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AI/ML Driven Robotic Solutions for Sustainable Crop Management

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ABSTRACT: Frequently praised as India's lifeblood, the agricultural sector employs an astounding 70% of the country's labour force and accounts for morethan 42% of all employment worldwide. Leaf diseases are a serious threat to agricultural output because they can destroy entire harvests and compete with crops for essential nutrients. Conventional leaf management techniques are labor-intensive and ineffective, which lowers yields and increases hardware requirements. A promising solution to this problem is the innovative method of incorporating robotics into farming, which is best represented by Agribot. This technical development intends to revolutionize weed control tactics and usher in a new era of agricultural sustainability by concentrating on the diagnosis and mitigation of leaf diseases.

The suggested device delivers remedies that will beutilized as a defense against the ailment and aids in the detection of plant illnesses. Typically, we employ a Convolutional Neural Network (FASTER CNN) with various layers for prediction. TensorFlow, an object detection API, is used to provide a method for detecting diseases from plant leaf pictures. Through rigorous training, the CNN algorithm extracts crucial information from images, enhancing the accuracy of disease detection. Additionally, the accuracy value is computed. Our information processing system learning approach learns frequently and may be less complicated in plant disease detective work when extensive schooling is combined with an outstanding sample of datasets.

KEYWORDS: Agriculture, CNN Algorithm, ImageProcessing, leaf disease detection

I. INTRODUCTION

The primary occupation in India is agriculture. India ranks second in the agricultural output worldwide. Here in India, farmers cultivate a greatdiversity of crops. Various factors such as climatic conditions, soil conditions, various disease, etc affect the production of the crops. The existing method for plants disease detection is simply nakedeye observation which requires more man labour, properly equipped laboratories, expensive devices etc.

Improper disease detection may led toinexperienced pesticide usage that can cause development of long term resistance of the pathogens, reducing the ability of the crop to fight back. The plant disease detection can be done by observing the spot on the leaves of the affected plant. The method we are adopting to detect plant diseases is image processing using Convolution neural network (FASTER RCNN). So this researchdevelops design of how machine learning can be used in automatically detecting plant diseases by seeing the plant leaves. Our objective is to construct a system that takes images as input, and after precise testing, it gives the disease name in the output. To implement our proposed method, we have collected data manually and used a faster R- CNN algorithm and some necessary tools.

II. OBJECTIVES

Objectives of our proposed model are as follows:

- 1. To detect unhealthy regions of plant leavesparticularly Tomato Plant.
- 2. Robot receives image information and identifies, classifies the plant leaf diseases using texture features.
- 3. This module employs machine learning techniques and detects whether selected leaf is healthy or not. It uses image processing modules fordetection. If the disease is detected then a commandprompt shall be sent.
- 4. Perform performance analysis using Convolutional Neural Networks (CNN) matrices for evaluation purposes.



III. LITERATURE SURVEY

SK Mahmudul Hassan et al.,[1] The timely identification of plant diseases prevents the negative impact on crops. They proposed a novel deep learning model based on the inception layer and residual connection. Three distinct datasets related to plant diseases were used to train and evaluate the suggested model. 99.39%, 99.66%, and 76.59% of the performance accuracy was achieved on the plant village, rice disease, and cassava datasets, respectively.

Kowshik B, et al., [2] this area of research appears to have a lot of promise in terms of improved accuracy. The proposed method uses a convolutional neural network and a Deep Neural Network to identify and recognise cropdisease symptoms effectively and accurately.

Waleed Albattah, et al., [3] determined manualexamination for crop diseases is restricted because of less accuracy and the small accessibility of human resources and to tackle such issues, there is a demand to design automated approaches capable of efficiently detecting and categorizing numerous plant diseases.

Smruti Kotian et al., [4] This study addresses the issue of cotton leaf disorders and suggests a technologically advanced solution based on KNN and Transfer Learning (ResNet50) algorithms. With an emphasis on detecting CurlDisease and Bacterial Blight.

B.V. Nikith et al.,[5] For the purpose of recognizing and categorising eight disorders of soybean leaves early on, this study integrates machine learning algorithms, like Support Vector Machines (SVM), K Nearest neighbours (KNN) and Convolutional Neural Networks (CNN).

Sunil S Harakannanavar et al.,[6] Within thus research, Convolutional Neural Networks (CNNs) are utilised to examine the identification of disease in plants using a dataset of 20,639 photographs.

Kalpesh Joshi1, Rohan Awale2, et al., [7] Usingdigital image processing and machine learning algorithms, this paper presents a method for detecting plant disease. The disease detection is done on the yields' various leaves. The presented system for plant disease detection is simple and computationally efficient which requires less time for prediction than other deep learning- based approaches.

Lili Lil, et al.,[8] Deep learning is a branch of artificial intelligence. It has been widely used in image and video processing, voice processing, and natural language processing. This review provides the research progress of deep learning technology in the field of crop leaf disease identification in recent years.

IV. METHODOLOGY

4.1 Datasets

The dataset for training is obtained from Leaf Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI). LIDC and IDRI consist of 1000 CT scans of both large and small leaf saved in Digital Imaging and Communications in Medicine (DICOM) format.



Fig 1: Detailed Block diagram of Agribot



Fig.1 illustrates a detailed block diagram of the Agribot. The method starts with acquiring the input test image and preparing it to make it more suitable for analysis. Then, for effective comparison, it is transformed into an array format. In the interim, the chosen database is subjected to extensive preprocessing and segregation, guaranteeing that every element is suitably arranged and renamed into its own folder for convenient access. The next crucial step that enables the system to identify and categorise patterns in the photos is training the model with Convolutional Neural Networks (CNNs). This is where the action is concentrated. The model is prepared for use after training. The result is displayed once a comparison is made between the training model and the test image. If the study finds any abnormalities, such flaws or illnesses in the plant, the software quickly identifies the problem and suggests possible solutions, making mitigation strategies more efficient. This all-encompassing strategy guarantees that the system not only detects issues but also offers usefulideas for resolving them.

4.2 Pre-processing process

Pretreatment or the pre-processing is the first stage of image processing. This stage involves getting the image from hardware-based sources. The images then go through further pre-processing steps as shown in Fig 2. The three main steps are: a) Grayscale conversion b) Noise removal c) Image Enhancement

In preprocessing stage, the median filter is used to restore the image under test by minimizing the effects of the degradations during acquisition. The median filter simply replaces each pixel value with the median value of its neighbors including itself. Hence, the pixel values which are very different from their neighbors will be eliminated.

4.2.1 Grayscale conversion

Grayscale image contains only brightness information. Each pixel value in a grayscale image corresponds to an amount or quantity of light. The brightness graduation can be differentiated in grayscale image. Grayscale image measures only light intensity 8bit image will have brightness variation from 0 to 255 where '0' represents black and '255' represent white. In grayscale conversion colour image is converted into grayscale image shows. Grayscale images are asier and faster to process than coloured images.All image processing technique are applied on grayscale image.

4.2.2 Noise Removal

The objective of noise removal is to detect and remove unwanted noise from digital image. The difficulty is in deciding which features of an image are real and which are caused by noise. Noise is random variations in pixel values. We are using median filter to remove unwanted noise. Median filter is nonlinear filter, it leaves edges invariant. Median filter is implemented by sliding window of odd length. Each sample value is sorted by magnitude, the centremost value is median of sample within the window, is a filter output.

4.2.3 Image Enhancement

The objective of image enhancement is to processan image to increase visibility of the feature of interest. As seen in Fig 2. contrast enhancement issued to get better quality results.



Fig 2: Data flow diagram of pre- processing



4.3 Image segmentation process

Image segmentation is of many types such as clustering, threshold, neural network based and edge base as shown in Fig 3. We use mean shift clustering, a potent technique that is well-known for its capacity to locate densely populated areas in an image, for our particular implementation. By using a sliding window technique, this algorithm systematically moves over the image space in order converge on regions with the highest density. Thealgorithm's use of several sliding windows allows itto identify areas of higher density, which is important for differentiating between good and diseased leaf areas. Because mean shift clustering is so good at spotting abnormalities or departures from the norm, it's a great option for identifying inconsistencies that could be signs of illness or leafdistress. In agricultural contexts, this approach makes it possible to precisely detect and classify the health status of leaves, which facilitates prompt intervention and management strategies.



Fig 3: Image Segmentation process

4.4 Feature extraction process

There are several different approaches in the field of feature extraction for leaf analysis, all of which are designed to extract relevant data that is essential for determining the health state of leaves. These methods include deep learningbased feature extraction, colour histograms, texture analysis, and shape-based features. In our case, we use texture analysis, which is a technique that can capture complex surface features and patterns found in leaf structures. Texture analysis allows leaf textures associated with various health issues to be characterised by taking local picture patches and obtaining statistical descriptors or frequency domain representations from them. Through a methodical examination of textural characteristics on the leaf surface, our technique seeks to identify minute differences that may be signs of illness or other abnormalities.

4.5 Training

Training dataset was created from images of knownCancer stages. Classifiers are trained on the created training dataset. A testing dataset is placed in a temporary folder. Predicted results from the test case, Plots classifiers graphs and add feature-sets totest case file, to make image processing models more accurate.

4.6 Classification

The binary classifier which makes use of the hyper-plane which is also called as the decision boundary between two of the classes is called as Convolution Neural Network. Fig 4, illustrates how classification process takes place. Some of the problems are pattern recognition like texture classification makes use of CNN. Mapping of nonlinear input data to the linear data provides good classification in high dimensional space in CNN. The marginal distance is maximized between different classes by CNN. Different Kernels are used to divide the classes. CNN is basically a binary classifier that determines hyper plane in dividing two classes. The boundary is maximized between the hyperplane and two classes. The samples that are nearest to the margin will be selected in determining the hyperplane is called support vectors.





Fig 4: Classification process

4.6.1 CNN layers



Fig 5: CNN layers

Figure 5 illustrates the CNN layer wherein they include the convolution layer, max pooling layer and the activation layer which is discussed in brieffurther.

4.6.1.1 Convolution layer

This layer in leaf identification involves methodically going through the whole leaf image tofind pertinent patterns, then organising those patterns into a 3x3 matrix, as seen in Fig 6. The resulting convolved feature matrix, called the kernel, captures the texture and shape of the leaf in critical detail. Every value in the kernel denotes a weight vector that indicates how important a certain trait is to differentiating between healthy and unhealthy leaf regions. The neural network learns to extract relevant information from the leaf picture through this convolutional process, which makes it possible for later layers to identify minute characteristics that are essential for precise categorization. The kernel extracts unique patterns and features from the input image as it moves across it, creating a compact representation that serves as the basis for more in-depth analysis inside the leaf identification framework.



Fig 6: Convolution layer



4.6.1.2 Pooling Layer

In the leaf detection procedure, convolution is followed by pooling, which divides the convolved feature matrix into non-overlapping rectangular segments, each of which has four subregions, as shown in Fig 7. Max pooling and average pooling are the two main pooling strategies used. The mostnotable features that were recovered during convolution are essentially preserved since max pooling chooses the maximum value inside each subregion. On the other hand, average pooling calculates the average value inside the subregion, resulting in a more comprehensive feature representation. The main benefits of the pooling layer are increased computing efficiency and less risk of overfitting due to lower dimensionality feature maps. Pooling promotes spatial invariance and makes it easier to extract key features by combining data from nearby locations.



Fig 7: Output Matrix for pooling layer

4.6.1.3 Activation layer

The normalisation phase is a crucial step in the analysis of leaves in Convolutional Neural Nets (CNNs). It involves adjusting the values retrieved from features to a standardised range, which improves the stability and performance of the model. By ensuring that the input data falls into a predetermined range this normalisation makes it easier to interpret data consistently across samples. Moreover, a key component of leaf analysis is the convolutional function used, such as the Rectified Linear Unit (ReLU). ReLU activation functions introduce non-linearity and improve the network's capacity to recognise intricate patterns in leaf pictures by selectively passing positive values and suppressing negative inputs.

V. PERFORMANCE ANALYSIS

Convolution and pooling layers are used by convolutional neural networks (CNNs), which are essential for processing image input, to identify patterns. Figure 8 displays the dataset's accuracy that was used. As the model is exposed to the dataset and starts to acquire pertinent patterns, accuracy is typically low during the early training phases. The activation function of ReLU, which is recognized for incorporating non-linearity into the model, is essential in allowing the network to comprehend intricate correlations present in the data. The accuracy usually increases with training, indicating the network's capacity to extrapolate from the training data to previously unknown cases.



Fig 8: Accuracy Vs Training steps



The activation function of ReLU helps the model learn and represent complex characteristics in the pictures, which improves the overall efficacy of leafdisease.

Model	%Accuracy
Jahnavi J.V.(CNN), [7]	94%.
Mahmudul Hassan, [1]	95.39%
Cotton Leaf Disease Detection Using MachineLearning, [4]	86%.
B. V. Nikith, [5]	91.5%.
Proposed work(CNN)	98.6%.

Table 1: Comparative Analysis of different models

The accuracy % for each method is shown in Table

1. As the table shows, the recommended architecture offers a higher accuracy rate than the other models and architectures mentioned above. Therefore, using the proposed model can assist in lowering mistake rates.



Fig 9: Loss Vs Training steps



The Adam optimizer in Tensorflow is an algorithm used in deep learning models, as seen in Fig. 9. in the figure above. Every graph on show is the finished product that was obtained after anomalies were disregarded.

VI. CONCLUSION

The suggested approach emphasizes how vital the agricultural sector is to India, as it employs the great majority of the labor force and is the engine of the country's economy. Nonetheless, the industry has formidable obstacles, chief among which is the risk that leaf diseases pose to crop productivity. Traditional management approaches demand more labor and are frequently inefficient, which lowers yields and increases resource requirements.

Agribot serves as an example of how the arrival of robots has caused a paradigm change in agricultural techniques. Robotics integration in farming operations has the ability to transform weed control strategies and more successfully tackle the problem of leaf diseases. Agribot provides a possible answerto this urgent problem with its concentration on identifying and treating leaf diseases. The use of cutting-edge technology like TensorFlow and Convolutional Neural Networks (CNNs) is essential to Agribot's efficacy. The aforementioned technologies facilitate the creation of resilient disease detection systems that employ machine learning algorithms to scrutinize plant leaf photos and precisely discern indications of illness. The CNN algorithm improves the accuracy of illness diagnosis by learning how to extract important information from images through extensive trainingon a variety of datasets.

All things considered, the system depicts a future inwhich cutting edge technology are essential to changing agricultural methods. Farmers can maximize output, minimize the influence of illnesses on agricultural yields, and improve resource allocation by utilizing robotics and artificial intelligence. A major step in attaining agricultural sustainability and guaranteeing food security for future generations is the integration of these technologies.

REFERENCES

- 1. S. K. Mahmudul Hassan and A. K. Maji, "Plant Disease Identification Using a Novel Convolutional Neural Network," January 14, 2022.
- 2. K. B., S. V., N. M. Madhav, K. G., and S. Karpagam, "Plant Disease Detection Using Deep Learning," March 2021.
- 3. W. Albattah, M. Nawaz, A. Javed, M. Masood, and S. Albahli, "A novel deep learning method for detection and classification of plant diseases," September 28, 2021.
- 4. Cotton Leaf Disease Detection Using Machine Learning, in Proceedings of the 2nd International Conference on Advancement in Electronics & Communication Engineering (AECE 2022), July 14-15, 2022.
- B. V. Nikith, N. K. S. Keerthan, P. M. S., A. T., "Leaf Disease Detection and Classification," in Proceedings of Procedia Computer Science, vol. 218, 2023.
- 6. S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, "Plant leaf disease detection using computer vision and machine learning algorithms," in Proceedings of GlobalTransitions, April 2022.
- 7. Savitha G., Hithyshi K., Harshitha J., Jahnavi J.V., Malak Naaz, "Deep Leaf Detect Implementation: Utilizing CNN for Accurate Leaf Disease Detection in Agricultural Systems", April 2024.
- 8. K. Joshi, R. Awale, S. Ahmad, S. Patil, and V. Pisal, "Plant leaf disease detection using computer vision techniques and machine learning," 2022.
- 9. S. Ingale and V. B. Baru, "Plant leaf disease detection recognition using machine learning," in Proceedings of International Journal of Engineering Research & Technology (IJERT), vol. 8, no. 06, June 2019.
- 10. U. N. Fulari, R. K. Shastri, A. N. Fulari, "Leaf disease detection using machine learning," in Proceedings of Research Gate, September 2020.
- 11. V. Monigari, G. K. Sri, T. Prathima, "Plant leaf disease detection," in Proceedings of International Journal for Research in Applied Science & Engineering Technology (IJRASET), July 2021.
- 12. V. Singh, A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," in Proceedings of Information Processing in Agriculture 4, 2017.





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