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A Comparative Analysis of Convolutional Neural Networkbased Transfer Learning Models for Plant Disease Detection

T. Seshu Chakravarthy[1], Assistant Professor, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh.

Induri Deepthi[2], **Kodavala Bhavya**[3], **Kornepati Divya Rani**[4], **Inturi Sri Sai Kalyan**[5]
[2,3,4,5] UG Students, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh.
E-Mail ID: tschakravarthy@vvit.net[1],deepthiinduri@gmail.com[2], kodavalabhavya938@gmail.com[3], kornepatidivyarani@gmail.com[4],kalyanchowdary951@gmail.com[5]

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Abstract

Agriculture holds a significant role in the economy of many countries by providing food security, employment opportunities, and contributing to the overall economic growth of the nation. However, the spread of plant diseases can pose a significant threat to crop production and result in reduced yields, food scarcity, and ecological imbalances. The current manual process of diagnosing plant diseases is not only time-consuming but also prone to errors, relying heavily on the expertise of pathologists. To tackle this challenge, this paper presents a user-friendly and accessible machine learning-based plant disease detection system that uses Convolutional Neural Network (CNN) based transfer-learning models to detect and categorize plants as either healthy or diseased and provides information on the precautions for the identified disease. By comparing the performance of three cutting-edge CNN architectures, VGG16, ResNet50, and EfficientNetV2S, on publicly available plant disease dataset, this paper aims to determine a model for detecting and classifying various plant diseases. We found that ResNet50 achieves the highest accuracy of 96.5%. This proposed system can enable timely and accurate disease detection, helping farmers take preventive measures and reducing the risk of crop loss.

Keywords: Plant Disease, CNN, VGG16, ResNet50, EfficientNetV2S, Machine Learning.

Introduction

Plant diseases pose a significant challenge to the agriculture industry globally and have a huge impact on crop productivity. Timely detection of these diseases is crucial for farmers to take preventive measures and mitigate the risk of significant crop losses. Traditional approaches to disease detection, such as laboratory tests and contacting crop specialists, are often time-consuming, expensive, and not always accurate. In this paper, we suggested

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a plant disease detection system that leverages the power of Convolutional Neural Networks (CNNs) to provide real-time disease identification based on images uploaded by farmers.
CNNs are frequently used in image and video identification tasks. CNNs are designed in a way to automatically learn and extract features from images through multiple layers of filters and use these features to classify and recognize objects within the images. CNNs have become a popular approach for a wide range of computer vision tasks, including image segmentation, object detection, and more recently, plant disease detection.

By training the CNN model on a large dataset of plant disease images, the system can accurately identify the type of disease and suggest an appropriate preventive measure. The system is designed to have a low computational load, enabling it to be implemented on real-time devices such as smart phones with simple applications. It is cost-effective, time-saving, and provides accurate results, making it suitable for real-time use.

Moreover, this technology can reduce the negative impact of widespread pesticide use on the environment and human health. Farmers can reduce the use of harmful chemicals by accurately identifying plant diseases, allowing them to take preventive measures before resorting to pesticides and promoting sustainability in the agriculture sector while protecting the environment. We evaluated the performance of our proposed system using several metrics and compared them with existing approaches. The results show that our proposed system provides accurate and efficient identification of plant diseases, enabling farmers to take preventive measures in a timely manner before significant crop losses occur.

In this paper, we considered the Plant-Village dataset with images of 26 different types of plant diseases across various crops, including apple, blueberry, corn, cherry, grape, orange, potato, pepper bell, peach, raspberry, strawberry, soybean, squash, and tomato. The dataset includes images of diseases caused by viruses, fungi, and bacteria. Some of the diseases included in the dataset are Apple Scab, Black Rot, Powdery Mildew, Bacterial Spot, Early Blight, Late Blight, Powdery Mildew, Leaf Scorch etc,.

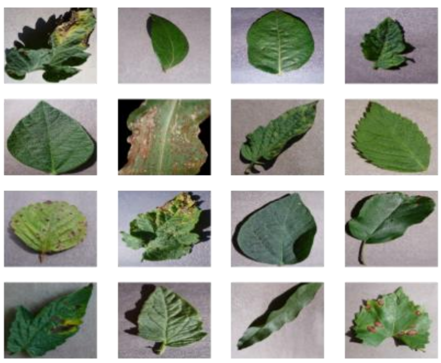

Fig.1. Plant Leaf Images

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Literature Survey

In the past, several machine learning techniques were used for early plant disease identification, which were often found to be difficult and time-consuming. However, with the latest advancements in Convolutional neural networks (CNN), the accuracy of image classification and segmentation has significantly improved. As a result, CNN has emerged as a powerful tool in various fields, including natural language processing, video analysis, and image recognition.

This paper presents a Deep Learning model aimed at detecting and classifying various diseases affecting plant leaves, using the "Plant-Village" dataset. The proposed model utilizes a CNN architecture to differentiate between different types of plant leaf diseases, achieving an accuracy rate of 96.5%.[1]

In this paper, the authors developed a CNN model by using AlexNet architecture for feature extraction and classification along with Stochastic Gradient Descent (SGD) algorithm. The dataset achieved a high accuracy rate of over 96.50%. [2]

This paper focuses on training a CNN model to classify three plant species, potato, tomato, and pepper bell.In this paper ReLU and SoftMax activation functions were used.The study found that the model attained an average accuracy of 87%. [3]

In this paper, the authors compared the results of the proposed model with other existing models and techniques such as traditional image processing methods, Support Vector Machines and Random Forest algorithms. The outcome showed that the proposed ConvNet model outperformed these methods in terms of both accuracy and speed. [4]

In this paper, the authors proposed a CNN model to detect the diseased plants with the help of image processing using OpenCV. The data was divided into 60% training and 40% validation with a batch size of 32, and the number of epochs as 30. It attained an accuracy of 94.87%. [5]

In this paper, the authors utilized a DL approach to accomplish automatic plant disease detection, based on a simple classification component that leverages the feature extraction capabilities of ResNet. This deep learning architecture displayed an accuracy of 96.63%. [6] [7-15]

Problem Identification

Traditional methods of identifying plant diseases through expert analysis are limited by their susceptibility to environmental and human factors. Furthermore, existing algorithms for processing and classifying images have poor flexibility when dealing with large data sets, making them unsuitable for automatic disease monitoring and processing. Mobile applications that do exist for plant disease identification lack the ability to recommend effective precautions and pesticide treatments that are safe for plants and fruits. Additionally, current plant disease detection systems are limited in their scope, focusing on

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only a few specific crops and their diseases, making it difficult to apply their results to a broader range of plant species. Accurately distinguishing between plant diseases with similar symptoms is also a significant challenge.

To overcome these limitations, we propose anML model that utilizes a broad collection of leaf samples from different crops to train our algorithms. This approach will provide us with the necessary data to accurately distinguish between different types of plant diseases, including those with similar symptoms. By incorporating effective precautions and pesticides, treatments that are safe for plants and fruits, our model will be able to recommend appropriate remedies for specific diseases. Our proposed model aims to provide a method that is more flexible and efficient for identifying and treating plant diseases.

Methodology

Step 1: The first step involves collecting image data from the "Plant-Village" dataset.

Step 2: Next, the data undergoes pre-processing to ensure its suitability for training the CNN transfer-learning models. Pre-processing activities involve image rescaling, reshaping and conversion to an array format. After pre-processing, pertinent features such as colour, texture, and shape are extracted from the images. These features are used to train the model to identify the presence of plant diseases.

Step 3: The dataset is split into training set(80%) and testing set(20%). The training dataset is used to optimize the model's parameters. Subsequently, the testing dataset is utilized to evaluate the accuracy of the model's predictions.

Step4: The training dataset serves as the input to Convolutional Neural Network models, and the model weights are modified to enable accurate disease recognition. A comparative analysis of the ResNet50, EfficientNetV2S, and VGG16 models is conducted to determine the best-performing model.

Step 5: Based on the performance metrics, best transfer learning model is chosen for the plant disease detection system.

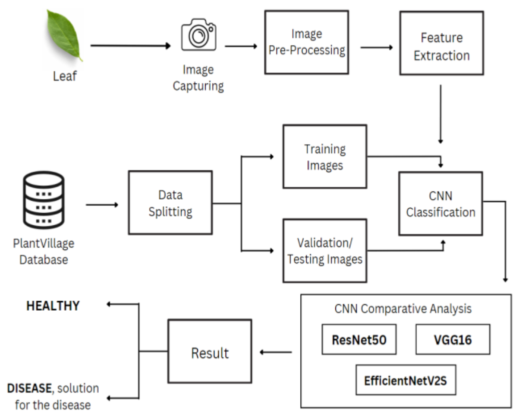

Fig.2. Proposed Methodology

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A. ResNet50

ResNet50 is a deep CNN architecture that belongs to the ResNet(Residual Network) family of models. The architecture is designed to overcome the problem of vanishing gradient, which occurs when the network becomes very deep, by adding skip connections to the network that allow it to learn residual functions.

ResNet50 consists of 50 layers, with the first layers performing simple operations such as convolution and pooling. The later layers perform more complex operations and skip connections are added between the blocks, allowing the network to learn residual functions.

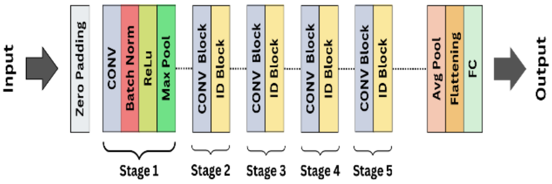

Fig.3. ResNet50 Architecture

The input to the network is generally an image of size 224x224x3 (RGB channels), and the final layer is a global average pooling layer, which is subsequently by a fully connected layer and SoftMax activation function.

B. VGG16

VGG16 is a deep CNN architecture. It stands for Visual Geometry Group 16. It is composed of 16 layers, where the first 13 layers perform convolution and pooling operations, while the final three layers are fully connected layers. For image classification tasks, the input to the network is usually an image with dimensions of (224x224x3), which is processed by several convolutional layers with kernel size of 3x3 and a stride of 1. This result is fed into max-pooling layers that employ a window size of 2x2 and a stride of 2.

VGG16 architecture comprises 3 fully connected layers as its last layers, with 4096, 4096 & 1000 neurons, respectively. Rectified Linear Unit (ReLU) activation is used in the first two fully connected layers, while SoftMax activation is used in the final layer.

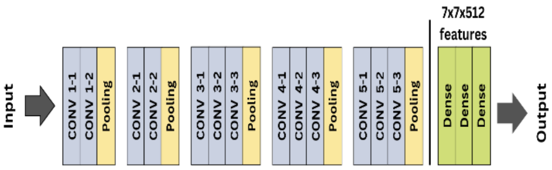

Fig.4. VGG16 Architecture

VGG16 is known for its uniformity, with all the convolutional layers using 3x3 filter size and 1-pixel padding. Although VGG16 has a significant number of parameters, resulting in computational and memory challenges, it remains a popular and widely used architecture in the computer vision community.

C. EfficientNetV2S

EfficientNetV2S is an advanced neural network architecture that leverages compound scaling to achieve superior performance and greater computational efficiency compared to the original EfficientNetV2 models. Trained on large-scale image datasets, such as ImageNet, the model demonstrates excellent generalization to new, unseen images, making it a promising candidate for real-world computer vision applications. The EfficientNetV2S model comprises 21 layers and is designed to be computationally efficient while also maintaining high accuracy on various computer vision tasks.

The model applies a series of convolutional layers with varying kernel sizes and strides to an input image of size (224x224x3). Additionally, SE blocks are incorporated to learn the importance of different channels in feature maps. The last layer of the model consists of a global average pooling layer, followed by a fully-connected layer and SoftMax activation function. Notably, the EfficientNetV2S model achieves superior performance with fewer parameters and lower computational resources compared to other models. Through the use of compound scaling, the EfficientNetV2S model optimizes performance by leveraging depth, width, and resolution.

Implementation

A. Data Collection:

Plant-Village Dataset was used in this study. This dataset includes 54,303 images of both healthy and diseased plant leaves. The dataset includes images of 14 different crop species with 38 categories further classified into 26 different types of diseases. The dataset is unprocessed, so it needs to be preprocessed before being used in the model.

B. Data Pre-processing:

Data Pre-processing transforms raw data into format suitable for model training. We loadlibraries such as NumPy, Pandas, Matplotlib, TensorFlow, and Keras. Next, the dataset is partitioned into training set(80%) and testing set (20%) to optimize the parameters of models and evaluate the accuracy of its predictions, respectively. The training dataset is then augmented using *ImageDataGenerator*, which applies various transformations like shear, zoom, and flip to increase the dataset's diversity. This process helps increase the dataset's size and introduce slight distortions, reducing overfitting during the training phase. It is then resized to the input size of the network. Finally, the dataset is normalized to determine its mean and standard deviation. This normalization process is then applied to every image in the dataset.

C. Model Building:

We conducted a comparative analysis of three Machine Learning models, namely ResNet50, EfficientNetV2S, &VGG16, to determine their effectiveness in feature extraction process and classification tasks on an image dataset. These are then evaluated based on the models' performance using various metrics, including accuracy, precision, recall, F1-score, and training time, to identify the best fit.

D. Feature Extraction:

The VGG16 model is set as non-trainable, with only the dense layer added to be trained. There are 26 nodes in the dense layer. The model is compiled with Adam optimizer, which is a popular optimization algorithm that combines the advantages of gradient descent with momentum and RMSprop. The model is trained for 20 epochs, with a batch size of 256, a learning rate of 0.001, and an image size of 224x224.

In ResNet50 model, the output of the base model is passed through a global average pooling layer to obtain a fixed-length feature vector, which is then fed into three dense layers with ReLU activation functions to gradually reduce the dimensionality. The model is trained for 30 epochs with a batch size of 32 and an image size of 224x224. The number of steps per epoch is set to 200.

In EfficientNetV2S model, the base model is loaded with pre-trained weights from the ImageNet dataset, and made non-trainable. The new model is constructed with an input shape of (224, 224, 3), and the input is pre-processed. The output of the base model is passed through a global average pooling layer to obtain a fixed-length feature vector, which is then fed into three dense layers with ReLU activation function. The model is trained for 30 epochs with a batch size of 32, and an image size of 224x224 with steps per epoch set to 200.

The final dense layer employs a SoftMax activation function to generate class probabilities. To prevent overfitting, the *EarlyStopping, ModelCheckpoint,* and *ReduceLROnPlateau* callbacks are used during training.

E. Classification:

Upon completion of the training process, the model is capable of classifying unlabeled images of plants. When an image is provided as input to the model, it compares the features extracted from the image with those of training and testing images and generates the output in the form of the plant name along with the disease name. The model determines the plant and disease name from the output by identifying the class with the highest probability.

Results

This study highlights the significance of plant disease recognition in current times. The classification performance of VGG16, ResNet50, and EfficientNetV2S were evaluated in this study.

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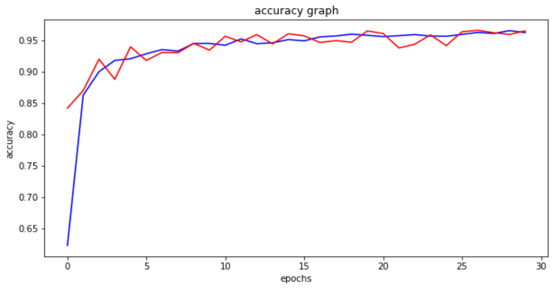
Table.1. Results This table concludes ResNet50 is efficient

Architecture	Training Acc.	Validation Acc.	Testing Acc.
VGG16	92.41%	91.49%	91.78%
ResNet50	96.59%	96.30%	96.49%
EfficientNetV2S	96.06%	95.53%	95.84%

ResNet50 achieved the highest training accuracy of 96.59%, followed by EfficientNetV2S with 96.06%, and VGG16 with 92.41%. These findings indicate that all three architectures are capable of achieving high accuracyin both training and validation phases of plant disease detection, with ResNet50 performing the best among the evaluated models.ResNet50's superior performance in both training and validation phases can be attributed to its advanced architecture, which allows for more efficient feature extraction and classification.



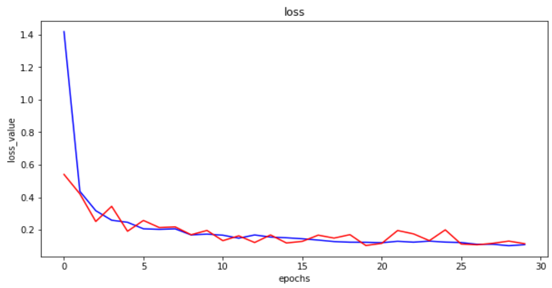


Fig.5. Accuracy graph ofResNet50 model Fig.6. Loss graph of ResNet50 model

Flask web application framework

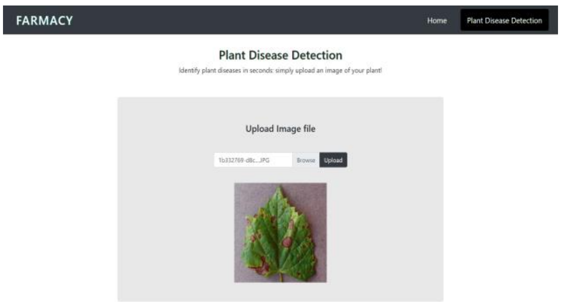


Fig.7. Image Uploading Page

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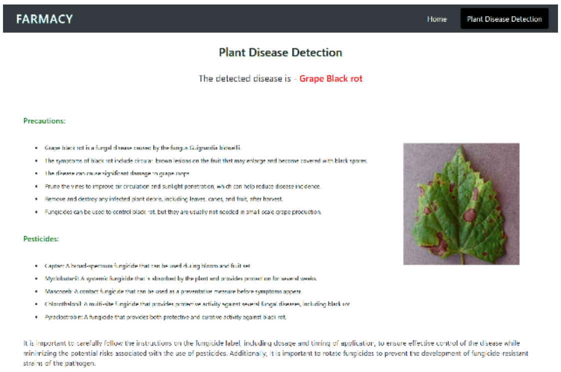

Fig.8. Output Page

Conclusion

Agriculture is a crucial sector in the economy, and this paper highlights the need to use modern technologies and come up with new solutions to identify crop diseases and help farmers. This study shows that the ResNet50 model had higher accuracy in detecting plant diseases than the EfficientNetV2S and VGG16 models. This model can help detect crop diseases early on, which can help farmers stop the spread of diseases and increase their crop production. By using this system, farmers can make farming more efficient and sustainable while reducing the negative impact of widespread pesticide use.

Future Scope

In the future, this research can be furthered by integrating the model with real-time disease detection systems and exploring different learning rates to improve accuracy and efficiency. Additionally, the integration of IoT devices on large-scale farms can enhance the system's effectiveness by providing real-time data and timely alerts.

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