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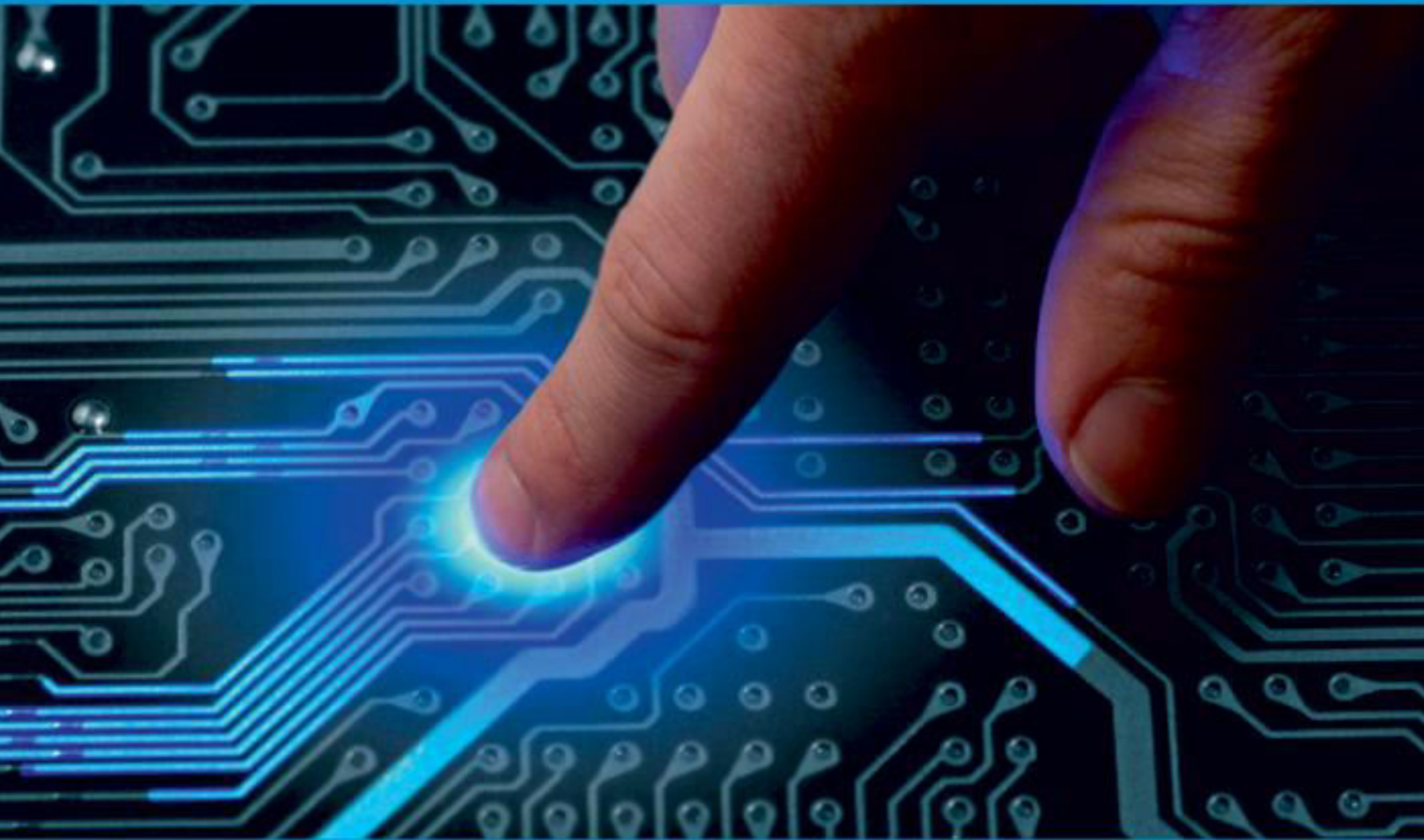

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Enhancing Tomato Plant Leaf Diseases Detection through Ensemble of Deep Learning Models

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ABSTRACT: Farmers face financial risks if they fail to detect diseases in their tomato plants or apply incorrect treatments based on wrong assumptions. This study developed an ensemble of ResNet and DenseNet models to increase the detection accuracy of tomato plant leaf diseases. The model was developed, validated, and tested using an open-source Kaggle dataset with 10,000 plants. Using known statistical evaluation metrics, the model increased accuracy from the ResNet101 by 97.75% by 1%. The proposed study achieved an Accuracy of 98.80%. Our model proved to be better than ResNet101, DenseNet VGG16, Xception, and InceptionV3.

KEYWORDS: Deep Learning (DL); Machine Learning (ML); Convolutional Neural Network (CNN); Ensemble; hyper-parameters; feature Extraction; Image processing.

I. INTRODUCTION

Tomatoes are consumed widely and have a significant global impact, with an increase of 164% in the amount of land dedicated to tomato farming over the past 40 years [1]. Lower or lower-quality harvests can be caused by several leaf infections that can harm normal tomatoes. As a result, detecting and categorizing tomato diseases early and accurately will enable minimizing output losses and ensuring optimal output [1]. The process of managing and monitoring plant health typically involves scouting and checking the plant manually at regular intervals. However, this approach is not only expensive and time-consuming but also prone to misjudgment, which can lead to a delayed diagnosis. To overcome these challenges, machine learning algorithms are being widely used to automate the classification of plant diseases. These methods rely on features that are manually extracted by specialists, resulting in high costs and time consumption [2].

To overcome the limitations of feature extraction, one must consider the power of deep learning. By automating this process, deep learning can provide an effective way to extract meaningful features from complex data sets [3]. Classifying plant diseases is a common application of deep learning, as it has been shown to surpass traditional machine learning methods. [4]. Models based on Deep Learning use certain variables that need to be adjusted before they can be applied. These variables are called Hyperparameters [5]. The performance of an algorithm in a given learning task is often determined by the configuration of its model parameters. To achieve better results, machine learning engineers can adjust the hyperparameters. Although deep learning models have been used to detect plant diseases in various crops such as tomatoes, potatoes, rice, corn, and cherries, there are some limitations. These limitations include variations in the visual symptoms of the same disease between cultivars, differences in image capture conditions, variability in image backgrounds, non-uniform image backdrops, and noisy images. In response to these challenges, we propose an ensemble approach to classify diseases in tomato leaf plants.

II. RELATED WORK

There are different algorithms and methodologies for identifying diseases on plant leaves. Many different organizations and researchers have studied and have done work on this topic using different algorithms. Some of them are summarized below:

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In 2023, P. Gweme et al [6], developed a predictive model for identifying tomato plant leaf diseases. They utilized deep learning algorithms such as CNN and resNet, fine-tuning the hyper-parameters to enhance the accuracy of the predictions. They obtained a dataset from Kaggle and were able to achieve an accuracy rate of 90%.

In October 2023, Theodora Sanida et al. [7] used CNNs for the identification of diseases in tomato plants. Transfer learning was employed to improve accuracy and training time. The VGGNet architecture, which had been pre-trained using ImageNet, served as the basis for the model and included two inception blocks.

Shima Ramesh, et al., suggested that 42% of agriculture production suffers losses due to plant leaf diseases. To tackle this issue, a method called the 3C's technique can be used to detect these diseases from input images. The technique involves three main steps: image pre-processing, image segmentation, and feature extraction. After these steps are completed, the K Nearest Neighbour (KNN) classification is applied to classify the disease [8].

In 2022, Priyanka N.Bande and Mr. Kranti Dewangan, investigate the application of deep learning models in precise farming for detecting and classifying plant diseases. In their study, they employed various deep learning models such as VGG-16, ResNet-50, AlexNet, DenseNet-169, and InceptionV3 for automatically diagnosing plant diseases [9]. In April 2023, S. Srinivas et al. proposed a system that uses convolutional neural networks, specifically the Inception V3 model, to identify and classify diseases in tomato leaves. As a deep learning technique for disease identification and classification in tomato leaves, they utilized the Inception V3 model, which is a CNN architecture extensively used for image recognition tasks. For training the Inception V3 model on the Kaggle dataset for tomato leaf disease, which provided a diverse range of images for different diseases affecting tomato plants, the researchers employed it. [10].

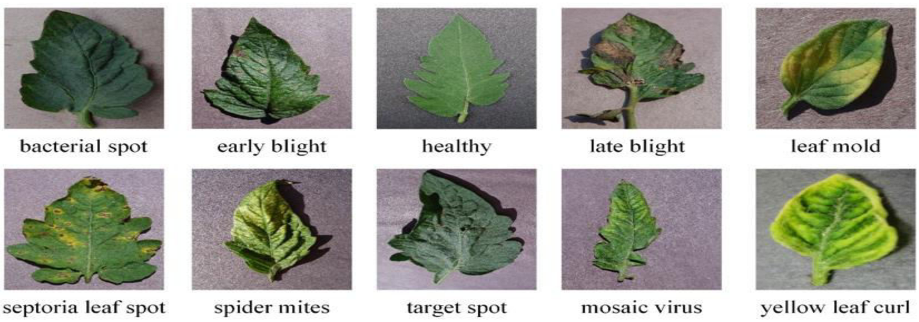
In June 2023, Samuel Giftson Durai et al., A CNN and ResNet50 image segmentation were used in a proposed multi-level deep learning model to detect early blight and late blight potato infections from leaf images. Their model achieved a high accuracy of 99.75% on a potato leaf disease dataset. [11].

S. S. Harakannanavar et al., in 2022, automatic detection and classification of diseases in a tomato plant leaf was attempted by various authors using different pre-trained convolutional neural networks. Four models were considered, including VGG-19, VGG-16, Res-Net, and Inception V3, and their performance was evaluated on two different datasets. The first dataset consisted of controlled images acquired in a laboratory, while the second dataset was collected from the field under natural light conditions using a cell phone. The second dataset was found to be more challenging for various pre-trained neural network models as it was representative of a real-world situation. The authors observed that parameter tuning produced more accurate results than feature extraction. They also found that the average performance on the laboratory-based dataset was 10% - 15% better than on the field-based dataset. [12].

III. METHODS & MATERIALS

A. Data Set:

- Online dataset from Kaggle: https://www.kaggle.com/code/taha07/plant-disease-detection/data
- It has 10,000 images in each class.
- Dataset divided into 80% training and 20% testing.



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B. Experimental Setup:

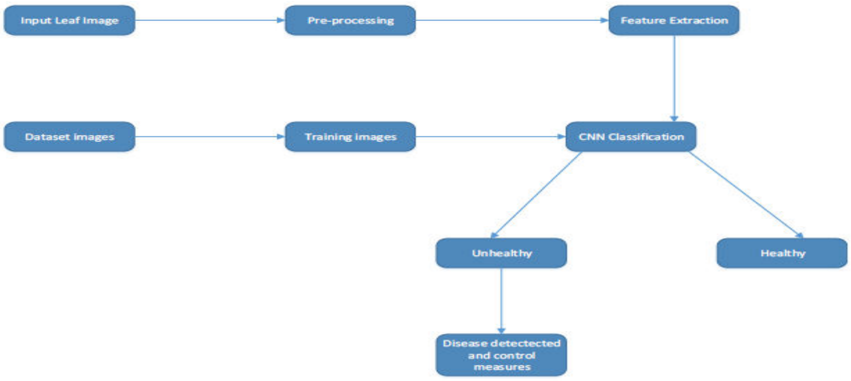
- The models were developed using Python language, Numpy, Matplotlib, Tensorflow, Scikit, and Seaborn.
- Windows OS PC with Corei5@2.30GHz and 2.40GHz.

C. Data Preprocessing:

Before feature extraction, the dataset was subjected to cleaning and pre-processing, which included normalizing pixel values, shrinking photos, and eliminating noise. The primary goal of this stage was to enhance the consistency and quality of the input data.

```
In [2]: batchSize = 32
        imageShape = (224, 224)
        epochs = 10
        channels = 3
```

D. Proposed Method



E. Feature Extraction

Use the ResNet feature extractor for automatic extraction of relevant features from the pre-processed images.

F. Classification-Model Training

Input ResNet features into DenseNet.

G. Model Evaluation

Assess the performance of the trained model using appropriate statistical evaluation metrics (f1 score, accuracy)

ALGORITHM	ACCURACY
Our Model (ResNet + DenseNet)	0.9880
ResNet101	0.9775
DenseNet121	0.9694
Xception	0.9050
InceptionV3	0.8405
VGG16	0.3957

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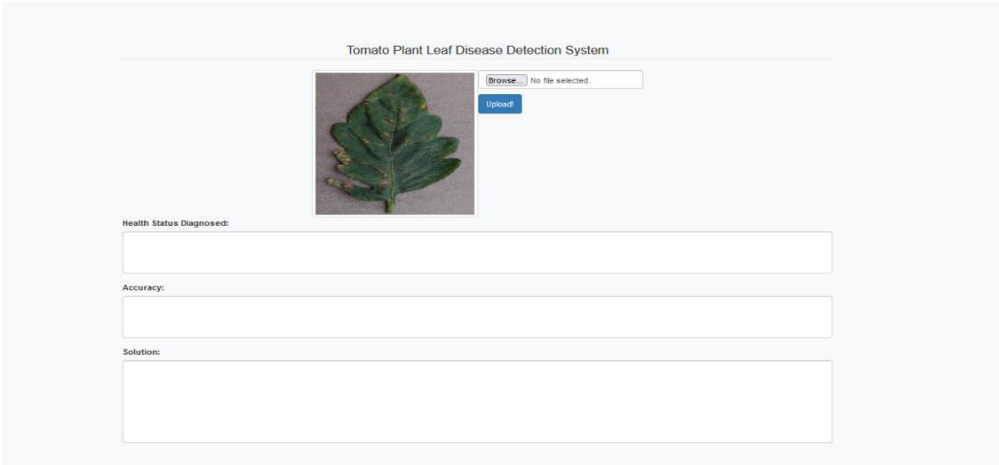
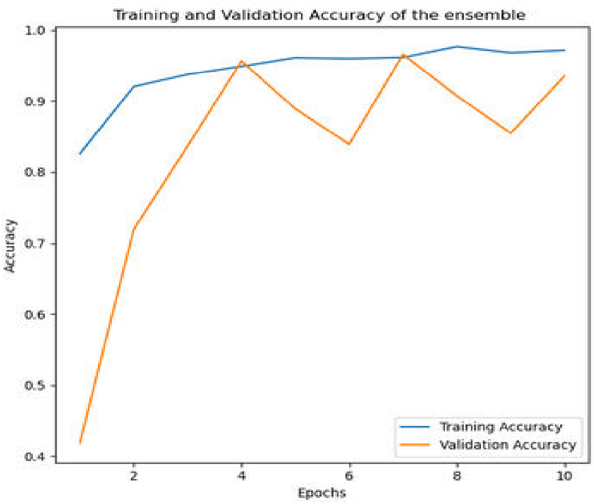
H. Algorithm Deployment

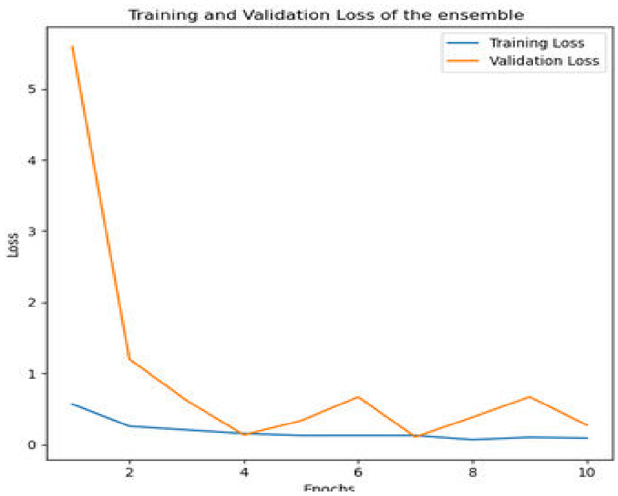
Develop a user-friendly interface for practical adoption.



IV. RESULTS

Throughout the epochs, training accuracy continuously outperforms validation accuracy; by the ninth epoch, training accuracy has increased from 83% to 97%. The range of validation accuracy is 86% to 97%, with sporadic stabilisations between 89% and 92%. The model's capacity to distinguish between healthy and unhealthy leaves has improved, as seen by both accuracy curves. The current results point to effective learning, but ideal outcomes would see loss approach zero and accuracy reach 100% for both training and validation. The training and validation loss curves both gradually decline, yet the fifth epoch's small rise in validation loss raises the possibility of overfitting. If the investigation is carried out past the tenth epoch, it will become clear whether the validation loss is increasing or decreasing. The ensemble model works well overall, however there is a chance of overfitting.





V. CONCLUSION AND FUTURE WORK

Maintaining optimal production and avoiding yield losses requires the accurate identification and classification of tomato leaf diseases. Healthy tomato plants can be harmed by a variety of leaf diseases, which can result in fewer or lower-quality crops. This study uses an ensemble of deep learning algorithms to identify tomato plant leaf diseases,

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yielding greater accuracy than individual models. To reduce mistakes resulting from biases or restrictions in individual models, the ensemble technique integrates predictions from numerous models. After evaluating the algorithm's performance accuracy, we discovered that it greatly raises the accuracy of disease identification. Our model achieved a 98% accuracy rate, which is better than previous models. Our future research will focus on improving the accuracy of our algorithm and expanding its use to include additional plants.

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