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3A Comparative Study of Pre-trained Transfer Learning Models in Convolutional Neural Networks for the Prediction of Diseases in Plant Leaves

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ABSTRACT

Pest infestation is the biggest problem crops confront, reducing yield and food quality. Automatic plant disease detection technology is crucial to agricultural operations because it encourages productive growth and increased yields. Neural networks (NN) are frequently employed in learning approaches to manage imaging applications. The study is to evaluate and recommend a prediction model for leaf diseases employing Convolutional Neural Networks(CNN) pre-trained Transfer Learning Models. The pre-trained transfer learning models in Deep Learning (DL) are utilized in this study to predict the leaf diseases in plants. CNN's pre-trained models, including ResNet50, VGG16 and EfficientNet are used to categorize and predict damaged plant leaves. Jupyter Notebook, a Python-based software environment, is utilized for implementation. The Plant Village dataset was created with the intention of providing effective methods for the identification of 39 distinct plant diseases. It contains 61,486 images of landscapes and foliage from plants. This collection includes plant ailments caused by bacteria, fungus, and other causes.The model's experimental outcomes demonstrate that the efficiency of CNN models and the results findings shows that the EfficientNet outperforms the ResNet50 and VGG16 in predicting the plant leaf diseases. The study explores and examines the effectiveness of using several sophisticated CNN's to improve the accuracy of leaf disease detection.

INTRODUCTION

The two largest industries today are agriculture and the food business, owing to the world's growing population and growing need for food to sustain life. Plant diseases can harm leaves at any point throughout growth and harvest, drastically lowering crop production and cost. Disease has become one of the biggest problems facing agriculture, especially with paddy leaves where it slowly lowers yield and deteriorates rice health. Different image processing and soft computing technologies mitigate the problem in the agriculture sector, yet sometimes the disease's elimination remains a barrier[1].

Diseased plants typically have visible lesions or marks on their branches, leaves, fruits, and flowers. In general, each and every disease scenario has a unique visual patterning that helps identify problems. Plant leaf surfaces serve as the primary diagnostic tool since most disease symptoms may initially manifest on them [2]. Identification of leaf diseases is therefore crucial in the agricultural sector. But it requires a large workforce, more processing time, and in-depth knowledge of plant diseases. Using an automated method is definitely advantageous because manual disease diagnosis requires a significant amount of time and labor. Conventional methods are widely applied, but their accuracy, speed, and scalability may be restricted. Therefore, the efficacy and precision of plant disease detection may be improved by combining conventional techniques with cutting-edge technology like artificial intelligence and image recognition [3].

Machine Learning (ML)/Deep Learning (DL) is a subfield of Artificial intelligence that focuses on creating algorithms and mathematical models that allow systems to recognize patterns and make predictions or inferences without a requirement for specialized programming. The primary goal is to create systems that can automatically increase efficiency when they are exposed to data or experience. Figure 1 depicts the flow of the ML/DL process.

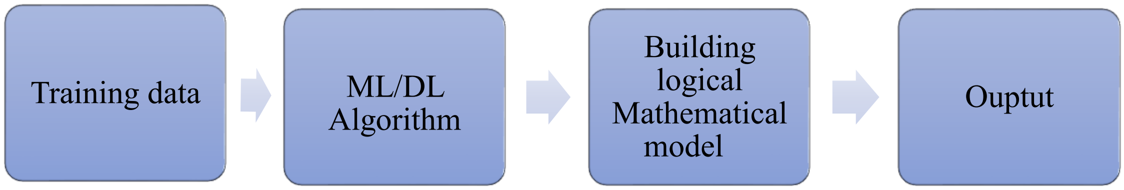

Figure 1: Block Diagram for ML/DL prediction system

The study of plant diseases has benefited greatly from the developments in deep learning (DL) technology in recent years. The ability to communicate original image characteristics and have end-to-end characteristics is made possible by the automatic extraction of image features on plant diseases, which eliminates the need for labor-intensive feature extraction and classifier design in traditional image recognition methods. Due to these characteristics, DL technology in plant disease detection has attracted a lot of attention and is now a well-liked research topic DL's models consist of networked nodes, or neurons, known as NNs, which process and interpret incoming data before producing forecasts. The input layer collects data, the output layer generates predictions or classifications, and the hidden layers process information to build a neural network. Activation functions are used by NN nodes to produce nonlinearities, which allow the network to absorb complex relationships in the input. When training deep learning models, backpropagation is employed. In order to reduce the difference between the actual and expected results, the model anticipates errors and uses the data to modify the model's parameters [4].

In recent years, several methods for classifying diseases of plant leaves have been studied and applied. Neural networks, such as CNN, appear to be the most successful approach for diagnosing plant illnesses, though, because of its flexibility and feature extraction capability, which allows them to dynamically gather characteristics.

The study described in [5] uses efficient net and densenet deep neural networks (DNNs) to identify plant pathology disorders in apple leaves. In order to extract and combine attributes, DNN models were used in this work instead of sophisticated filtering techniques. However, data augmentation is required to obtain high accuracy and avoid overfitting. DNN models such as EfficientNet and DenseNet can detect leaf diseases well even with limited training data. Concatenating features and uniformly scaling models to reuse features reduce parameters while maintaining 99.8% and 99.75% accuracy, respectively. Three common diseases that damage banana leaves are depicted in the large image collection known as the Banana Leaf Spot Diseases (BananaLSD) dataset, which was described in [6]. These diseases include Sigatoka, Cordana, and Pestalotiopsis. The BananaSqueezeNet model was developed using the data. The 937 images of banana leaves that were captured in banana fields were supplemented with 1600 additional images to form the BananaLSD dataset.

An Efficient Channel Attention Network (ECA-Net) is suggested in [7], drawing its foundation from ResNet50 and DenseNet201. It has trustworthy transfer learning techniques. This combination improves illness diagnosis accuracy while simultaneously increasing efficiency compared to previous approaches. The hybrid technique delivers a remarkable 99.54% training success rate with a validation accuracy of 98.67% when it comes to accurately recognizing diseases. Table 1 lists the various DL models especially pre-trained models in the detection of leaf diseases.

Table :1 Leaf disease detection methods and it performance

S.No	Authors, year	Methods used	Performance
1	H.Amin et.al 2022[8]	(CNNs), EfficientNetB0, and DenseNet121 for feature Extraction Data augmentation -to add variety in the number of images Compared with REsNet15 and Inception V3	Accuracy-98.56% ResNet 152-98.37% Inception V3-96.27%
2	Rajeena et.al, 2023[9]	Otsu thresholding, EfficientNet CNN , Transfer Learning Compared with VGG and Resnet. Dataset: PlantVillage and PlantDoc databases	Accuracy=98.85% Precision= 88%
3	Li et.al 2023[10]	Multi-scale and attention modules -Feature Extraction ACGAN model -Data Augmentation method. Compared with , ResNet50, DCDenseNetNasNetMobile DenseNet121 and MobileNetV2	DenseNet121 -98.84%
4	Demilie et.al, 2024[11]	Generative Adversarial Networks (GANs), CNN, Transfer learning using InceptionV3	GAN techniques improved the accuracy of diagnosis and recall rate of CNNs.
5	wani et.al, 2024 [12]	pre-trained AlexNet, GoogleNet, Resnet18 and VGG16 networks	Accuracy - 97.25%
6	Liu et.al, 2024[13]	Pre-trained CNN models	Accuracy - 66.8%
7	Banarase et.al (2024)[14]	AlexNet, DenseNet121, ResNet-50, and MobileNetV2	Accuracy - 99.36%.

8	Nasoor et al. (2024)[15]	lightweight DL methods mobileNetv2, mobileNetv3-small, shuffleNetv2, and squeezeNet.	Accuracy:97.12% , Precision-97.14%, Recall:97.1% F1-Score: 97.12%
9	Rai et.al 2024[16]	Bagging Ensemble Method Tranfer Learning models- MobileNet,InceptionV3, VGGG16, InceptionResNetV2 and Xception.	Accuracy: 99.48% Sensitivity: 99%
10	Nobel et.al. 2024[17]	Channel Attention Network (ECA-Net) transfer learning algorithms ResNet50 and DenseNet201	Accuracy: 98.67%

The review of the literature indicates that CNN model classification is used by most plant leaf recognition systems. In two of the studies, image enhancement techniques are used to construct the fake datasets. Nonetheless, the literature assessment indicates that almost all plant leaf samples were considered in one or more studies.

The popularity of CNN recently and its effectiveness in resolving many agricultural issues are the driving forces behind this study. Additionally, there are now ongoing research studies that use CNN to tackle a range of agricultural issues. Because of its success, CNN is presently thought to be the most popular and often used methodology in agricultural research

The major contributions of the paper includes the following

1. To give an outline of recent developments using DL models for plant disease identification and classification.
2. To demonstrate how plant disease detection and classification accuracy can be increased through the use of various transfer learning approaches with CNN techniques.
3. To determine an efficient pre-trained transfer learning models in CNN for reliably predicting plant diseases

3. Methodology

The study uses three pre-trained transfer learning models with CNN for the prediction of plant leaf diseases and to increase the accuracy of the models it uses RMSprop optimizer .The Deep learning based leaf disease prediction is divided into three phases as follows.

- Data preparation
- Building, Training, and Assessing the Model
- Interpretation and Deployment

Step 1 : Data Preparation

Transforming unprocessed data into a format that our models can be trained and tested in is part of the crucial preprocessing and preparation stage. This stage aims to normalize and preprocess the data, remove null and trash values, and increase the accuracy and performance of ML models. The data preparation stage is where a DL is first implemented. It consists of processes for preparation, data augmentation, and data acquisition. Data is required for DL models irrespective of the flaws in the models, if the input data is of low quality, the outcomes will be inaccurate... The original dataset, which was utilized for testing, validation, and training, included common percentages of 70:20:10, 80:10:10, and 60:20:20.

Step2: Building, Training, and Evaluating the Model

Model Training is the process of giving labeled data (input features and associated target values) to the algorithm created in order for it to gain insight into the underlying patterns and correlations in the data.

Model Evaluation: After training, it's critical to evaluate the manner in which the model performs on new data. Evaluation metrics allow us to assess accuracy, precision, recall, and other factors.

A suitable DL model architecture is chosen . Faster classification times and more accurate classification results can be obtained with an effective model design. After building the model architecture, various hyperparameters are chosen for the training and evaluation processes. It may generate several parameter combinations and cycle through them using the grid search technique to identify the optimal one.

Step 3: Inference and Deployment

The process of taking an ML model from its construction stage to its practical application in real-world circumstances is called model deployment, or inference. To put it simply, it entails granting end users or other systems in a production environment access to the trained model's predictive capabilities. DL architecture has the capacity to swiftly apply its learned model's learning skills to fresh data and outputs the right solution based on data it has never seen before is known as inference.

3.1 Pre-trained transfer Learning Models

a)EfficientNet

EfficientNet uses a technique called the compound coefficient to scale up models in a simple yet effective manner. Instead of raising width, depth, or resolution at random, compound scaling uses a preset set of scaling factors to balance each dimension. The idea behind the compound scaling strategy is to balance the width, depth, and resolution characteristics by scaling with a constant ratio. The following equations illustrate the mathematical process.

$$Dept\ d = \alpha^{\emptyset}, Widt\ w = \beta^{\emptyset}\ ,\ Resolution\ r = \gamma^{\emptyset}, (1)$$

(1)

Such that $\alpha.\beta^2.\gamma^2 \approx 2 \quad \alpha \geq 1, \beta \geq 1, \gamma \geq 1$, where the values of α, β, γ are determined using a grid search algorithm. ∅ determines ∅ determines an increase in the network's computational resources. The user defines this parameter and the factor indicating that $\alpha.\beta^2.\gamma^2$ is near to 2 binds them together. A convolution operation's FLOPS (Floating point operations per second) is proportional to d, w^2, r^2 , meaning that it will double as the network depth doubles. If the network width or resolution doubles, the FLOPS will still increase four times. CNNs' convolutional processes control the computing costs. Scaling the network using the above equation will increase the FLOPS by $(\alpha.\beta^2.\gamma^2)^{\emptyset}$. Since $\alpha.\beta^2.\gamma^2$ is approximately 2, so every new ∅ , the total FLOPS increase by $2^{\emptyset}$.

A tiny grid search with ∅ set to 1 yields values for α, β, and γ, assuming twice as many resources are available. For ∅ = 1, α is 1.2, β is 1.1, and γ is 1.15, maintaining $.\beta^2.\gamma^2 \approx 2$. Next, the models EffcientNet B1 through B7 are created by scaling up the baseline network with different values ∅. After that, the values of α, β, and γ are set. To achieve even higher performance, look for values of α, β, and γ. However, the cost of the search seems to be much higher at the larger moel. Therefore, to overcome this issue, the search is restarted from scratch using a small network. The networks are based on the theory that larger input images need more channels to capture finer-grained patterns on the larger image and more layers to increase the receptive field.

a) ResNet50

A distinct set of residual blocks is present in each of the five blocks that make up ResNet-50[18], which consists of fifty layers. It allows the network to generate representations of the input data by allowing the retention of data from previous levels. Convolution is applied to the input image by the network's top layer, the convolutional layer. A max-pooling layer is then used to down-sample the convolutional layer's output. The output of the max-pooling layer is further processed using a number of additional blocks. Two convolutional layers, a batch normalization layer, and a rectified linear unit (ReLU) activation function comprise each residual block. The network's last, fully connected layer maps the output of the final residual block to the output categories. In the completely linked layer, the total number of neurons is equal to the number of output classes. To train networks, fewer than 30 epochs were used. The learning rate was set at 0.001.

b) VGG16

The CNN-based Visual Geometry Group (VGG) model was used to increase the precision of sick leaf detection. The input of VGG is a 224 x 244 RGB picture. Prior to being input into the VGG convolution network, each image in the training set has its mean RGB value determined. The convolution step is fixed, and either a 3x3 or 1x1 filter is used. The total number of convolution and fully connected layers determines the range of the three VGG entirely linked layers, which can be VGG11 to VGG19. Furthermore, the VGG network comprises five pooling layers dispersed throughout numerous convolutional levels, but none beneath any one of the convolutional layers [19].

4. Findings and Discussions

4.1 Dataset Description

The Plant Village dataset was created with the intention of providing effective methods for the identification of 39 distinct plant diseases. It contains 61,486 images of landscapes and foliage from plants. This collection includes plant ailments caused by bacteria, fungus, and other causes. Because leaves are crucial to a farmer's capacity to recognize plant diseases early in the growing season, images of plant leaves are used to detect plant diseases. The same criterion is used to choose the leaves dataset. The plants listed below are utilized in the application of the information obtained from the Plant Village dataset: To refine the gathered data, preprocessing methods like rotation, flipping, zooming, and color adjustments are applied. In this study, 70% of the training data and and 30% testing data is used to predict plant diseases [21]. The sample healthy and diseased leaves were shown in figure 2.

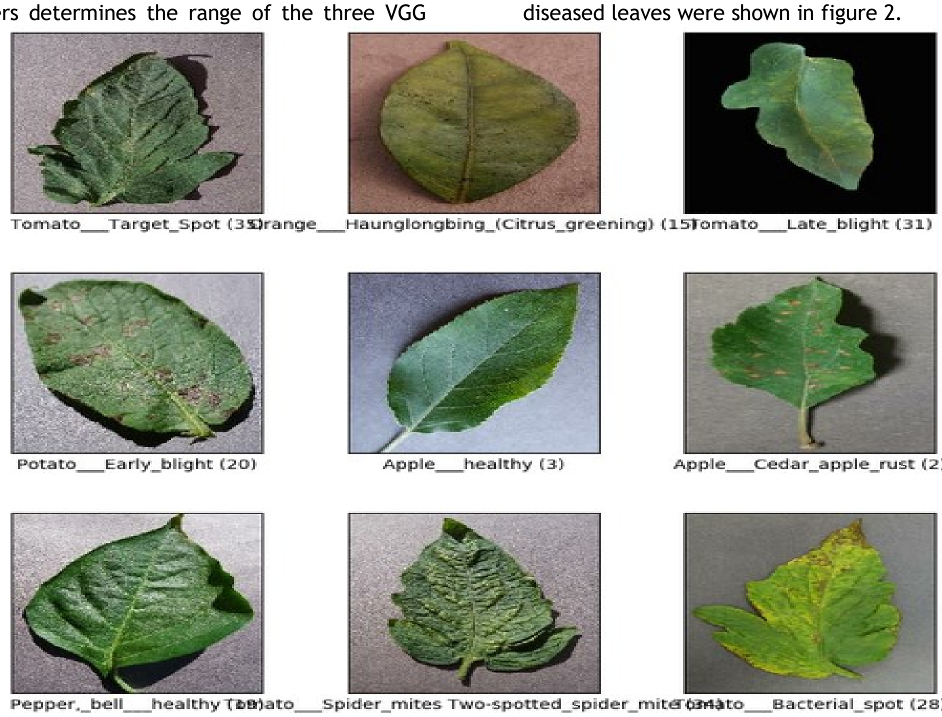

Figure 2: Sample Healthy and damaged leaves
(Image Courtesy https://www.tensorflow.org/datasets/catalog/plant_village:

The study considered only 3 different types of plant leaves including pepper, potato and Apple and the training and testing were conducted and the efficiency of the prediction is estimated with the metrics in the next section.

4.2 Performance Metrics

Performance criteria such as accuracy, precision, recall, and F1-Score were used to further evaluate the model's efficacy [22].

(i) Accuracy

One common performance indicator used in classification challenges is accuracy. The percentage of correctly identified cases relative to all items in the dataset is known as accuracy. Divide the total number of predictions the model made by the number of correct forecasts to arrive at the measure.

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \quad (2)$$

(ii) Precision

The ratio of accurately predicted positive observations to the total number of expected positives is known as precision or positive predictive value.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

(iii) Recall (Sensitivity, True Positive Rate)

The ratio of accurately predicted positive observations to all observations made during the actual class is known as recall.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

(iv) F1 Score

The harmonic mean of recall and precision is the F1 score. The F1-score is a statistic that considers recall as well as precision. It is defined as follows:

$$F1 - Score = 2 * \frac{Precison*Recall}{Precision+Recall} \quad (5)$$

Figure 3 shows the graphical representation of the metrics performance for the pretrained transfer learning models like ResNet50, VGG16 and EfficientntNet. In the dataset under consideration, it is discovered that efficientNet performs better than ResNet50 and VGG16 in terms of leaf disease prediction. Accuracy, precision, recall, and F1-Score for EfficientNet all exhibit an upward trend in the performance metrics. The results of the experiment showed that the ResNet-50 model performs better than the VGG-16 model. The compound scaling strategy is similarly effective for scaling other CNN architectures. Table 2 lists the accuracy scores of the methods after they were compared to other pretrained models such as Inceptionv3, MobileNetv2, GoogleNet, and DenseNet20.

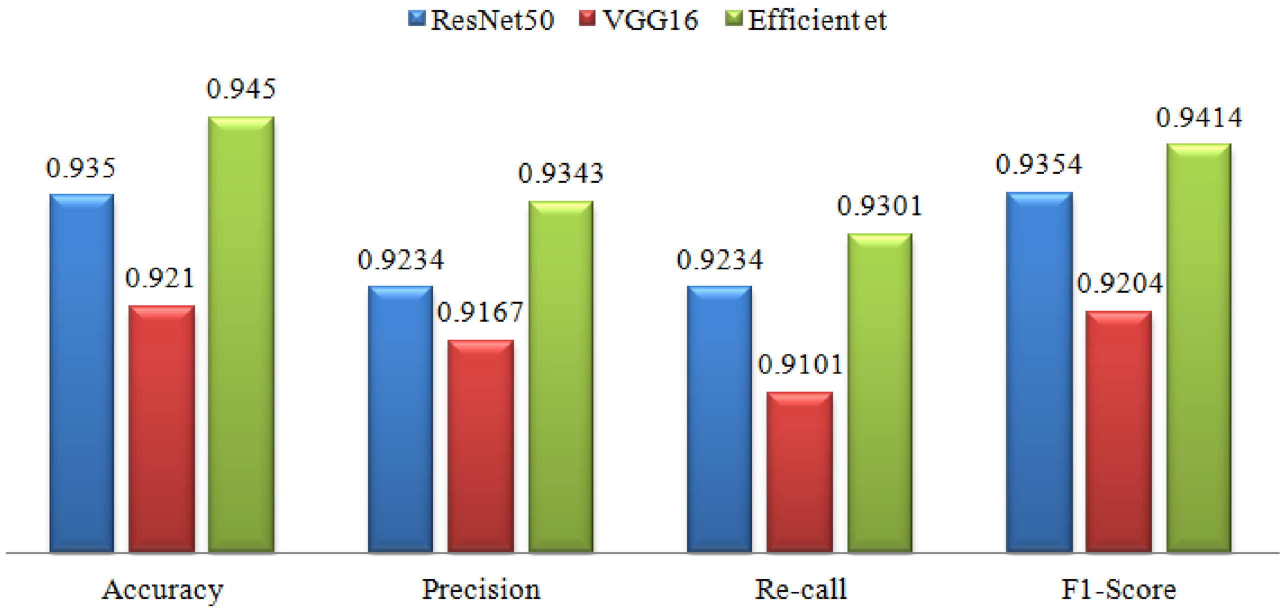

Figure :3 Evaluation of Pre-trained Transfer Learning Models

An important consideration when striving for high accuracy is not the model's structure. The excellent quality of the training data, along with its initial processing and augmentation, provide the most significant accuracy gains. These adjustments, though, need to be made after the subsets have been divided into training and validation. If not, data leaking could occur as a result of an image and its modification showing up in both training and validation sets. For the method to converge and generalize, handling class differences is also essential. Because random initializations might alter the results, completing many training sessions with the same hyperparameters, if time and computing resources permit, may lead to improved accuracy.

Table 2: Comparative Analysis with the existing Works

S.No	Models	Accuracy
1	Genaev et al, 2024[7]	90.34%
4	wani et.al, 2024 [12]	91.93%
2	Nasoor et al. (2024)[15]	92.76%
3	Rai et.al 2024[16]	89.50%

The scalable design of EfficientNet can be adjusted to accommodate different computing requirements. It is capable of handling a large range of image resolutions and sizes. Moreover , because of its effective architecture, which significantly cuts down on time spent on training, EfficientNet is more cost-effective and time-efficient with more accuracy

It makes it possible for expanding EfficientNet models to attain cutting-edge accuracy with orders of magnitude less parameters. The development of DL methods opens up new avenues for research and applications including the use of digital imagery to identify plant diseases. Quick and accurate simulations are necessary to enable the early implementation of appropriate measures. Whether maximizing or minimization is the desired outcome dictates the network architecture to be employed in the construction of the classifier system.

DL's ability to build features entirely automatically without human intervention has led to good results in numerous sector studies. Numerous researches have proposed methods using DL to classify and identify plant diseases. Therefore, by feeding accurate information into the classification framework, the study investigates CNN with the aim of creating a tool for researchers who must design and implement the classification technology for leaf diseases. Additionally, the methods and procedures for detecting plant diseases can be modified for use in other industries, offering insights into the potential applications of ML and DL across a range of academic fields. This research can be expanded to examine the possible advantages and disadvantages of these methods in terms of output loss and utilization of resources.

CONCLUSION

The purpose of this study was to evaluate the efficacy of the different CNN models by examining their findings and outcomes. The effcientNet model outperforms the ResNet50 and VGG16 models .The ResNet50 is found to be superior to VGG16 in the prediction of leaf diseases in the PlantVillage dataset. The CNN models' study revealed that the field of plant disease detection and classification is still developing and needs more research. Plant leaf disease detection and classification across a range of crops is a significant issue and a difficult process, partly because of a dearth of available datasets and the difficulty of building a machine learning model with rigid performance. Finally, this study recommends that future researchers can focus on building prediction models for classifying and diagnosing illnesses in different plant domains.

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