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App-Based Solution to Identify and Solve Disease in Plants/Crops

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ABSTRACT—Crop diseases must be promptly identified and prevented if productivity is to be increased. Since CNNs have demonstrated outstanding achievements in the field of machine vision, deep convolutional neural network (CNN) models are used in this paper to recognise and diagnose plant illnesses from their leaves. Conventional CNN models need a lot of parameters and are more expensive to compute. In this study, we switched from ordinary convolution to depth=separable convolution, which lowers the number of parameters and lowers the computational cost. The models that were put into use were trained using a public dataset that included the leaves of 14 different plant species, 38 different categorical illness classes, and healthy plant leaves. Several factors, including batch size, dropout, and various numbers of epochs, were taken into account to assess the models' performance. The utilised models used InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively, to obtain disease-classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% that were higher than those of conventional handcrafted-feature-based techniques. The implemented deep-learning model outperformed other deep-learning models in terms of accuracy and required less training time. Also, utilising the optimised parameter, the MobileNetV2 architecture is suitable with mobile devices. The accuracy results for disease identification demonstrated that the deep CNN model is promising and can significantly influence the effective disease identification. It may also have potential for disease detection in real-time agricultural systems.

I. INTRODUCTION

In order to supply food for 7 billion people, the agriculture sector has long used modern science. People who work in the agriculture sector, however, are exposed to a variety of dangers that jeopardise the safety of human society's food supply. Climate change, livestock grazing, plant diseases, etc. are a few of the known threats. Among the many dangers, the impact of plant disease is particularly significant because it not only results in significant losses of crops intended for human consumption but also has a profound impact on both the lives of farmers and the health of society as a whole. Farmers' primary source of income is the cultivation of healthy crops. Human experts go through a laborious procedure of inspection during the harvesting of plants, and removing mature plants, ensuring they are healthy and fit for human use and free from any disease. Nevertheless, this conventional visual method of determining the name of the illness a certain plant is experiencing takes a lot of time and is costly, especially if the farmhouse is large and there are many plants. Additionally, it only seems sense that this process be mechanised in order to satisfy the increasing wants of the population given the apparent global population growth that is occurring day by day.

In comparison to the traditional visual identification of plant illnesses, the early detection of plant diseases has become considerably simpler, less time-consuming, and cheaper with the advent of machine learning models. Recent years have seen a lot of study in this area, and as a result, machine learning models are gradually taking the place of the industry's old methods for identifying plant illnesses. The objective of this thesis is to implement two different machine learning models, namely Convolutional neural network (CNN) and K-nearest

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Neighbor (KNN), on the Plant Village dataset and to assess the performance of the aforementioned models using the metrics of accuracy, precision, recall, and F1-Score. The study's primary objective is to identify diseases in tomato leaves collected from the plant community. specifically from the Plant Village dataset's disease identification of tomato leaves (J and Gopal, 2019). The originality of this work comes from its use of the Explainable Artificial Intelligence (XAI) approach and Local Interpretable Model-Agnostic Explanations to explain the judgements made by the aforementioned models in a transparent and understandable manner (LIME). The specialty of this paper lies in the fact that it aims at not only implementing but also explaining and providing transparency to the users on the predictions made by the machine learning models, which is very uncommon and not to be found in many research papers in this particular domain.

II. BACKGROUND STUDY

Kuniaki Uto , Mauro Dalla Mura , Yuka Sasaki and Koichi Shinoda(2020) An essential phenotypic characteristic that is connected to photosynthesis is leaf angle dispersion. Leaf-scale airborne photographs with great spectral and spatial resolution are now available, thanks to the recent development of drones and high-resolution photography technologies. This work represents the first attempt to distinguish between plants with various leaf angle distributions using a single leafscale image. A collection of rice leaf surfaces is first approximated by a hemiellipsoid surface, presuming that a rice leaf surface resembles a portion of a hemiellipsoid surface. Under various direct sunlight orientations, timeseries of shade distributions on the hemiellipsoids with various structural parameters are produced. By examining the statistical characteristics that effectively distinguish hemiellipsoids with various densities, such as skewness, kurtosis, and the most probable intensity,

Ayan Chaudhury, and John L. Barron (2020) Using a database of whole plant leaves, we offer a method for identifying the plant species using the contour data from occluded leaf images. Matching occluded leaves with entire leaf datasets is an open and under-researched subject, despite the recent considerable study of contour-based 2D form matching. Due to the wide variety and intricate leaf architecture, classifying occluded plant leaves is considerably more difficult than complete leaf matching. Our approach is inherently poor since matching an occluded contour with all the full contours in a database is an NP-hard task. Secondly, a -Spline curve is used to represent the 2D contour points. Following that, we use the Discrete Contour Evolution (DCE) technique to extract interest points from these curves. .

Ronnie Concepcion, Sandy Lauguico, Elmer Dadios, Argel Bandala, Edwin Sybingco, Jonnel Alejandrino2020) Because to the complicated nature of chlorosis and the error-prone sphere of colours and textures affected by angle photosynthetic light source, visual evaluation of plant health status and disease severity may result in subjective assessments. It is crucial to quantify the effects of damaging diseases on leaves in order sssto understand how pathogens and plants interact. The integration of computational intelligence and computer vision for tomato Septoria leaf spot necrotic and chlorotic region computational assessment is the suggested answer to this problem. Individually photographed tomato leaves from healthy and diseased plants are included in the dataset. With the aid of the CIELab colour space, non-vegetation pixels were removed. The split leaf was used to extract five Haralick texture features and RGB colour components. The key predictors were chosen using a hybrid neighbourhood component analysis and ReliefF algorithm..

CHANGJIAN ZHOU, SIHAN ZHOU, JINGE XING , AND JIA SONG (2021) Many major grain-producing nations have implemented steps to limit their grain exports as COVID-19 has expanded over the globe; food security has sparked significant worry from a number of stakeholders. One of the most crucial concerns facing all nations is how to increase grain output. Crop infections, however, are a challenging issue for many farmers, thus it's critical to understand the severity of crop diseases promptly and properly to support staff in taking additional intervention steps to reduce plants being further affected. A hybrid deep learning model that combines the benefits of deep residual networks and dense networks was developed in this paper for the identification of tomato leaf disease. This model may reduce the amount of training process parameters to improve calculation accuracy as well as enhance

Suhaili Beeran Kutty,Noor Ezan Abdullah,Dr. Hadzli Hashim(2020) The major topic of this paper was the classification of the watermelon leaf diseases Anthracnose and Downey Mildew using neural network analysis. A few samples of infected leaves were gathered, and they were photographed with a digital camera that had been calibrated specifically in a lab setting. Based on colour feature extraction from the RGB colour model, where the RGB pixel colour indices have been collected from the designated Areas of Interest, the categorization of the watermelon leaf illnesses is

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made (ROI). The Neural Network Pattern Recognition Toolbox in MATLAB and the Statistical Package for the Social Sciences (SPSS) were used in the suggested automated classification model to classify disorders. Based on calculations in this paper, it was determined that the type of leaf diseases was identified with a 75.9% accuracy**.**

III. MODULE DESCRIPTION

Selection of method and metrics

Several classifiers can be used for plant disease detection, and a wide range of methods have been employed in the past. Convolution Neural Network (CNN) and K-nearest Neighbor were the classifiers employed in this thesis to carry out the detection (KNN). Local Interpretable Model-agnostic Explanations was the XAI technique utilised to provide an explanation capability for the predictions generated by the classifiers (LIME). Accuracy, precision, re-call, and f1-score were the measures used to assess the aforementioned models. Each classifier was assessed using the same four assessment metrics, and the outcomes of both classifiers were utilised to determine which model performed the best at identifying disease in tomato leaves using the Plant Village dataset**.**

Then, labels for each plant image are additionally matched to a distinct Any machine learning model's pre-processing stage is crucial, since it should impact the performance and outcomes of the models selected. The following procedures were used in this report to ensure that the models gave the best results possible.

After reading and resizing the photos, we then transform them into an array using the np.array() function. Next, we calculate the e value using LabelBinarizer(). Ultimately, the plant village dataset is divided into two sets, the train set and the test set, with a ratio of 75:25.

Configuration of the Classification Models

Following is the CNN architecture that was utilised in this study to detect plant diseases: the first block includes a convolutional layer with 32 filters of the size 3 x 3, and the activation function was the ReLU activation function. Following that, we carry out batch normalisation, select the Max Pooling layer with a pool size of, add a dropout layer with a 25% drop-out, and complete the operation.

The neural network's convergence was accelerated by the use of batch normalisation, which is typically applied after each layer so that the output of the preceding layer can be normalised. This enables each layer to function independently of the others in the network. Dropout layer is a method for preventing By randomly turning off specific portions of the neurons, the model is prevented from overfitting. Incoming and outgoing connections from the neurons are also turned off when some sections of the neurons are turned off, which improves model learning and prevents the model from generalising to the test dataset.

Classification & Detection of Diseases

Image segmentation is the division of a picture into different segments with the same features or that are somewhat comparable. Many techniques, such as the k-means clustering algorithm and the conversion of RGB images into HIS models, can be used for segmentation. K-means clustering is used to categorise objects into K number of classes based on a set of features. The process of classifying an object involves decreasing the sum of its squares' distance from its matching cluster.

The training and testing of the datasets are done using classifiers. Support vector machines (SVM), k-nearest neighbours, neural networks, fuzzy logic-based classifiers, etc. may be used. These techniques are used to identify and classify leaf diseases**.**

IV.METHODOLOGY

EXISTING SYSTEM:

Traditional logic-based reasoning helps to some extent automate the process of reasoning for pest diagnosis and control measures, but it has obvious flaws like insufficient learning ability, low data utilisation rate, and inaccurate rate to be improved, which do not meet the requirements of practical application. The challenge is made more challenging by the fact that objects in fine-grained tasks frequently share both tiny and substantial intraclass variations, many object scopes, and intricate backgrounds. Given the growing body of knowledge on diseases and insect pests, issues like incomplete data and extended wait times are unavoidable. which cannot make the model's complexity grow. When compared to the conventional classification network, the method of generalisation ability augmentation significantly improves identification accuracy. as well,The approach can identify peach and tomato leaf diseases in real time while requiring less memory and lower performance. Additionally, it can be used in other disciplines of agricultural disease diagnosis in similar application settings.

DISADVANTAGES:

An existing model suffers from the problem of few shot learning and needs a lot of training data.

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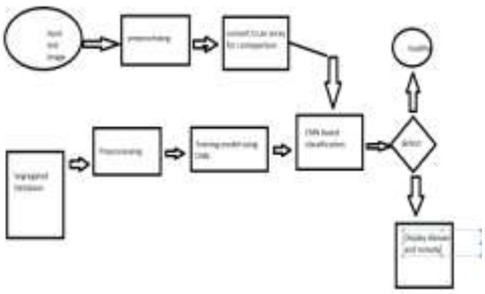
Because of the numerous relationships and the scant knowledge in knowledge maps, this strategy is ineffective**.**

PROPOSED SYSTEM

Many disease-related illnesses and convulsions can affect plants. There are a number of factors that can be distinguished by how they affect plants, including environmental disturbances brought on by changes in temperature, humidity, amount of food consumed, amount of light, and the most prevalent bacterial, viral, and fungal illnesses. In the proposed system, we employ the CNN algorithm to identify disease in plant leaves because, given appropriate data, CNN can provide the highest level of accuracy. We split the dataset into distinct training and testing ratios phase-wise to prevent overfitting. With regard to 80% training and 20% testing picture data, we attained an accuracy of 98.42% in InceptionV3, 99.11% in InceptionResNetV2, 97.02% in MobilenetV2, and 99.56% in InceptionResNetV3.EffectiveNetB0 for coloured images. The proposed system in the research has the capacity to handle complex situations and is effective at detecting various illness types. The accuracy of the convolution neural network as determined by the validation results is 94.6%, demonstrating its viability and pointing the way towards an AI-based deep learning solution to this complex problem.



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V.RESULTS AND DISCUSSIONS

VI. CONCLUSION

Crop protection is a difficult issue in organic farming. This requires in-depth understanding of the crop being farmed as well as any potential pests, diseases, and weeds. To detect plant diseases using photos of healthy or sick plant leaves, a particular deep learning model has been designed in our system based on a special architectural convolution network. A real-time video entrance system that permits unattended plant care can be added to the system previously mentioned. Another feature that can be introduced to some systems is an intelligent one that treats known illnesses. According to studies, controlling plant diseases can contribute to a 50% boost in yields..

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