LEAF DISEASE DETECTION USING MOBILENET

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Abstract: *The agriculture industry is critical to ensuring global food security, hence early diagnosis of plant diseases is critical. Deep Learning (DL) algorithms have emerged as powerful tools for automating the detection of leaf diseases, resulting in better crop management and higher agricultural yields. Deep Learning models, particularly Convolutional Neural Networks (CNNs), have proven to be extremely effective at automating disease detection in plants. DL algorithms can learn complicated patterns and features that distinguish between diseased and healthy leaf photos, allowing them to accurately identify numerous plant illnesses. The study used a dataset full of field images that we pre-trained on deep convolutional neural network called MobilNet and a method known as transfer learning by demonstrating the potential of deep learning approaches in detecting leaf disease. To achieve this goal, the transfer learning model was fine-tuned using a variety of hyperparameters and achieved an 95% accuracy rate*

Key Words: *Disease detection, Deep learning, MobileNet, Transformer etc*

1.INTRODUCTION

In recent years, the agricultural sector has witnessed a transformative shift in the way plant diseases are diagnosed and managed. Traditional methods of disease identification, which often involve visual inspection by human experts, are labour-intensive and may lead to delayed interventions, potentially causing significant crop losses. To address these challenges, the integration of Deep Learning (DL) techniques has emerged as a groundbreaking approach for the automated and accurate detection of leaf diseases in plants.

Deep Learning is a subset of machine learning that focuses on training artificial neural networks to automatically learn and extract intricate patterns from data. Specifically, Convolutional Neural Networks (CNNs) have proven to be highly effective for image-related tasks, making them particularly suited for leaf disease detection. The use of DL for leaf disease detection offers several advantages, including speed, accuracy, and scalability. It enables early disease identification, allowing for timely interventions, reducing crop losses, and promoting more sustainable farming practices. Moreover, DL can be applied in remote sensing applications, where large agricultural areas can be monitored efficiently.[3]

1.1 Problem Statement

In the most of studies, the Plant Village dataset was utilized to assess the performance of the DL models. Although this dataset contains many photos of many plant species and their illnesses, they were captured in a laboratory. As a result, it is projected to generate a substantial dataset of plant diseases in real-world settings. Although some research uses hyperspectral pictures of ill leaves, and various DL frameworks are used for early identification of plant leaf diseases, issues that impede the broad application of HSI in plant disease detection remain unresolved.

That is, labeled datasets for early plant disease detection are difficult to get, and even experienced specialists are unable to pinpoint where the invisible disease symptoms are and designate totally invisible disease pixels, which is critical for HSI to detect plant disease.[2]

1.2 Purpose

DL-based systems are designed to identify plant diseases at an early stage. This enables farmers and agricultural experts to take prompt action to mitigate the spread of diseases and minimize crop losses The primary purpose is to protect crops from diseases. Timely detection allows for targeted interventions, such as applying the right amount of pesticides or adopting disease-resistant crop varieties, to safeguard agricultural yields. By identifying and managing diseases effectively, DL helps increase crop productivity. Healthy plants are more likely to produce higher yields, contributing to food security and economic sustainability.

Accurate disease detection and management reduce the need for excessive pesticide use, which can have negative environmental consequences. DL helps in using pesticides more judiciously, minimizing ecological harm. DL provides valuable data and insights to farmers and agricultural experts, empowering them to make informed decisions about disease management strategies, irrigation, and other agricultural practices. DL-based disease detection serves as a platform for ongoing research and development in the field of agricultural technology. Researchers continuously refine models, improve data collection techniques, and explore novel applications.[1]

2. LITERATURE SURVEY

C Jakulin Et al., [1] stated that CNN and other DL technique of classification in ML can be used for plant disease detection. Lili Li et al., [2] mentioned that plant village dataset has images taken in lab. It is expected to establish a large dataset in real condition. Torki et al., [4] this review summarizes the progress made in Deep learning techniques for plant disease detection and provides insights into the challenges and future directions of the field. Ferentinos., [5] this survey provides an overview of various deep learning techniques applied plant disease detection including CNNs and discusses their advantages and disadvantages.

3. PROPOSED SYSTEM

The proposed system aims to advance the field of leaf disease detection by introducing a novel deep learning model that is trained on a meticulously curated and diverse dataset of leaf images. The project is driven by the need for more accurate and robust disease identification in plants, with a specific focus on enhancing the existing methodologies by harnessing the power of cutting-edge deep learning techniques. The proposed system uses the plant disease classification merged dataset with 88 classes which has above 76000 images and accuracy as performance matrix

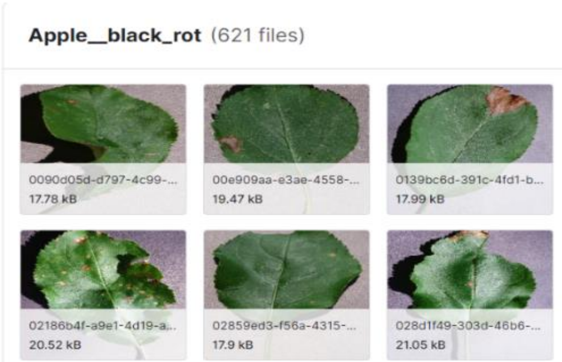
The new dataset is utilized to train the deep learning model using a carefully devised training strategy. Transfer learning from pre-trained models is explored, enabling the network to leverage knowledge from related tasks while adapting to the specific challenges of leaf disease detection. The training process involves hyperparameter tuning, optimization techniques, and regularization to ensure the model's robustness and performance. The foundation of the proposed system is the development of a new dataset that covers a wide range of plant species, diseases, and environmental conditions. This dataset is compiled from various sources, including field images, controlled environment data, and remote sensing imagery, to ensure diversity and representativeness. Rigorous data curation and annotation are carried out to provide accurate labels for each image, and data augmentation techniques are applied to increase the dataset's size and diversity.

3.1 Dataset

Plant Disease Classification Merged Dataset., [6] This dataset is compiled from various sources, including field images, controlled environment data, and remote sensing imagery, to ensure diversity and representativeness. Rigorous data curation and annotation are carried out to provide accurate labels for each image, and data augmentation techniques are applied to increase the dataset's size and diversity. What cannot be avoided in general is a bias among the classes, since in some cases different shooting conditions were used for the images (e.g. classes with mainly laboratory images or different soil in the background)

The samples of leaf images in the database are shown in

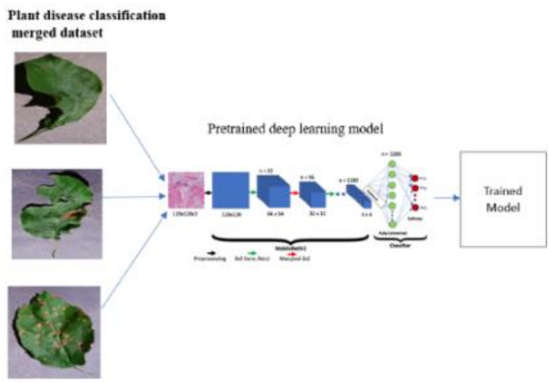
Fig 1. Plant Disease Classification Merged Dataset



3.2 Model Description

We have trained the dataset on pretrained model known as MobileNet V2. Mobilenets are low powered models that we can use effectively for classification of leaf images and also used to extract features.

Fig 2. Model Architecture

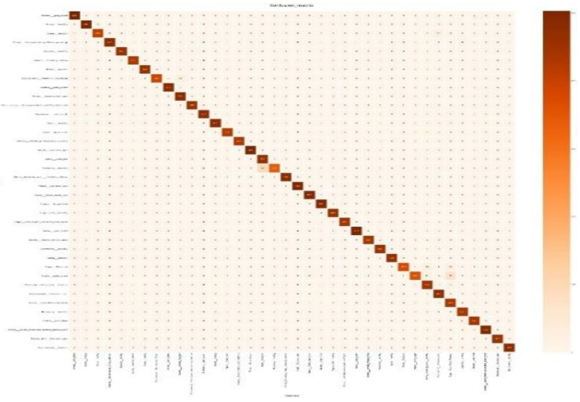


Training the Model- The next step is to compile the model and then train it on a training dataset. The following parameters need to be specified for compiling the model:

We have used the Adam optimization technique because it always leads to a smoother way than other optimization techniques. Adam is an optimization algorithm that uses adaptive moment estimation to generate more efficient neural network weights [7]. We have used the optimizer: Adam with betas= (0.9,0.999) and epsilon=1e-08 ,learning_rate: 5e-5. loss → In our case we have used "sparse categorical_cross entropy". Sparse categorical cross entropy can be used for integer targets instead of categorical vectors [8]. In order to fit the model we have used the batch size 256epochs → An epoch is a measure of how many times the whole training set of images is used once.

The confusion matrix [9,10] of project is shown in Fig.3

Fig.3 Confusion Matrix



4. RESULTS

The model is validated with training and testing dataset. The model results in 95% accuracy for 80% of training set and 93% accuracy for testing set. The model is fine tuned with Gemini API to improve vision techniques

FIg 4. Predicted Disease

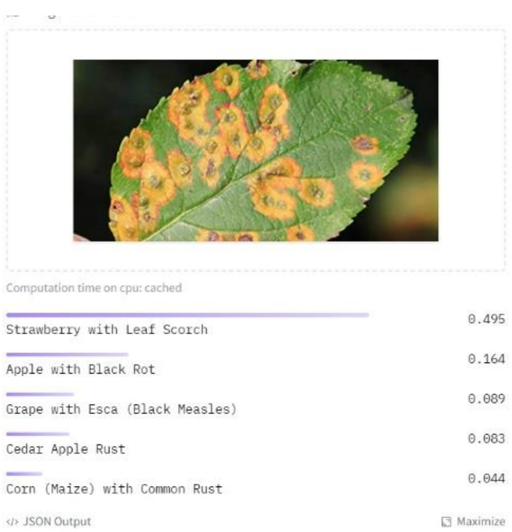
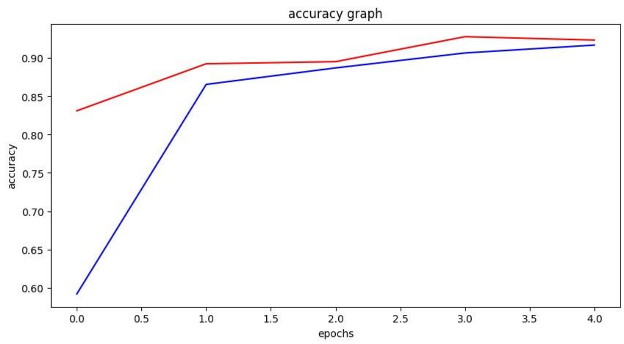


Fig 5. Performance Matrix



The hardware specification i.e CPU: Intel core i5 or i7, RAM: 8GB of RAM, Storage: 250GB SSD and Software Specification i.e Operating system: Windows 10, Python 3, Frameworks: Transformers 4.27.3, Pytorch 1.13.0, Tokenizers 0.13.2, CNN architecture: Mobillenet is recommended to carry out this project.

5. CONCLUSION

In conclusion, early detection of plant diseases is crucial to reduce crop yield loss. The use of deep learning models such as Mobile Net can help detect plant diseases with high accuracy. The research also highlights the importance of evaluating models using field based database to gain a comprehensive understanding of their capabilities. The proposed model identifies the type of disease based on the plant leaf image using Mobile Net. The results of this research have the capacity to enhance the efficiency and efficiency of identifying and treating diseases in the agriculture. In future we are planning to implement it with dl powered drones and internet of things (IoT) sensors with more accuracy.

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