and refining the remedy suggestions based on a broader database of plant diseases and treatments.

Outputs:

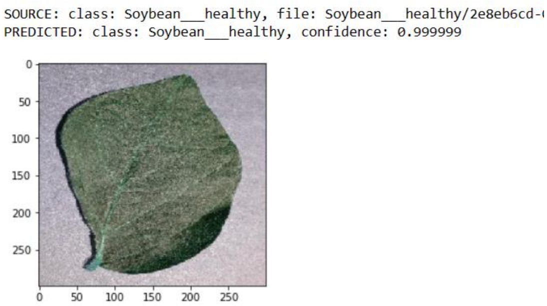

Figure 9: soyabean Healthy

Figure 10: Tomato Late blight

Fig:8,9 for single image plant predication Classification Accuracy

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Table 1: Single image plant prediction classification Accuracy

Plant Name	Predicted class	Classification Accuracy
Tomato	Tomato Late blight	0.987
Potato	Early blight	0.91
Soyabean	Soyabean Healthy	0.99

Table 2: Comparison of the Existing and Proposed Method

Module	Existing Classification Accuracy	Proposed Classification Accuracy
Vgg16	95.33%	98.42%
CNN	89.72%	92.6%
For inception v3	92.1 %	93.20%

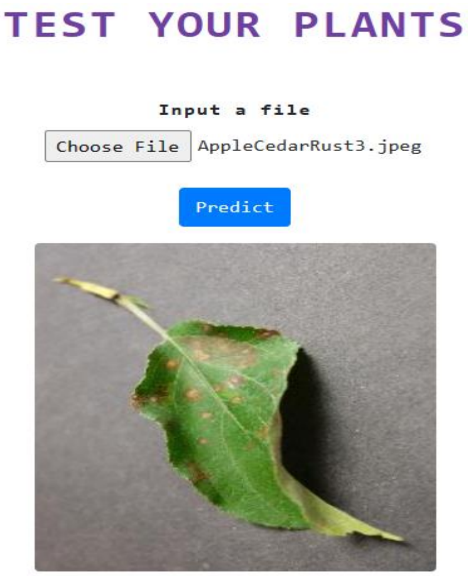

Figure 11: Apple cedar Rust

Result

Crop: Apple
Disease: Cedar Apple Rust

Cause of disease:

Cedar apple rust (Gymnosporangium juniperi-virginianae) is a fungal disease that depends on two species to spread and develop. It spends a portion of its two-year life cycle on Eastern red cedar (Juniperus virginiana). The pathogen’s spores develop in late fall on the juniper as a reddish brown gall on young branches of the trees.

How to prevent/cure the disease

1. Since the juniper galls are the source of the spores that infect the apple trees, cutting them is a sound strategy if there aren’t too many of them.
2. While the spores can travel for miles, most of the ones that could infect your tree are within a few hundred feet.
3. The best way to do this is to prune the branches about 4-6 inches below the galls.

Result shows Apple cedar Rust cause and Remedy of the Disease.

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Figure 12: Corn common Rust

Result

Crop: Corn(maize)
Disease: Common Rust

Cause of disease:

Common corn rust, caused by the fungus Puccinia sorghi, is the most frequently occurring of the two primary rust diseases of corn in the U.S., but it rarely causes significant yield losses in Ohio field (dent) corn. Occasionally field corn, particularly in the southern half of the state, does become severely affected when weather conditions favor the development and spread of rust fungus

How to prevent/cure the disease

1. Although rust is frequently found on corn in Ohio, very rarely has there been a need for fungicide applications. This is due to the fact that there are highly resistant field corn hybrids available and most possess some degree of resistance.
2. However, popcorn and sweet corn can be quite susceptible. In seasons where considerable rust is present on the lower leaves prior to silking and the weather is unseasonably cool and wet, an early fungicide application may be necessary for effective disease control. Numerous fungicides are available for rust control.

Result: Shows that corn common rust cause and remedy of the disease.

Output Graphs:

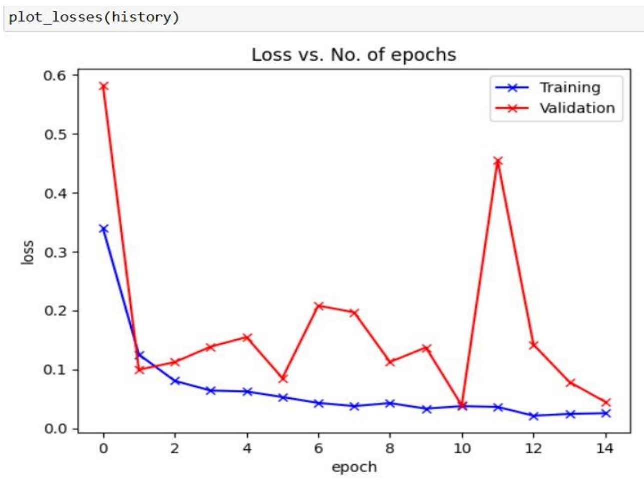

Figure 13: Training and validation loss history

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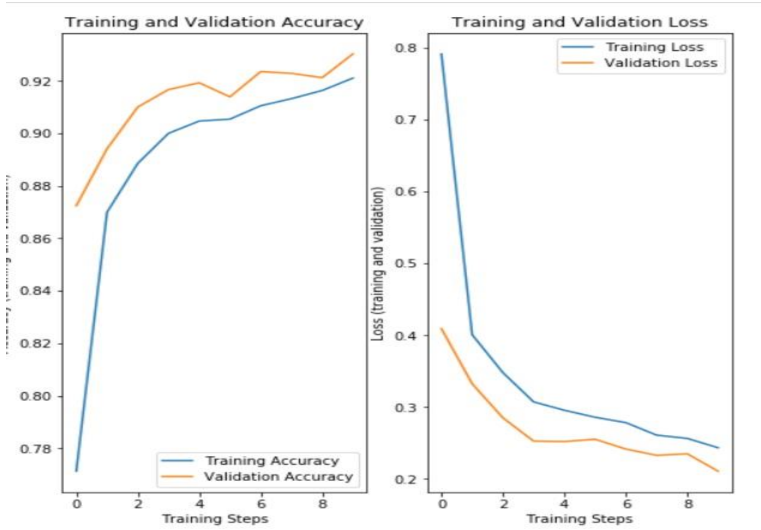

Figure 14: Training and validation Accuracy vs Loss graph

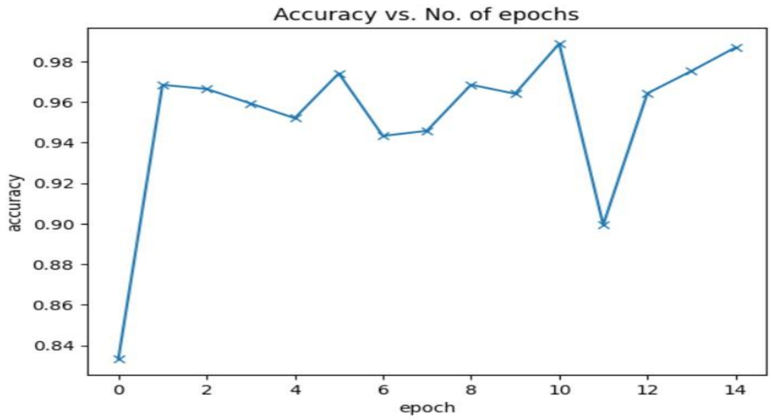

Figure 15: Accuracy graph

IV. CONCLUSION

Utilizing advanced deep learning models such as VGG16 and Inception V3 offers transformative potential in the field of agriculture, particularly for plant disease detection. Their demonstrated efficacy in distinguishing a range of plant ailments underscores their role in timely disease intervention. The decision to adopt either VGG16 or Inception V3 hinges on considerations like computational capabilities and desired accuracy levels. Nonetheless, it's crucial to recognize inherent challenges, including the consistency of datasets, varying environmental factors, and the elusive nature of model decision-making.

As the domain progresses, there's scope for refining these models, ensuring their broader and more impactful real-world application, ultimately driving agricultural sustainability. The present study accentuates the profound impact of transfer learning—leveraging pre-established CNN architectures—for heightened precision and efficiency in disease identification. By exploring two distinct transfer learning methodologies, shallow and deep, the research sheds light on their respective performance in retraining prominent CNNs, like Inceptionnet-v3 and VGG16. While both methods showcased impressive accuracy on testing data, the imperative nature of exactness in halting disease progression tilts the balance in favor of deep transfer learning. This is notwithstanding its extended training duration, as it outperforms in terms of accuracy and reduced training losses.

Significantly, VGG16's unmatched performance, when fine-tuned with deep transfer learning, earmarks it as an ideal choice for integration within agricultural robotic systems. The study's emphasis on region-specific datasets further underscores the potential for bespoke solutions tailored to individual regions, setting the stage for further exploration and advancement in this sphere.

REFERENCE

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.

[2] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture, 161, 272-279.

[3] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers in Industry, 114, 103140.

[4] Barbedo, J. G. A. (2018). A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems Engineering, 180, 96-111.

[5] Zhang, S., Huang, W., & Zhang, C. (2017). A novel approach to detect plant disease using deep convolutional neural network. In 2017 IEEE International Conference on Cyborg and Bionic Systems (CBS) (pp. 179-182). IEEE.

[6] Brahimi, M., Arsenovic, M., Laraba, S., Sladojevic, S., Boukhalfa, K., & Moussaoui, A. (2018). Deep learning for plant diseases: detection and saliency map visualisation. Human and Ecological Risk Assessment: An International Journal, 24(7), 1808-1824.

[7] Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. Proceedings of the National Academy of Sciences, 115(18), 4613-4618.

[8] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors, 17(9), 2022.

[9] Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Computers and Electronics in Agriculture, 154, 18-24.

[10] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computational intelligence and neuroscience, 2016.

[11] Raza, S. E. A., Prince, G., Clarkson, J. P., & Rajpoot, N. M. (2015). Automatic detection of diseased tomato plants using thermal and stereo visible light images. PloS one, 10(4), e0123262.

[12] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318.

[13] Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. Frontiers in plant science, 8, 1852.

[14] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90.

[15] Devi, M. P., Ganapathysubramanian, B., & Sarkar, S. (2020). Hyper-spectral band selection using deep learning: An application to early plant stress detection. Computers and Electronics in Agriculture, 168, 105143.

[16] Liu, B., Zhang, Y., He, D., & Li, Y. (2018). Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry, 10(1), 11.

[17] Boulent, J., Foucher, S., Théau, J., & St-Charles, P. L. (2019). Convolutional neural networks for the automatic identification of plant diseases. Frontiers in plant science, 10, 941.

[18] Yu, X., Wang, J., Kankanhalli, M. S., & Gou, J. (2018). Deep learning for plant identification in natural environment. Computational Intelligence and Neuroscience, 2018.

ISSN PRINT 2319 1775 Online 2320 7876
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[19] Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. Computational intelligence and neuroscience, 2017.

[20] Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases. Computers and Electronics in Agriculture, 72(1), 1-13.

[21] Jean, N. S., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). DeepSat–a learning framework for satellite imagery. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1407-1416).

[22] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).

[23] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[24] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[25] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

[26] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

[27] Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. IEEE Geoscience and Remote Sensing Letters, 14(5), 778-782.

[28] Hughes, D. P., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv preprint arXiv:1511.08060.

[29] Reyes, A. K., Caicedo, J. C., & Camargo, J. E. (2017). Fine-tuning deep convolutional networks for plant recognition. In 2017 36th International Conference of the Chilean Computer Science Society (SCCC) (pp. 1-8). IEEE.

[30] Dong, J., Xia, G. S., Chen, B., Feng, G., & Zhang, L. (2016). Subcategory-aware convolutional neural networks for object proposals and detection. In 2016 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1-10). IEEE.