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Plant Disease Detection Using Deep Learning and Remedy Suggestion - A Review

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Abstract: India and other growing nations value their agricultural industries. Agriculture-related interventions have an impact on 58% of rural India's livelihood. It is essential to recognise and categorise any ailments that a plant may have in order to reduce any significant loss in the quantity and yield of plant species. Many methodologies and procedures are used to overcome these issues, including cutting-edge technology like image processing. The tomato plant's leaves are initially affected when it contracts a specific type of disease. This study consists of four sequential procedures to identify the illness kind. The four phases include pre-processing, leaf segmentation, feature extraction, and classification.

Keywords: neural network, convolutional neural network, leaf segmentation, disease detection

I. INTRODUCTION

In countries like India, it is essential to introduce technical innovation into the fields related to agriculture productivity. Research projects and speculative study methods are being used in the crucial field of qualitative farming with the goal of increasing yield and food crop quality while lowering costs and increasing income. Complex interactions between soil, seeds, and growth-inducing substances enable agricultural architecture. Today, one of the main agricultural goods produced is fruits and vegetables. The evaluation of a product's value and its enhancement have always been important aspects of the strategy for buying valuable and surplus commodities. Diseases affect or interrupt critical processes such as transpiration, photosynthesis, fertilisation, pollination, and germination, among others, impairing a plant's ability to function normally. Microorganisms are harmed by unfavourable environmental circumstances.

As a result, the first stage of plant disease diagnosis carries a lot of weight. Farmers must be regularly observed by experts, but this can be expensive and time-consuming. So, it is of the biggest practical importance to create low-cost, quick, and reliable methods for intelligently identifying illnesses from symptoms that seem to be on a plant leaf. In this study, we present a technique for identifying the exact disease that a plant leaf might harbour. One method to determine the type of illness a crucial crop like tomatoes may have is to implement image recognition technologies, which display the application's operation graphically. This is a significant contributing factor to the growing acceptance of digital technologies.

II. LITERATURE SURVEY

In J. Arun Pandian et.al [1], the author offered a creative employing a 14-layered DCNN to recognise plant illnesses from photos of the leaves. Many open datasets were used to create a new dataset. Individual class sizes in the dataset were balanced using techniques for data augmentation. The three techniques employed to improve the photographs were Basic Image Manipulation (BIM), Deep Convolutional Generative Adversarial Networks, and Neural Style Transfer (NST). 58 different leaf classes of both healthy and diseased plants, as well as one leafless class, are included in the collection's 147,500 images. A multi-graphics processing unit (MGPU) environment was employed for training the proposed model of DCNN during the duration of 1000 epochs.

In Sk Mahmudul Hassan et.al [2], the author claims that deep learning-based algorithms beat conventional classification techniques including KNN, SVM, RF, LR, ANN, and others. Instead of using traditional feature extraction techniques that rely on features like colour, shape, SIFT, texture-based, GLCM, histogram, Fourier description, etc., deep learning uses features that are automatically learned from the networks, which is more effective and results in more accurate classification results. There are several deep learning architectures used to identify plant diseases.

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In Sunil S. Harakannanavar a et.al [4], the Aura leaf spot, Rust, Brown spot, and gray spot are five types of apple leaf illnesses seen on leaf, according to the author, and are covered in this essay. That is a problem in Apple. In this study, deep learning techniques were utilised to improve convolution neural networks for spotting disease in apple leaves. The complex photos and laboratory images from the dataset for apple leaf disease are used in this investigation (ALDD). The images below were created using picture annotation and data augmentation techniques. A new deep-CNN was built using Rainbow concatenation and the Google network inception structure. The suggested INAR model was tested using a testing dataset that included 26,377 images of diseased apple leaves. The machine learning model was taught to identify five prevalent diseases on apple leaves. The obtained results show that INAR-SSD model offers an effective high-performance strategy for detecting apple leaf illness and can detect these diseases in real-time with better precision and faster detection speed as compared to earlier approaches.

In Jun Liu et.al [5], the author compares the difficulty of diagnosing plant pests and diseases with conventional methods. In this article, the classification network, detection network, and segmentation network are used to showcase current advancements in the application of deep learning to identify plant illnesses and pests. Also, each technique's benefits and drawbacks are examined. We describe typical datasets and assess the effectiveness of earlier research. The effectiveness of earlier research is assessed, and standard datasets are introduced. This article discusses potential challenges associated with applying deep learning to real-world applications for recognising plant diseases and pests. The problems are also examined, as well as possible solutions, directions for research, and suggestions.

In Gokulnath BV et.al [6], the author suggests that the system for classifying and diagnosing plant diseases uses a variety of computational techniques, all of which will be thoroughly analysed by the author. Many complex algorithms had to be used in order to complete the intended task. To improve the predictability of the computational model, numerous more fusion models were created and thoroughly explored. The study's findings emphasise the value of automated systems in assisting users in finding plant illnesses without the need for human involvement. It is necessary to build prescriptive models, which are in high demand soon. Many machine learning techniques that are frequently used to forecast plant diseases are examined in this study to determine how they could be improved in the future for greater accuracy, robustness, and affordability. This assessment covers the pre-processing, segmentation, feature extraction, and classification processes of image processing approaches based on plant symptoms.

In Dr. Gajula Ramesh et.al [7], According to the author, since plant illnesses completely depend on microscopic processes, human vision is only partially capable of identifying and analysing them. Using computer-based image rearranging techniques, plant diseases are accurately classified and identified. A k-mean clustering procedure is used to identify disease on a real-time leaf image. The GLCM filter first detects the data, then extracts its features. SVM-based methods are frequently employed for classification, but they perform poorly with respect to texture features. Features-based matching procedures are carried out using Back Propagated ANN, a cutting-edge type of artificial intelligence. The proposed method, which is used in the Matlab software, performs significantly better in terms of accuracy than traditional methods.

In Ms. Nilam Bhise et.al [8], the author claims that the Deep Neural Network, a component of the Deep Learning algorithm, is used to identify crop illnesses. In essence, the method has been tested on a variety of plant species with various diseases. The Keras and Tensorflow libraries were used to create this model, which was then implemented on Android. The Mobile Net model exceeds the competition and offers higher sickness diagnosis accuracy, according to the system's overall findings. Further plant species and their diseases will be included in the experiment.

In Bin Liu et.al [9], The author explains They consider tomato leaf samples from their survey that have abnormalities. With the use of these disease samples from tomato leaves, farmers would find it straightforward to identify diseases based on their early-stage symptoms. The tomato leaf samples are first resized to 256 by 256 pixels in order to improve the sample quality. By using K-means clustering, the data space is partitioned into Voronoi cells. It is possible to extract the edges of the leaf sample using contour tracing. Following feature extraction, the characteristics gathered are categorised utilising machine learning algorithms including KNN, SVM, and CNN. CNN (99.6%), SVM (88%) and KNN (97%) are used to evaluate the suggested model's accuracy on disordered data.

In Shima Ramesh Maniyath et.al [10], the algorithm's objective is to find anomalies that show up on plants in their natural or greenhouse habitats, according to the author. Usually, the image's background is plain to prevent occlusion. The algorithm's precision was contrasted with other machine learning models' accuracy. 160 photos of papaya leaves were

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utilised to validate the method using the Random Forest classifier. The classification accuracy of the model was roughly 70%. While training, many images can be used, and feature points like SURF and SIFT (Scale Invariant Feature Transform) can be combined with global features to boost accuracy (Speed Up Robust Features).

Fig. 1 Table Analysis

Author and year	Dataset Used	Methodology/Algorithm	Drawback
J. Arun Pandian, 2022 et.al [1]	collection of open datasets of images of 16 species	Deep Convolutional Neural Network (DCNN)	The proposed model is trained only on face-up leaf images.
Sk Mahmudul Hassan,2022 et.al [2]	Plant Village data, Cassava data, Hops data, [illegible] disease data, Rice disease data	CNN architecture	Although a number of models were compared, accuracies of the models are ambiguous.
Gaurav Shrivastava, 2022 et.al [3]	Rice disease dataset, Plant Village dataset	ANN and SVM classifiers	Proposal of low-cost decision system while two different models are used in which SVM is less accurate, efficient.
Sunil S. Harakannanavara, 2022 et.al [4]	Tomato leaf samples	k-means, Discrete Wavelet Transform (DWT), Support Vector Machine (SVM), KNN and CNN	Only one crop dataset used, hence the model could have been trained to detect a greater number of diseases.
Jun Liu, 2021 et.al [5]	Tomato leaf samples	Convolutional Neural Networks (CNN)	Small dataset size problem due to self-collection.
Gokulnath BV, 2020 et.al [6]	open dataset	Machine Learning	Lack of comparison on the different techniques presented
Dr. Gajula Ramesh, 2020 et.al [7]	open dataset of ten species	Back propagated ANN approach	Focus lies majorly on generalised disease classification for multiple diseases
Ms. Nilam Bhise, 2020 et.al [8]	Plant Village dataset	Convolutional Neural Networks	Limited information on accuracy and precision
Bin Liu, 2019 et.al [9]	The apple leaf disease dataset (ALDD)	Convolutional Neural network	Limited number of diseases detected with reduced detection performance
Shima Ramesh Maniyath, 2018 et.al [10]	Papaya leaf	HoG feature extraction, random forest classifier	Training dataset size is very less and hence the accuracy is also reduced

III. DISCUSSION

In fact, convolutional neural networks (CNNs) are a powerful technique for developing computer models that convert unstructured visual inputs into labels for suitable classification. They fall within the category of multi-layered neural networks, which can be taught to learn the characteristics needed for categorization. In contrast to conventional techniques, multi-layered neural networks that may be taught to learn the features needed for classification require less pre-processing. For the purpose of identifying leaf sickness, employing a variation of the LeNet design may yield the best results.

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LeNet consists of fully linked, max-pooling, convolutional, and activated layers. LeNet is a fundamental CNN model. According to this design, the LeNet model categorises leaf diseases. To the original LeNet design, additional pooling layers, convolution layers, and activation layers are incorporated in this model. Each and every block contains all three layers. The architecture makes use of three such blocks that are soft-max activating and entirely associated. For feature extraction, pooling layers and convolutional layers are used; for classification, a fully connected layer is employed. Through the use of activation layers, the network is given nonlinearity. Using the convolution approach, the convolution layer extracts features. As depth increases, so does the sophistication of the retrieved features.

The size of the filter doesn't vary as we move from one block to the next, but the number of filters does. There are 20 filters in the first convolution block; there are 50 filters in the second block and 80 filters in the third. As pooling layers are utilised in each of the blocks, the size of the feature map has decreased; a greater number of filters are therefore required to make up for this. in order to guarantee that the size of the images is preserved after the convolution procedure. Using max pooling layers reduces the dimension of feature maps, speeds up model training, and lessens the sensitivity of the model to even the slightest change in the input.

IV. IMPLEMENTATION

The most crucial and last step in the software development process is implementation. Examples of utilisation include accepting specifications or calculations, transforming them into a framework, application, or product segment with the aid of computer programming, and releasing them into the environment where they were designed to function.

Data: In this project, the data is taken from Kaggle, a well-known provider of datasets. The Kaggle website offers a huge selection of datasets, ranging from the earliest to the most recent. The dataset consists of numerous rows of reports on diseased plants.

Before training the data, the dataset needs to go through a lot of pre-processing. The characteristics of a complete training dataset are as follows:

• Label:
1. Diseased
2. non-Diseased

Pre-processing and feature extraction: Data pre-processing is the process of transforming raw data into something that can be used by a deep learning model. The first and most important stage in developing our model is this one. The data must be pre-processed, sorted, and put through several tests before being used for training and testing with different models.

These actions comprise:

Data collection: This entails gathering leaf images from diverse places, such as plantations or fields. High-quality photos that have enough information to identify the important elements are required.

Image enhancement: This involves cleaning out any noise or artefacts that may have been added during the acquisition process in order to improve the quality of the photos. The photos can be improved using methods including denoising, contrast enhancement, and sharpening.

Image Segmentation: Identifying and isolating the regions of interest from the background in the leaf photos is known as image segmentation. This would entail separating the affected part of a leaf from healthy leaf portions in the case of a diseased leaf.
Feature extraction: This method entails removing pertinent features from the divided regions of interest. Taking out characteristics like texture, colour, and feature may be necessary in the event of a diseased leaf.
Data normalisation: This process entails sizing the extracted features to a standard range or distribution to make sure they are similar amongst various samples.

Data augmentation: In this process, extra training data is produced by transforming the original images in various ways, including rotation, translation, and scale. The model's resilience may be enhanced as a result.
Overall, the pre-processing stage is critical for ensuring that the leaf images are ready for analysis and can provide accurate and reliable results for the detection of plant disease.

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Sequential Model: When a neural network is built using a sequential model, layers are piled one after the other to create a hierarchical structure. Every layer in the network receives the output from the layer before it and applies its own set of processing to the data. The deep learning model that is developed has a final loss of 0.0905 and final accuracy of 0.9738.

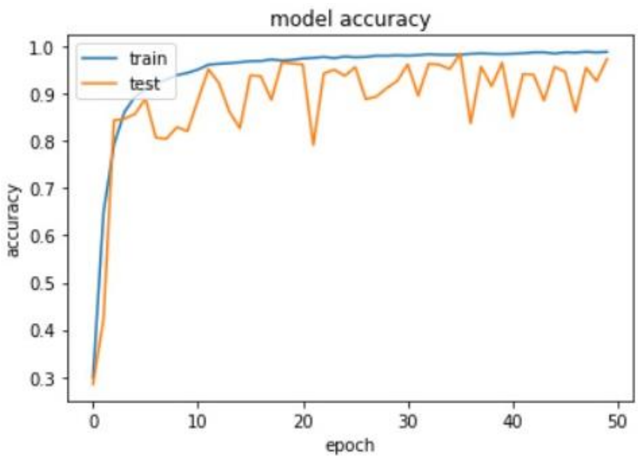

Fig.2 Graph of Model Loss

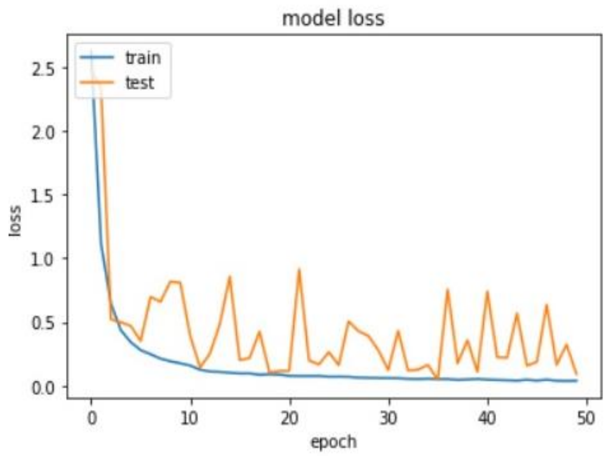

Fig.3 Graph of Model Accuracy

V. CONCLUSION

Although there are several automated or computer vision methods for categorising and identifying plant diseases, more research is still needed in this field. The sole commercially available techniques also deal with identifying plant species based on pictures of the leaf. In this study, a novel method using Deep Learning techniques was examined to efficiently classify and diagnose plant illnesses from leaf photos. The model that was created could distinguish between healthy leaves and 13 distinct disorders that could be visually diagnosed. The entire detection process includes gathering the pictures required for pre-processing, augmenting, training, and validating. To gauge how well the recently created model functioned, many tests were undertaken.

Since the provided method hasn't been used to the field of identifying plant diseases, there hasn't been any comparison of results obtained using a similar method. The goal of this research's future endeavours is to collect images that will improve the database and the model's accuracy by employing various augmentation and fine-tuning techniques.

The major goal of the upcoming works is to create a full system made up of server-side architecture components with a training sample and an Android application for smartphones that may detect illnesses in fruits, vegetables, as well as plants based on photos taken with the phone's camera. Farmers would benefit from this application because it will make it simpler for them to identify plant illnesses and decide whether to use pesticides or not rapidly and precisely.

Future work will also focus on expanding the model's range of applications by training it to recognise plant diseases in a larger range of geographical contexts, merging drone-shot aerial photos of orchards and vineyards with convolutional networks that recognise objects, and more. The authors want to considerably advance sustainable development by expanding their study and improving crop quality for future generations.

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