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Plant Leaves Disease Detection (Efficient Net)

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***Abstract*: The Indian economy heavily depends on agricultural productivity. One of the reasons that disease detection in plants is crucial is because disease in plants is common in the agricultural sector. If sufficient care is not taken here, serious consequences result on plants, as a result of which the corresponding product quality and quantity the impact on productivity. Finding plant diseases using a useful automatic technique is one that minimizes a lot of work of monitoring in large agricultural farms, as well as at the very beginning itself it recognizes disease symptoms on plant leaves at a very early stage. This paper presents a solution using machine learning with help of EfficientNetB3 model. A public dataset of 87K rgb images of healthy and diseased crop leaves is used, which is categorized into 38 different classes. An EfficientNetB3 model is trained to identify healthy and disease plant leaves.**

***Keywords*: Efficient Net, Leaf disease detection.**

1. Introduction

One of the most common jobs in India is farming. All nations' economies depend heavily on agriculture. The basic goal of agricultural advancement is to satisfy the population demand is increasing. In addition to having a significant economic impact, agriculture is regarded as the foundation of the economy in developing nations. Agriculture has long been associated with the production of essential food crops. Sometimes less amount of crop quality in agriculture is because of diseases of plants. Plant diseases have an impact on agriculture's social, ecological, and economic factors as well as plant development and crop yield. Farmers can suffer huge financial losses as a result of plant leaf diseases. Most of the main symptoms of plants are microscopic, so the identification of diseases is restricted by human visual capabilities.

The procedure of diagnosing diseases with our unaided eyes will always be challenging. The farm must be continuously watched in order to achieve this. This procedure is laborious. When the farm is large, this is also highly expensive. The farmers typically employ expensive methods and the usage of pesticides as solutions to reduce the effects of these diseases. The plant and the surrounding area are harmed when chemical measures are used.

Due to this challenge, even agricultural professionals struggle to identify the diseases and come up with a fix. Leaves are the most important part of plant. A leaf's main job is to maintain the plant's life. In case of plants, leaves are the most important part for fast growing of plants and increase productivity of plants.

Disease that affects a plant's leaf directly disrupts the plant's life Disease that affects a plant's leaf directly disrupts the plant's life cycle. Bacterial, fungal, and other diseases are those that frequently harm leaves. Therefore, it is essential to find plant diseases early. This paper is use Efficient Net B3 model for identifying plant diseases on giving the image of leaves are input.

2. Literature Survey

There are many researchers conducted on plant disease prediction.

Anand H. Kulkarni et al. [1] developed a model for early and accurate plant disease identification using artificial neural network (ANN) and several image processing techniques. Given that the suggested strategy is based on ANN Gabor filter for features and a classifier for classification extraction, it produces superior outcomes with an increased rate of identification as much as 91%. Different plants are classified using an ANN-based classifier uses a blend of textures, colour, and illnesses characteristics to identify those disorders.

Revathi et al. [2] developed a model for the identification of plant visual disorders. The plant is captured on camera and prepped for digital imaging. it was extracted techniques including colour space, texture, and edge detection Next, the elements are carried out. The characteristics that are retrieved the classifiers with are supplied. This study seeks to determine the infection of cotton leaves using image processing technique.

Sharada P. et al. [3] developed a model for the disease identification by using a deep learning method The dataset utilized for the deep learning method's execution includes a collection of pictures of several kinds of crops, along with their attributes and good image. Alex Net is one of two architectures, as well as GoogleLeNet, which also offers a 99% accuracy rate. Because of this, their model revealed a low categorization rate for various types of photos on a contrasting background.

Savita N. Ghaiwat et al. [4] a review of the various classification methods that can be used to categorize plant leaf diseases. The easiest of all methods for class prediction appears to be the k-nearest-neighbour technique for the test scenario provided. Finding the correct parameters for SVM looks to be one of its limitations if training data is not linearly separable.

Sindhuja Sankaran et al. [5] Plant diseases are discovered in their early stages by early symptoms. For the purpose of

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providing analytical information about the representation of the plant based on its colour preferences. in addition, the method for processing images K-means grouping algorithm has also been utilised to determine the End of the illness and, at long last, Fuzzy Logic implemented for the disease classification.

Mrunalini R et al. [6] The method for categorising and identifying the various plant diseases is discussed in the paper. A machine learning-based recognition system will be highly helpful for the Indian economy since it saves time, money, and effort. The Color Co-occurrence Method is the method suggested in this for feature set extraction. Neural networks are used to detect illnesses in leaves automatically. The suggested method can considerably aid in the precise detection of leaves and appears to be a crucial method in cases of steam and root infections while requiring less computational work.

3. Proposed Methodology

Crop diseases must be promptly identified and prevented if productivity is to be increased. In this paper Efficient net B3 model are implemented to identify and diagnose diseases in plants from their leaves. Efficient Net is a convolutional neural network design and scaling method that uniformly scales all dimensions of depth, width, and resolution using a compound coefficient. With a set of predefined scaling coefficients, this model scales network width, depth, and resolution equally. An open dataset of 87 K rgb photos of healthy and diseased crop leaves is utilised to train in this implemented model. These images are divided into 38 different classes. Crops including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper, Potato, Raspberry, Soyabean, strawberry, and Tomato are included in the dataset. The model that was implemented performed better in terms of Accuracy when compared to other models. The EficientNet model is promising and can significantly impact the effective identification of diseases; it may also have potential in the detection of diseases in real-time agricultural systems, according to the accuracy findings in the identification of diseases.

A. Why we use EfficientNet B3 Model?

EfficientNet is used because it is higher accuracy and better efficiency over existing CNNs. And this model uniformly scales network width, depth, and resolution with a set of fixed scaling coefficients.

B. Implementation

Implementation steps are,

1. Data Gathering
2. Data Loading
3. Data Pre-processing
4. Model Creation
5. Data Splitting
6. Model Training
7. Model Validation
8. Result Visualization

1) Data gathering

Data gathering, or acquiring the appropriate dataset for this project's execution, constitutes the first implementation phase. The dataset includes crops including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper, Potato, Raspberry, Soyabean, strawberry, & Tomato. For the purpose of identifying plant diseases, an open dataset of 87 K rgb photos of healthy and diseased crop leaves is employed.

2) Data loading

The next phase is data loading after the dataset has been collected for the identification of plant diseases. Copying and loading data or data sets from a source file, folder, or application into a database for processing is known as data loading. Here dataset is loaded directly from Kaggle to google colab using the Kaggle directory for colab and Kaggle api authentication key.

3) Data pre-processing

Before running the data, the first stage is data preprocessing. Data preprocessing is a method for turning unclean data into a clean dataset that can be processed. Whenever data is collected from various sources, it is collected in raw format, which make analysis impossible. Here data preprocessing is performed for resize of image, & colour conversion. It is a critical that we pre-process our data before feeding it into a model.

4) Model creation

Model creation is the next crucial stage. Here, EfficientNetB3 models are developed to recognize and diagnose plant illnesses from the affected plants' leaves. This model will diagnose the leaf disease given an image of the leaves as input and will also provide any necessary control measures. Efficient Net B3model is initialised with pretrained ImageNet weights and max pooling as the pooling type. For normalization, batch normalization layer is added with 0.99 as momentum value and with a learning scale factor of 0.001 where the feature axis is normalised. The Dense layers is initialised with outer space dimensionality of 256. The regularization function applied to the kernel weights as an L2 Regularise from Keras with a regularisation factor of 0.016. The Regularization function applied to the Output layer and the bias vector are L1 regularizes from Keras with regularization factors of 0.006. ReLu Activation function is used for these layers.

5) Data splitting

Data splitting, sometimes referred to as train-test split, is the division of data into smaller subsets for separate model training and evaluation. The data splitting ratio in this case is 90:10. In this case, 90% of data is used for training and 10% is used for validation.

6) Model training

A dataset is referred to as a training model while a model is being trained. The sample output data and the related sets of input data that have an impact on the output make up this set. To compare the processed output to the sample output, the training model is utilised to run the input data through the algorithm. Here total 40 epochs is used for the training. And if the observed value does not improve, 1 epoch must pass before the learning rate is adjusted, and 3 epochs must pass before the training is stopped.

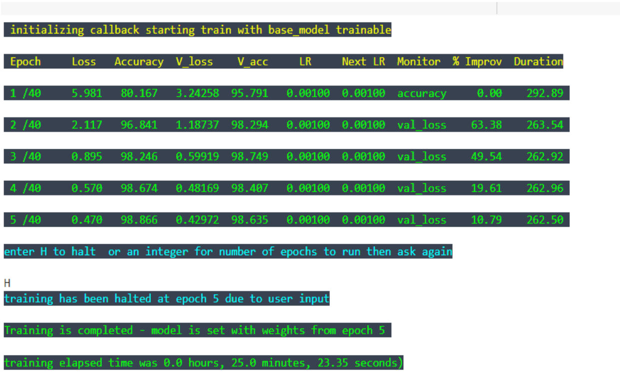

Fig. 1. Model training

7) *Model validation*

Model validation is the process of comparing a trained model to a testing data set. The data set that is used to create the training set is the same one from which the testing data set is created. Here, the Keras Image Data Generator is utilised with a scalar processing function, validation data is used as a data frame, and data is loaded in batches of 30 in a categorical manner. Furthermore, 10 percentage of the data is used for the validation.

8) *Result visualization*

As a result, a graph is drawn to show the accuracy and loss. The training accuracy and training loss are shown using a red line. and green line represent the accuracy and loss of the validation. Blue dot represents epoch with best validation accuracy in accuracy graph and lowest validation loss in loss graph.

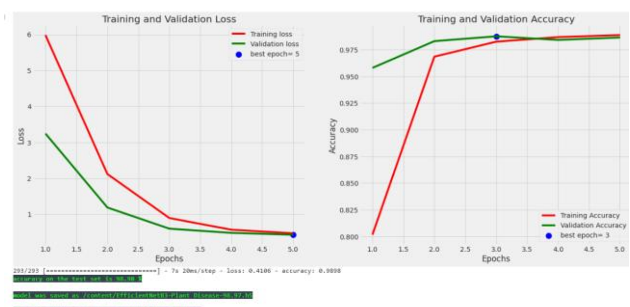

Fig. 2. Result visualization

4. Results

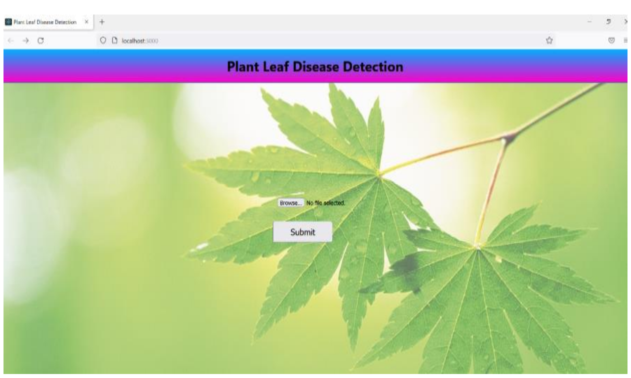

Fig. 3. Home page for plant leaves disease detection

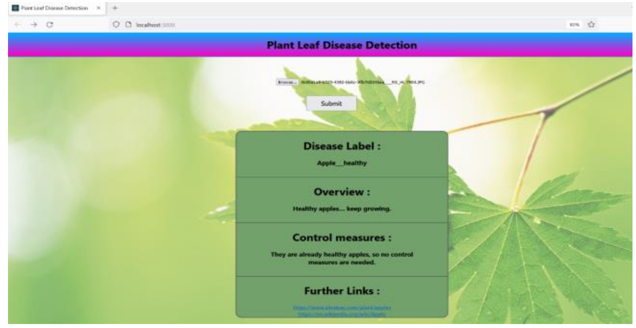

Fig. 4. Page for healthy leaves

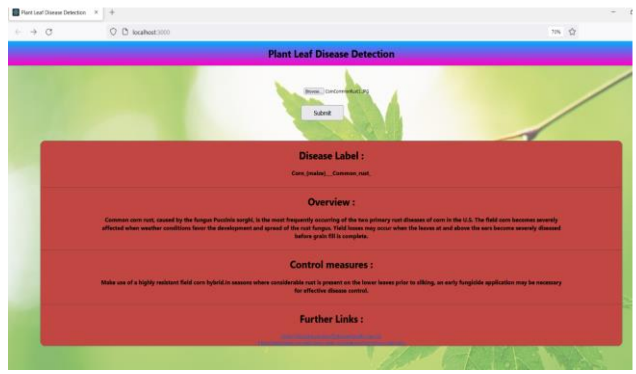

Fig. 5. Page for disease leaves

5. Conclusion

As a result, a model is created for identifying diseases that impact plants. A plant leaf disease detection approach based on the Efficient Net model is provided in this paper. When you input a leaf image, the programme determines whether the leaves are healthy or not. If it is not healthy, it can diagnose and foretell plant diseases and also offer the necessary disease control methods. The dataset used for training is made up of 87 K rgb images of both healthy and sick crop leaves. 38 distinct classes have been created for these photos. The dataset includes crops like apple, blueberry, cherry, corn, grape, orange, peach, potato, raspberry, soybean, strawberry, and tomato. Finally, this work is producing an accuracy of 99%.

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