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Plant Leaf Disease Classification using Transfer Learning using EfficientNetb5

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***Abstract*—One of the biggest achievements in artificial intelligence is image classification. Plant diseases have become more prevalent, which has caused numerous issues and difficulties for farmers and agricultural experts worldwide. Maintaining biodiversity and maintaining the ecosystem's balance depend on keeping an eye on and conserving plants and their leaves. In this research, we describe the classification system for plant leaf diseases that we created using Keras Deep Learning modules and Convolutional Neural Networks. To train the model, we applied transfer learning and used EfficientNetb5, and we attained a test accuracy of 99.20%.**

***Index Terms*—Artificial Intelligence, Image classification, Plant Leaf Diseases,Keras Deep Learning modules, Convolutional Neural Networks,Transfer Learning, EfficientNetb5**

I. Introduction

Plant are one of the most crucial components of our ecology. The leaves that make up plants prepare food for them. They are crucial to many daily processes, including photosynthesis, the production of medicinal herbs, the production of green leafy vegetables, and many more. Farmers are aware of the true value of plants and leaves because they provide sustenance for around 95% of all living things on the planet. By assessing the condition of the plants and leaves that are being cultivated in a particular location, we may gauge the success of agricultural production and wildlife habitats.

The first sign of environmental issues is a change in the plant, leaf density in a specific location [1]. Bacteria and other microbes that impair the plant's growth by destroying its leaves and other parts are what cause plant illnesses. Therefore, it is crucial to keep track of the distribution of plant diseases in a certain area in order to determine whether or not the ecosystem is in balance.

For farmers, agricultural scientists, managers, and enthusiasts alike, classifying and keeping track of plant disease species can be particularly challenging because most plants have similar characteristics, such as color, leaf type, and so on. Leaf disease on plants Classification and monitoring lighten the load on farmers, agricultural scientists, and agriculture managers while assisting in the data collection and analysis of leaf diseases. In this study, we used transfer learning and Convolutional Neural Networks (CNN) to create a system for classifying plant leaf diseases.

Although there are several methods for classifying images, machine learning and deep learning are the most widely used. In machine learning, the characteristics of the photos must be explicitly mentioned while training (thus feature extraction is rather laborious and time-consuming). For image categorization in machine learning, the SVM (Support Vector Machine) is employed [12]. But there are some drawbacks: [13] SVMs do not immediately provide probability estimates; instead, we must apply a pricey five-fold crossvalidation procedure to estimate the probability.

Deep learning has recently produced incredibly impressive results for a variety of picture classification tasks, including the identification of plant leaf diseases. Therefore, adopting deep learning instead of machine learning models for image categorization will offer several benefits. Our deep learning model needed a lot of image-based data to be trained.

38 classifications of leaf diseases make up the dataset we obtained from Kaggle . To train our deep-learning model, we used 80,000 photos of leaf diseases in total. We can employ a pre-trained model if we apply deep learning, eliminating the requirement to create new models. Additionally, we didn't need a sizable dataset to train. We can develop a deep learning model faster because it also cuts down on computation (or training) time. EfficientNet was the pre-trained model that we used.

II. Literature Review

To assist farmers and agricultural scientists globally, the development of an effective and dependable method to categorize plant leaf diseases was crucial. The researchers made an effort to classify plant leaf diseases using artificial intelligence and deep learning techniques in order to make it practicable.

"Review on Convolutional Neural Networks(CNN) Applied to Plant Leaf Disease Classification" by J. Lu et al. [4] The efficiency of the Plant Leaf Disease Classification created with

CNN and VGG16 was mentioned by J. Lu et al. A Large-scale discussion was held over the use of deep learning in the classification of plant leaf diseases.

The study "Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques" was conducted by Sardogan et al. [5] Sardogan and colleagues focused on using a CNN algorithm to identify plant leaf diseases from photos of diseased leaves. On MATLAB R2018b, he created a network and carried out his experiments. He created numerous buttons with built-in disease prediction features.

"Using deep transfer learning for image-based plant disease identification" is the subject of research by J. Chen et al. [6] utilizing the transfer learning technique, in which the new model is trained utilizing the information of the old model, J. Chen et al. used VGGNet and the Inception module to create their deep learning model. The validation accuracy they attained was 91.83%, and the average accuracy was 92.00%.

"Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance" is the subject of research by T. Rumpf et al. [7] Support vector machine technology was utilized by T. Rumpf et al. to classify foilar sugar. He talked about predicting plant diseases before they manifest physical signs. The range of categorization accuracy was 65% to 90%.

Overall, the research literature highlights the CNN algorithm's enormous potential for classifying plant diseases and its application to different architectures. These studies have shown that deep learning technologies have the potential to help agricultural managers and scientists effectively manage and control plant diseases by providing accurate and rapid diagnosis. Addressing problems with data accessibility, generalization, and interpretability is crucial to enhancing the validity and implementation of these models in actual field situations. More research and validation are required to show their effectiveness as reliable approaches for classifying plant leaf diseases and to look into their possible incorporation into global agriculture systems.

III. Proposed Model and Methodology

It will take a long time to train a new deep-learning model. So, depending on a model that has already been trained, we could apply transfer learning to build our own model. Our work will be easier because the trained model doesn't need to be trained from scratch because all of the weights have already been trained and set. We don't require any extra images or data to train our model because the weight is already established. We applied the EfficientNetb5 CNN model, which was pre-trained [8]. This neural network architecture, which contains more than 300 deep layers, is depicted in Figure 1.

The study's objective was to find a resolution to the classification problem with plant leaf diseases. To address the mentioned difficulty, a deep learning model is trained using the CNN method and EfficientNetb5, and the outcomes are satisfactory. The deep learning model needs to undergo prolonged training, much like people do, to improve its predictions. This involves a number of essential steps, such as:

1) Data Collection
2) Data Preprocessing
3) Model Architecture Selection
4) Transfer Learning
5) Training and Validation
6) Tuning of Hyperparameters
7) Evaluation Metrics
8) Comparison and Analysis
9) Validation on External Dataset

Data Collection: Images of diseased leaves are used to assemble a diverse collection of leaf disease positive cases. Make sure the data is large enough and representative to ensure effective model training and evaluation. There are roughly 80,000 photos of leaf disease in the collection. There were 38 classes in the dataset that we obtained from Kaggle.

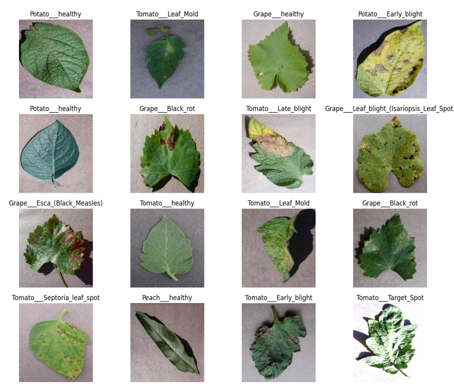

Fig. 1. Some of the leaf diseases

The image up top shows both healthy plants and plants that have indications of various diseases.

Data preprocessing: includes actions such as standardizing image sizes, cropping the image, normalizing pixel values, reducing noise, and handling any missing or corrupted data. For the CNN and Inception V3 model training stages, this stage ensures consistency and high-quality data [14].

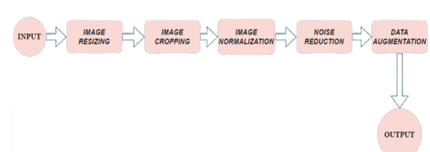

Fig. 2. Stages of Data PreProcessing

Model Architecture Selection: The appropriate CNN architecture is chosen, and the EfficientNetb5 module is included, for the purpose of detecting leaf illness. The Efficient-Netb5 module provides efficient feature extraction, and CNNs are suitable for workloads requiring image classification.

Transfer Learning: The EfficientNetb5 module makes use of transfer learning to benefit from weights that have already been taught on a sizable dataset. It involves using the knowledge of an old or current model to create a new model. The performance of the model is enhanced by optimizing its parameters using the leaf disease dataset [8].

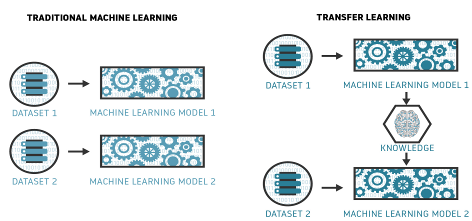

Fig. 3. Transfer Learning Process

Training and Validation: From the dataset, training, validation, and test sets have been produced. Using the proper loss function and optimizer, the training set is used to train the CNN model with the EfficientNet module. Model performance on the validation set is monitored to prevent overfitting. There were 70000, 8300, and 1700 images in the training set, validation set, and test set, respectively [9].

Tuning of the hyperparameters: The learning rate, batch size, and number of epochs are some of the hyperparameters that are modified to improve the model's performance and convergence [10].

Evaluation Metrics: The efficiency of the model in identifying leaf diseases is assessed using evaluation parameters such as accuracy, sensitivity, specificity, precision, and logarithmic loss [11].

Comparison and analysis: The performance of the CNN model with the EfficientNetb5 module is compared to that of other models or existing diagnostic methods when it comes to the classification of plant leaf diseases. The study looks at the benefits and drawbacks of the advised course of action. The 300+ layer deep EfficientNetb5 was chosen because it has more convolution layers and efficiently harvests features in contrast to other architectures. EfficientNetb5 is also a more accurate architecture when compared to other architectures.

Validation on an External Dataset: Using an external dataset, the trained model is assessed for its ability to generalize and resilience in detecting leaf illnesses from multiple sources. This will provide us with information on the progress made in developing a deeper learning model that is superior to the existing, more conventional models.

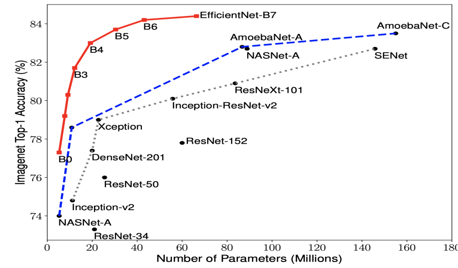

Fig. 4. Comparison of Various Architectures

Using the CNN and EfficientNetb5 modules, this methodology enabled the construction of a reliable and accurate deep learning-based leaf disease classification system. One of the top architectures used for image classification is Efficient-Netb5. It is an upgraded version of EfficientNetb0 that was released in 2019. In comparison to other architectures, it is more accurate and less error-prone, and it includes more than 300 layers [2]. The study's findings will aid in improving patient care and diagnostic capabilities while the pandemic is still ongoing

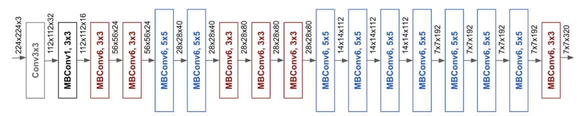

Fig. 5. EfficientNetb5 Architecture

IV. Results and Discussion

Finally, we created a deep learning model that predicts the recurrence of plant disease by combining the concepts of picture categorization using CNN and the learned model, EffiecientNetb5.

Images of leaf disease are used as input for our deep learning algorithm. We used 224 * 224 images with red, blue, and green color channels to train the model. Therefore, before applying our deep learning model to predict leaf illnesses, we must resize the image to the suggested size. Before being produced, the image goes through every layer of EfficientNetb5. It is demonstrated how well the deep learning model performs throughout both training and validation. If a model has little loss and the highest accuracy, it is regarded as being better.

To evaluate the performance of the deep learning models on the validation set, we used validation loss as a metric and training loss as a statistic. Ten epochs are covered by the EfficientNetb5 model, and its accuracy was verified. After 10 epochs, the results remained constant. At that time, the required model worked well, with a low loss rate and a high accuracy rate. The accuracy percentages for validation and testing were 98.73% and 99.20%, respectively.

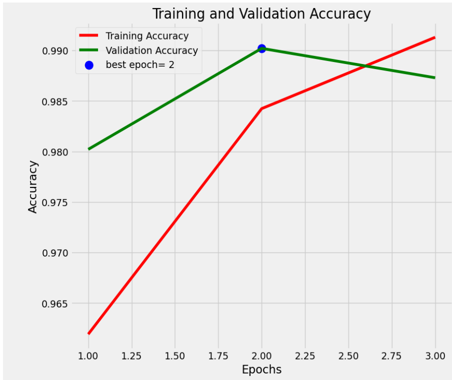

Fig. 6. Training and Validation Accuracy

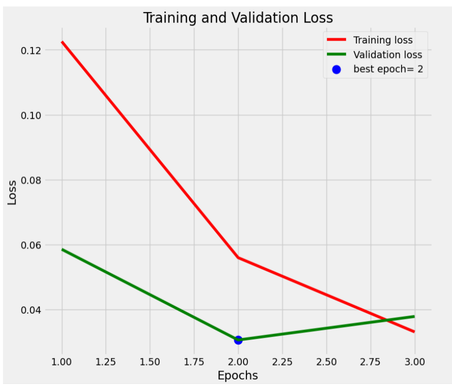

Fig. 7. Training and Validation Loss

V. Conclusion and Future Scope

A. Conclusion

The eventual goal of this model is to help construct a powerful AI-driven diagnostic tool for classifying plant leaf diseases, which would allow farmers and agricultural experts to accurately predict the disease and create treatments for it. By utilizing the capabilities of deep learning technology, this technique aims to enable early identification and reduce the effect of various disease-causing bacteria and microorganisms on the health of the plant.

In order to train the deep learning model that can identify plant diseases, we were successful in applying CNN (Convolutional Neural Network) analysis to photos of plant diseases. For picture recognition, it makes use of feature abstraction. Because CNN is one of the most sophisticated picture classification algorithms and provides exact, accurate predictions with little loss, it was our choice.

The transfer learning method used by EfficientNetb5 improves model accuracy while decreasing loss. This technique can be applied globally to regulate or track the spread of plant diseases. We believe that the project could benefit from considerably more sophisticated artificial intelligence components in later iterations. We can predict plant diseases using our model.

B. Future Scope

- to increase the deep learning model's efficiency and accuracy.
- help boost the dataset's representation of plant diseases.
- to improve the model in order to commercialize it as a product that can be used to forecast diseases from photos of leaves.
- to provide statistical information to demonstrate both the disease's prevalence and its treatment options.

Acknowledgment

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