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Crop Disease Detection and Pesticide Recommendation Using CNN

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Abstract: Agriculture plays a crucial role in India's economy, supporting the livelihoods of 58 percent of the population and contributing 17-18 percent of the GDP. However, plant pests anddiseases pose significant challenges, leading to biotic stress that hampers yield potential and diminishes the quality and quantity of food. Safeguarding crops against diseases is imperative to meet the increasing food demand. Globally, the losses caused by pathogens, pests, and weeds account for 20-40 percent of agricultural productivity. The detection of diseases in cultivated plants is a vital and complex task in agricultural practices. Conventional methods of disease detection and classification are time-consuming and labor-intensive, making it difficult to find optimized solutions. This issue is particularly problematic as farmers and professionals in developing countries require efficient methods to monitor and identify diseases affecting their crops. The implementation of program-based identification for plant diseases offers advantages such as improved detection, reduced human effort, and time savings. In this article, a smart and efficient technique is proposed to detect and classify plant diseases with higher accuracy than existing methods. The pro- posed technique employs Convolutional Neural Networks (CNNs)and focuses on leaf diseases as the main area of interest.
Index Terms: Leaf, Diseases, CNN

I. INTRODUCTION

The three basic needs—food, shelter, and clothing which are crucial for human survival and are often referred to as the primary physiological needs where Food plays a vitalrole in human life and is of immense importance for several reasons. It is essential for human survival, physical health, energy, disease prevention, growth, mental well-being, and cultural significance. Emphasizing a balanced diet, nutrition education, and sustainable food practices contribute to a healthier, happier, and more sustainable future. India is the second one maximum populated. Wherein agriculture is the spine of it. Our united states is renowned for agriculture and plays a completely crucial function within the Indian economy.Around 70 percentage of rural regions rely upon agriculture.It is of paramount importance in India for food security, livelihoods, economic growth, rural development, sustainable practices, social and cultural significance, and the overall well- being of the country. The government and various stakeholders continuously strive to promote agricultural development, im- prove farmer incomes, and ensure sustainable and inclusive growth in the agricultural sector.

Crop sicknesses can have extensive effects on yield man- ufacturing, main to reduced crop high-quality and quantity. Farmers face numerous demanding situations in crop ailment detection, which can impact their ability to efficiently control and mitigate the effect of sicknesses. They may lack awarenessand information about crop illnesses, restrained assets andinfrastructure, misdiagnosis, time and labor constraints, lack ofaccess to ailment surveillance systems, and price of disorder detection. These factors can lead to delays in detection and inappropriate control measures.

Fig. 1. Deffected Leaf

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In developing nations, farmers face the want to closely display their plants to hit upon and perceive diseases. How- ever, this assignment can be difficult because of restricted sources, technical information, and time constraints. There- fore, software-based identity of plant diseases is beneficial because it simplifies the detection process, reduces the attemptrequired from individuals, and saves time. These packages are frequently designed to provide consumer-friendly interfaces and databases in order that farmers can quick access applicable information and discover potential illnesses affecting their plants. Overall, plant disease detection plays a critical role in effective disease management, crop protection, and ensuring sustainable agricultural practices.

In this paper, we've designed the CNN model which is supposed to helps farmers in detection of ailment in plants and its remedy. CNN models excel at analyzing visible facts, consisting of photos, and extracting significant features from them. The pics are used to train the version, and the output is decided by means of the input leaf. A inflamed leaf is taken and its photo is processed as input and from the patterns that appear on the leaves ,the ailment is detected. CNN fashions offer a powerful device for automatic plant ailment detection. They leverage the competencies of system mastering to research and classify photographs, enabling early detection, correct diagnosis, and powerful sickness control in agricultural systems. We purpose to discover illnesses specifically Apple Scab Disease, Strawberry Leaf Scorch Disease and Corn Northern Blight Disease.


Fig. 2. Fruits

II. LITERATURE SURVEY

1) S. Khirade etAl. developed digital image processing and back propagation neural network (BPNN) to detect fac- tory complaints using leaves. BPNN was used to insert the infected part into a splint and extract features such as color, texture, morphology, and edge set.[1]
2) Garima Shrestha et al. used a convolutional neural net- work to decode the factory claim, which was able to rate 12 movement states with a sensitivity of 88.80 and a low F1 score of 0.12.[2]
3) Loyce Selwyn Pinto and others (and others). In this arti- cle, Image processing is used to describe and categorize complaints about sunflower crops using K-Means clustersand color machine learning algorithms. The score setincludes difference, energy, mean, homogeneity, standarddeviation, and tastelessness[3].
4) Jitesh P. Shah et al.[4]. studied 19 documents on thecondition of rice, fruits and stores based on criteria such as size, no. classes, segmentation and preprocessing methods, Siphers and their Delights, etc. In the soybean study, Crop Discovery of complaints about CNN viabilityunder growth conditions is presented.
5) Caffe, a deep learning platform, was used to train a plant disease detection model based on plant image classification and deep webs, with an accuracy of 91-98 percent..[5]
6) Deep neural network and semi-supervised algorithms were trained to discriminate between crop species and disease status from 86,147 images with a recognition rateof 1e-5 in less than 5 epochs.[6]

III. METHODOLOGY

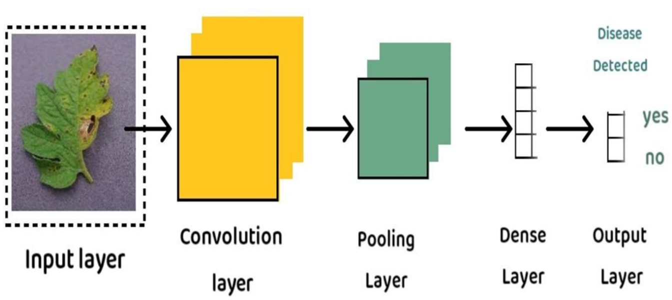

Fig. 3. CNN Layers

The crop disease detection and cure recommendation typi- cally involves the following steps:

1) *Data Collection:* Gather a dataset of snap shots that consists of each wholesome flora and plants suffering from diverse sicknesses.
2) *Data Preprocessing:* Preprocess the accumulated photos to enhance their exceptional and facilitate powerful education.
3) Dataset Split: Divide the dataset into schooling, valida- tion, and checking out sets. The education set is used to train the CNN version and trying out set is used to assessthe final overall performance of the educated version.
4) *Model Architecture Selection:* An appropriate CNN ar- chitecture for crop sickness detection need to be decided on. Popular CNN architectures for picture class encom- pass Alex-Net, Res-Net, and Dense-Net.
5) Model Training: During training, the model learns to extract relevant features from the pictures and optimize its parameters to reduce the type mistakes.
6) *Hyperparameter Tuning:* This consists of tuning param- eters along with learning charge, batch size, variety of layers, activation functions, regularization techniquesand optimizer settings.
7) *Model Evaluation:* Evaluate the skilled model the usage of the testing set to assess its performance in crop dis- ease detection. Metrics together with accuracy, precision, keep in mind, and F1-rating can be used to assess the version's category overall performance.
8) *Deployment and Prediction:* Once the trained CNN version has been evaluated and deemed excellent, itcould be deployed for actual-international crop ailment detection. New snap shots of plants may be fed into the model, and the version will expect the presence of illnesses primarily based at the discovered patterns and features.

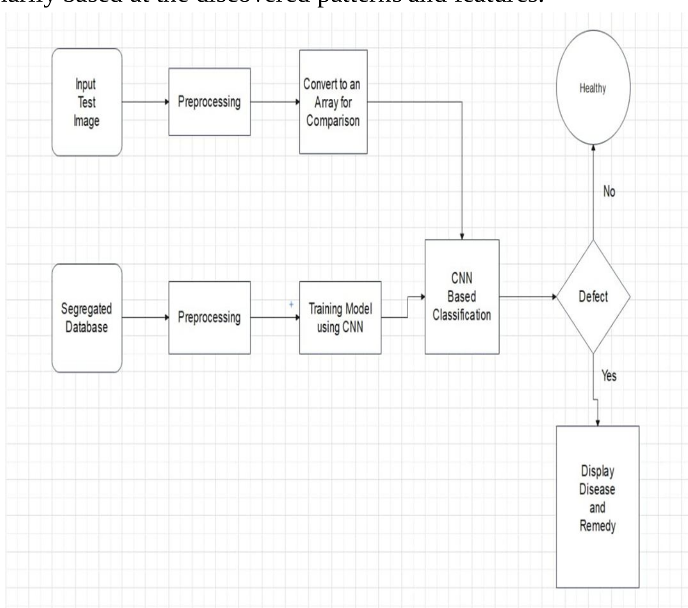

Fig. 4. Architecture of the System

A. *Tools And Techniques*

1) *Image Pre-processing Techniques*

In this step, the photo is processed to convert it's size, color and the quality of the images that generate our dataset. It includes numerous steps through which the photo goes.These stages are:

a) *Image Resizing:* The dimensions of the image are adjusted to the scale of the formation snap shots theuse of the imresize() method in MATLAB. Resizing snap shots is key passes due to the fact the pixel values can alternate if the overall training length changes as properly due to the fact the take a look at pics are not identical.
b) *Smoothening:* Image smoothing progressively ad- justs the pixel values A total of pixels make certaina easy photograph. As properly as This function also converts the image from a shade picture to a grey scale photo RGB2GREY().
c) *Noise Filtering:* Noise is an unwanted addition to photos that makes it difficult to discover and extract functions. Therefore, the noise filtering procedure con- sists of getting rid of or averaging the pixel values that add noise to the picture. The process used in our noise cancellation system is the "median filter out"

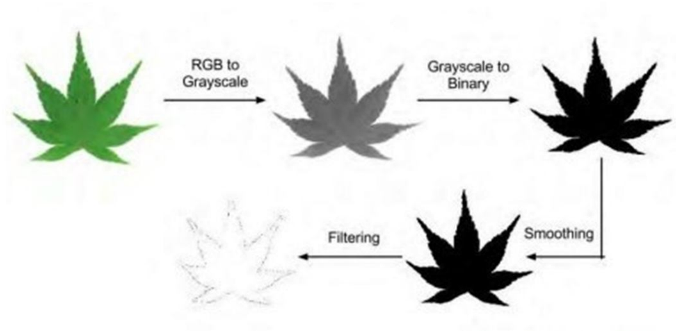

Fig. 5. Preprocessing

2) Feature Extraction Techniques

Feature extraction is a dimensionality reduction tech- nique that helps to represent the features of the partsof interest in an image in a compact vector. This operation is very useful when the image size is largeand Feature renders are scaled for faster image matchingand retrieval required to complete tasks quickly.

Gray Level Co-occurence Matrix : GLCM stands for Gray-Level Co-incidence Matrix. It is a texture analysis method used to capture the spatial relationships of pixel intensities inside an image. GLCM calculates the frequency of occurrence of pairs of pixel intensities at diverse spatial offsets in an photo. It presents statis- tical statistics approximately the distribution of pixel intensity values and their spatial relationships, which may be used as texture capabilities for duties together with crop ailment detection. GLCM-based capabilities provide precious facts about the feel characteristics ofan picture, which may be used to distinguish specialcrop diseases or abnormalities.

2	2	3	4
4	3	4	2
3	4	3	4
3	2	3	2

Image

$i \backslash j$	2	3	4
2	#(2,2)	#(2,3)	#(2,4)
3	#(3,2)	#(3,3)	#(3,4)
4	#(4,2)	#(4,3)	#(4,4)

Corresponding GLCM layout

Fig. 6. GLCM

3) Classification

Classification is a very popular supervised learning method which is used to classify categories of recent observations based totally on training information. Here the application learns from a given records set or obser- vations and then classifies new observations into one-of-a-kind training or companies. This algorithm is used to detect the disease. Therefore, the end result can be that disease is located or not located.

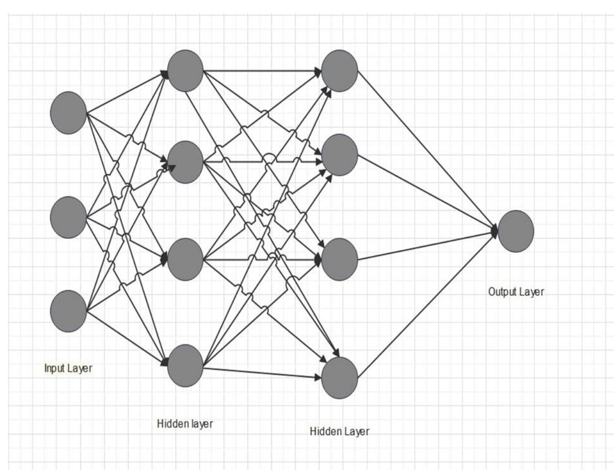

Fig. 7. Convolutional Neural Network

a) *CNN:* In the domain of plant disease diagnosis, CNN models are meant to automatically learn and extract useful information from photos. They can categorise plants intodifferent disease groups and apply transfer learning to recognise disease-specific patterns. They are appropriatefor real-time or high-throughput plant disease detection systems and can rapidly analyse several photos at the same time. They have shown great accuracy in plant dis-ease diagnosis when compared to standard approaches, lowering the likelihood of miss-classification and false- positive or false-negative findings. Regular three-layer neural networks

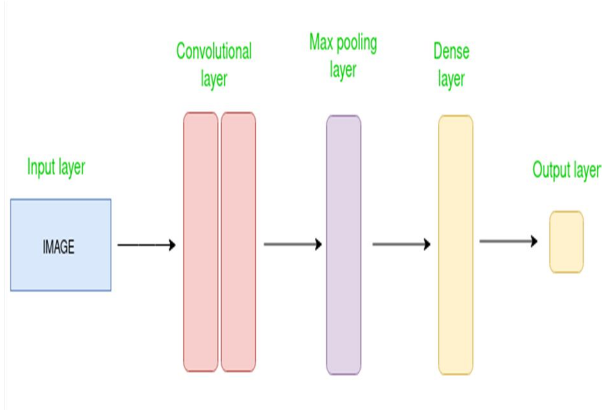

Fig. 8. C

- *Input Layer:* This layer will take data and send itto the rest of the network.
- *Hidden Layer:* The hidden layers are ultimately responsible for neural networks' remarkable per- formance and intricacy. They accomplish a varietyof tasks at the same time. For instance, data trans- formation, automatic function construction, and so on.
  - *Convolutional Layer:* CNNs employ convolution to recognise local patterns or features in images, such as edges, textures, or other visual structures.
  - *ReLU (Rectified Linear Unit):* It introduces non-linearity by producing the maximum of zero and the input value. It aids the network in learning complicated linkages and detecting non-linear patterns in data.
  - *Max-pooling Layer:* When max-pooling is applied to a model, max-imal pools minimise picture dimensions by lowering the amount of pixels in the preceding convolution layer's output.
  - *Fully Connected Layers:* The output is flattened into a 1D vector and sentinto one or more fully connected layers after multiple convolutional and pooling layers.
- Output Layer: The output layer is the last level type. The output level contains the problem's resultor output. The raw photos are sent into the input layer, and the output is generated in the output layer.

IV. RESULT

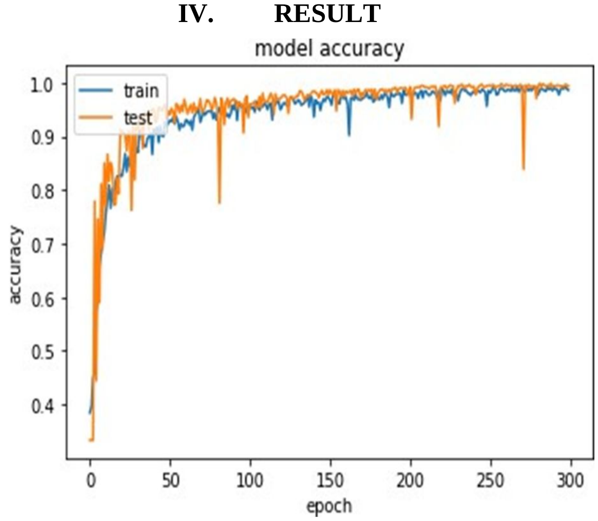

Fig. 9. Accuracy

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DISEASE NAME	INPUT	OUTPUT
1. **Apple Scab Disease**		Image Testing Completed.. Apple_scab Disease PESTICIDE- Superstar 65wp Dodine 65%wp Fungicide. DIRECTION TO USE- 600-800gm in 300 liter of water per acre.
2. **Strawberry Leaf Scorch Disease**		Image Testing Completed.. Strawberry_Leaf_scorch Disease PESTICIDE- Cabrio Top. DIRECTION TO USE- 1-2gm in one liter of water per acre.
3. **Corn Northern Blight Disease**		Image Testing Completed.. Corn_Northern_Blight Disease PESTICIDE- Deloro Fungicide. DIRECTION TO USE- 1.5-2gm in one liter of water per acre.

Fig. 10. Result Table

V. FUTURE SCOPE

The future scope for crop disease detection and cure rec- ommendation projects is promising and offers several potential advancements. Crop disease detection and cure recommenda- tion projects lies in leveraging emerging technologies, improv- ing accuracy and real-time monitoring, enhancing accessibil- ity through mobile applications, promoting data sharing and collaboration, integrating AI and robotics, developing disease forecasting systems, and adopting a multi-crop, multi-disease approach. These advancements have the potential to revo-lutionize disease management practices, enhance agricultural productivity, and contribute to sustainable and resilient farmingsystems.

VI. CONCLUSION

Finally, the crop disease detection and cure suggestion project is critical in agricultural practises. The initiative intendsto enhance agricultural disease identification and managementby integrating sophisticated technologies such as computer vision and machine learning. Early disease diagnosis can avoidextensive infections, decrease yield losses, and boost overall crop output. Furthermore, offering accurate and timely dis- ease management suggestions helps farmers to apply suitable measures and minimise the negative impact on their crops.To accomplish precise and economical crop disease diagnosis,the research employs Convolutional Neural Networks (CNNs) and picture preprocessing approaches. It also employs feature extraction techniques such as GLCM to extract significanttexture information from photos in order to enhance illness categorization.

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