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Identifying corn leaves diseases by extensive use of transfer learning: a comparative study

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ABSTRACT

Deep learning is currently playing an important role in image analysis and classification. Diseases in maize diminish productivity, which is a major cause of economic damages in the agricultural business throughout the world. Researchers have previously utilized hand-crafted characteristics to classify images and identify leaf illnesses in Maize plants. With the advancement of deep learning, researchers can now significantly enhance the accuracy of object classification and identification. Using the "Corn or Maize Leaf Disease Dataset" from the Kaggle website, four forms of maize leaf diseases were investigated: blight, common rust, gray leaf spot, and healthy. The pictures obtained from these corn leaf illnesses are categorized using four deep convolutional neural network (CNN) models that have been pre-trained (GoogleNet, AlexNet, ResNet50 and VGG16). Accuracy, precision, specificity, recall, F-score, and time are the six metrics used to assess the performance of any transfer learning (TL) model. MATLAB programming software is used to design and train the TL models. The accuracy of each item in the dataset has been checked. It has been determined that GoogleNet, AlexNet, VGG16, and ResNet50 each have an accuracy of 98.57%, 98.81%, 99.05%, and 99.36%, respectively.

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1. INTRODUCTION

The maize crop is among the most adaptable new agricultural crops, allowing it to thrive in a variety of agro-climatic situations. After rice and wheat, it is the third most important agricultural product. Maize is the two most common grown cereal crop, earning it the title of "Queen of Cereals." It has an energy density of 3365 Kcal/kg and comprises 10.11% protein, 79.95% starch, and 4.19% fat. During the kharif season, maize is mostly grown in highland areas. Maize is a mixture of lemon yellow, and gamboge in hue. The internal diversity of maize is its distinguishing trait. Different varieties of maize, such as popcorn, grain maize, baby corn and sweet corn are mostly grown in India.

The maize crop is susceptible to a variety of diseases as well as crop-eating insects. Maize leaf diseases mostly result in lower yields and economic losses for farmers. Machine and deep learning are both defined in a layered structure in artificial intelligence. Significant applications [1]-[3] and methods are currently increasing the demand for artificial intelligence (AI) approaches. The use of AI approaches in the health field has shown promising results, such as the identification of malaria cells [4]. The study of plant diseases and their severity estimate has gained a lot of interest from academics researchers and in recent years as a result of technological advancement [5].

Plant disease classification [6] makes use of advanced technology to detect and classify plant diseases. As conventional ways (where manual checking is completed and farm owners have limited access to information, exposure, and technological support) are ineffective [7]. This highlights the critical need to develop computer assisted methodologies and classification models that can identify diseased and wholesome plants at an early stage, allowing for prompt treatment.

In latest decades, the convolutional neural network (CNN) [8] has been utilized a lot in the sector of image recognition because it doesn't rely heavily on particular features. It has also been used to understand infections in plants. Mohanty *et al.* [9] used AlexNet and GoogleNet approaches to categories and recognize 26 diseases in 14 plants in PlantVillage. The rate of correct recognition can be between 97.82% and 99.35%. Sladojevic *et al.* [10] used CNN to find diseases on plant leaves. They also used a fine-tuning process to focus on improving the CaffeNet model, which led to high detection outcomes.

Deep CNN [11] have led to a new advancement in the field of machine learning in latest days (ML). The algorithms of machine learning (ML) are really good at figuring out what features an object has and how to classify it [12], as well as in a variety of related subjects [13], [14]. It can take images and pull out features layer after layer. New studies have shown that intelligent computer processor vision is getting better at things like finding brain and breast cancer [15], finding cars without helmets [16], and finding face masks [17]. During the review of extant literature, different deep neural networks [18]-[21] are used to find the correct results. Using CNN [22], made a model for identifying plants based on the leaf vein pattern. Using the learning vector quantization (LVQ) algorithm, CNN was utilized to develop automatic feature categorization and extraction [23] of tomato plant leaves disorder. DL [24] is aimed at multi-class based plant disease classification with 32 epochs, 96.02% accuracy is reached. The ResNet [25] used to classify images of plant seedlings in order to farm plants. This paper is arranged as follows: The methodology is covered in section 2 followed by results and discussion in section 3. Section 4 describes the conclusion in detail.

2. METHOD

The algorithms utilized in this study are detailed in this section. This work focuses on identifying the best appropriate pre-trained CNN model for classifying maize or corn leaf diseases using a transfer learning. The CNN pre-trained models, transfer learning principle, and evaluation metrics are the three sub-sections of this part.

2.1. Transfer learning concept

In most situations, CNN algorithms are applied to huge datasets rather than small ones. When just a tiny dataset is available, the transfer learning principle might be effective. Figure 1 depicts the notion of transfer learning in which a trained model that has been used on a bigger dataset may be applied on a smaller dataset and provide a satisfactory result. The transfer learning approach has recently been used to great success in a variety of industries, including medical picture categorization, manufacturing, and baggage scanning [26].

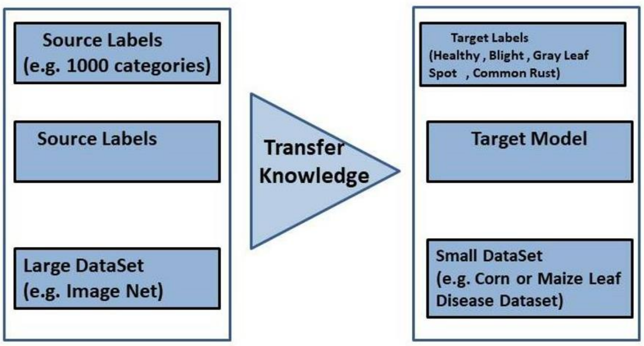


Figure 1. Transfer learning concept

2.2. CNN pre-trained models

AlexNet [26], Vgg16 [27], GoogleNet [27], and ResNet50 [28] are four pre-trained deep CNNs models utilized in this work. To classify maize or corn leaf diseases. The following is a basic description of these models.

2.2.1. AlexNet

Amidie *et al.* [26] proposed the AlexNet model. AlexNet used deep layers of 650K neurons with sixty million parameters to categorize more than 1000 distinct classes. Five convolutional layers with 3 pooling layers, two fully connected layers (FCs), and a softmax make up this network [29]. Figure 2 depicts the network architecture.

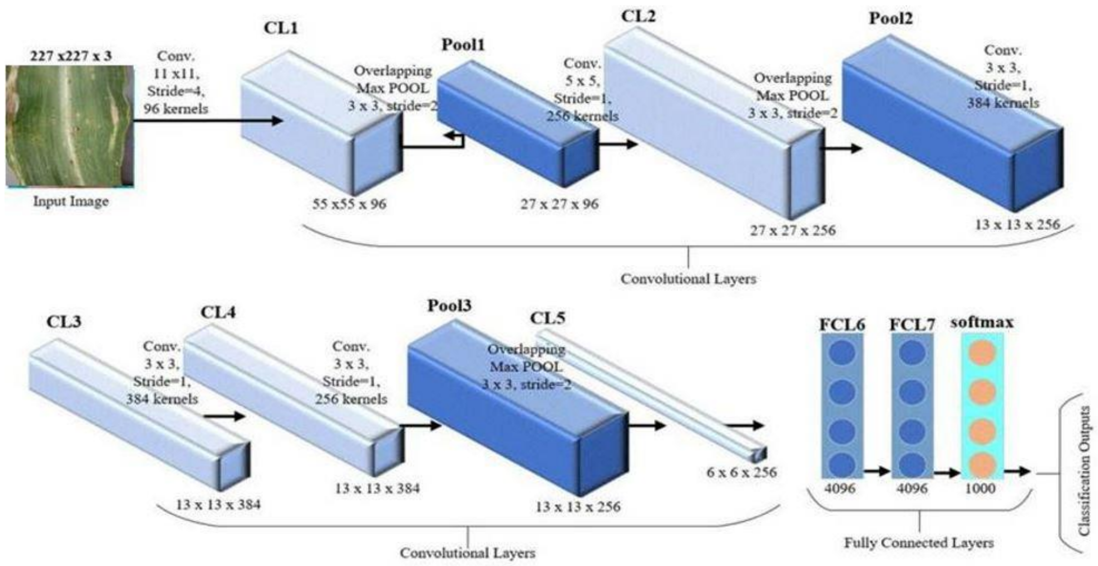


Figure 2. AlexNet architecture

2.2.2. Vgg16

Vgg16 is a CNN model learned on approximately a million photos from the ImageNet database [30]. The model, which has sixteen deep layers, and classify images into up to 1,000 classes. The input picture size for this network is 224*224*3 [29], and it offers rich features for a large range of images. Vgg16's model architecture is seen in Figure 3.

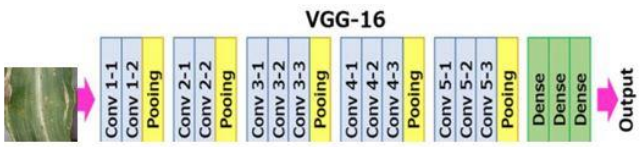


Figure 3. Vgg16 architecture

2.2.3. GoogleNet

The GoogleNet is provided in this paper, and it is based on Szegedy *et al.* [28], the 2014 ILSVRC winner [31]. For its main auxiliary classifiers, the GoogleNet has four fully connected layers (FCL), seven million variables, nine inception modules, four max-pooling layers, and three average pooling layers. Five FLCs, and three SoftMax layers [32]. GoogleNet is depicted in Figure 4 as an architecture.

2.2.4. ResNet50

Figure 5 depicts the residual network's (ResNet). ResNet50 is a deep CNN with 50 layers that has previously been trained on over a million images [31]. ResNet has been effectively used for transfer learning in the field of diagnostic image classification [26].

Table 1 summarizes the number of layers and image input size for each of the above-mentioned models in this study. Table 2 lists the many parameters that were utilized to train CNN models. The CNN training requires a lot of computing power. As a result, Table 3 summarizes all of the experiments. On MATLAB R2021b with the transfer learning tools, the testing and training procedures are carried out. Figure 6 shows the overview of system architecture.

To identify and diagnose the kind of corn disease, the maize pictures are processed by one of the transfer learning models. Due to the small number of photos in the corn diseases dataset and the fact that deep learning training needs a big dataset, a "data augmentation" strategy is used to increase the number of images accessible for training. Data augmentation uses several changes, such as random erasure, image rotation, flipping, image cropping, and color change, to add more photos to a set of data.

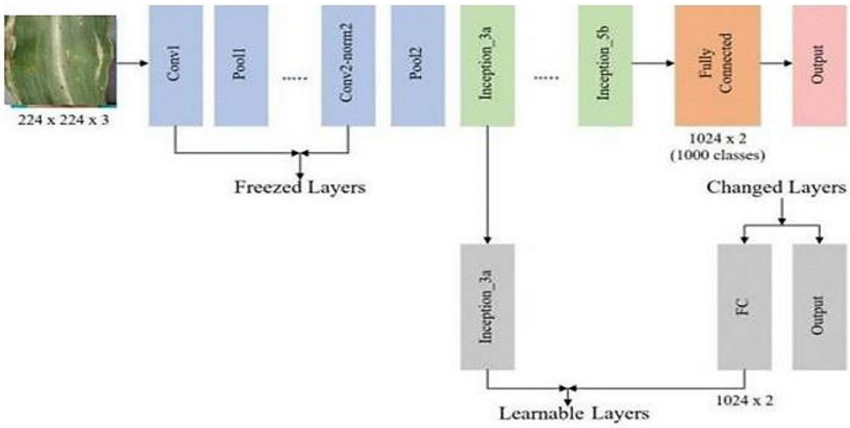


Figure 4. GoogleNet architecture

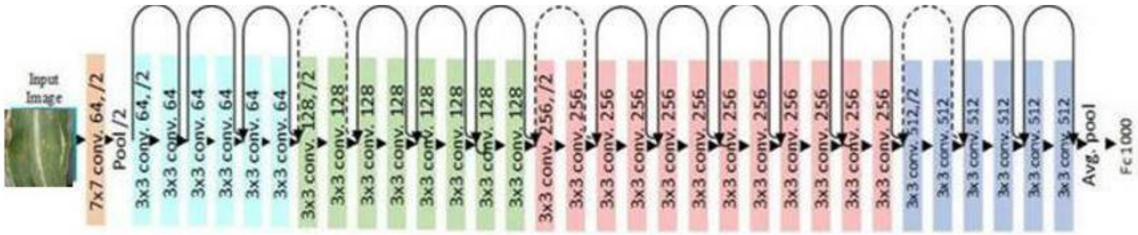


Figure 5. ResNet50 architecture

Table 1. Number of layers and image input size for each model

Model	Number of Layers	Input Image Size
AlexNet	25	227×227
GoogleNet	144	224×224
ResNet50	177	224×224
Vgg16	41	224×224

Table 2. Training parameters

Software	Network	Learning Network	Mini Batch Size	Train: Test Image Percentage
MATLAB Software	AlexNet		10	
	Vgg16	1.00E-04	10	70%:30%
	GoogleNet		10	
	ResNet50		10	

Table 3. Machine specifications

Hardware and software	Specifications
Processor	"Intel(R) Core(TM) i7-11800H @ 2.30GHz"
GPU	NAVIDIA GeForce RTX 3070
RAM	16 GB
OS type	Microsoft Windows 10 Home, 64 Bit

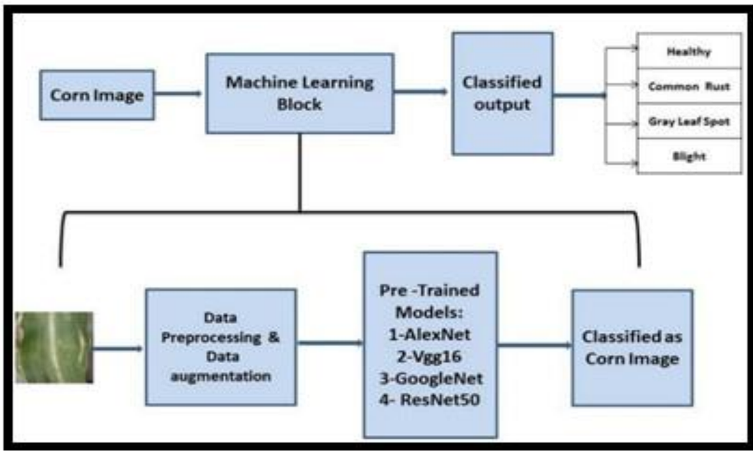


Figure 6. Overview of system architecture

2.3. Performance metrics

By calculating various metrics, the performance of the suggested approaches is compared to that of the various pretrained models [33]. For the sake of comparison, four metrics are calculated. The first is the sensitivity ("recall"), which is the number of positive class instances properly classified it may be computed as (1).

$$Recall\ (or\ Sensitivity)\ =\ \frac{TP}{(TP+FN)} \tag{1}$$

The number of positive cases that are correctly identified as positive is called the true positive (TP). The number of positive samples that are wrongly labeled as negative is called the false negativeor (FN) Specificity is a measure of how likely it is that a secondary class will have true negatives, which is roughly the same as the chance that the negative label is true. It is shown by (2).

$$Specificity\ =\frac{TN}{(TN+FP)} \tag{2}$$

Where TN represents the number of items that are correctly identified as negative and FP represents the number of cases that are incorrectly labeled as positive. Sensitivity and specificity are two measures of an algorithm's performance that focus on its ability to distinguish between a single class. The most often used parameter to evaluate performance of the classifier is accuracy [34]. The accuracy of the model was calculated every 20 iterations throughout the evaluation stage. This measure determines the percentage of properly categorized samples and precision are used to describe represented by (3).

$$Accuracy\ =\frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{3}$$

Precision is described as number of positive instances divided by number of TPs and number of FPs, and this is given as (4).

$$Precision\ =\ \frac{TP}{(TP+FP)} \tag{4}$$

This metric is concerned with correctness, i.e., it assesses the algorithm's predictive power. Precision is used to describe how "precise" the model is in terms of number of positive predictions and number of actual positive predictions.

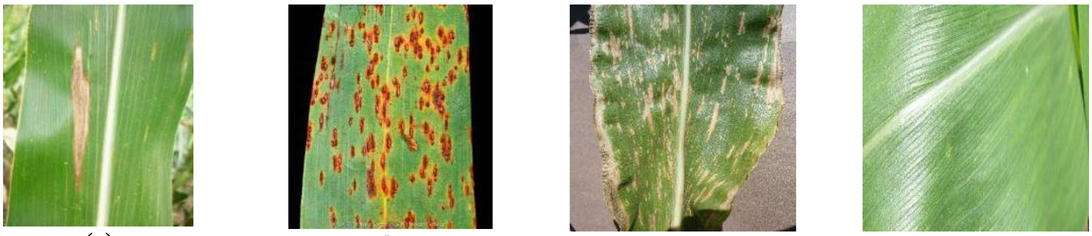
F-score is the last measurement since it shows harmonic average precision and recall:

$$F-score\ =\frac{2\times(Precision\times Recall)}{(Precision+Recall)} \tag{5}$$

it emphasizes positive class analysis. A high score for this metric indicates that the model surpasses its competitors in the positive class.

2.4. Collection of data

The most crucial aspect of system training is the collecting of data for just any system. The techniques in deep learning require a large dataset for model training. The more accurately the model is trained, the better it will perform in testing. The dataset was obtained from the Kaggle website which is called "Corn or Maize Leaf Disease Dataset ". Figure 7 shows example of four classes in the dataset. Blight disease shown in Figure 7(a), common_rust shown in Figure 7(b), Figure 7(c) shown the spot, and Figure 7(d) healthy.



(a) (b) (c) (d)

Figure 7. Examples of corn leaf disease dataset images (a) Blight, (b) Common_Rust, (c) Gray_Leaf_Spot, and (d) Healthy

3. RESULTS AND DISCUSSION

Four transfer learning (TL) models were trained in this comparison study to categorize four classes of corn or maize disease images ("Blight, Common Rust, Gray Leaf Spot, and Healthy"). The primary goal of this study was to compare four TL models by determining crucial metrics that distinguish the system's efficiency. These are the accuracy, sensitivity (recall), precision, specificity, and F score. AlexNet, GoogleNet, Vgg16, and ResNet50 were the four models. The results are shown in Table 4. ResNet50 outperforms the remaining four models in four measurable parameters for all four TL models trained in this study. ResNet50 has a 99.36%. This is followed by VGG16 with 99.05%, AlexNet with 98.81%, and GoogleNet at the bottom of the ranking with 98.57% for the most measured parameters.

Table 4. Performance metrics (%) for four TL model

Metrics (%)	TL models			
	GoogleNet	AlexNet	Vgg16	ResNet50
Accuracy	98.57%	98.81%	99.05%	**99.36%**
Sensitivity (Recall)	98.72%	98.47%	99.74%	99.23%
Specificity	98.50%	98.96%	98.73%	99.42%
Precision	96.75%	97.72%	97.26%	98.73%
F-score	97.73%	98.09%	98.49%	**98.98%**

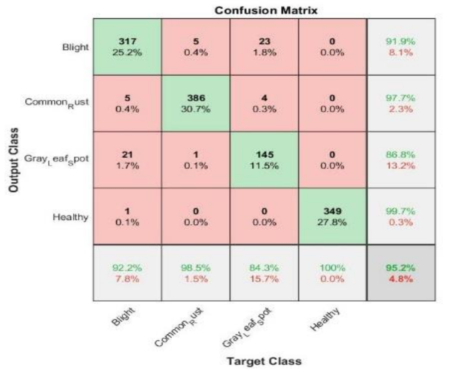
Recall is greatest for VGG16 at 99.74%, trailed by ResNet50 at 99.23%, GoogleNet at 98.72%, and AlexNet at 98.48%. Here GoogleNet surpassed on AlexNet in this parameter in a comparable pattern, ResNet50 came out on top in terms of specificity, precision, and F-score, with scores of 99.42%, 98.73%, and 98.98%, respectively. AlexNet is in the second place with 98.96% for specificity, Vgg16 with 98.73% and GoogleNet with 98.50% for specificity. In terms of precision, AlexNet exceeded on GoogleNet and Vgg16 with 97.72% for AlexNet and 97.26% for Vgg16 and 96.75% for GoogleNet. Finally, Vgg16 took the last place with 98.49% for F-score, 73.89% for AlexNet, and 74.62% for GoogleNet The final item to discuss is time. For system performance, time is critical. The validation and training times were computed to determine which system required the least amount of training and validation. ResNet50 had the fastest training and validation time of 9 minutes. ResNet50 was followed by Vgg16 and AlexNet, who each took 12 and 16 minutes respectively. The slowest model was GoogleNet, which took 36 minutes to complete. Table 5 presented a comparison of these findings with other similar studies in corn disease classification.

This study classified four types of corn diseases and obtained more findings that are accurate. Figure 8 shows the confusion matrices for the four transfer learning models utilized to categorize four corn classes. Confusion matrix to AlexNet model is described in Figure 8(a) and (b) shows the confusion matrix to GoogleNet model, Figure 8(c) shows the the confusion matrix of Vgg16 model and the confusion matrix of ResNet50 model in Figure 8(d). Figure 9 shows some of the classification images that were created for the four different groups. Classification image of healthy is described in Figure 9(a), Rust described in Figure 9(b),

Figure 9(c) Blight, and Figure 9(d) Gray_Leaf_Spot. TL is capable of classifying images of any conceivable kind. The dataset utilized in this study is divided into four categories (healthy, Common Rust, Gray-Leaf-Spot, Blight). The data was separated into two parts: 70% and 30% (training-testing). Corn images were trained using four TL models: vgg16, AlexNet, GoogleNet, and ResNet50. Accuracy, recall, specificity, F-score, and precision were all used to evaluate these models. ResNet50 outperformed the other models, as seen in Table 5 and Figure 8, which exhibit general findings and confusion matrices, respectively. ResNet50, on the other hand, got top position in terms of speed as well. Figure 10 shows the Features extracted from some layers to ResNet50 model.

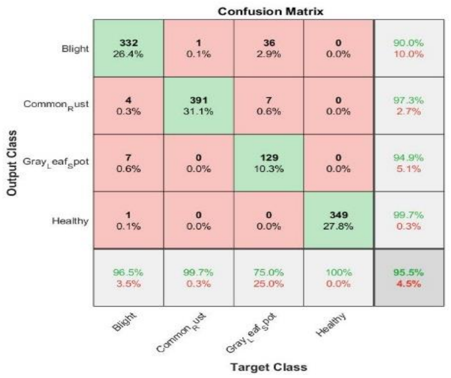
Table 5. Comparison with other recent similar articles

Authors	Dataset	Model	Accuracy	Precision
Adhinata *et al*. [35]	PlantVillage and PlantDoc datasets (4 classes)	TL and CNN	93%	91%
Singh *et al*. [36]	PlantVillage dataset (2 classes)	TL (AlexNet)	99.16%	-
This work	Corn or Maize Leaf Disease (4 classes) Dataset	ResNet50	99.36%	98.73%
		AlexNet	98.81%	97.72%
		GoogleNet	98.57%	96.75%
		Vgg16	99.05%	97.26%



(a)

(b)

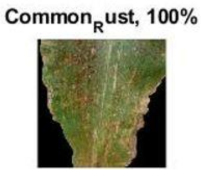


(c)

(d)

Figure 8. Displays the confusion matrices for (a) AlexNet, (b) GoogleNet, (c) Vgg16, and (d) ResNet50 models respectively

(a)



(b)

(c)

(d)

Figure 9. A few of the categorized photos of corn (a) Healthy, (b) Rust, (c) Blight, and (d) Gray_Leaf_Spot

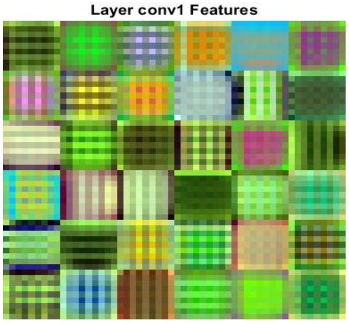


Figure 10. Feature extraction from some layers in ResNet50

4. CONCLUSION

In this study, four pre-trained TL models were employed to identify four corn or maize disease classes, and the ResNet50 model obtained 99.36%. The task became more complicated, yet it is critical that there be room for future expansion. The suggested study can be utilized as a practical tool to assist farmers in recognizing and protecting maize crops from the aforementioned illnesses.

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