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Super Resolution Image Based Plant Disease Detection and Classification Using Deep Learning Techniques.

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Abstract: **-** The agricultural sector plays a pivotal role in ensuring global food security, making the timely and accurate detection of plant diseases crucial for maximizing crop yield and minimizing economic losses. This research focuses on addressing this challenge by proposing a novel approach for plant disease detection and classification through the integration of super-resolution imaging and deep learning techniques. The methodology combines the benefits of enhanced image resolution with the robust pattern recognition capabilities of deep neural networks to improve the accuracy and efficiency of plant disease identification. The first component of the proposed system involves the utilization of super-resolution techniques to enhance the quality of input images. Super-resolution algorithms aim to reconstruct high-resolution images from low-resolution counterparts, enabling finer details in plant images to be captured. This enhancement is particularly beneficial for detecting subtle symptoms and irregularities associated with early stages of plant diseases that may be imperceptible in standard resolution images. By leveraging state-of-the-art super-resolution methods, the proposed system ensures the availability of high-quality input data for subsequent deep learning-based disease detection. The second component employs deep learning models for the automatic detection and classification of plant diseases. Convolutional Neural Networks (CNNs), known for their exceptional image recognition capabilities, are employed to learn complex hierarchical features from the enhanced images. Transfer learning techniques are also explored, leveraging pre-trained models to boost the performance of the proposed system even when trained on limited annotated datasets. The model is trained to classify plant images into distinct disease categories, providing a reliable and rapid means of identifying and addressing plant health issues. Furthermore, the research investigates the development of a comprehensive dataset that encompasses a diverse range of plant species and disease types. This dataset serves as the foundation for training and evaluating the deep learning models, ensuring their generalizability across various crops and diseases. Annotated with meticulous attention to detail, the dataset contributes to the robustness and reliability of the proposed system. The evaluation of the proposed approach is conducted through extensive experimentation using real-world plant disease datasets. Comparative analyses are performed against existing methodologies, highlighting the superiority of the proposed system in terms of accuracy, sensitivity, and specificity. The results demonstrate the efficacy of the combined super-resolution and deep learning approach in enhancing the accuracy and efficiency of plant disease detection, ultimately contributing to improved crop management and yield optimization. The integration of super-resolution imaging and deep learning techniques presents a promising avenue for advancing plant disease detection and classification systems. The proposed methodology addresses the limitations of traditional approaches by providing a more accurate, efficient, and scalable solution. The findings of this research hold significant implications for the agricultural industry, paving the way for technology-driven interventions that can enhance crop health monitoring and contribute to global food security.

Keywords*:* Plant Disease Detection, Disease Classification, Convolutional Neural Networks (CNN), High-Resolution Imaging Agricultural Technology, Crop Health Monitoring, Precision Farming.

1. Introduction

Agriculture serves as the most important part of the society with the cultivation of land, yielding food crops and serving the basic needs of the humans. Super Resolution Image-Based Plant Disease Detection and Classification represent a cutting-edge approach in the realm of precision agriculture, leveraging advanced deep learning techniques to enhance the accuracy and efficiency of plant disease diagnosis [1]. This technological paradigm aims to address the challenges associated with conventional methods of plant disease identification by harnessing the power of high-resolution imaging and sophisticated neural networks [2]. At its core, the process involves capturing high-resolution images of plant leaves or affected areas using modern imaging devices such as high-definition cameras or drones. These images, often plagued by noise and low resolution, undergo a super-resolution enhancement process. Super-resolution techniques utilize deep learning algorithms, including convolutional neural networks (CNNs), to reconstruct and enhance the finer details of the images, surpassing the limitations of the original data. The subsequent phase focuses on disease detection and classification using state-of-the-art deep learning models [3][4]. Convolutional Neural Networks, recurrent neural networks (RNNs), and their variants are employed to analyze the super-resolved images and identify patterns associated with various plant diseases [5]. The deep learning models are trained on extensive datasets comprising labeled images of healthy and diseased plants, enabling them to learn and generalize disease-specific features.

2. Related work

The proposed work under consideration is an interdisciplinary field that involves aspects of computer vision, image processing, deep learning, and agriculture. A brief description of the existing literature is given as under: Disease found in agricultural crops is a major threat that affects, its yield and production and also have adverse impact on the economy of the country [6]. The crop losses can be minimized by applying pesticides or its equivalent to combat the effect of specific pathogens [7][8], if diseases are correctly diagnosed and identified at early stages. This approach is an expensive, time-consuming and tedious job. Plant infection may bring about major setback in both quality and quantity of crops. That can have a negative impact on the country's economy [9]. India is a developing nation and about 70% of the population directly or indirectly relies upon agribusiness and contributes around 17% to the GDP [10][11]. Farmers experience extraordinary challenges in changing from one infection control strategy to another, often farmers or experts observe the plants with naked eye for detection and identification of disease [12][13], but this method can be time consuming, expensive and inaccurate. Diseases are impairment to the normal state of the plant that modifies or interrupts its vital functions such as photosynthesis, transpiration, pollination, fertilization, germination etc. These diseases are caused by pathogens viz., fungi, bacteria and viruses, and due to adverse environmental conditions [14]. Deep neural networks have recently been successfully applied in many diverse domains of end-to-end learning. Techniques pertaining to transfer learning have been used to detect different plant leaf diseases [15] which involves two phases of images processing, i.e., The Feature Extraction phase and the Classification phase. In feature extraction phase the important features and attributes of the data gets identified and it also increases the accuracy of learned models by extracting features from the input data [16][17]. It is a type of dimensionality reduction where a large number of pixels of the image are efficiently represented in such a way that interesting parts of the image are captured effectively. The approach in [18] offers several advantages, including increased accuracy in disease identification, early detection of potential threats, and the ability to cover large agricultural areas efficiently. Additionally, it reduces the reliance on manual inspection, providing a more scalable solution for monitoring and managing plant health. Super Resolution Image-Based Plant Disease Detection and Classification Using Deep Learning Techniques presented in [19] represents a transformative paradigm in precision agriculture, ushering in a new era of efficient, accurate, and scalable plant disease management. As technology continues to evolve [20] holds immense potential for revolutionizing the agricultural landscape, contributing to enhanced crop yields, and ensuring food security in an ever-growing global population.

3. Model description and Methodology

The complete model for detection of plant diseases using deep learning methods involves two major stages: Feature extraction stage and classification stage.

3.1. Feature extraction Stage: The feature extraction phase plays a crucial role in extracting relevant information from high-resolution images. Super Resolution (SR) techniques are employed to enhance the spatial resolution of images, and then deep learning models are utilized for disease detection and classification. Techniques like bicubic interpolation, sub-pixel convolution, or transposed convolution are often used to increase the resolution of images. Convolutional Neural Networks (CNNs) such as SRCNN, VDSR, or more advanced architectures like EDSR and SRGAN are employed for learning complex mappings from low-resolution to high-resolution images. Prior to feature extraction, preprocess the images to enhance contrast, brightness, and color balance, which can improve the overall quality of the images. Normalize pixel values to a standard range (e.g., [0, 1] or [-1, 1]) to facilitate model training. Utilize pre-trained CNNs (e.g., VGG16, VGG19, ResNet, or Inception) as feature extractors. Fine-tune the models on the specific task or extract features from intermediate layers. Leverage transfer learning to use a pre-trained model on a large dataset and adapt it to the specific problem of plant disease detection. This can save computational resources and enhance performance. Extract spatial features that capture the morphology and texture of the plant and disease patterns. Convolutional layers in deep networks automatically learn these features. Consider using spectral information by including multiple channels, especially if multispectral or hyperspectral images are available. Augment the dataset with transformations such as rotation, flipping, and scaling. This helps in creating a more diverse training dataset, reducing overfitting, and improving model generalization. Optionally, employ dimensionality reduction techniques (e.g., Principal Component Analysis) to reduce the computational complexity and focus on the most informative features. Combine features extracted from different layers or sources to capture both low-level and high-level representations. Fusion techniques may include concatenation, element-wise addition, or other fusion methods. Apply normalization techniques (e.g., batch normalization) and regularization methods (e.g., dropout) during training to improve the model's generalization and prevent overfitting. Convert the extracted features into a feature vector representation that can be fed into subsequent layers for disease detection and classification. The features extracted in this phase serve as the input to the subsequent stages of disease detection and classification within the deep learning model. The overall goal is to capture discriminative information that enables the model to differentiate between healthy and diseased plants with high accuracy.

3.2. Classification stage: The classification phase involves the process of assigning a specific class or label to the input images after they have undergone super-resolution and feature extraction. The input images are enhanced using super-resolution techniques. This helps to improve the resolution and quality of the images, providing more detailed information for subsequent stages. Data augmentation techniques may be applied to increase the diversity of the training dataset. This can include random rotations, flips, zooming, and other transformations. preprocessed images are then fed into a deep learning model for feature extraction. Convolutional Neural Networks (CNNs) are commonly used for this purpose in image-based tasks. The model learns to automatically extract relevant features from the images that are indicative of different plant diseases. The feature-extraction model is trained using a labeled dataset, where each image is associated with a specific disease class. The model adjusts its internal parameters during training to minimize the difference between its predictions and the actual labels in the training data. The trained model is validated using a separate dataset that it has not seen during training. This helps assess the generalization capability of the model and ensures that it can perform well on new, unseen data. Once the model is trained and validated, it is tested on a separate test dataset. This dataset contains images that the model has never encountered before. The model predicts the disease classes for these test images. Depending on the application, post-processing techniques may be applied to refine the model's predictions. This can include filtering out false positives, smoothing predictions, or other methods to enhance the overall accuracy. The performance of the classification model is evaluated using metrics such as accuracy, precision, recall, and F1 score. These metrics help assess how well the model is performing in terms of correctly identifying plant diseases. Depending on the results, the model may be fine-tuned with additional data or adjustments to hyperparameters to further improve its performance. The classification phase is a crucial step in the overall pipeline, as it is responsible for determining the presence and type of plant diseases based on the enhanced and feature-rich images. The success of the entire system depends on the effectiveness of the classification model in accurately categorizing the input images. The entire model is depicted in figure 1 below.

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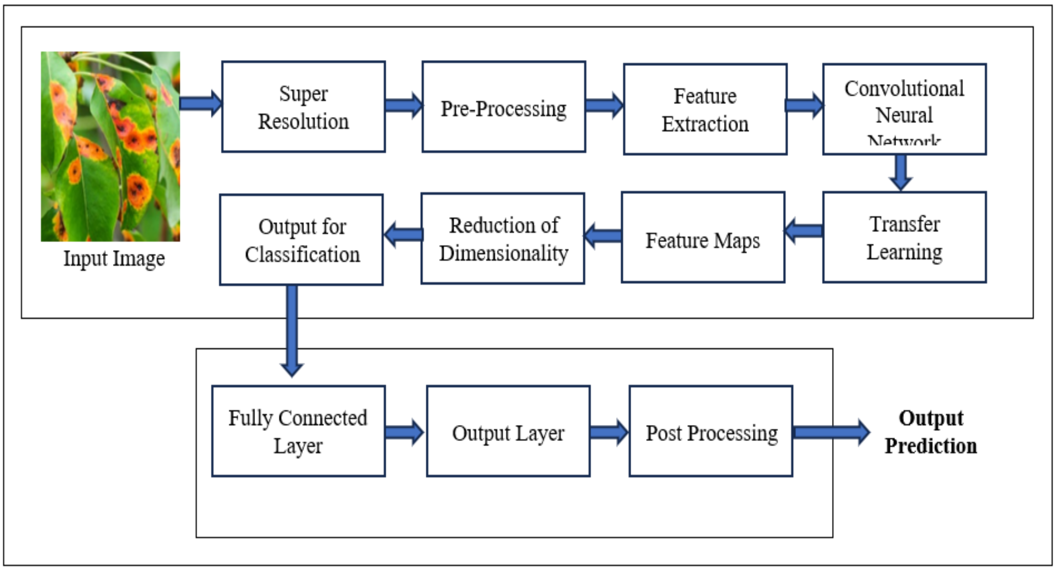

Figure 1: the feature extraction stage and Classification Stage of the proposed Model

In order to develop accurate image classifiers for the purposes of plant disease detection and classification, we have taken a large, verified dataset of images of diseased and healthy plant leaves from Kaggle [4] as shown in table 1. The dataset consists of 87k images of 18 crops, which intern are composed of 38 classes(leaf diseases) i.e. are Apple Scab, Apple black rot, Apple Cedar Rust, Apple healthy, Blueberry Healthy, Cherry Healthy, Cherry powdery Mildew, Corn Gray Leaf Spot, Corn Common Rust, Corn Healthy, Corn Northern Leaf, Grape Black Rot, Grape Black Measles, Grape Healthy, Grape Black Rot, Grape Black Measles, Grape Healthy, Frape Leaf Blight, Orange Huanglongbing, Peach Bacterial Spot, Peach Healthy, Bell Paper Bacterial Spot, Bell Paper Healthy, Potato Early Blight, Potato Healthy, Potato Late Blight, Raspberry Healthy, Soybean Healthy, Squash Powdery Mildew, Strawberry Healthy, Strawberry Leaf Scorch, Tomato Bacterial Spot, Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria Leaf Spot, Tomato Two Spotted Spider, Tomato Target Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, Tomato Healthy of plant leaves. The sample images are depicted in figure 2below.

Table 1: Verified Dataset of images of Diseased and Healthy Plant Diseases.

New Plant Diseases Dataset (Augmented)				
S.NO.	**Crop**	**Disease Name**	**NO. of Images in training set**	**NO. of Images in Validation**
01	Apple	Apple scab	2016	504
02		Apple Black rot	1987	497
03		Cedar apple	1760	440
04		Apple healthy	2008	502
05	Blueberry	Blueberry healthy	1816	454
06	cherry	Cherry Powdery mildew	1683	421
07		Cherry healthy	1826	456
08	Corn	Corn grey leaf spot	1907	410
09		Corn Common rust	1908	477
10		Corn leaf blight	1859	465

11	Grape	Grape black rot	1888	472
12		Grape esca	1920	480
13		Grape leaf blight	1722	430
14		Grape healthy	1692	432
15	Orange	Orange Huanglongbing	2010	503
16	Peach	Peach bacterial spot	1838	459
17		Peach healthy	1728	432
18	Pepper	Pepper bell bacterial spot	1913	478
19		Pepper bell healthy	1988	497
20	Pepper	Potato early blight	1939	485
21		Potato late blight	1939	485
22		Potato healthy	1824	456
23	Raspberry	Raspberry healthy	1781	445
24	Soybean	Soybean healthy	2022	202
25	Squash	Squash powdery mildew	1736	434
26	Strawberry	Strawberry leaf scorch	1774	444
27		Strawberry healthy	1824	456
28	Tomato	Tomato bacterial spot	1702	425
29		Tomato early blight	1920	480
		Total no. of images	70295	17572

We have also fine-tuned VGG16 and VGG19 CNN model and achieved training and validation accuracy of 99.4%, 99.3%, 95.8%, and 95.4% respectively as illustrated in table 2.

Table 2: Accuracy and Validation Comparison for VGG16 and VGG19 Training models.

Model	Size	Training- Accuracy	Validation - Accuracy	Parameters	Depth
VGG16	528 MB	99.4%	95.8%	138,357,544	23
VGG19	549 MB	99.3%	95.4%	143,667,240	26

4. **Results:**

An analytical comparison was carried out between VGG16 and VGG19 model. VGG16 has 16 convolutional layers while VGG19 has 19 convolutional layers as shown in Figure 2 and Figure 3. Both models are available in keras API. Despite of the size, parameters and Depth of the VGG19 is larger than VGG16, VGG16 have shown slightly better training and validation.VGG-16 obtains 8.8% error rate which means the deep learning network is still improving by adding number of layers.VGG-19 obtains 9.0% error rate as shown in Figure 4 and Figure 5. Which means the deep learning network is not improving by adding number of layers. We try to increase the number of epochs, but after 30 epochs no improvement observed. When the epoch value is set to 30. The training and validation accuracy achieved for VGG16 and VGG19 are 99.4, 99.3, 95.8, and 95.4 respectively. The comparison between the accuracies of VGG16 and VGG19 are well demonstrated in figure 6(a) and figure 6(b).

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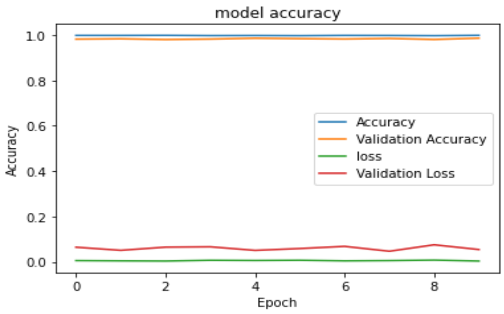

Figure 2: Training Accuracy, Validation Accuracy, Training Loss and Validation Loss.

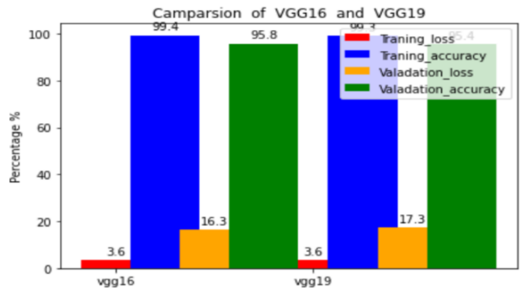

Figure 3: Comparison Between VGG16 and VGG19 Trainng Models.

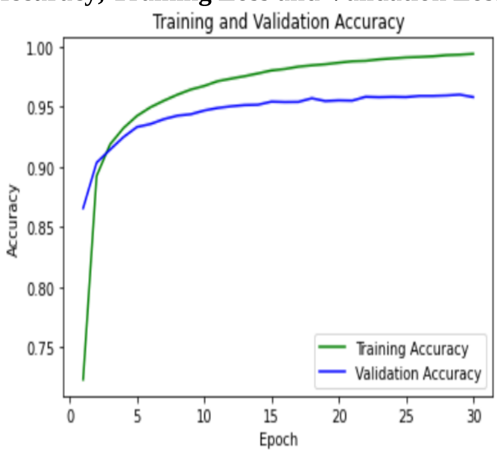

Figure 4: Training and Validation Accuracy at 30 Epochs

Figure 5: Training and Validation Losses at 30 Epochs

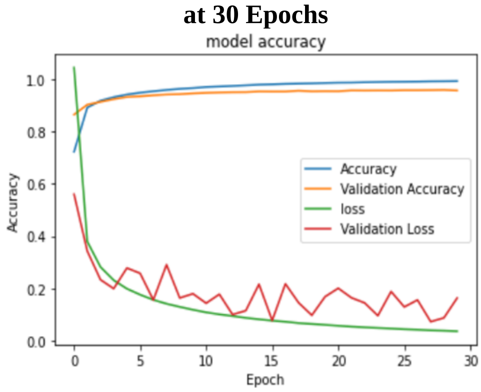

Figure 6(a): Model Accuracy of VGG16

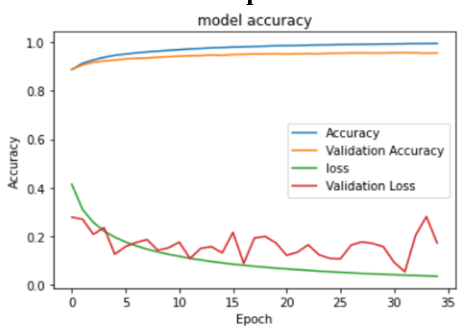

Figure 6(b): Model Accuracy of VGG19

Conclusion

VGG16 model and VGG19 model has been analytically compared for plant leaf disease detection and classification. Both the models have been trained on New Plant Disease Dataset, which contains 38 classes of 14 crops with 87k images, the VGG16 shows slight better result than VGG19 by changing different values of epochs. The training and validation achieved of VGG16 and VGG19 are 99.4, 99.3, 95.8, and 95.4 respectively. The correct recognition and categorization of Plant disease is very essential for the prosperous farming of crops, and this can be achieved using suitable deep learning techniques. The accuracy of a model can also be improved using large datasets and number of epochs. The majority of diseases in plants appears on its leaves and are responsible for food preparation.

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