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Plant Disease Detection From Images Using Deep Learning Techniques based on the Internet Of Things

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ABSTRACT- Plant disease identification and evaluation in a timely and accurate manner is crucial for efficient farming operations for crop yield optimization. Employing the most recent advances in technology, specifically the combination of deep learning and the Internet of Things (IoT), this paper offers an efficient approach to identifying plant diseases. We propose a transfer learning-based deep learning classification model which makes use of pre-trained models including CNN, AlexNet, ResNet, InceptionV3, and VGG-16. To provide wider accessibility, high-resolution images of tomato plant leaves displaying disease symptoms are gathered from a dataset and saved in cloud storage using Internet of Things devices. Following the image extraction from the cloud, images are preprocessed using data argumentation, normalization, color space conversion, background removal, and noise removal. Different plant disease classes are classified using the pre-trained models CNN, AlexNet, ResNet, InceptionV3, and VGG-16. The deep learning models' accuracy is increased using the transfer learning technique, which also cuts down on the workout duration. The VGG-16 model outperforms other models in the experiment, recognizing plant illnesses with an astounding accuracy of 93.7% on average, proving the efficacy of the suggested approach. This novel method has the potential to transform the identification of plant diseases and support sustainable farming methods.

Keywords: Agricultural IoT, Deep Learning, Machine Vision, Crop Health, Disease Prediction, Image Classification, Pre-trained Models.

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1. INTRODUCTION

In modern agriculture, the ability to identify diseases in tomato leaves is essential for both early intervention and minimizing crop losses. Visual inspection is a useful method for identifying diseases in tomato plants since they can develop a variety of diseases, such as blights, wilts, and fungal infections, which show up as unique visual signs on their leaves. Deep learning and machine learning techniques have become effective tools for automating the detection process in recent years [1]. There are various ways to go about this endeavor. First, an image dataset containing tagged images of both healthy and diseased tomato leaves can be used to train machine learning techniques like decision trees and support vector machines (SVMs) [2]. Through the extraction of relevant data from the photos, such as color, texture, and shape, these models are trained to differentiate between different diseases. Conversely, deep learning methods—in particular, convolutional neural networks, or CNNs—are excellent at identifying complex patterns in images and can be trained to recognize certain symptoms of diseases.

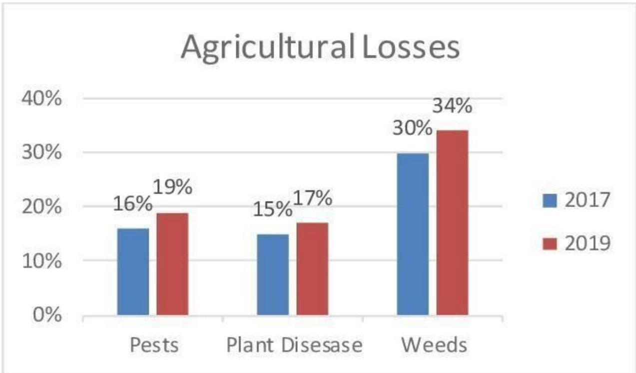

Figure 1 Agricultural Losses

Their ability to distinguish between healthy and damaged leaves across various disease types has demonstrated impressive success. These techniques use complex algorithms to analyze multiple visual properties, including color, texture, and form, to distinguish between healthy and infected leaves. Models are trained using datasets that contain images of both diseased and healthy leaves. Conventional Neural Networks (CNN) are used in this paper's model creation because of their advantages when working with images, particularly when it comes to image classification and producing better outcomes.

Figure 1 Agricultural Losses illustrates their possible application in treating plant diseases, which are a significant cause of agricultural losses. The diagram shows that, even with a minor decline in 2019, weeds and pests are still major contributors to losses caused by plant diseases. With its ability to train image-based models on large datasets of both healthy and diseased plant leaves, deep learning presents a promising solution [3]. Then, by analyzing fresh images, these models can potentially lessen the losses observed in the "Plant Diseases" category by detecting disease early and enabling targeted treatment. Deep learning can also be applied to large-scale disease monitoring and analysis, which can help reduce overall loss and inform preventative measures. A more comprehensive diagram that demonstrates the relationship between plant disease detection and deep learning could incorporate images, accuracy metrics, and a simplified workflow that Outlines the steps involved.

Thus, we present a deep learning-based transfer learning method with an integrated IoT approach to identify plant diseases from leaf images. Using this technique, farmers can upload photos of their plants' leaves via a network connection or gather them directly in the field. The images are then safely saved in cloud storage. To predict diseases, a data analysis component retrieves these images from the cloud. To predict different plant diseases, we use deep learning models in conjunction with transfer learning. This method minimizes the amount of data and the time needed for model testing and training. To predict plant diseases, pre-trained models such as CNN, AlexNet, ResNet, InceptionV3, and VGG-16 are modified and improved. Findings are saved on cloud servers and can be accessed by researchers, farmers, and agricultural specialists for planning mitigation and diagnosis.

Key contributions of this proposed method:

(i) Applying transfer learning for efficiency: Pre-trained models reduce data requirements and speed up model development.
(ii) Deep learning for accurate diagnosis: These models offer high accuracy in identifying specific plant diseases.
(iii) Enhancing the effectiveness of the model by integrating IOT with the prediction model.

2. RELATED WORKS

Various deep-learning models and techniques have been discussed in this section. Several researches about deep learning models detecting diseases in plants have been done, and few of them have been discussed here. Tomato is a widely fruit grown in India. Diseases affect their growth and decrease their production in the market. In recent years Artificial Early disease detection in a variety of crops has been made possible in large part by artificial intelligence and machine learning.

The authors of this research [4] used convolution neural networks to classify and detect diseases. This CNN model consists of eight layers: two fully connected layers, three max-pooling layers, and three convolutional layers. Nine distinct categories of illnesses have been classified by the authors. In the course of this study, 7000 images in all were examined. The accuracy ranged from 76% to 100% depending on the kind of illness. In this study, an average accuracy of 91.2% was reached. To campare performance, the same researchers also conducted tests using various pre-trained models. For VGG16, the accuracy was 77.2%; for Mobilenet, it was 63.75%; and for Inception, it was 63.4%.

In paper [5], a variation of CNN has been called LeNet to detect and classify diseases in tomato leaves. They used 18160 images belonging to 10 different classes. In this experiment, researchers have resized every image to 60 X 60 resolution to speed up the training process. LeNet is a variation in the classic CNN model which consists of convolutional, activation, pooling, and fully connected layers. They have also added additional layers to the original LeNet architecture. The accuracy achieved in this experiment was 94%. The researchers in paper [6] have used 4 architectures of CNN to detect the leaf diseases. LeNet (2 convolutional layers), VGG16(13 convolutional layers), ResNet50, and Xception(36 convolutional layers). The researchers have used 14,903 images which belong to 9 different classes. Adding these many layers to their architecture is a complex task. As you add more convolutional layers, the overall complexity of these models increases.

Use of Random Forest Classification algorithm to classify the healthy and diseased images[22]. The Histogram of an Oriented Gradient (HOG) is used for feature extraction. A feature descriptor employed in computer vision and image processing for the recognition of objects is the Histogram of oriented gradients or HOG. The accuracy was 70.4%. Random Forest model accuracy was slightly better compared to other classification machine learning models. The author also used three-component descriptors – Hu moments, Haralick texture, and Color Histogram. Hu moments extract shape, Haralick texture extract texture, and Color Histogram represents the color distribution in an image.

In comparison to conventional machine learning models, the use of Deep Learning models for plant disease detection and classification has demonstrated improved accuracy. A comprehensive review of the Deep Learning models used for detecting plant diseases is provided by the authors in their publication [23]. All of the deep learning models from 2012 to 2018 have their parameters, salient characteristics, and pros and cons mentioned. A breakdown of all the models' performance measures during these years is given.

A method based on the Convolutional Neural Network (CNN) and Learning Vector Quantization (LVQ) algorithms was presented in [24]. A neural network that incorporates competitive learning with supervised learning is called Learning Vector Quantization. The average accuracy that the researchers were able to achieve was 86%. There was a total of five distinct classifications utilized. One for healthy leaves and four for leaf diseases.

3. PROPOSED METHOD

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The Images from the datasets are uploaded from the cloud. Those images are preprocessed using data argumentation, normalization, color space conversion, background removal, and noise removal are performed. Then the images are classified using deep learning models such as CNN, AlexNet, ResNet, inceptionNet, and VGG net. Fig2 shows the proposed method.

These models are already pretrained models and used for classification of tomato leaf diseases. Theses method is also uploaded in the cloud for wider usage. It classifies the leaf as normal, leaf late blight, Tomato mold leaf , Yellow virus leaf

3.1 . Data Pre-processing

In this section, we proposed a Data Pre-processing architecture

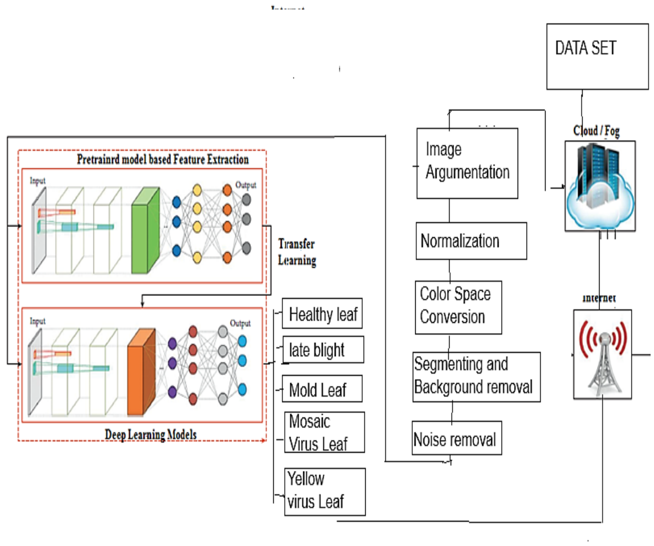

Figure 2 Proposed model

For the Plant disease detection model, we use Deep learning models which are particularly good at extracting complex patterns from image data, making them well-suited for plant disease detection. However, to fully utilize raw images, we require careful preprocessing to unlock their full potential. Here's an in-depth look at some important methods:

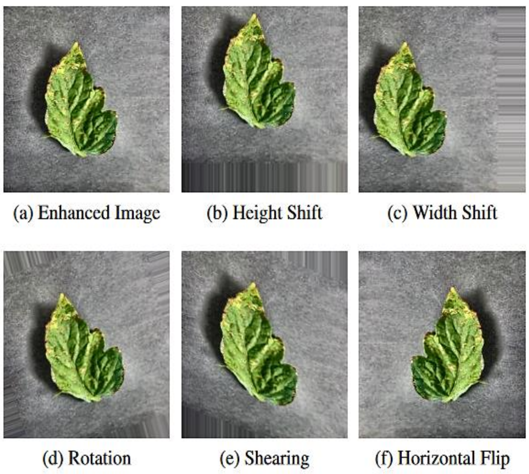

Figure 3: Augmented tomato Leaves

Image Augmentation: A common problem in deep learning is data scarcity. Augmentation artificially enlarges the dataset with diverse variations of existing images, enhancing model generalizability and preventing overfitting. Techniques like Rotation, flip, scaling, cropping, color jittering, noise addition, and elastic deformations are common methods [7] applied to given dataset leafs. For the proposed method, argumentation such as Enhanced image, height, width shift, rotation , shearing and horizontal flips are applied. *Figure 3* shows the augmented leaves.

Data Normalization: Standardised input values are frequently assumed by deep learning algorithms. By scaling pixel intensities to a standard range (such as 0–1 or mean–standard deviation), normalization promotes convergence and increases training stability [8]. The dataset images are normalized for further processing.

Color Space Conversion: Certain features specific to a disease can be emphasized by converting RGB images to other color spaces. HSV highlights saturation and hue, which helps identify illnesses based on color. CIELAB is a color perception tool that helps identify subtle symptoms [9]. We used CIELAB is a color perception tool that helps identify subtle symptoms [9]. *Figure 4* shows enhanced images.

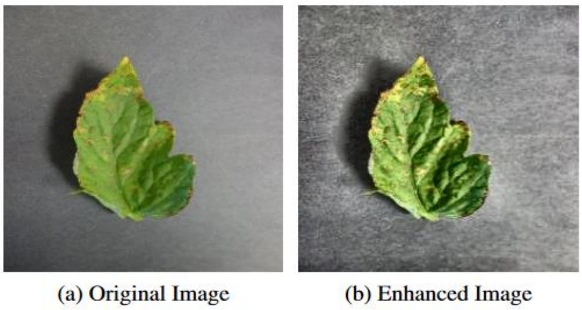

Figure 4. Enhanced Image

Segmentation and Background Removal: Plant diseases rarely affect the entire image. Isolating the relevant region (i.e., leaf) through techniques like thresholding, level sets, or deep learning- based segmentation methods improves disease detection accuracy by focusing on the affected area [10].Hence segmentation using thresholding method is performed on the given dataset images.

Noise Reduction and Filtering: Confusion in Deep learning models can arise from noise introduced during acquisition or transmission. Techniques like Gaussian filtering, median filtering, and bilateral filtering smoothen images while preserving edges crucial for disease identification [11]. In the proposed method, we applied gaussian filtering to remove noises.

Transfer Learning: Transfer Learning: Apply learned models to huge ImageNet, such as VGG16 or ResNet. datasets to leverage pre-learned features and accelerate training, especially with limited data [12]. In the proposed method we have applied 5 pretrained network and compared their results.By carefully

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selecting and applying these data preprocessing techniques, we can prepare our image data for optimal performance in deep learning-based plant disease detection models. Experimentation and evaluation are key to finding the best approach for our specific needs.

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3.2 . Transfer Learning based Deep Learning Models

In this section, we proposed five transfer learning models

Convolution Neural Network (CNN):

Deep learning neural network architectures such as convolutional networks are utilized primarily in the field of recognizing patterns in images [14]. A prime instance of an artificial neural network is CNN. Three layers comprise a traditional artificial neural network (ANN): input, hidden, and output. Convolutional, non-linearity, pooling, and fully-connected layers make up the layers of a CNN that resembles this [13]. A great deal of tasks requiring image-driven pattern recognition are handled by CNNs. Natural language processing (NLP), computer vision, and image classification are a few additional applications for CNN [13]. *Figure 5* shows the architecture of CNN.

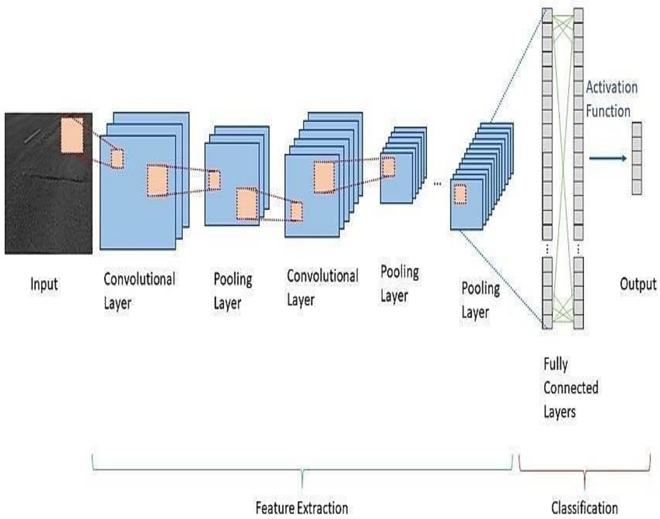

Figure 5. CNN architecture

ResNET

In the proposed method, ResNet employs skip connections, which function as informational "magic highways," to counteract vanishing gradients. These shortcuts guarantee that important visual cues about healthy and diseased plant tissues reach the diagnosis station (final layers), unlike regular roads (convolutional layers) where details can be lost [15]. Consider the analysis of leaf images. While regular models may find it difficult to retain subtle color changes that are layered deeply, ResNet's shortcuts allow it to learn intricate disease patterns while retaining essential fundamental information. Because of this, ResNet is an effective tool for detecting plant diseases early and accurately, which could save crops and livelihoods [16]. *Figure 6* shows the architecture of ResNet.

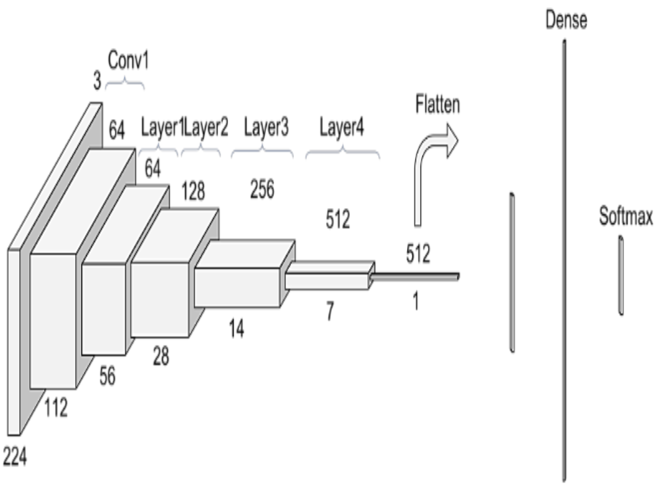

Figure 6. ResNet Architecture

Alexnet:

The science of computer vision was greatly enhanced by the groundbreaking convolutional neural network (CNN) architecture known as AlexNet, which was first introduced in 2012. The network, which was created by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, was essential to deep learning's success in image recognition applications. Eight layers made up the architecture: three fully connected layers, five convolutional layers, and a softmax activation for classification at the top[17].One unique feature of AlexNet was that its activation functions were rectified linear units (ReLU). ReLU made it possible to solve the vanishing gradient issue, which sped up training convergence. By normalizing the responses of nearby neurons, local response normalization (LRN), which was incorporated into the first two convolutional layers, improved the network's capacity for generalization. *Figure 7* shows the architecture of AlexNet.

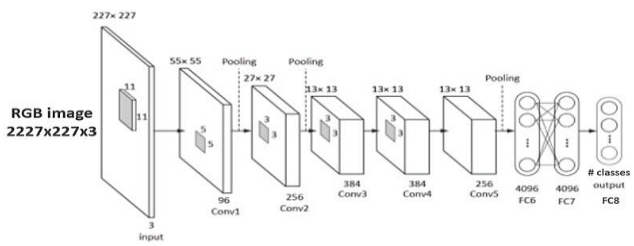

Figure 7. AlexNet Architecture

VGG-16:

In the proposed methodology, VGG-16, known for its deep architecture, utilizes a sequential arrangement of convolutional layers followed by max-pooling layers, culminating in fully connected layers. This structured design enables the model to capture intricate features of plant images, essential for accurate

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disease detection[18]. Unlike some traditional models, VGG-16's approach enhances feature learning, ensuring that subtle color changes indicative of plant diseases are effectively retained during the training process. With its well-defined architecture, VGG-16 stands as a robust tool for early and accurate plant disease detection, contributing significantly to crop preservation and agricultural sustainability.

Inception-V3:

In the proposed method, Inception V3, developed by Google, stands out for its intricate design, incorporating inception modules that capture multi-scale features within images. The Inception module proposed by Inception Neural Network uses different sizes of filters and maximum pooling to reduce the dimension of the data [19]. This architecture has demonstrated outstanding ability in the early and precise identification of a variety of diseases, demonstrating that it is extremely successful in the domain of detecting plant diseases. Better optimisation methods, lower computing costs, a deeper network of neural networks, and increased efficiency are all features of Inception V3. 20]. The utilization of Inception advanced feature extraction capabilities enhances its ability to discern subtle visual cues, contributing to precise disease diagnosis. Its robustness lies in the diverse set of features captured by the inception modules, facilitating the extraction of both global and local information from leaf images. Studies use the versatility and robustness of Inception V3, positioning it as a pivotal tool in advancing the field of plant disease detection and precision agriculture. *Figure 8* shows the architecture of Inception V3.

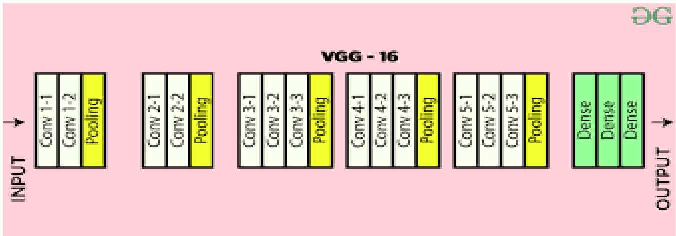

Figure 8. Inception V3 Architecture

Transfer Learning: Transfer Learning: Utilize pre-trained models like CNN, AlexNet, ResNet, InceptionV3, and VGG-16. on large ImageNet datasets to leverage pre-learned features and accelerate training, especially with limited data [12].In the proposed method we have applied these 5 pretrained network and compared their results for plant disease prediction.

4. EXPERIMENTAL RESULT

We utilized the Plant Disease Image Dataset [21], which comprises images of various plant diseases and healthy plants. The dataset consists of three classes: Diseased Plants (Tomato leaf late blight, Tomato mold leaf, Tomato leaf mosaic virus, Tomato leaf yellow virus, Tomato leaf bacterial spot,), Healthy Plants (Tomato leaf) . Initially, the dataset contained 1000 images of diseased plants, 1500 images of healthy plants, and in subsequent releases, the dataset was expanded to include 3000 images of diseased plants, 5000 images of healthy plants, and 1000 images of other anomalies. All images were standardized to a resolution of 256x256 pixels. During the training phase, 90% of the dataset was used for training the deep learning model, while the remaining 10% was reserved for testing. Additionally, validation was performed on the training dataset using a 10% validation split. Cross- validation with k=5 using stratified k-fold was employed to ensure robust model evaluation. *Figure 9* shows the tomato leaves from dataset. *Figure 10* shows sample output leaves.

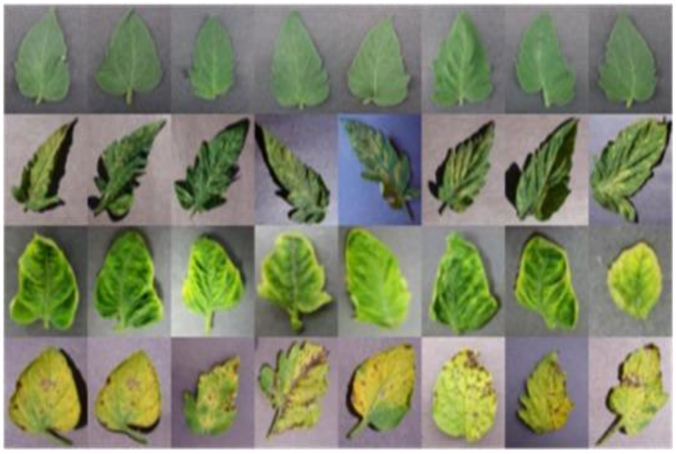

Figure 9. Different types of Tomato leaves

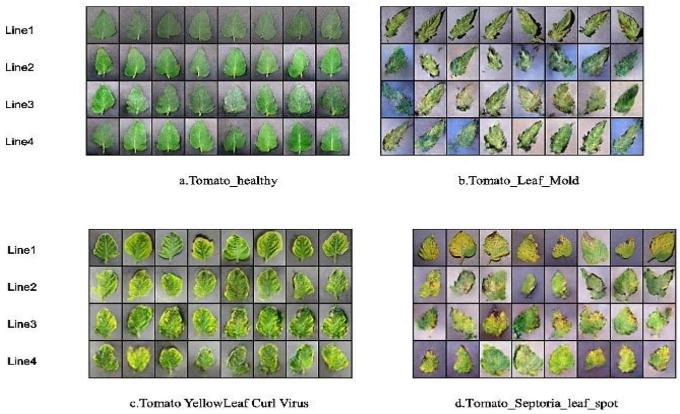

Figure 10 . Sample output of diseased tomato leaf

4.1 Performance Metrics:

The performance of the proposed plant disease detection model was evaluated using the following metrics.

(i) Accuracy: This statistic, which is computed as the ratio of correctly categorized samples to the total number of samples, assesses the overall correctness of the model's predictions.

$$Accuracy = \frac{TruePos + TrueNeg}{TruePos + TrueNeg + FalsePos + FalseNeg}$$

(ii)Sensitivity (True Positive Rate): Sensitivity measures the model's capacity to accurately identify unhealthy plants among all real instances of disease.

$$Sensitivity = \frac{TruePos}{TruePos + FalseNeg}$$

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(iii) Specificity (True Negative Rate): Specificity measures the model's ability to correctly identify healthy plants among all actual healthy instances.

$$Specificity = \frac{TrueNeg}{TrueNeg + FalsePos}$$

By evaluating these metrics, we can assess the effectiveness and performance of the deep learning model in accurately detecting plant diseases and distinguishing them from healthy plants and anomalies. *Table1*, *table 2*, *table 3*, *table 4* . *Table 5* shows the comparison of five used models for healthy tomato leaf, Tomato leaf late blight , Tomato mold leaf, Tomato leaf mosaic virus and Tomato leaf yellow virus.

Table 1: Comparison of Different Models for Healthy tomato leafs

Models	Accuracy	Sensitivity	Specificity
CNN	0.865	0.822	0.893
AlexNet	0.876	0.841	0.912
ResNet	0.898	0.876	0.921
Inception V3	0.915	0.892	0.928
VGG-16	0.931	0.907	0.947

Table 2: Comparison of Different Models for Plant Disease - Tomato leaf late blight

Models	Accuracy	Sensitivity	Specificity
CNN	0.872	0.909	0.888
AlexNet	0.899	0.928	0.905
ResNet	0.915	0.934	0.917
Inception V3	0.927	0.945	0.931
VGG-16	0.942	0.956	0.947

Table 3: Comparison of Different Models for Plant Disease –Tomato mold leaf

Models	Accuracy	Sensitivity	Specificity
CNN	0.856	0.818	0.879
AlexNet	0.879	0.832	0.918
ResNet	0.904	0.892	0.926
Inception V3	0.921	0.908	0.934
VGG-16	0.935	0.921	0.946

Table 4: Comparison of Different Models for Plant Disease –Tomato leaf mosaic virus

Models	Accuracy	Sensitivity	Specificity
CNN	0.879	0.906	0.890
AlexNet	0.900	0.926	0.908
ResNet	0.916	0.938	0.919
Inception V3	0.928	0.947	0.933
VGG-16	0.942	0.958	0.948

Table 5: Comparison of Different Models for Plant Disease –Tomato leaf yellow virus

Models	Accuracy	Sensitivity	Specificity
CNN	0.863	0.817	0.887
AlexNet	0.883	0.830	0.920
ResNet	0.907	0.897	0.928
Inception V3	0.922	0.921	0.935
VGG-16	0.937	0.923	0.948

5. DISCUSSIONS

According to the experimental investigation, the VGG-16 outperforms the other approaches in terms of results. The VGG model's superior capacity of obtaining higher level characteristics from images makes it better. Higher precision results from this. As the amount of levels with small kernels increased, non-linearity also grew, which is a positive trend in deep learning. However, the high level of computation and vast number of parameters associated with VGG16 represent a drawback.

6. CONCLUSION

In this study, we applied transfer learning-based deep learning models with the integration of IoT for predicting various plant diseases. The deep learning models used include VGG-16, Inception V3, AlexNet, ResNet, and CNN. Utilizing pre-trained data from these models has significantly enhanced the accuracy and efficiency of the system while reducing the prediction time for plant disease detection using transfer learning. Integration of Medical IoT with deep learning has facilitated quick and accurate prediction of plant diseases. Among all the models, VGG-16 demonstrated the highest accuracy of 94.2% for plant disease prediction, 93.5% for anomalous plant detection, and 92.1% for healthy plant identification.

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