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Transfer Learning Based Plant Species Classification Using MobileNetV3 and PlantVillage Dataset

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Abstract—Identification of plant species is vital for the advancement of various applications ranging from precision agriculture to crop diseases surveillance and biodiversity recording. While the task has historically been accomplished through manual assessment of plant characteristics by botanists or agronomists, this traditional approach poses considerable scalability issues due to reliance on experts' knowledge and vulnerability to inter-observer variance when dealing with high-volume plant specimen analysis. Over the past decade, however, the use of data-driven techniques has increased substantially, leading to impressive improvements in plant image classification, which can be mainly attributed to convolutional neural networks' ability to learn distinctive visual features from raw imagery. Motivated by the promising results of recent advancements in this area, the current study presents a plant species classification framework based on transfer learning with MobileNetV3 as the main neural network architecture and PlantVillage dataset as the training data. The chosen model was known for the ability to offer competitive accuracy with significantly reduced computation costs, which made it possible to use the model with low-performance computing resources without compromising results' quality. To ensure proper functioning of the learning algorithm, the dataset was preprocessed in multiple ways, including resizing images to the necessary dimensions, normalising pixels' values within the desired numerical range, and assessing classes distribution through visual inspection. Finally, the learning procedure was implemented on Google Colab, where model accuracy and crossentropy loss were calculated on a validation set after every epoch.
With an impressive accuracy of 97.87

Index Terms—Plant Species Classification, Transfer Learning, MobileNetV3, Convolutional Neural Networks, Deep Learning, PlantVillage Dataset, Image Classification, Precision Agriculture.

I.INTRODUCTION

Agriculture serves not only to sustain humanity but also to drive national economies forward. An important requirement of agriculture is the precise determination of species used in production. The ability to do so will help to keep an eye on crops' condition and detect diseases in time, resulting in increased yields. Although species identification still remains a mainly manual process involving professional expertise, advances in computer technologies promise faster and more precise methods.

Thanks to recent breakthroughs in the field of machine learning, specifically deep learning, a significant development took place in the area of computer vision and image-based classification of various objects. Convolutional Neural Networks (CNNs), which specialize in processing and extracting information from image data, prove highly useful in the classification task.

However, building an accurate deep network requires vast amounts of data and extensive computing power, both of which may lack when needed. The technique known as transfer learning can be considered as a solution for that issue by leveraging pretrained models that have already learned important characteristics from huge datasets.

This project proposes an application of transfer learning using MobileNetV3 architecture in order to classify plant species by their leaves. The choice of the model is made based on its efficiency and suitability for real-world applications, whereas the PlantVillage dataset, featuring many plant species, will be used as a source of training samples.

The aim of the research work is to develop an efficient and accurate automatic plant species classification system based on image recognition using transfer learning.

II.LITERATURE REVIEW

In recent years, great effort was exerted to enable computer algorithms to classify plant species and detect plant diseases. Thanks to the emergence of large datasets for plants, an automatic plant image recognition system that works efficiently without the

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need for huge amounts of manual work has become possible to develop.

The Convolutional Neural Networks architecture is known for being very efficient in detecting complex features from images. Consequently, such an architecture is ideal for plant image classification. However, it is expensive to train such an architecture from scratch, particularly due to the large number of labeled data required.

This is where transfer learning comes into play, by taking advantage of the pre-training on general datasets and fine-tuning the model for specialized tasks, the training process can be made faster and more efficient, while at the same time improving the results achieved by the algorithm.

One of the common themes found in the research articles related to plant classification or disease detection is that the network structure that they are using is inspired by MobileNets. This is due to the nature of the task since these networks are efficient and relatively small and therefore suitable for realtime applications.

The comparison between the CNN-based networks and the transfer learning ones proves the superiority of the latter in most cases and the ability to improve the classification results thanks to the improvements made.

Based on these ideas and concepts, this project aims to develop a system for classifying plant species using the transfer learning approach on MobileNetV3 networks. For this purpose, Plant Village dataset will be used as an experimental dataset.

III.DATA PREPROCESSING

For the experiment, a variety of plant leaf images from different plants will be used, both healthy and sick. Given that all images have different sizes and qualities, it is important to preprocess them before using them as input data.

First of all, each picture will be resized to have identical dimensions since it reduces computation time and allows feeding each image into the model in the right format. Normalization was performed next to adjust pixel values to ensure proper training. Moreover, preliminary exploration and visualization were made to investigate class balance and evaluate the quality of input images.

The described above preprocessing procedures are fundamental in increasing the effectiveness of models as they remove any noise in the data and prepare input images properly for training.

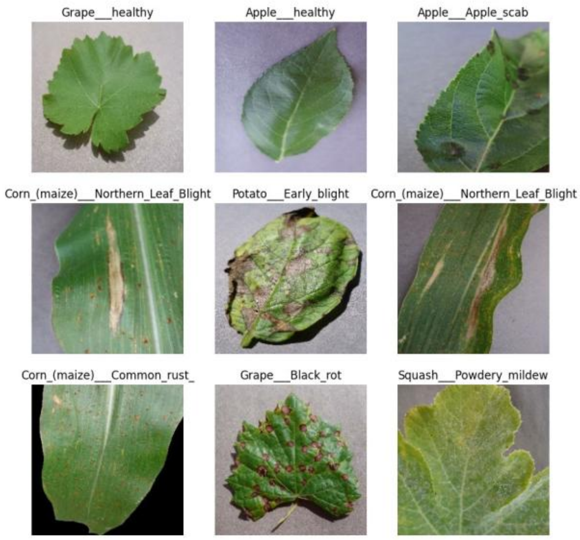

Fig. 1: Sample Images from PlantVillage Dataset

IV.PROPOSED METHODOLOGY

To begin with, the presented work aims at developing a plant species classifier using a transfer learning method. As opposed to building a deep learning network from scratch, a pre-trained model of MobileNetV3 is used in this study, which will allow tuning the model for classification tasks.

Firstly, the procedure involves collecting images of leaves of various plants from the PlantVillage dataset. Subsequently, the gathered data is processed using resizing and normalization to adapt it for training. Finally, after preparing the data, we can use MobileNetV3 as the main model for our tasks. It should be highlighted that MobileNetV3 is pretrained on the ImageNet dataset; therefore, it already recognizes general visual features like edges, textures, etc. In the current research, it is decided to use all of the pre-trained base layers and only modify the classification layers to fit the needs of this particular task.

During the training process, the system learns the specifics of the input data and identifies unique patterns for the corresponding classes. After analyzing the data, the final output layer outputs a probability

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distribution over all of the classes, and the class that has the greatest value is taken to be the predicted label.

V.MODEL ARCHITECTURE

MobileNetV3 is a lightweight neural network architecture that was explicitly designed for image classification tasks. Specifically, this neural network architecture offers efficient performance on constrained devices due to its computational efficiency and high accuracy.

MobileNetV3 architecture uses depthwise separable convolutions that significantly decrease the number of parameters compared to common convolution operations in CNNs. Thus, this architecture allows processing an image faster than standard convolution architectures while retaining their performance. Moreover, SE blocks that enable squeezing and excitation of features allow the network to focus on the most useful channels in feature maps. In this way, the network can capture essential patterns of plant leaf images more accurately.

Batch normalization is used to improve the convergence speed and stabilize the training process. As for non-linear activations, their purpose is similar – improving convergence and training process stability.
As the base network, a pre-trained MobileNetV3 (pre-trained on ImageNet) will be utilized. Since the task is related to image classification, only general feature extraction layers are kept untouched while classification layers are redefined according to the number of classes (plant species). That is, the last few layers of the network will be trained while other layers remain unchanged.

VI.DETAILS OF TRAINING

VI-A Training Configurations

The training was conducted via the Google Colab service using the CPU runtime mode. Even without employing GPU, the training turned out to be effective owing to the lightweightness of the model architecture.
In order to estimate the model's capability to generalize, the training dataset was split into training and validation subsets. During training, the batch size was fixed to 32. In order to obtain faster convergence, the model was optimized using the Adam optimizer. Since the problem involved multiclass classification, the categorical cross-entropy was chosen as the loss function. As an indicator of performance, the accuracy was considered.

VI-B Experimental Set-Up

In order to study the influence of training time on the model's performance, training was conducted for varying numbers of epochs. Specifically, the training was done separately for 3 epochs and 5 epochs.
The experimental set-up described above is sufficient to compare the influence of extra epochs on both the stability of learning and its efficiency.

VI-C Training

In the course of training, the model was fitted using the training subset, and the validation step was performed after each epoch. In other words, the procedure makes it easier to observe training dynamics and possible issues such as overfitting and slow learning.
The training process is represented by the following piece of code:

```
history = model.fit(
train_ds, validation_data=val_ds, epochs=E
)
```

where *E* refers to the number of training epochs.

VI-D Model Selection

After conducting the experiment and comparing obtained results, it became evident that the model trained for 5 epochs demonstrated better validation performance than the one trained for 3 epochs. It exhibited greater accuracy and more stable learning. Accordingly, the model trained for 5 epochs is chosen for further investigation and usage.

VII.MODEL EVALUATION

The performance of the developed model was measured using the validation data set. Some of the important parameters used for measuring the performance are training accuracy, validation accuracy, training loss, and validation loss. Such parameters play an important role in evaluating the learning process of the model as well as its generalization capability.

The accuracy obtained from the classification task was found to be 97.87%, which shows high performance. Moreover, the small difference between training accuracy and validation accuracy shows that the developed model has no issue of overfitting.

VII-A Evaluation Metrics

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Apart from accuracy, there are other evaluation metrics like precision, recall, and F1-Score that are employed to measure the effectiveness of the model. Precision can be described as the ratio of the number of correctly predicted positive cases over the total number of predicted positive cases, whereas recall can be described as the ratio of the number of correctly predicted positive cases to the total number of actual positive cases. The F1-Score can be stated as the harmonic average of precision and recall.
Mathematically, these metrics can be written as:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

Where TP, FP, and FN stand for true positives, false positives, and false negatives respectively.

VII-B Confusion Matrix

Confusion matrix is an effective way of analyzing the performance of a classifier model through presenting the number of correct and incorrect classifications of data.
In this study, the structure of confusion matrix is used to describe the performance of the classification. Confusion matrix involves true positive (TP), true negative (TN), false positive (FP), and false negative (FN) as shown in Table I.

TABLE I: Structure of Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

True positives and negatives form the diagonal elements of the matrix. Misclassification is seen in false positives and negatives in the matrix. More correct classification can be observed from high numbers along the diagonals.
It should be noted that class-specific confusion matrix is not provided in this study. However, the high classification accuracy achieved in this model is enough proof of its correctness and effectiveness since there is minimal misclassification.

VIII.RESULTS AND DISCUSSION

As seen from the experimental results, the proposed transfer learning approach based on MobileNetV3 architecture is effective for plant species classification. As seen from the results presented above, the model was tested on the dataset called PlantVillage and its performance was assessed based on accuracy and loss criteria.
During the learning process, the model demonstrated an increasing level of accuracy at each epoch, which means that it was able to effectively learn from data. Moreover, the decreasing value of the training loss proves that the optimization of model parameters was conducted successfully.

Similar trends can be identified when assessing the validation results. Namely, the increasing value of the validation accuracy demonstrates that the model can effectively work with unseen data. At the same time, the decreasing value of the validation loss shows that stable learning takes place.
The final level of classification accuracy for the proposed solution reaches 97.87%. Thus, the ability of the model to effectively identify plant species is proved. Moreover, the proximity of training and validation results suggests that there is almost no overfitting problem.
When speaking about the potential use of the model, it should be emphasized that the use of MobileNetV3 architecture brings an advantage. Indeed, in comparison with traditional convolutional neural networks, the proposed model works more efficiently and requires lower computational power.

IX.ACCURACY GRAPH

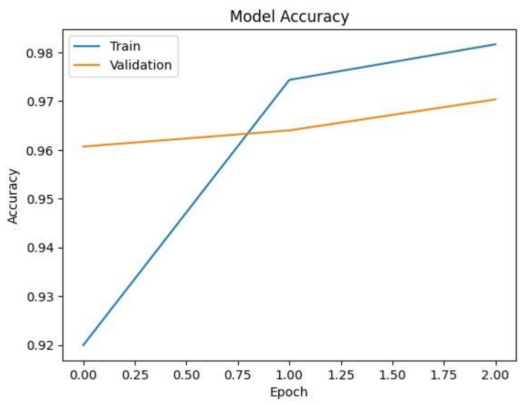

Fig. 2: Variation of model accuracy across training and validation

The accuracy graph shows improvement during training epochs. indicating good generalization without significant overfitting.

X.LOSS GRAPH

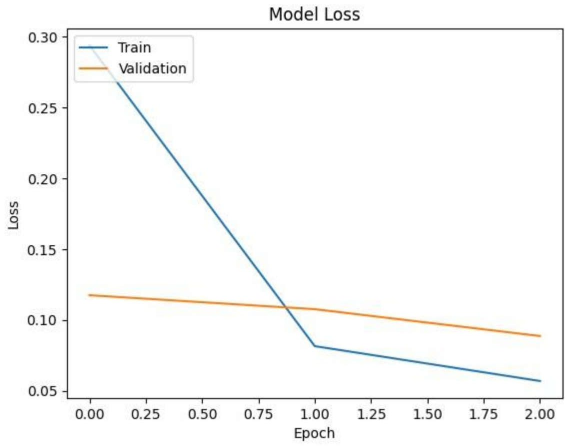

Fig. 3: Model loss observed during both training and validation

The loss graph shows decreasing trend which indicates model convergence.

XI.PERFORMANCE COMPARISON

The performance comparison presented in Table I shows that the proposed MobileNetV3-based TABLE II: Comparison of Different Models

Model	Accuracy	Training Time
CNN Model 1	94.32%	High
CNN Model 2	95.76%	Medium
CNN Model 3	96.45%	Medium
MobileNetV3	97.87%	Low

model outperforms the other convolutional neural network models in terms of classification accuracy. It achieves an accuracy of 97.87%, which is higher than all the compared models.

In addition to improved accuracy, the proposed model requires less training time due to its lightweight architecture. While the other CNN models involve higher computational complexity, MobileNetV3 is designed to be efficient without compromising performance.

These results indicate that the proposed approach provides a better balance between accuracy and computational cost. Such characteristics make it suitable for practical applications, especially in scenarios where computational resources are limited.

XII.ADVANTAGES OF PROPOSED SYSTEM

The suggested classification algorithm for plants provides numerous advantages compared to conventional classification algorithms and modern deep learning systems.

The first advantage of the suggested algorithm is associated with the computational efficiency provided by the utilization of MobileNetV3 architecture. Because of the low computational requirements, the model can be easily deployed on mobile devices without a loss of accuracy.

The second benefit of the suggested method is associated with the ability to reach high accuracy using a relatively small number of training examples. It becomes possible due to the implementation of transfer learning techniques allowing to incorporate previously learned knowledge into the new system. Another benefit of the suggested algorithm is high classification performance. The model achieves high accuracy equaling 97.87

Besides, the developed system allows to eliminate the necessity of involving specialists in the process of plant identification and classification, which is very beneficial for solving real-life problems.

Finally, the suggested algorithm for plant species identification and classification is very versatile because it can be used in different areas and even be improved to provide higher precision and more functionality.

XIII.APPLICATIONS

The proposed algorithm for the plant species classification may be applicable in many cases related to practical activities in such spheres as agriculture and environmental control.

Firstly, this classification approach can be used for smart agriculture, when farmers will have an opportunity to use this system to make decisions on plant identification and monitor their crops based on leaf images. Such information may help farmers better manage their crops.

Secondly, it can be implemented into a mobile app that will allow the user to take pictures of plant leaves and automatically classify them as belonging to different species. Such a system may be helpful to farmers, students and researchers working with plants.

Moreover, the proposed plant species classification system can be widely used by scientists in botany and agriculture for carrying out researches. It will significantly decrease manual efforts required for this procedure and will help researchers work with large amounts of data.

It also can be used in decision making processes of automated farm. It will be useful to determine what kind of plants grow in particular territory and to monitor plant diseases and health condition.
The developed model may become a useful instrument for education because it will demonstrate how to classify plants using computer vision and machine learning algorithms.

XIV.CONCLUSION

The proposed framework is based on a plant species classification technique that leverages transfer learning using MobileNetV3. The technique was tested by evaluating the model on the PlantVillage dataset after applying the necessary preprocessing steps.

Experimental findings reveal that the accuracy of classification achieved using the proposed approach is relatively high at 97.87%. As such, the proposed approach proves to be effective in classifying leaf pictures to identify plant species. Furthermore, by employing lightweight networks together with the transfer learning technique, it is possible to build an efficient model with low computational complexity. The findings further indicate that the model generalizes well since it is able to generalize when used on new data. This makes the model applicable in practical situations where it helps the users make decisions quickly and accurately.
The application areas of the proposed method include helping researchers, students, and farmers identify different types of plant species.

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