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Plant Leaf Disease Predictor Using Deep Learning

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Abstract: ***Artificial intelligence includes deep learning as a subset. Due to its advantages, autonomous learning and feature extraction have been hotly debated in academic and industrial circles in recent years. Image and video processing, voice processing, and natural language processing have all benefited from it. Simultaneously, it has grown into a centre for agricultural plant protection research, which includes, among other things, plant disease recognition and insect range evaluation. Deep learning can assist avoid the drawbacks of artificially selecting disease spot features, improve the objectivity of plant disease feature extraction, and accelerate research and technological change. In this review, we look at how deep learning technology has progressed in the field of agricultural leaf disease detection in recent years. The current trends and challenges in using deep learning and sophisticated imaging techniques to detect plant leaf disease are discussed in this paper. Our findings are expected to be valuable to researchers interested in detecting plant diseases and insect pests. We also discussed some of the current problems and issues that need to be addressed.***
Keywords: Analysis, Deep Learning, Prediction, Plant Leaf, Resnet 50.

I. INTRODUCTION

Plant disease outbreaks have a negative influence on agricultural production. If plant diseases are not discovered in a timely manner, food poverty will increase. Initial detection is necessary for plant disease prevention and control, as well as agricultural production management and decision-making. Plant disease identification has become increasingly important in recent years. Plants that have been affected with a disease frequently have visible markings or lesions on their leaves, stems, flowers, or fruits. In general, each illness or pest situation has its own distinct visual pattern that can be utilised to identify problems. The leaves of plants are usually the major source for identifying plant illnesses, and most disease symptoms may be seen on the leaves. In most situations, on-site identification is done by agricultural and forestry professionals, or farmers identify fruit tree diseases and pests based on their experience. Not only is this procedure subjective, but it is also time-consuming, difficult, and inefficient. Farmers with less experience may make mistakes during the identification procedure and use medications blindly. Environmental pollution will result from increased quality and output, resulting in unwarranted economic losses. Research into the application of image processing techniques for plant disease recognition has become a popular research issue in response to these obstacles. Figure 1 depicts a method for diagnosing plant diseases using image recognition processing technologies. Dubey and Jalal used the K-means clustering method to segment the lesions regions, and combined the global colour histogram. The GCH, CCV, LBP, and CLBP were used to extract features Improved SVM was used to detect and identify a variety of apple illnesses, with a classification accuracy of 93%. Researchers evaluated four tomato leaf diseases, including early blight and late blight, using stepwise discriminant and Bayesian discriminant principal component analysis (PCA) leaf mildew and leaf spot, and extracted 18 characteristic parameters such as colour, texture, and shape information from tomato leaf spot images. Principal component analysis and fisher discriminant methods were used to extract the characteristic parameters and construct the discriminant model. The accuracy of the two methods reached 94.71% and 98.32%, respectively.

II. LITERATURE SURVEY

The author of this research described how several image processing and deep learning approaches are utilised to identify and categorise illnesses in turmeric leaves. To facilitate efficient feature extraction, the dataset of 800 leaf pictures from various categories was pre-processed and segmented. To train the model, deep learning methods such as support vector machine, decision tree, and Nave Bayes were used. Technologies for managing fungi-caused turmeric plant diseases in order to provide high-quality crop harvests. Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes (NB) algorithms were built on the MATLAB platform, and the results of 10-fold cross validation were used to validate the study.

The author describes the pathogens that infect the turmeric plantation and their treatment in this study. If symptoms are not addressed early on, the end effect is low quality and yield. The procedure for The purpose of this article is to predict leaf blotch in turmeric plant [LBTP] for early identification of leaf blotch. blotch disease of the turmeric plant utilising digital image processing (DIP.) Digital photographs of turmeric leaves are taken at various stages and saved in a database. The photos are pre-processed, segmented, and analysed, and the RGB colour components are determined. removed. The moments are calculated

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using a colour histogram. Green is the dominant colour. component in leaves, therefore its colour moments are retrieved and compared to recorded data. Healthy leaf database values The comparative research is beneficial to us.

III.METHODOLOGY

Deep learning is a sophisticated deep learning technique that has alleviated the typical deep learning burden of feature engineering. It no longer requires subject expertise, and all credit belongs to deep learning. The artificial neural network is at the heart of deep learning (ANN). Artificial neural networks are mathematical models that imitate the main principles of brain activity through their neurons and synapses. TensorFlow is a popular library for implementing neural networks. It includes all artificial neural network libraries. TensorFlow may be used to do classify the result on both text and pictures.

A. Convolutional Neural Network (CNN)

To detect disease in plant leaves, Convolution Neural Networks (CNNs) are utilized. CNN is a development of a basic ANN that produces superior picture results. Because photos produce recurring patterns of a certain item (any image). Convolution and pooling are two fundamental aspects of CNN. Convolution is used to discover pattern edge of a picture, while pooling is used to minimize image size. The following CNN architectures were used to solve a problem.

B. Datasets Deliberation

To detect plant diseases, two datasets are employed. The first datasets have many classes, whereas the second contains 38 classes. Each plant is represented by a number of photos in both databases. The first datasets contain a total of 2952 photos. The final results of this work are based on the Plant Village datasets, which covers 38 distinct plant classifications. It is also freely accessible on the internet.

IV. PROPOSED MODEL AND MODEL DESIGN

A. Existing System

Previously, plant disease analysis was done manually by an expert in that subject. This needs a large amount of labour as well as a long processing time, which we contrasted using a dataset scraped from the Kaggle website and run independently using the tool tensor flow. The analysis was calculated based on the loss and accuracy percent based on epoch analysis.

B. Proposed System

The proposed method employs classification algorithms to extract properties of diseased leaves and to classify plant diseases. Throw residual deep learning neural network model with 50 layers method to improve system accuracy and algorithm execution speed by evaluating, splitting, and configuring datasets using tensor flow.

C. Dataset Preparation

The dataset was prepared with leaves of the plant which has been downloaded and implemented from Kaggle. The dataset contains of list of plant leaves which contains various diseases and it contains some healthy plants also so that we will be able to predict accurately which plant contains disease and which is a healthy leaf.

V. WORKFLOW

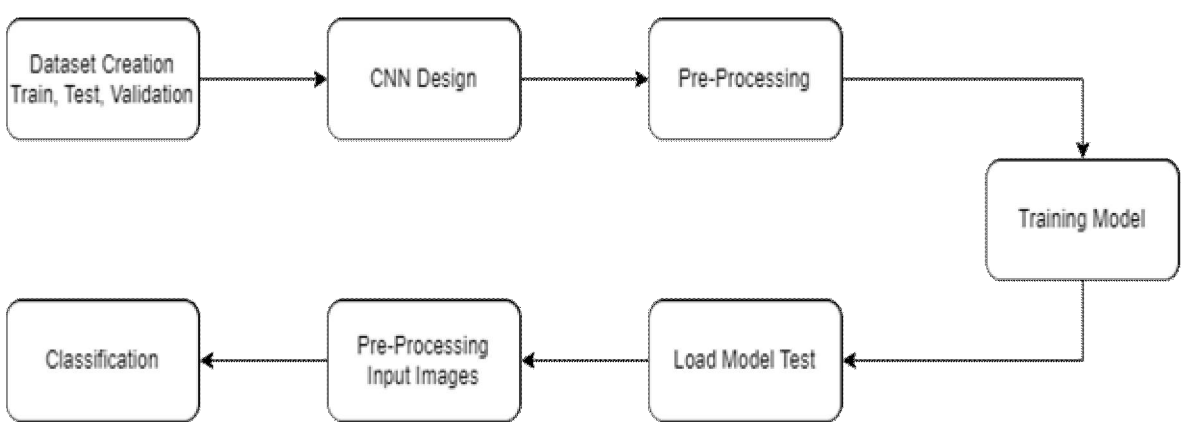

Fig 5. Work Flow

VI. DATASET

Dataset in Table

Datasets are classified as

- Plant Name
- Disease Prediction
- Disease Name

Plant Name	Healthy or Diseased	Disease Name
Tomato	Diseased	Early_blight
Tomato	Diseased	Late_blight
Tomato	Diseased	Leaf_Mold
Tomato	Diseased	Septoria_leaf_spot
Tomato	Diseased	Spider_mites Two-spotted_spider_mite
Tomato	Diseased	Target_Spot
Tomato	Diseased	Tomato_Yellow_Leaf_Curl_Virus
Tomato	Diseased	Tomato_mosaic_virus
Tomato	Healthy	-

Fig.6. Dataset sample

VII. ACCURACY GRAPH

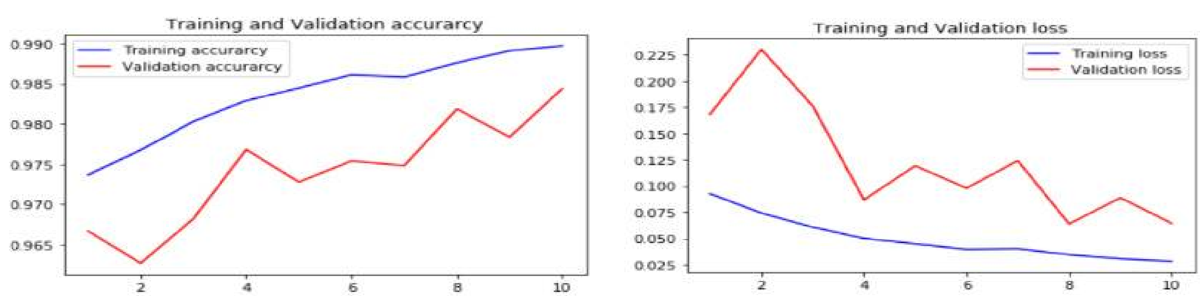

Fig.6. Accuracy, Validation and Training Graph

VIII. CONCLUSION

Based on the data, it has been shown that integrating these algorithms with the Tenser Flow tool can boost accuracy while decreasing error. The accuracy rate has risen from 0.81 to 0.97. This article utilises a dataset downloaded from Kaggle to assess the performance of three distinct classifiers, notably the RESBET 50, DBNs, CNN, and K-Means method.

The Tenser Flow tool is used for testing. The goal of deleting rules is to separate normal methods from dangerous applications. According to the test findings, we discovered that the RESNET 50 method outperforms other algorithms such as DBNs, CNN, K-Means, and DMCN. Finally, it is asserted that it is the best when compared to these three algorithms.

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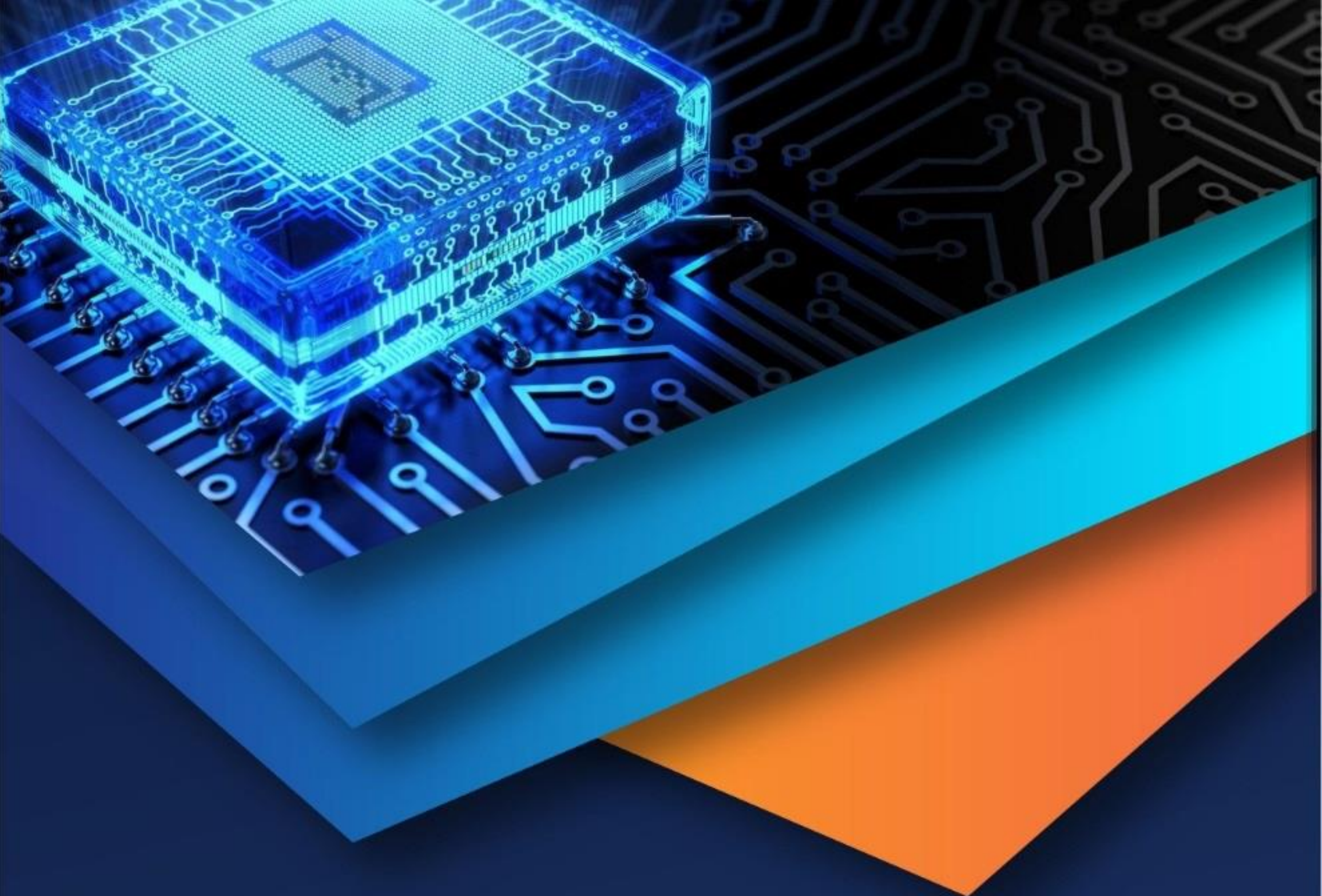

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