Plant Leaf Classification Using a Compact Deep Learning Model Use of VGG-16

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Abstract- Systematic plant-based categorization has never been difficult. Targeted crop safety is dependent on automated technologies that detect and classify plants. Classical machine learning approaches have been used to categorize leaves using handcrafted features from the shape of plant leaves, which have yielded promising results. However, we concentrate on classifying plant leaves using non-handcrafted traits. To accomplish this, we employ the use of deep learning for extraction of features and categorization. Deep Convolution Neural Networks have recently demonstrated impressive achievements in picture classification and object detection challenges. This paper proposes using the built-in, compact VGG-16 model to detect and classify ten plant species from the Plant dataset. The proposed models are utilized to classify ten other classes.When contrasted with other pre-trained models, VGG -16 fared better in categorizing leaf images. Computerized plant species categorization could be beneficial to food engineers, agricultural professionals, researchers, and the general public.
Keywords- Machine learning, Deep Convolution Neural Networks, Agricultural professionals, Categorization

I. Introduction

There are around 500,000 plant species globally, many of which have only been discovered lately. They are food, medicine, recreation, genes, poisons, animal feed, and building supplies. Several species may become extinct as a result of this in the near future. As a result, a plant classification system is required. Plants can be classified into several types based on their blooms, fruits, leaves, and other components. Although 3D objects depict living plants, still photos capture 2D projections. Hence, using flowers and fruits to extract characteristics may increase complexity because their qualities may be shown in three dimensions with remarkable clarity. Plant leaves are two-dimensional at the same time.Furthermore, most plant species have distinct leaves that vary from one another in a variety of ways, including colour, shape, texture, and margin. As a result, plant classification based on leaves is efficient and effective in identifying plant species. Additionally, leaves can be located and collected at any time, while blooms and nuts are seasonal and plant-specific.

[1]The preparation and evaluation of the model involved 1040 photos. The identification and categorization of illnesses in sugar beet leaves were carried out with a prediction performance of 96.47% using the Yolov4 deep learning model on the data set with image processing algorithms. This finding led to the conclusion that the proposed model can be employed effectively in the process of identifying and categorising diseases in sugar beet leaf tissue.[2]Vegetable leaves are gathered into 25 categories, totaling 7226 RGB pictures. To train multiple models, these photos undergo the machine learning process. There are several various varieties of classifiers that can be employed, including Linear Regression (LR), Decision Tree (DT), K-Nearest Neighbors (KNN),Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Naive Bayes (NB). Models are assessed using accuracy (Acc), precision (Pr), recall (Re), and F1-score after training (F1-S). The outcome demonstrates that MLP outperformed another classifier with an accuracy of 90.68%.[3].The constructed Convolution Neural Network (CNN) based Holding Vector Network (HVN) model is provided features that aid in the detection and classification of the 3 distinct nutrient ranges. In accordance with the results, the created CNN-based HVN model has 95% training accuracy and 92% validation accuracy. Because of its excellent accuracy, scalability, and cost-effectiveness, the proposed model may be used by various types of producers to forecast nitrogen distribution in live time.

[4]The efficiency of the suggested method was evaluated using different topologies of single-layer and two-layer neural network structures after the network was trained with 60% of the photos and the remaining images were retained for testing. The implementation of a two-layer structure with eight neurons in the 1st layer and 8 neurons in the second layer resulted in an optimal accuracy of 73.7%, according to the data.[5]The pre-trained INC-VGGN system is a deep convolutional neural network for crop diseases diagnosis that was training or education on the unique dataset. The base network's pre-trained weights and features are imported into the newly constructed neural network to fulfil the assigned work of plant disease identification for our dataset. To address the overfitting issue, a dropout layer is created, and deep feature learning is performed using the Kohonen learning layer. The upgraded base network classifies the severity classes in the training sets after calculating percentages. Lastly, the framework's performance is computed for several performance indicators and achieves higher accuracy than earlier models.[6]The relief feature selection picked the most relevant features. The accuracy of gray-level co-occurrence matrix (GLCM) features was 98.71%, while feature dimension reduction using PCA was 98.97%. The recommended method's time required for processing was substantially shorter than

that of two deep learning approaches, CNN and GoogleNet, which yielded classification accuracy results of 86.82% and 94.05%, correspondingly.
[7]A SVM classifier combined with CNN is used to recognise and label several types of rice crop illnesses. Using ReLU and softmax functions, the suggested deep learning-based approach attained the highest validation accuracy of 0.9145. Following proof of identity, an accurate remedy is proposed, which might help agricultural-related individuals and organisations in initiating suitable disease-fighting actions.[8]The Deep CNN model is used to generate classification features, which are subsequently classified using classifiers such as Support Vector Machine (SVM), K Nearest Neighbour, Random Forest, Naive Bayes, and Logistic Regression (LR). The results are compared to those of other deep learning classifiers that are currently available.The SVM and LR classifier outperform some of the remaining already trained deep learning models in terms of accuracy, precision, and recall. We also discovered that we could surpass a number of previously trained deep-learning models in the precision of classification while using significantly less parameters. [9]By removing characteristics from the Logits layer & lowering the feature using the Chi-Squares approach, the most effective strategy was discovered.Cubic was the most successful SVM kernel. The program's categorization overall performance has already been found to be 97.60%.[10]The created model more accurately categorises leaves with illness. The test study has a 95.71% prediction performance for tomatoes and a 98.40% prediction accuracy for grapes. The proposed study explicitly advocates for raising agricultural food output.

II Proposed model

The data provided to a network is a measured visual. (224, 224, 3). The first two layers have a total of 64 channels with identical padding and a filter dimension of 3*3. After a stride (2, 2) max pool layer, two additional layers with convolution layers with a total of 128 filter dimensions and filter dimension are added. (3, 3). This is followed by the identical stride (2, 2) maximum pooling layer as earlier layer. Then you'll find two convolution layers with filtration sizes of (3, 3) and 256 filters, respectively. There are then two sets of three convolution layers and a max pool layer. Each one contains 512 filters of the same size (3, 3) and padding. This image is then fed into a two-layer convolution layer stack.Instead of the 11*11 filters used by AlexNet and ZF-Net, the convolution and max-pooling layers in this model employ 3*3 filters. Additionally, it uses 1*11 pixels in a few of the layers to change how much data is conveyed via every channel. Before every layer of convolution, a 1-pixel padding (same padding) is applied to avoid altering the spatial features of the image.
ReLU serves as the activation function for all layers that are hidden.ReLU is better for computation since it allows for faster learning and reduces the risk of vanishing gradient problems.The proposed architecture is given in Fig.2.

A Neural Network's Elements:

Input Layer: This layer receives input features. It brings data from external sources into the net; no processing is done here; nodes just send the information (features) to the hidden layer.
Hidden Layer:The process of convolution and max-pooling layers in this model use 3*3 filters as opposed to AlexNet and ZF-Net's 11*11 filters. Furthermore, it alters the amount of data transmitted through each channel by using 1*11 pixels in a few of the layers. To prevent changing the spatial characteristics of the image, a 1-pixel padding (the same padding) is applied before each layer of convolution.

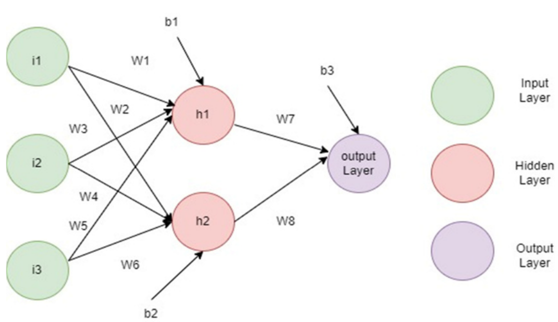

Figure 1 Neural Network

Layer 1-Hidden Layer calculated as using Eqn(1),

$$Y(1) = W(1)X + b(1)c(1) \tag{1}$$

Y(1) represents the vectorized output of layer 1;
W(1) represents the vectorized weights for neurons in the hidden layer, namely w1,..., wn; n = 1, 2,...,
X represents the vectorized input features, namely i1, i2, and i3.
b represents the vectorized bias for neurons in the hidden layer, namely b1 and b2.
Any linear function has the vectorized form c(1).
Output Layer: This layer communicates the network's learned knowledge to the outside world.
Layer 2 Output Layer is calculated as using Eqn(2),

$$Z(2) = W(2)a(1) + b(2) \quad (2)$$
$$a(2) = Z(2) \quad (3)$$
Final Layer calculated as follow,
$$Z(2) = \{W(2) * W(1)\} * X + \{W(2) * b(1) + b(2)\} \quad (4)$$
Consider that,
$$W(2) * W(1) = Wi \quad (5)$$
$$W(2) * b(1) + b(2) = bi \quad (6)$$
While applying eqn (5)& (6) in (4) ,Final Output is given as in eqn(7),
$$Z(2) = Wi * X + bi \quad (7)$$
Activation Function:The activation function determines the ability to stimulate a neuron by computing the weighted sum and then adding bias to it. The activation function's objective is to introduce non-linearity into a neuron's output.It is an abbreviation for Rectified linear unit. It is one of the most common activation functions. Specifically performed in the hidden layers of a neural network. Its implemented as,
$$R(a) = \max(0, a) \quad (8)$$

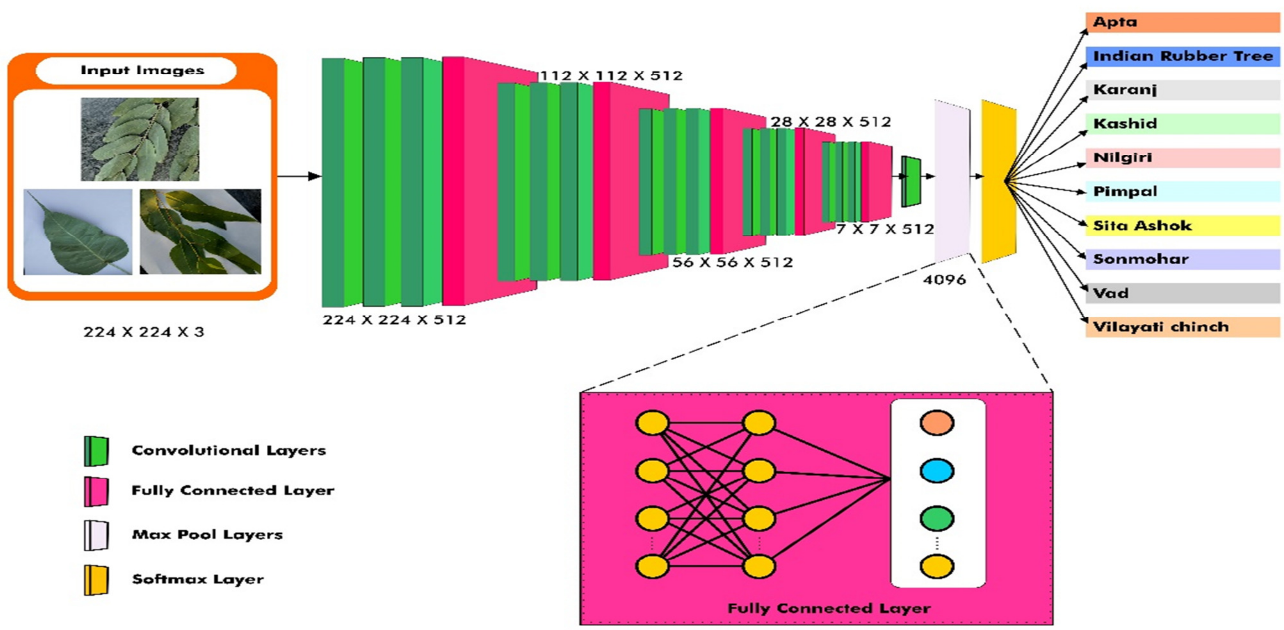

Figure 2 Leaf Architecture for VGG16

III Result and Discussion

AEvaluation Metrics

A classifier's accuracy is measured statistically as the ratio of right predictions (both True positives (Tp) and True negatives (Tn)) to the total of all predictions (including False Positives (Fp) and False Negatives (Fn)) made by the classifier. (Fn). Therefore, the following is the formula for calculating binary accuracy in eqn 9:
$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (9)$$
Both of the classes can be used to determine precision. The classifier's capability to refuse to classify a negative sample as positive is known as the precision of the negative class. The classifier's capacity to avoid classifying a positive sample as negative is known as the precision of the positive class. Precision has a greatest value of 1, and a worst value of 0 calculated using eqn 10&11.
$$Precision(positive) = \frac{Tp}{Tp + Fp} \quad (10)$$
$$Precision(negative) = \frac{Tn}{Tn + Fn} \quad (11)$$

The recall is computed as the ratio of Positive samples that were correctly categorized as Positive to the overall number of Positive samples. The recall of the model assesses its ability to detect Positive samples. The greater the recall, the more positive samples were discovered.
$$Recall = \frac{Tp}{Tp + Fn} \quad (12)$$

Table 1 Comparison table

Ref	Model	Accuracy (%)
[11]	K-means approach	97
[13]	VGGNet pre-trained	92
[14]	MobileNetV2 and NASNetMobile	97
[16]	OMNCNN model	98.7
	Proposed model	99.01

Fig. 3 shows the comparison of different models with proposed model with reference [11, 13, 14, 16].

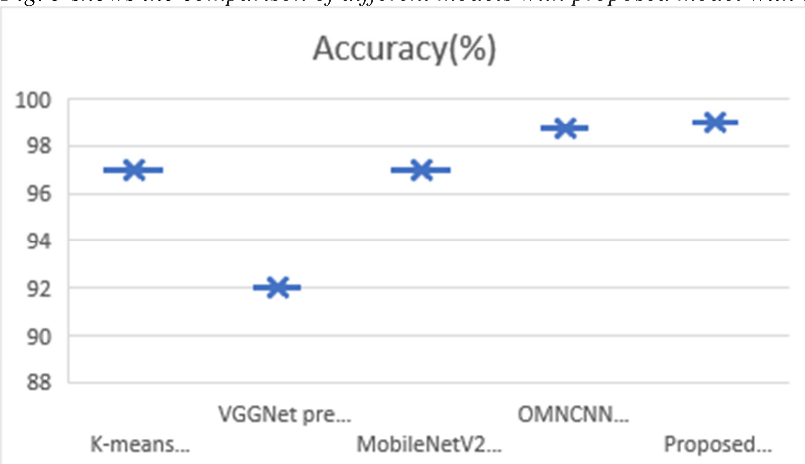

Figure 3 Comparison of different models with proposed model

Based on the equation (9, 10, 11, 12), this calculation computed the performance for the provided collection of leaf images and obtained greater accuracy than the previous one. During the training phase, attain more accuracy while decreasing the loss function, as demonstrated in Figs. 4(a) and 4(b).

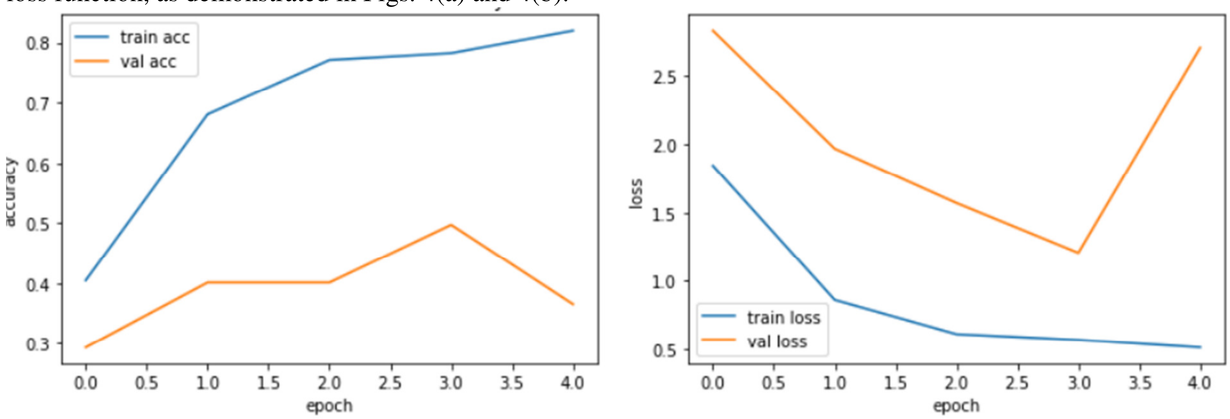

Figure 4 (a) Training and Testing accuracyFigure 4 (b)Training and Testing loss

IV Conclusion

In this study, a collection of diverse crop leaf kinds was compiled using publically available data. The techniques were used on the convolutional neural network-based VGG16 model. To enhance the performance that is measured and compared, the suggested model is created and put to the test. The evaluation metrics parameters are greater and expanded when compared to other accessible datasets and methods. The accuracy of our suggested study project's classification of leaves increased as a result by 99.1. Leaf images, classification, and analysis are essential processes in continuously attempting to enhance the performance of on-field crops, but our model achieved the highest performance, promoting agricultural progress.The development of the agricultural sector and an increase in food production are the main objectives of the research.The acquisition and preparation of real datasets for use in deep learning models that include several crop leaf images is a future objective. It is anticipated that Inception V3 and CNN models built on ResNet will be used in the future to analyse cropped images substantially more thoroughly. Our work encourages and supports farmers, which ultimately boosts agricultural income and aids in the growth of powerful nations.

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