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LEAF DISEASE DETECTION USING DEEP LEARNING TECHNIQUES

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Abstract: Agriculture is an important business in order to meet the basic needs of food for the expanding global population. The global economy and human nutrition both depend on the growth of grains and vegetables. Many farmers grow in remote areas of the world and suffer large losses as a result of their reliance on manual monitoring of grains and vegetables and their lack of correct knowledge and disease detection. The use of digital farming methods could be an innovative solution to easily and quickly detect plant leaf diseases. In order to solve these issues, this research proposes a method for recognizing plant leaf illnesses and taking preventive action in the agricultural industry using image processing and Convolutional Neural Networks (CNN). Leaf disease is a major threat to agricultural production and food security worldwide. Early detection and identification of leaf diseases can significantly reduce crop losses and improve crop yield. The use of deep learning in plant disease recognition can minimize the drawbacks associated with the artificial selection of disease spot features, make the extraction of plant disease features more objective, and accelerate the pace at which new technologies are developed. In this research paper, we propose a novel approach for leaf disease detection based on deep learning techniques. This research paper contributes to the development of effective and efficient methods for detecting and identifying leaf diseases, which can ultimately benefit farmers and help ensure global food security.

***Keywords* – Disease Detection, Feature Extraction, Image Processing, Deep Learning, CNN**

I. INTRODUCTION

In India, a developed country, around 70% of people are employed in agriculture. Farmers can select the ideal insecticides for their plants from a wide range of qualifying crops. A considerable loss in productivity as a result of crop damage would have an effect on the economy. The leaves of plants, which are their most delicate part, are where illness symptoms first manifest. The crops must be examined for diseases from the very beginning of their life cycle until they are prepared for harvest. The development of automatic and semi-automatic plant disease detection systems has utilized a number of techniques in recent years, and automatic disease detection by merely monitoring the symptoms on the plant leaves makes it both easier and more economical. These techniques have already shown to be more efficient, affordable, and accurate than the traditional method of manual observation by farmers. Over the past ten years, integrated pest management (IPM) strategies have largely supplanted conventional techniques for spraying insecticides. Whatever the approach, precise disease detection at the point of onset is the first step in effective illness management. Due of its success in identifying different outlines, deep learning algorithms are currently predominantly used for pattern identification. DL automates feature extraction. When compared to other traditional machine learning techniques, the

DL reduces error rate and computational time while achieving a high accuracy rate in the classification task. The main objective of our work is to diagnose plant diseases and provide remedies using Residual Neural Network (ResNet). To the advantage of both farmers and customers, the agriculture sector must incorporate technology and digitalization. The use of technology and regular monitoring allows for the early detection and elimination of diseases. A greater agricultural yield is sought. In recent years, deep learning has greatly outperformed traditional techniques in the area of digital image processing. Utilizing deep learning for plant disease recognition can reduce the negative effects of artificially selecting disease spot features, improve objectivity in the extraction of plant disease features, and quicken the pace of technological development.

II. RISK ANALYSIS

Image size: The program's security depends on the size of the image. It takes less time to extract the key from smaller photos since we have less options for choosing pixels. There are w*h pixels overall in an image with a height of h and a width of w. The intrusive party or attacker must test all conceivable arrangements of the pixels they decide on in order to extract the key from the image. By expanding the image, we may increase the application's security.

III. LITERATURE SURVEY

A CNN model is used in a prior study [1] to categorize the various plant diseases acquired from the Plant Village dataset. The AlexNet architecture will classify the numerous plant diseases into 38 different distinct classes. Additionally, the suggested system offers a decent way to anticipate plant diseases and can aid in their early detection. On the suggested system, alternative learning rates could be explored in the future.

[2] It concentrated on applying a CNN model to forecast the pattern of plant diseases using images from a given dataset (a trained dataset) in the field and historical data. The system will include the widest variety of plant leaves imaginable, enabling farmers to learn about leaves that might not have previously been domesticated and providing a list of all potential plant leaves, which helps them decide which crop to grow.

In [3] Convolutional neural networks and transfer learning are used in the working model to categorize various plant leaf diseases. CNN is a kind of deep learning neural network and is effective at classifying images. Comparing the suggested technique to the traditional method of manually observing each plant leaf, it is quicker and more accurate. The CNN model is employed to accurately predict several plant diseases. Performance evaluation criteria for the model, such as accuracy, precision, recall, and F1 score, are used during testing.

[4] The suggested Pomegranate Disease Classification System Using a neural network called Back Propagation that primarily uses the method of Color and texture are employed as the features to segment the defective area. To avoid occlusion, the image is typically taken with a plain background. The algorithm was compared to other machine learning models for accuracy.

IV. PROPOSED SYSTEM ARCHITECTURE

A system architecture is a conceptual representation of a system's structure, behavior, and other characteristics. Designed subsystems and system components that work together to create the entire system might make up a system architecture. The organization and structure of the software system are specified by the architecture. Additionally, it discusses the links between the various software system components, levels of abstraction, and other features. An architecture can be used to specify a project's objectives or to direct the creation of a brand-new system. This section will look at the numerous steps that must be taken in order to create, employ, and get the most likely results from different classifiers. Out of all the various results and accuracies provided by various models, we will use the model that yields the best results and accuracy for identifying leaf disease.

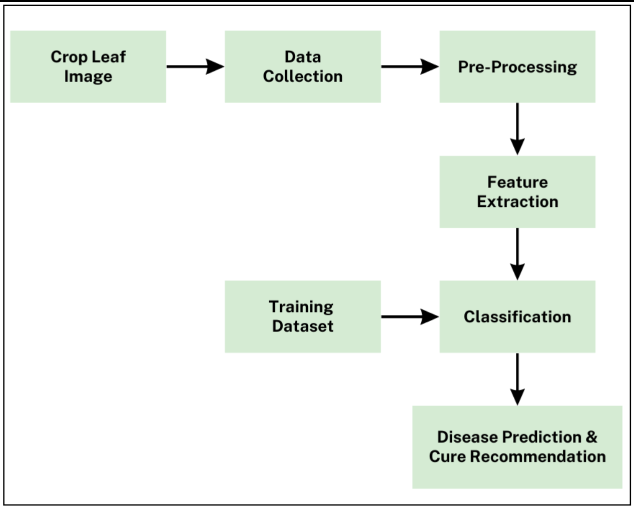


Fig 1: proposed system architecture

Data Collection: The first step is to collect leaf images that are healthy and infected with various diseases. This data can be collected from various sources such as databases or by capturing images using a camera or smartphone.

Data Pre-processing: The collected data needs to be pre-processed to remove noise, adjust the brightness and contrast, and resize the images to a uniform size. This step is important as it helps to improve the accuracy of the disease detection algorithm

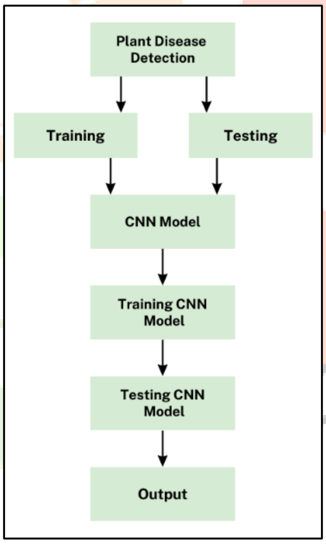
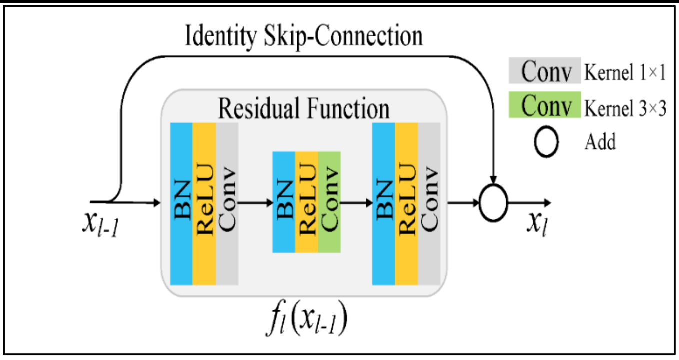


Fig 2: classification system architecture

ResNet:

The ResNet architecture is based on the idea of residual learning, which is the concept of adding shortcut connections (or skip connections) between layers to help the network learn the residual mapping instead of the original mapping. The residual mapping is the difference between the input and output of a layer, and it allows the network to learn a more accurate representation of the input. The ResNet architecture has several different versions, but the most commonly used is ResNet-50, which has 50 layers. The ResNet-50 architecture has a series of convolutional layers, followed by a series of residual blocks. Each residual block consists of two or three convolutional layers, followed by a shortcut connection that adds the input of the block to its output.



In this diagram, the input is passed through a convolutional layer, followed by batch normalization and ReLU activation. The output is then passed through a max pooling layer and a series of residual blocks. Each residual block consists of two or three convolutional layers with batch normalization and ReLU activation, followed by a shortcut connection that adds the input of the block to its output. The output of the final residual block is passed through average pooling, a fully connected layer, and a softmax activation function to produce the final output.

V. PROJECT DESIGN

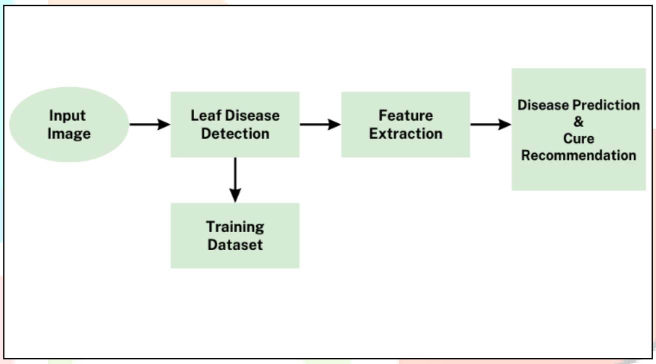


Fig 3: data flow diagram

Here, the input image is initially tested using the training dataset. After testing, features are extracted from the image. The classifier then received information about these characteristics as well as whether the image showed a healthy or diseased leaf as input. The classifier then establishes a link between the returned features and the likelihood that a disease is present. The leaf illness is diagnosed in the subsequent stage by comparing the input image to the pre-existing images in the collection. The best feasible treatment is advised together with the forecast of the sickness the plant will contract.

VI. RESULTS

The entire dataset is divided into training and testing sets at random. The ResNet model is trained using the training dataset. These sets are typically divided into portions of 20% to 80%, 40% to 60%, 60% to 40%, 80% to 20%, etc. The training dataset can be expanded to include additional photos to produce the most accurate results. In this study, the model is trained using 80% of the dataset, then tested using the remaining 20%. As shown in Table 1, this collection includes 50257 images of plant leaves from several distinct categories, including images of prevalent plant diseases. Since colored images provide more accuracy than grayscale images, all of the images utilized in this work are colored images. The images were all taken at various perspectives and under various circumstances.

TABLE I
performance of resnet model for healthy and unhealthy leaf

Classification Label	Total No. of Leaf images	Correctly Classified Images	Accuracy of output
Apple Scab	2016	1908	94.67%
Apple Black Rot	1987	1822	96.20%
Apple Healthy	2008	1885	93.86%
Corn Common Rust	1907	1802	94.45%
Corn Healthy	1859	1783	95.89%
Grape Black Rot	1888	1775	94.01%
Grape Healthy	1692	1608	95.03%
Pepper Bell Bacterial Spot	1913	1844	96.38%
Pepper Bell Healthy	1988	1903	95.68%
Potato Early Blight	1939	1888	97.34%
Potato Healthy	1824	1748	95.8%
Potato Late Blight	1939	1831	94.38%
Tomato Early Blight	1920	1836	95.59%
Tomato Healthy	1926	1827	94.82%
Tomato Late Blight	1851	1757	94.87%

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Label: AppleCedarRust1.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust2.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust3.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust4.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleScab1.JPG , Predicted: Apple___Apple_scab
Label: AppleScab2.JPG , Predicted: Apple___Apple_scab
Label: AppleScab3.JPG , Predicted: Apple___Apple_scab
Label: CornCommonRust1.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust2.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust3.JPG , Predicted: Corn_(maize)___Common_rust_
Label: PotatoEarlyBlight1.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight2.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight3.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight4.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight5.JPG , Predicted: Potato___Early_blight
Label: PotatoHealthy1.JPG , Predicted: Potato___healthy
Label: PotatoHealthy2.JPG , Predicted: Potato___healthy
Label: TomatoEarlyBlight1.JPG , Predicted: Tomato___Late_blight
Label: TomatoEarlyBlight2.JPG , Predicted: Tomato___Late_blight
Label: TomatoEarlyBlight3.JPG , Predicted: Grape___Black_rot
Label: TomatoEarlyBlight4.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight5.JPG , Predicted: Tomato___Late_blight
Label: TomatoEarlyBlight6.JPG , Predicted: Apple___healthy
Label: TomatoHealthy1.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy2.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy3.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy4.JPG , Predicted: Tomato___healthy
Label: TomatoYellowCurlVirus1.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus2.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus3.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus4.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus5.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus6.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
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Fig 4: actual vs predicted labels of classes

IMPLEMENTATION DETAILS

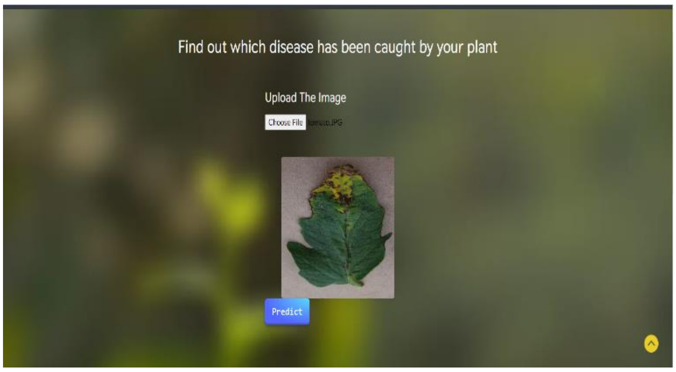
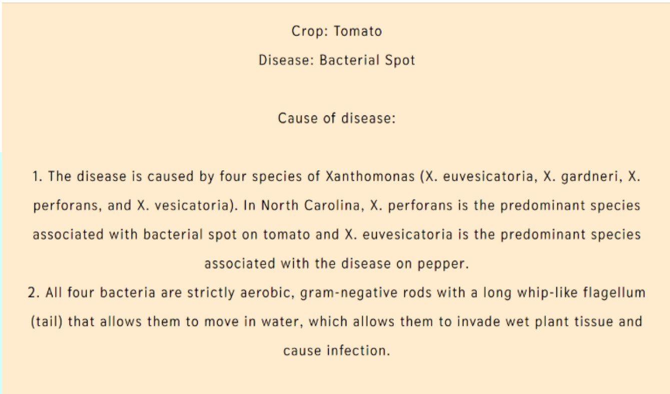


Fig 5: user interface



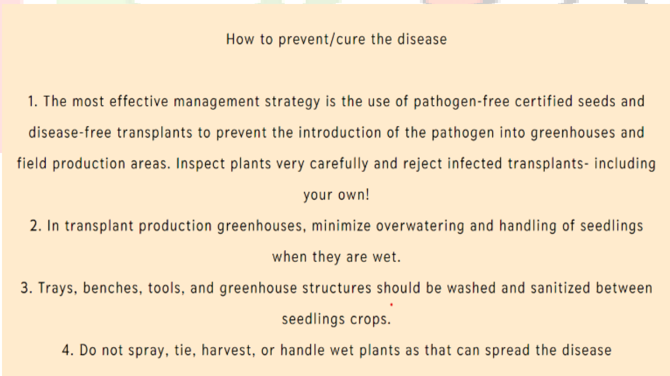
Crop: Tomato

Disease: Bacterial Spot

Cause of disease:

1. The disease is caused by four species of Xanthomonas (X. euvesicatoria, X. gardneri, X. perforans, and X. vesicatoria). In North Carolina, X. perforans is the predominant species associated with bacterial spot on tomato and X. euvesicatoria is the predominant species associated with the disease on pepper.
2. All four bacteria are strictly aerobic, gram-negative rods with a long whip-like flagellum (tail) that allows them to move in water, which allows them to invade wet plant tissue and cause infection.

Fig 6: prediction of disease and its causes



How to prevent/cure the disease

1. The most effective management strategy is the use of pathogen-free certified seeds and disease-free transplants to prevent the introduction of the pathogen into greenhouses and field production areas. Inspect plants very carefully and reject infected transplants- including your own!
2. In transplant production greenhouses, minimize overwatering and handling of seedlings when they are wet.
3. Trays, benches, tools, and greenhouse structures should be washed and sanitized between seedlings crops.
4. Do not spray, tie, harvest, or handle wet plants as that can spread the disease

Fig 7: preventive measures against the disease

VII. IMPORTANT LIBRARIES /PACKAGE

Keras: The open-source software program known as Keras offers a Python interface for artificial neural networks. Keras offers the TensorFlow library interface.

TensorFlow: A machine learning and artificial intelligence software library called TensorFlow is open-source and cost-free. Despite being applicable to a wide range of activities, deep neural network training and inference are given particular emphasis.

VIII. CONCLUSION

In conclusion, this study proposed a deep learning-based approach for automated detection and classification of plant leaf diseases using ResNet architecture. Leaf diseases are detected and identified using Deep Learning and image processing techniques. With the discovery, it will be simpler to spot plant diseases early on and stop crop loss and disease transmission. The objective of this algorithm is to find anomalies on plants living in the wild or in greenhouses. Usually, a plain background is used when taking the picture to prevent occlusion The proposed method achieved high accuracy in identifying and differentiating between different types of diseases affecting plants. Through our experiments and evaluation, we showed that the ResNet model outperformed other commonly used deep learning models, such as VGG and Inception-v3. The proposed method has several advantages, including its ability to handle large datasets and its capability to learn high-level features from images.Overall, this study provides a significant contribution to the development of automated plant disease detection systems and paves the way for further research in this area.

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