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An Early Detection And Cure For Tomato Leaf Disease Using CNN

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Abstract: Detecting diseases in plants and that goes unnoticed willaffecttheagriculturaloutput.Typically,farmersandexperts closely monitor plants, but this method is often time-consuming, expensive,andinaccurate.Toaddressthis,theproposed workaims to develop an early leaf disease detection technique using CNN for image processing. CNN, a type of ANN tailored for pixel input, proves effective in image recognition for the detection of plant diseases.Index Terms - Component,formatting,style,styling,insert.

I. INTRODUCTION

Agricultural production, an ancient method of obtaining food, is a crucial income source globally. Plants play a vital role for both human and animals, providing food, oxygen,and other necessities. Government and experts are actively working to enhance food production successfully. When a plant is diseased, it affects the entire environment and all living organism. Various diseases, such as bacterial and fungal, can affect plants, influenced by factors like sunlight, water, humidity, pests, temperature. Insufficient food crop output leads to food insecurity. Significant climate changes also impact plant development, creating unavoidable natural tragedies. Early detection of Tomato leaf diseases is crucial to prevent large-scale crop losses. Farmers need to use the right insecticides for their crops, as excessive use of pesticides can harm both crops and farmland. Seeking expert advice helps avoid misuse of chemicals. Researchers focus on plants to support farmers and agriculture. Detecting visible diseases is straight forward,and early intervention is possible with regular monitoring. However, this phase is limited to extreme casesor low crop output. Innovations include automated disease detection tools, benefiting farmers in both small and large-scale cultivation[5]. These tools provide precise outcomes, detecting disorders quickly.They heavily rely on deep learning and neural networks.The study employs Deep CNN to identify healthy and infected leaves, aiding in early disease detection in Tomato leaf.

11 . LITERATURE SURVEY

R. K. Lakshmi and N. Savarimuthu,(2021) focuses on utilizing deep learning techniques for the detection of plant leafdiseases.The authors likely discuss existing methods and approaches for plant disease detection, highlighting the challenges and limitations associated with traditional tech- niques. They may explore the significance of automated dis- ease detection systems in agriculture and the potential benefits of employing deep learning algorithms for this purpose. Additionally, the review might cover relevant studies and research efforts in the field of computer vision and machine learning applied to agricultural tasks, emphasizing the need for a ccurate and efficient disease detection methods to enhance crop management and yield.

Konstantinos et al.,(2018) developed CNN-based deep learning models for plant disease detection and diagnosis from the modest images of leaves. A database of 87,848 images,including healthy and diseased leaf images,witha set of 58 different classes of plant and disease combinations belonging to 25 different plants, was created. A success rateof 99.53% was observed by instructing various architectures and obtaining the plant and disease combinations. Because of its high efficiency,this model could be recommended for early warning, and it can be further extended to work in real-time farming in Plant disease Identification.

Seraworketal.,(2018)investigated the use of CNN to detect diseases insoyabeanplants through image analysis. Employing the LeNet architecture, they developed a model capable of categorizing soya bean plant diseases based on environmental images. Their dataset, sourced from the PlantVillage database, consisted of 12,673 images depicting healthy and diseased leaves across four classes, capturing various environmental conditions. Results showed CNN's effectiveness in accurately classifying diseases, achieving an impressive 99.32% accuracy. However,theauthors noteddataimbalance in the data set's classification and recommended batch normalization to expedite processing and improveaccuracy.

Malvika Ranjan et al.,(2015) initiated their investigation into plant leaf disease detection by first acquiring images. Theyextracted colordata,includingHSVfeatures,from the segmentation outcomes. Subsequently, an ANN was trained by feature values capable of accurately distinguishing between healthy and diseased samples.Through the integration of various image data processing techniques and ANN, the present study proposesan approach for the early and dependable identification of cotton leaf disease.

Srdjan Sladojevicet al.,(2016) introduce a novel approach titled "Deep Convolutional Neural network Supported Identificationof Crop Diseases by Plant Image Classification" for constructing a model to recognize crop diseases based onplant image classification and deep convolutional networks. The methodology utilized, along with the innovative training technique, enables the rapid and straightforward setup of a practicalsystem.The study meticulously outlines all essential procedures for implementing this disease recognition model, starting withthe collection of photographs to establish a comprehensive database, which is subsequently evaluated by agricultural experts. The experimental outcome of the developed model demonstrate precision ranging from 91% to 98% for individual class tests, with an average precision of 96.3%.

III. Proposed System

CNN is a type of deep learning method used for image processing and classification. CNN haswide applications in analyzing visual imagery and classification. In the proposed systemasgiveninFig.1,image classificationis done by taking an input image. Image preprocessing is used to convert and simplify the image which reduces the effort in processing the image. CNN will have an input, output and several hidden layers like normalization and fully connected layerswork together to produce a desired pattern of input image. Feature extraction extracts useful features from input images in order to identify and classify the image. The analyzed image is classified as either healthy or diseased and given as output.

Leaf Disease	Remedy Suggested[9]
Tomato Bacterial Spot	Agrimycin-100
Tomato Early Blight	Difolatan
Tomato Late Blight	Captafol
Tomato Yellow Leaf Curl Virus	Dimethoate
Tomato Septoria Leaf Spot	Dithane Z-78

Tomato Target Spot	Mancozeb
Tomato Mosaic Virus	Trisodium Phosphate

Table1: Leaf disease and remedies suggested

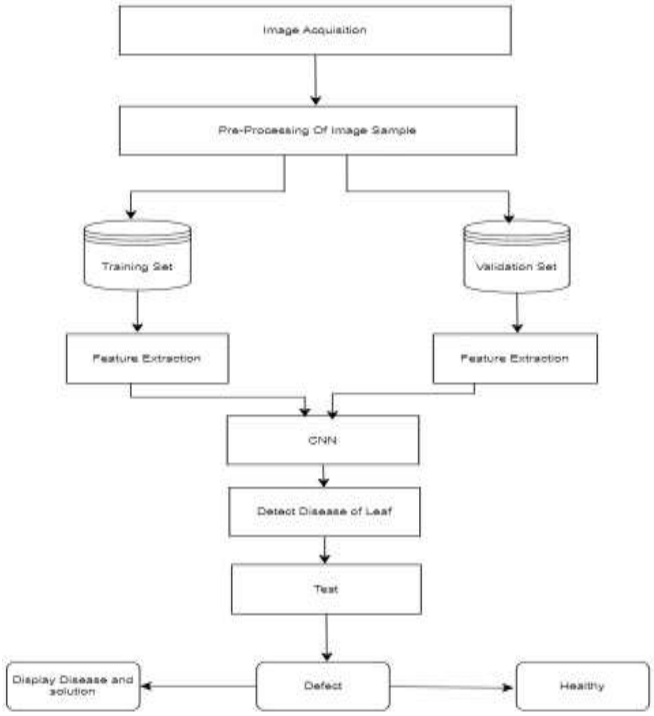

Fig.1.Flow diagram of the proposed system

IV. EXPERIMENTAL RESULT AND OBSERVATION

The work aim to assess the effectiveness of a proposed approach for plant disease classification using CNN. Real-time tomato plant images of different sizes were utilized for experimentation. The algorithm has been trained with the data that is acquired from the Kaggle dataset and the experimentation is performed on the random images and the performance is being evaluated.
The work was carried out using IDLE platform.IDLE is a free open-source platform which supports python program- ming for implementing the concepts of Deep learning,Machine Learning etc., has been used for building the system. Python programming language is widely used in solving precision problems. Libraries like Keras, NumPy can be imported easily which makes mathematical operations simpler while process- ing large sets of data.

The following steps indicate the experimental activities:

1. **Data Collection:**

Images of both diseased and healthy plants leaves were collected from various sources like direct images taken using camera and images of the testing dataset are taken from the Plant Village dataset available in Kaggle.

2. Image Preprocessing:

(i) Loading the Image: The 'load_img()' function from Keras preprocessing module is used to load the input leaf image specified by 'tomato_plant' path. The 'target_size' parameter resizes the image to 128x128 pixels, which matches the input size expected by the trained model.

(ii) ConvertingtoNumPyArrayandNormalization: The

'img_to_array()' function converts the loaded image to a NumPy array. Then, the pixel values of the image are divided by 255 to normalize them. Normalization ensures that pixel values fall within the range of [0, 1], which is typically doneto help the model converge faster during training.

(iii)Expanding Dimensions: After normalization, the dimen-sionsoftheimagearrayareexpandedtomatchtheinputshape expected by the model. The 'np.expand_dims()' function adds an extra dimension to the array at axis 0, converting the shape from 3D to 4D.This extradimension represents the batchsize, as the model expects input in the shape of'(batch_size,height, width, channels).'

3. Split Dataset:

(i)TrainingSet: The training_set object contains batches of images and their corresponding labels for training the model. These batches are generated from the images located in the training/subdirectoryof the dataset directory.

The flow_from_directory() method automatically splits the images in the training/ subdirectory into training and validation sets based on the validation_split parameter. By default,80% of the images are used for training , and 20% for validation.

(ii) Validation Set: Similarly, the valid_set object contains batches of images and their corresponding labels for validating the model. These batches are generated from the images located in the validation/ subdirectory of the dataset directory. The images in the validation/ subdirectory serve as the validation set to evaluate the performance of the model during training.

4. Feature Extraction:

CNN automatically extract hierarchical features from input images through layers of convolutional and pooling operations,capturing patterns at differentlevels of abstraction.CNN learntorepresent images in a hierarchical manner, where lower layers capture simple features like edges and textures, and higher layers capture more complex features and object compositions.

5. Classification and Prediction:

To predict the probabilities of the input image belonging to each class. This is performed by calling the model.predict function, which returns an array of class probabilities. 'np.argmax' function is used to determine the index of the predicted disease class based on the highest probability out- putted by the classification model.

V. RESULTS

The features extracted fromthe input image are compared with the model trained using the CNN technique. a classification methodology is applied to analyze a dataset of plants, determining whether they are healthy or diseased. This training model is developed from a segregated database. The automated system can detect diseased leaves that may not be identifiable through nakedeye observation, aiding in early disease identification and control.Despite the availability of various automated tools for disease identification in plants, a reduction in productivity may still occur. The system is tested using images of standard sizes such as 128x128, 256x256, and 512x512, evaluating the performance by calculating specific factors such as size, texture, patterns, age. Any input image is resized to its standard size before being processed by the system.The time taken for processing varies depending on the standard size of the images used in the dataset and providedas input to the system. After testing the system with various standard sized images, it is observed that the result in all the cases were almost similar.

To evaluate the performance of the proposed model, accuracy, precision, recall, and F1-score were used as quantitative metrics. The results, presented in Table 2, indicate the highest values of these metrics achieved up to the corresponding epoch number. The model achieved a highest validation accuracy of 95.6% over 50 epochs of training.

Table 3 provides summary of evaluation metrics used to assess the precision and recall for various diseased tomato leaf.

Table 2: Evaluation Metrics

No. of epochs	Accuracy	Precision	Recall	F1-Score
10	0.856	0.849	0.852	0.859
20	0.869	0.852	0.849	0.863
30	0.905	0.901	0.902	0.902
40	0.933	0.935	0.939	0.938
50	0.956	0.954	0.950	0.952

Table 3: Evaluation Metrics for Various Tomato Leaf Diseases

Types of Tomato Leaves Diseases	Precision	Recall	F1-Score
Tomato Mosaic Virus	0.963	0.975	0.971
Tomato Bacterial Spot	0.960	0.985	0.974
Tomato Septoria Leaf Spot	0.976	0.986	0.983
Tomato Yellow Leaf Curl Virus	0.985	0.995	0.988
Tomato Healthy	0.995	0.998	0.997

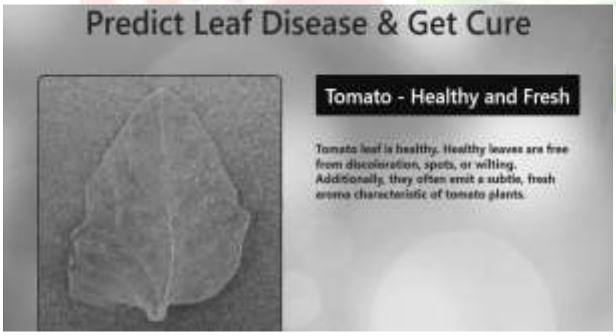

Fig.2.Healthy Plants Results

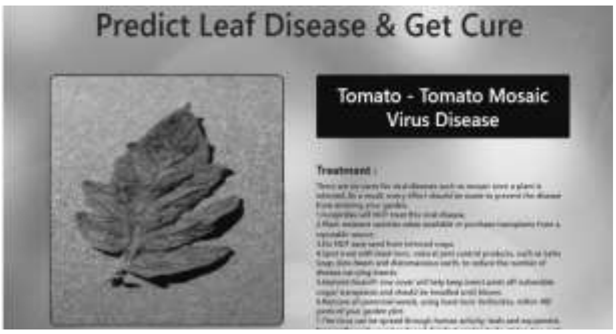

Fig.3.Diseased Plants Results

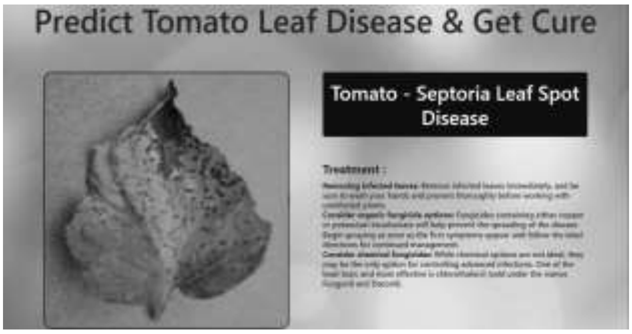

Fig.4.Diseased Tomato Leaf Results

VI. CONCLUSION AND FUTURE WORK

The agricultural sector remains one of the most crucial sectors in India, supporting the majority of its population. Detecting diseases in crops is vital for economic growth, with tomatoes being a key staple crop produced in large quantities. This paper focuses on detecting and identifying different diseases in tomato crops using a CNN and suggesting the cure for those diseases. Overall, the successful development and testing of this CNN-based disease detection system mark a significant stride in precision agriculture, promising improved crop yield, reduced losses, and enhanced food security through advanced technology.

To enhance the effectiveness of the tomato plant leaf disease detection system, several key strategies can be implemented. Incorporating additional sensor data such as temperature, humidity, and soil moisture alongside leaf images offers a comprehensive understanding of plant health. By amalgamating multiple data sources, the system can develop a holistic model for disease detection and prevention, thereby enhancing overall crop management strategies.

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