

Crop Disease Detection and Recovery of Plants through Leaf Image

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ABSTRACT - The production of crops is an important part of every country's economy, and agriculture is no exception. An agriculturally advanced nation relies on accurate plant disease identification more than anything else. In order to keep the agricultural sector healthy and productive and to avoid squandering money and other resources, it is vital to diagnose plant diseases quickly and efficiently. Every year, crop farmers lose a significant amount of money due to different plant diseases. In order to help farmers avoid crop loss, deep learning has the potential to detect diseases in plant leaves at an early stage. Consequently, a smart desktop program based on the Res-net model was selected for the purpose of predicting crop diseases in the actual world. By analysing images of plant leaves, the suggested desktop program hopes to aid farmers in spotting plant illnesses. At its core, the suggested app leverages the Res-net transfer learning model to identify the type of disease and differentiate between healthy and diseased leaves. Our aim is to assist farmers in conserving resources and avoiding financial losses through early detection of plant diseases and proper treatment recommendations for common pesticides. We will also provide detailed ideas to the farmer via his WhatsApp.

Keywords: Deep learning, Crop disease detection, Res-Net, Crop health estimation, Pesticide application.

1.INTRODUCTION

The agricultural revolution is happening at the same time as the industrial revolution, and agriculture is seen as the foundation of every nation. We can't survive without crops. As the leading cause of crop diseases, food insecurity ranks high among the most pressing global issues facing modern mankind. Beyond being a worldwide threat to food security, plant diseases can have a profoundly harmful impact on our daily life. Economic growth and consumer confidence depend on healthy crops. A crop's health can only be gauged by its growth and leaf condition. Accordingly, learning about the symptoms of different plant diseases can be accomplished by analyzing leaf pictures. If a farmer grows vegetables like potatoes, tomatoes, or peppers, they run the risk of becoming infected with a number of different diseases. For each year to incur substantial losses. Early blight and late blight are the two varieties of blight. A fungus causes early blight, while a certain bacterium causes late blight. If farmers can detect these diseases early and treat them successfully, they can save time and money. Within the next 25 years, experts predict that the global population will surpass 9 billion. A 70% increase in food production is necessary to keep up with the continuously increasing demand for food. Crop disease is a major issue for many nations, particularly those with a strong agricultural economy. Diseases

affecting potatoes are particularly worrisome because potatoes are the most widely consumed vegetable on Earth. But there's also serious cause for alarm regarding tomato and pepper infections. It is always better to be safe than sorry, as the old adage goes. To combat potato crop illnesses, researchers in the agricultural sector have been exploring deep learning. Machine learning approaches have shown promise as a result of the great advancements in computing, particularly in the area of data extraction from real-time image processing. Deep learning is becoming increasingly popular and has enormous value. It has a huge impact and will keep on having a positive impact by simplifying people's lives. Plant diseases affect not just the crop's quality and productivity but also its leaves, fruits, stems, and roots. Because of this, people all across the world eat less vegetables than they should. Annually, crop yield is reduced by 16% due to crop diseases. In order to implement new algorithms, tools, and techniques, "smart farming" relies heavily on deep learning. Extracting features, transforming, pattern recognizing, and classifying images are just a few of the difficult problems that machine learning helps farmers with. The goal of this research was to create a Res-Net-based method for detecting crop infections and identifying the disease kind. The findings of this study may help reduce crop yield losses if we can figure out a way to apply them in real time. Ban gladeshi and Indian farmers have long depended on their own expertise and experience to detect crop illnesses, as there is limited access to agricultural specialists in rural regions. Occasionally, a professional can diagnose the illness, but this process is typically too labor-intensive, costly, and time-consuming to be implemented extensively in underdeveloped countries. Artificial intelligence (AI) based solutions to these problems have been the subject of extensive research. Reduced crop damage can be achieved by speeding up the detection process with the use of machine learning or deep learning techniques. To identify leaf diseases, for instance, a Res-Net-based approach was suggested. In order to identify leaf illnesses, this study created a unique Res-Net architecture with 15 layers and attained an accuracy of 98.023%. A framework was suggested that used EfficientNetB0 and DenseNet121 to extract deep features from maize plants; nevertheless, the system's accuracy was only 93%. In order to classify four distinct kinds of maize leaves from the PlanVillage dataset, the author proposed a dense-optimized Res-Net. The trained Res-Net was able to successfully categorize data with an accuracy of 98.06%. suggested a potato leaf disease detection model. Res-Net is one of several deep learning models used to extract features from potato leaves. Next, popular machine learning methods such as SVM, Neural Networks, KNN, and Logistic Regression are used to classify the features that have been retrieved. The proposal's Res-Net and logistic regression accuracy rates were 97.8 percent. put forward a system that uses a particle swap optimization technique to categorize sunflower leaf diseases.

The detection accuracy of various diseases was 98.00% in this study. The majority of the aforementioned studies did not bother to tune their deep learning models for detection, instead using the default and built-in options. The suggested solutions also lack sufficient accuracy, which calls for additional study and development. Additionally, any preemptive treatment that includes a suggested application can drastically cut down on crop damage. Building a detection framework using deep learning that can provide farmers with first-rate advice and extremely accurate findings is the main objective of this project. An initial proposal has been made for a system that can detect diseases using deep learning. To test how well the system could identify agricultural diseases, it made use of Res-Net, one of many deep-learning models. Using a publicly available dataset, the framework is tested extensively through experiments. Tomatoes, peppers, and potato leaves are among the over 10,000 vegetable images included in this dataset. Measures of accuracy such as average training loss, training accuracy, validation accuracy, and prediction accuracy for testing trials are eventually taken into account when assessing the efficacy of the proposal. In addition, the study's findings informed the decision to develop an intelligent web application for real-world crop disease prediction using the Res-Net model. The proposed web software intends to help farmers detect plant illnesses by analyzing images of the afflicted leaves. By spotting plant illnesses in their early stages, it can help farmers save money and resources.

[1] The agricultural sector has encountered numerous challenges, as stated by Siva Prasad Patnayakuni et al. This research proposes a neural network for disease detection in tomato leaves that is based on transfer learning. The five tomato plant diseases—early blight, mosaic virus, bacterial spot, yellow leaf curl virus, and septoria spot—can be detected using this model. The experimental results demonstrated that compared to generic transfer learning, fine-tuning transfer learning yields a greater recognition rate. The classification accuracy achieved by this transfer learning method is 95.6%. The proposed model will be utilized to ascertain the future severity of the tomato leaf disease, the exact nature of which is presently a mystery. Several plant diseases can be detected using the data obtained from the tomato disease classification model.

[2] The group headed by Vibhor Kumar Vishnoi etc. In order to detect apple crop illnesses using leaf photos, this study suggested a deep convolutional neural network (CNN) model. As a bonus, it can make life easier for plant pathologists while also helping out novice apple orchard farmers. For 1000 epochs, the model was trained on 31,171 apple leaves. The model achieved an accuracy level of 98% when tested on the PlantVillage dataset. Extensive testing shows that the suggested model outperforms a number of pre-trained CNN models. Several metrics, such as accuracy and memory needs, showed that the method outperformed several other existing methods. The model's accuracy ranges from 97% to 99% across a variety of disorders. The model achieved a good balance between precision and accuracy. The suggested model is consistent and dependable, as shown by the AUC-ROC curve. Collecting additional high-quality leaf photos of apple plants grown in a variety of environments and at different phases of development could be an expansion of this effort. In order to enhance the model's ability to detect diseases at different phases for different apple crop varieties, more rigorous tests would be

possible with the huge dataset that includes increased image variability.

[3] It was Emmanuel Moupojou and colleagues. The FieldPlant collection contains 5,170 annotated photos of plant diseases gathered from actual plantations and made available to researchers. This dataset differs from PlantDoc in that it is made up entirely of field pictures that have been classified by plant pathologists. Nevertheless, other illness types can be added to the dataset. Being the first plant disease dataset that include annotated cassava photos, FieldPlant could find extensive application in disease control and research. We ran a battery of tests to see how well top-tier object identification and classification models worked. Results demonstrate that current models are insufficient for field-collected image plant disease detection and classification, even though FieldPlant outperforms PlantDoc in the classification challenge. As a result, accurate models should be developed to aid farmers in detecting crop illnesses and developing effective responses. One such solution could be to use model ensembling in conjunction with image segmentation on field photos in order to separate individual leaves from a larger picture

An examination of earlier research that was deemed a Literature Survey is presented in the second part of this publication. Section 3 provides a comprehensive description of the proposed methodology, outlining the path of action. The experimental evaluation is covered in Part 4, possible modifications are discussed in Section 5, and the essay concludes with a conclusion on the existing plan.

2. LITERATURE SURVEY

[4] According to Vasileios Balafas et al., it is crucial to accurately diagnose prevalent agricultural diseases. An upgraded YOLOv5s model is the basis of this study's proposed detection technique. In order for the model to learn and extract all leaf features, SE attention mechanism modules were first added to the 3rd, 6th, 9th, and 12th layers of the backbone network. A more accurate up-sampled feature map can be obtained by replacing the original up-sampling operator in the YOLOv5s model with the Content-Aware Reassembly of Features (CARAFE) up-sampling operator. With this update, author can accurately distinguish between various crop diseases and increase feature extraction in affected regions. Afterwards, the EIou loss function was used to replace the original YOLOv5 loss function, which substantially enhanced the model's performance. Lastly, the backbone network included the Ghost convolution module to simplify the model and conform to edge device deployment standards. Experimental comparisons showed that the suggested model outperformed popular models like YOLOv5s, YOLOv5m, YOLOv7, and YOLOv8 in terms of detection performance. The upgraded model not only accurately identified crop illnesses, but it also increased detection performance in difficult situations. Thanks to the model's successful downsizing, farmers can now more quickly and correctly identify and prevent crop illnesses, leading to higher crop yields and more income. On the other hand, detection accuracy could be much improved. The accuracy of crop disease and pest detection will be further enhanced in future studies by collecting additional image data and expanding the dataset.

[5] Peyal, Hasibul Islam, and colleagues... A 2D convolutional neural network (CNN) model has been built to identify 12

disease classes and 2 healthy classes in tomato and cotton crops in the proposed study. The suggested two-dimensional convolutional neural network (CNN) architecture has three convolutional layers, three max-pooling layers, and two fully connected layers. Because of its simplified structure, the proposed model uses less data storage space and has fewer parameters compared to transfer learning models. The model outperforms both heavyweight and lightweight transfer learning architectures, with an average testing accuracy of 97.3%. Heavyweight architectures include VGG16, VGG19, and Inception V3, while MobileNet and MobileNetV2 reach average accuracy ranging from 57% to 92%. Additionally, the model was tested against transfer learning models and its performance was assessed with a confusion matrix, ROC curve, and AUC score. According to the findings, the suggested model had remarkable performance, allowing plant doctors and farmers to precisely identify a range of diseases affecting tomato and cotton plants. The country's economy can benefit from this since it helps farmers save money and helps plant doctors combat diseases effectively. Because it uses a far smaller set of parameters, the suggested model uses three to four times less space for storage than transfer learning models. The model's lightweight structure makes it easy to apply on various devices, including mobile ones. The model's practical applicability was demonstrated by incorporating it into an Android application called "Plant Disease Classifier" that allows for smartphone-based diagnosis of plant diseases. The Android app can be said to have near-real-time disease detection with an average time of 4.84 ms. author used the Grad-CAM method to construct class activation maps, and then author made heatmaps to show which regions were responsible for classification, so you could see how well the trained model detected. But there are a lot of restrictions and difficulties in implementing the model in the actual world, and computational requirements are a big one. The suggested 2D CNN model is tiny on processing systems powered by Intel and AMD, but it might need some tweaking before it can be used more widely.

[6] Identifying prevalent agricultural illnesses is crucial, according to research by Wei Chen et al. An upgraded YOLOv5s model is the basis of this study's proposed detection technique. In order for the model to learn and extract all leaf features, SE attention mechanism modules were first added to the 3rd, 6th, 9th, and 12th layers of the backbone network. A more accurate up-sampled feature map can be obtained by replacing the original up-sampling operator in the YOLOv5s model with the Content-Aware Reassembly of Features (CARAFE) up-sampling operator. With this update, author can accurately distinguish between various crop diseases and increase feature extraction in affected regions. Afterwards, the EIou loss function was used to replace the original YOLOv5 loss function, which substantially enhanced the model's performance. Lastly, the backbone network included the Ghost convolution module to simplify the model and accommodate edge device deployment requirements.

Experimental comparisons showed that the suggested model outperformed popular models like YOLOv5s, YOLOv5m, YOLOv7, and YOLOv8 in terms of detection performance. This updated model not only increased the model's accuracy in detecting crop illnesses, but it also improved detection performance in complicated situations. The model was successfully reduced in size, which helps farmers improve agricultural productivity and income by detecting and controlling diseases in a timely and precise manner. Nevertheless, the suggested model's detection accuracy could

be substantially enhanced. The accuracy of crop disease and pest detection will be further enhanced in future studies by collecting additional image data and expanding the dataset.

[7] A thorough evaluation of the current status of DL/CNN architectures connected with IoT technology was carried out by Jean Pierre Nyakuri et al. Introduced. These designs have greatly improved precision agriculture, especially in the area of plant pest and disease detection. Modern convolutional neural network (CNN) designs and their Internet of Things (IoT) integration are the primary foci of this review, which aims to identify research gaps and opportunities. Early detection of crop health issues has been greatly enhanced by the combination of DL/CNN architectures with Internet of Things (IoT)-driven systems, including UAVs and embedded devices. The development and application of various convolutional neural network (CNN) architectures—from AlexNet and other early models to EfficientNet and YOLO—to specific applications in disease and pest detection have yielded remarkable accuracy rates—sometimes surpassing 90% and even reaching nearly 100%, as seen with models like GoogLeNet and MobileNet. Efficient solutions important for proactive crop management and food security have been made possible by developments in object detection architectures, such as Faster R-CNN, YOLO, and SSD, which have enabled exact localization and identification of pests and diseases inside crop photos.

For resource-constrained situations, such IoT devices, mobile and embedded systems, and UAVs for edge applications, lightweight models like Tiny-YOLOv3, EfficientDet, and MobileNet can build compact and extremely efficient models. Hardware limits and data-related concerns are two of the many obstacles that still need to be overcome before DL/CNN models can be fully integrated with Internet of Things (IoT) devices like UAVs and mobile platforms.

[8] Production was discussed by Mehedi Hasan Bijoy and colleagues. By spotting illnesses in rice leaves early on, farmers can protect their yield from potential damage. Several factors contribute to the relative ineffectiveness of current approaches for disease detection non rice leaves. In order for the solution to work in real-world settings with limited resources, the model should have few parameters and be lightweight. This research introduces a compact deep convolutional neural network (dCNN) model that can identify five prevalent leaf diseases in rice: brown spot, tungro, sheath blight, bacterial blast, and bacterial blight.

We compare the suggested model's performance to that of fourteen concurrent methods and twenty-one benchmark architectures. To help farmers cut down on output losses early on, extensive trial results show that the technology is effective and efficient in detecting infections. With significantly reduced asymptotic complexity, the suggested end-to-end method outperforms benchmark systems. It outperforms the state-of-the-art approaches as well.

To improve upon an already existing dataset, more data was gathered by hand and annotated by subject matter experts. Accurate performance with substantially lower asymptotic complexity is achieved in this study by introducing more kinds of rice leaf diseases and an end-to-end implementation of a fine-tuned dCNN model. The development of an API, an Android app, and a website all contributed to the creation of an integrated application that is well-suited to low-end devices.

In order to make the proposed method more credible and relevant, many validation studies were carried out. Additional experiments will be conducted to enhance its usefulness, and

the research will be expanded to identify crop problems other than rice leaf diseases in the future.

[9] The authors of the study include Anuja Bhargava... According to the research, a shortage of qualified annotation specialists is a big obstacle to plant disease diagnosis. When professionals fail to accurately distinguish between diseased plants and dead plants, this problem occurs. It is difficult and expensive to employ trained specialists to detect diseases, and this is particularly true for uncommon or recently developed illnesses. Another major obstacle is the utilization of deep learning methods for tuning, modeling, and training, all of which need a lot of resources. Small datasets work better with shallow designs. New disease detection models present different ways of looking at the problem of how to construct reliable systems for detecting plant diseases. To improve detection models, strategies including few-shot learning, machine learning, and deep learning should be explored. The authors of this study believe that smart agriculture will benefit from further studies into the identification, categorization, and quantification of plant diseases.

Below is a summary of some of the challenges and elements that could influence the process of classifying and identifying plant diseases.

(i) Methods for feature extraction and classification have a significant impact on how well plant disease detection systems work.

(ii) Instead of using real-time field photos, rather than photographs taken in a lab, the majority of the work that has been evaluated uses the PlantVillage dataset. A training and testing dataset is crucial to a classifier's success.

(iii) Background complexity is a common problem in real field photos, which hinders system performance and makes affected area segmentation challenging.

(iv) During their formative years, plants are vulnerable to nutritional deficits and pollution.

(v) Disease identification and estimation of infected regions and severity can aid in pesticide usage control.

(vi) It's important to think about how efficient real-time disease detection is on devices with limited resources.

(vii) It can be challenging to identify and combine hybrid symptoms because multiple diseases can manifest at the same time with different symptoms.

(viii) The selection and adjustment of hyperparameters can significantly impact the performance of the system.

(ix) The traits and attribute selection of diseases provide substantial obstacles for illness identification systems.

[10] A model ensemble approach was introduced by Emmanuel Moupojou et al. to encourage sustainable agriculture practices and prevent crop production losses. Using a combination of SAM and FCDD, this model is able to correctly detect and categorize plant illnesses in field photos. Researchers had access to the model through GitHub, while practitioners may use a dedicated mobile app. This new method overcomes the shortcomings of current classification models by making short work of field photographs with complicated backdrops, interlaced foliage, and varied lighting conditions.

On publicly available field plant disease datasets like PlantDoc, the study shows that the suggested approach improves classification accuracy by over 10% compared to current models. Using SAM to precisely encircle all recognizable things in a picture and FCDD to identify outliers, the model successfully distinguishes between background objects and real leaves. This helps with disease detection on individual leaves in the same image and allows for accurate classification.

Having said that, the FCDD component needs to be able to differentiate between real leaves and backgrounds with a lot of greenery. Further research into continuous learning approaches could allow the model to gradually adapt and learn from fresh data, allowing it to keep up with changing plant conditions and new illnesses.

When applied to field photos of plants in the wild, this approach greatly improves the accuracy of disease diagnosis.

[11] The work of Nirmala Paramanandham and colleagues. Presented a new design for detecting diseases in groundnut leaves, which makes use of innovative weight initialization techniques and an ensemble learning-enhanced residual network framework. Groundnut leaves can be classified into healthy, rusty, early rusty, healthy, early leaf spoty, and late leaf spoty states by the suggested architecture. Batch size and learning rate were fine-tuned by extensive hyperparameter optimization to achieve optimal performance. author found that a learning rate of 0.01 and a batch size of 32 were the best settings to use in author's ensemble technique.

Following 15 training epochs, DenseNet161 attained 91.47% accuracy with focal loss ($\gamma = 2$) and 91.84% accuracy with cross-entropy loss. With a cross-entropy loss of 92.57% and a focal loss of 94.08% ($\gamma = 2$), EfficientNetB5 showed competitive performance. Validation accuracies of 85.59% were achieved with cross-entropy loss and 85.35% with focal loss ($\gamma = 2$), even though VGG16 achieved slightly lower performance. MobileNetV2 demonstrated impressive performance, attaining an accuracy of 93.79% while dealing with cross-entropy loss and 95.59% when dealing with focal loss ($\gamma = 2$). With cross-entropy loss, InceptionResNetV2 achieved an accuracy of 88.29%, while with focal loss ($\gamma = 2$), it achieved an accuracy of 84.98%.

With cross-entropy loss, the suggested ensemble-based innovative architecture reached a superior accuracy of 97.225%, and with focal loss ($\gamma = 2$), it reached 95.756%. The architecture was trained for the same number of epochs. The architecture was evaluated on various disease datasets to assess its adaptability and transfer learning capabilities. These datasets included a number of common crops: rice (85.26%), sugarcane (83.12%), tomatoes (93.37%), corn (89.20%), and potatoes (94.68%).

Future research might benefit from this architecture's compatibility with Internet of Things (IoT) devices by allowing for the direct diagnosis and real-time monitoring of leaf diseases in agricultural settings. Through this linkage, farmers might gain access to real-time knowledge that could lead to preventive disease management techniques, which in turn could improve agricultural sustainability and crop yields.

[12] The goal of the multi-model network that Rubina Rashid et al. presented—a network that automatically exploits CNN methods in their various variants—was to fuse multi-contextual networks. At the decision level, this method combined the learned feature sets from the RL-block and the PL-blocks 1 and 2, as well as the width cardinality and environmental characteristics. In order to make the suggested model more accurate and effective, several feature sets were found on a global and local scale. The suggested model was useful for picking receptive fields' learning parameters so that feature maps at various layers could be observed. Additionally, a deep multi-model network was developed to combine visual information from 2D convolutional neural networks (CNNs) with contextual features from 1D data. This network showed great promise for a variety of applications including the detection and classification of plant leaf diseases. When

compared to the model without feature fusion, the experimental findings showed that MMF-Net with fused features performed much better in terms of accuracy. The enhanced performance was credited to training on a combination of diverse datasets, and MMF-Net achieved a total accuracy of 99.23% in recognizing maize leaf diseases. Lastly, a more precise, consistent, and all-encompassing model for plant leaf disease detection was built by investigating the fused detection properties. In addition to its potential use in practical Internet of Things (IoT) applications, this model proved to be an efficient method for illness classification in the agricultural and healthcare industries.

[13] The research objectives were satisfied by Ankita Gangwar et al., who, with the help of experts in plant pathology, developed three annotated datasets based on real-life examples. Tomato leaf photos with different backgrounds were included in these datasets. Images of healthy and sick young tomato plants, ranging in age from two to four weeks, were included in Dataset 3, while Images of infected patches on individual leaves were included in Dataset 2. For the purpose of disease region segmentation in tomato leaf images with simple and complicated backgrounds, a deep learning model called Tomato TransDeepLab was implemented. Even on young plants with complicated backgrounds, the model was able to detect numerous tiny lesions. It was 98.17 percent accurate and earned an IoU score of 89.09 percent. It proved to be very generalizable and data independent, as its performance was consistent across all three datasets with little fluctuation in accuracy and IoU. Tomato TransDeepLab outperformed state-of-the-art models in handling complicated backgrounds, detecting microscopic lesion areas, and performing segmentation, according to comparative analysis. These models include U-Net, ResUNet, DeepLabV3, and Tuned DeepLabV3+. Notably, it demonstrated its scalability and practical application with the minimal training period of 989 minutes. The model's accuracy in accurately segmenting both tiny and multiple diseased patches on individual leaves was further validated by visual examination. To further evaluate crop loss, a severity scale that ranges from 0 to 5 was used, supervised by plant pathologists. A possible crop loss of 1% to 5% was estimated by applying the model to Datasets 1 and 2, which may be reduced with prompt intervention. Because of this, the suggested method provided a solid answer to the problems of early disease detection, precise lesion segmentation, severity evaluation, and crop loss estimation in tomato plants. Tomato TransDeepLab demonstrated great promise as a useful tool for farmers when integrated with internet of things (IoT) platforms, websites, or mobile apps. Possible future applications of the technology include crop loss estimation, disease prediction, and segmentation in different crops.

[14] Out of the 118 papers that were initially considered, David J. Richter et al. reviewed 84 utilizing the PRISMA method. Using the search phrases "Plant Disease" OR "Leaf Disease" AND "CNN" AND "classification" AND "transfer-learning" from 2022 to 2025, the papers were retrieved from the Web of Science. Current trends and best practices were identified by summarizing and analyzing all eighty-four studies in terms of techniques and results. This investigation uncovered popular models like VGG16, InceptionV3, and MobileNetV2, however they didn't always produce the best results. There is a gap between the most popular models and the ones that perform better; the EfficientNet, DenseNet, and Xception model families produced the greatest results. Additionally, methods

for enhancing models were covered, including attention processes, ensemble learning, and domain-related pre-training. It was discovered that popular datasets, particularly PlantVillage, were far easier to learn from than laboratory datasets; hence, benchmarking and comparing studies were rendered meaningless because PlantVillage presented very few hurdles. For practical assessment, it was suggested to use field and hybrid datasets. Most recently acquired datasets were also found to be private, lowering the availability of publicly available data, according to the study. Field data was more commonly distributed than lab or hybrid datasets, and common places for data collecting included the United States, India, and China. There was also a ranking and analysis of preprocessing methods, data splits, picture sizes, augmentation strategies, assessment metrics, plant species, and hyperparameters. In sum, the study shed light on the existing condition of transfer learning for plant leaf disease categorization and made suggestions for future research that could be even better.

[15] With a focus on increasing computational efficiency, Tanjim Mahmud et al. conducted a study that evaluated various pretrained models to detect four types of rice leaf illnesses and healthy samples. Important scientific fields that contribute to agricultural productivity include image recognition and classification for the detection of leaf diseases. The images were preprocessed using CLAHE and Gaussian filtering, and features were extracted using Canny and Prewitt edge detection methods. With a 99% success rate, VGG16 and ResNet101 were victorious. The models were much more easily understood and put to use after using visualization techniques like Grad-CAM, Grad-CAM++, and LIME. Although the study performed well, it was limited by a tiny dataset, which may impact its ability to generalize to real-world situations. The authors intended to collaborate with agricultural specialists to broaden the dataset across different field conditions and geographic regions in order to overcome this constraint. To improve generalization and decrease overfitting, further work involved integrating domain adaptation, generative picture modeling, and data augmentation. To further enhance feature extraction and noise reduction, multi-resolution analysis was offered to detect subtle illness patterns in complicated backgrounds using frequency-domain filtering methods including Discrete Wavelet Transform and Butterworth filtering.

[16] For the purpose of identifying diseases in tomato leaves, Lima Hamad et al. introduced a hierarchical deep learning pipeline that used YOLO11 for leaf detection, the Segment Anything Model for segmentation, and a ResNet-50 classifier improved with LIME-based interpretability. Traditional classification models, which rely on full-plant images and have difficulty handling complicated field situations, have their shortcomings, which the framework aims to address. The classifier was trained to zero in on important leaf regions by removing irrelevant data using the suggested methodology. Both controlled and real-world datasets, such as PlantVillage and PlantDoc, were enhanced by this structure in terms of robustness and interpretability. The experimental findings showed that the model outperformed the baseline model without leaf isolation phases, with an in-domain accuracy of 96.76% and an out-of-domain accuracy of 55.33 percent. By demonstrating its generalizability under different environmental situations, SAM earned the best segmentation performance with an IoU of 0.95 and a Dice score of 0.96. Visualization using LIME increased trustworthiness by confirming that model attention was aligned with symptomatic

regions. The research laid the groundwork for plant disease diagnostic tools that are interpretable, automated, and ready for use in the field.

[17] A study by T. Ozcan et al. discussed how important it is to detect leaf diseases in order to increase agricultural yields and quality. The study used picture segmentation, data augmentation, and deep learning to identify and categorize leaf illnesses. Image augmentation, deep learning model training, and the BorB image segmentation algorithm were all parts of the suggested integrated solution. The freshly constructed EruCauliflowerDB dataset, which was made to identify and categorize two cauliflower leaf diseases, was one of three datasets utilized for experiments. Each step of the process was highlighted by separating the dataset into a training, validation, and testing subset. author compared three different versions of the approach. Thanks to the VGG16 design, the suggested solution was able to attain a perfect score on the test. The MangoLeafBD dataset was further tested, and the results showed resilience with a perfect score. Applying the approach to fifteen classes from the PlantVillage dataset yielded an accuracy rate of 99.78%. The computing resource demands, environmental variability, and dataset size were some of the restrictions that were present despite the great performance. Expanding EruCauliflowerDB with samples from diverse locations, validating across datasets, creating systems that can be used in real-time, incorporating hyperspectral or thermal imaging, investigating advanced segmentation methods, and conducting long-term studies spanning multiple seasons were all priorities for future work aimed at making agricultural AI more resilient.

3. METHODOLOGY

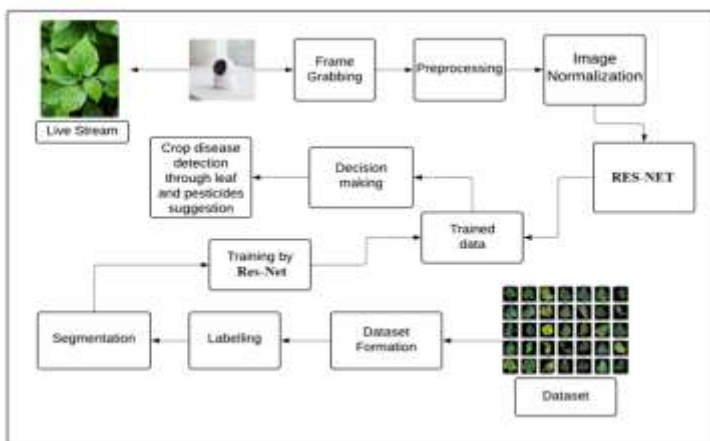


Figure 1: Proposed model System Overview

What each phase of the system diagram represented for Crop Disease Detection and Recovery of Plants through Leaf Image: Following these steps will describe a plant disease detection and recovery approach using leaf images.

Step 1: Dataset Generator

The first step in building a dataset is to take pictures of plant leaves in various states of health and sickness and save them for later use in training the model. To take real-time pictures of plant leaves for analysis during model testing, you can use the OpenCV library and the VideoCapture function from the cv2 package. Images of both healthy and diseased

plant leaves can be found in the dataset folder. Using the ResNet architecture, the model learns to identify patterns of plant illnesses from these photos as it evolves. Before training and testing the disease detection model, it is necessary to create a specific folder to keep all of the photographed leaves. This will ensure that the data is organized correctly.

Step 2: Data Labelling

The second step is data labeling, which involves annotating the previously captured leaf images using a labeling tool. Once the user imports the image into the labeling software, they mark the top-left and bottom-right corners around the diseased region of the leaf. These points generate the coordinates (x1, y1) and (x2, y2) that define the rectangular bounding box covering the affected area on the leaf. The collected coordinates and image annotations are then saved in an .xml file, which serves as the input annotation format for training the deep learning model. These labeled images are used to train the ResNet network so that the system can accurately detect and classify plant diseases from leaf images during testing.

Step 3: Library Installation

To develop and test the plant disease detection model, you must first install the TensorFlow Object Detection API on this Google Colab instance. Gather the necessary installation scripts and a copy of the TensorFlow Models Repository (<https://github.com/tensorflow/models>) before you start. To set up the environment, press the play button in the notebook. The necessary code cells are executed consecutively.

The following step involves configuring the environment for proper download and extraction of dependencies and GPU support libraries like cuDNN. Cloning the GitHub repository into the working directory is the next step after this setup to receive the TensorFlow models project. Lastly, the system is prepared to train and test the ResNet based model for disease detection in plant leaves from photos by installing the TensorFlow Object Detection API.

Step 5: Divide the picture folders into test, validation, and train.

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Step 6: Make TF Files

As a last step, the photos need to be transformed into TFRecord format. This is the data file format that TensorFlow uses to train deep learning models efficiently. The dataset photos and annotations are automatically converted into TFRecord files using Python programs. The training method can read massive datasets efficiently and swiftly in this format.

It is necessary to generate a class label map prior to executing the conversion scripts. The features that the model is trained to identify are defined by this label map. A file called "labelmap.txt" is created when the code section is executed in Google Colab. Each plant disease class is documented in this file on its own line, with the real names of the diseases replacing the placeholders like class1, class2, and class3.

To run the code, select the classes you want to use, and then hit the play button on the notebook. As part of this procedure, the dataset is transformed into TFRecord files and the "labelmap.txt" file is used to record the list of classes that can be detected. The ResNet-based model uses these files during training to correctly detect various plant illnesses in photos of leaves.

Step 7: Set Up Training Configuration.

Here we outline the model that will be trained first using the TensorFlow 1 Object Detection API. A configuration file defining crucial training settings is included with each model in the TensorFlow Model Zoo. Learn rate, batch size, number of training steps, dataset and model checkpoint file paths, and more can be configured in this configuration file. Here, we update the configuration file to accommodate our unique training job for identifying plant diseases from leaf photos.

The first section of the code displays the TF1 Model Zoo's available models. In addition, the script specifies which files to download in order to get the chosen model and its setup file. This setup facilitates the management of various models and the addition of new ones as needed. The name of the model that is to be trained is supplied in the "chosen_model" variable. To achieve precise feature extraction and disease classification in plant leaves, ResNet was chosen as the model for this application. Obtaining the model files and their associated configuration file is the next step.

Several training parameters need to be defined after the model and configuration file have been downloaded: the number of steps: You can tell how many times the model was trained with this parameter. It is common to choose 40,000 steps as an initial value. It is possible to add more steps after training if the loss keeps going down. Training takes more time when there are more steps, but learning is better.

batch size: This parameter specifies the amount of photos that are processed for each training iteration. The maximum batch size is limited by the GPU's memory capacity. Because more photos may be analyzed simultaneously with larger batch sizes, learning speeds up.

quantitative delay steps: In quantization-aware training, this parameter is utilized to imitate quantization during model training by injecting specific nodes into the network. Half of the total steps in training is a frequent beginning point.

Here we also specify the dataset location, the pre-trained model checkpoint path, the number of classes (plant disease categories), and more. To ensure that the training process has proper access to the dataset and model parameters, these values need to be added to the configuration file.

The pipeline configuration file, which includes all training parameters, is then created from the revised configuration file. By connecting the dataset, model checkpoint, and specified training parameters in this pipeline file, a unique configuration is generated.

Lastly, the script for training is tweaked so that it saves checkpoints every 1000 steps. This way, if necessary, the progress can be watched and the training may be resumed. In this way, we can be confident that while the model trains, we save its interim results for review and potential enhancements.

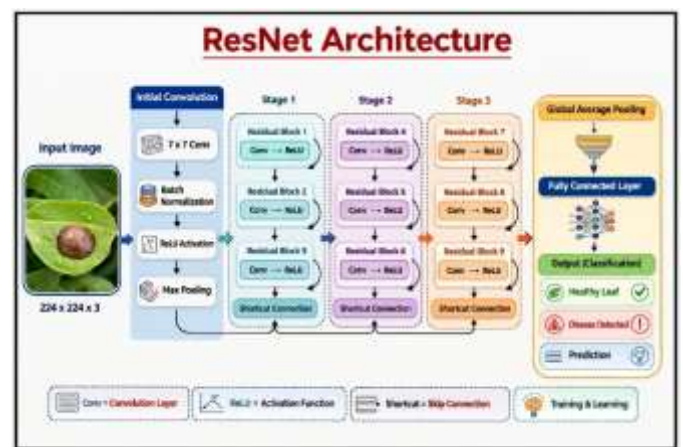


Figure 2: ResNet Architecture

Step 8: Train Custom TF1 Object Detector

The TensorFlow Object Detection API is used to train the object detection model. The script given in the TensorFlow Object Detection API, model_main_tf2.py, is used to run the training procedure. Everything related to training is handled by this script. It loads the dataset, applies the configuration parameters, and updates the model weights as training progresses.

All of the necessary arguments and parameters utilized by model main tf2 were initially documented in the Google Colab notebook.py, together with the location to the dataset, the configuration file, the steps to train, and the batch size, were already defined. This approach improves the accuracy of plant disease diagnosis in leaf photos by using ResNet, a deep learning model, for feature extraction and classification.

The overall amount of time needed to train the model can vary from two to six hours, depending on variables like the chosen model architecture, batch size, GPU availability, and the amount of steps for training. In order to enhance detection performance, the system is constantly updating the model parameters during training.

It is possible to export the trained model as a.tflite file once training is complete. Deploying files in this format is ideal for use with embedded systems or mobile devices. Next, the system may be thoroughly tested using the TFLite model in

real-time applications that detect plant illnesses from new leaf photos.

Step 9: Testing the model for Tree Logging

Crop disease identification is one application of the model's testing. At this point, the Python software is taking advantage of the camera to record live video; the frames are retrieved using the DroidCam, which links the mobile camera to the PC. The trained deep learning model analyses every frame of the live video stream. To identify plant leaf illnesses in real time, the system examines the recorded frames with the help of the trained TensorFlow Lite (.tflite) model file.

The technology notifies the user or farmer when it finds a sick leaf and displays the outcome instantly. In addition to capturing a picture of the affected plant, the device may also notify the user through WhatsApp of the presence of the illness. This allows farmers to detect plant diseases more rapidly and take corrective measures to safeguard their crops.

4. RESULTS AND DISCUSSIONS

An Intel Core i7 CPU, 16 GB of RAM, and a Windows-based computer system are utilized by the proposed crop disease detection system. The model is built and tested in the Anaconda environment, which gives access to Jupyter Notebook and Spyder, two development tools. The plant leaf image processing and disease detection model's Python code is developed, tested, and run on these platforms.

We use the Confusion Matrix parameters to conduct a comprehensive evaluation of the created crop disease detection algorithm. When comparing the actual illness labels on plant leaves with the expected outcomes, the confusion matrix provides insight into how well the classification algorithm is doing. The confusion matrix is used to compute critical assessment metrics like recall, accuracy, precision, and macro F1-score. To ensure dependable performance in real-world agricultural settings, these metrics assist find out how well the system detects and categorizes diseases from photographs of plant leaves.

$$\begin{aligned} \text{Accuracy} &= (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{TN} + \text{FN}) & - (1) \\ \text{Precision (P)} &= \text{TP} / (\text{TP} + \text{FN}) & - (2) \\ \text{Recall (R)} &= \text{TP} / (\text{TP} + \text{FP}) & - (3) \\ \text{Macro-F1} &= (2 * P * R) / (P + R) & - (4) \end{aligned}$$

At this point, we have TP for true positives, TN for true negatives, FP for false positives, and FN for false negatives.

The obtained results are shown below,

1. Confusion Matrix

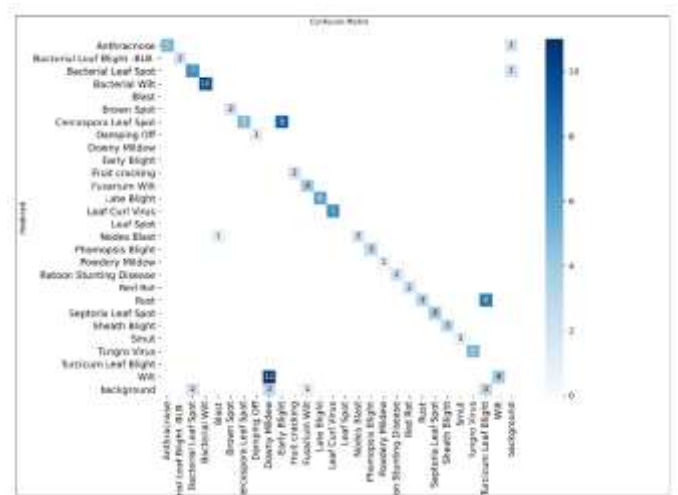


Figure 3: Confusion Matrix

A plant disease classification model's performance can be seen in the figure, which exhibits a confusion matrix. The model's anticipated illness classes are shown in the columns, while the actual disease classifications are shown in the rows. Color intensity (ranging from light blue to dark blue) reflects the frequency of forecasts, while the number of predictions for a certain class combination is displayed in each cell. Anthracnose, Bacterial Leaf Blight, Bacterial Spot, Brown Spot, Early Blight, Late Blight, and Tungro Virus are among the many plant diseases that the model accurately identified, as evidenced by the concentration of most values along the diagonal line. The model's predictions of different diseases than



the actual ones are represented by the few numbers that appear outside the diagonal, which are known as misclassifications. The model consistently and accurately identifies several crop diseases, with minimal classification mistakes, as shown by the

confusion matrix.

Figure 4: Dataset Sample Detection Visualization

This figure shows sample output The graphic displays the outcomes of a crop disease detection system, which uses a trained model to identify and categorize various plant disease images. The method predicts the name of the disease and draws a bounding box around the affected area, while each frame shows an image of a plant leaf held by a human. Bacterial leaf blight, sheath blight, nodes blast, tungro virus, brown spot, blast, and leaf curl virus are among the illnesses that have been

identified. By visualizing the model's ability to identify and categorize various crop diseases from photos, we can see that the system is capable of real-time plant disease detection, which is great news for agricultural monitoring and support.

5. CONCLUSION AND FUTURESCOPE

This research concluded by presenting a system for crop disease detection and plant recovery that uses leaf image analysis to tackle the increasing problems in modern agriculture. To improve yield quality and guarantee food security in the face of rising food demand, climate variability, and restricted access to agricultural specialists, it is crucial to identify crop diseases early and accurately. By using an automated, image-based solution instead of the old-fashioned human inspection methods, the suggested method can detect illnesses in their early stages, which in turn reduces crop losses and the need for pesticides. Supporting farmers in making educated decisions and adopting sustainable farming methods, the system provides exact disease identification and recovery advice.

The suggested solution is more effective and reliable because to the incorporation of machine learning and image processing. Critical visual properties of damaged leaves can be captured using preprocessing and feature extraction approaches. Analytical models, like linear regression, can forecast disease effect, yield loss, and recovery patterns. Treatment strategy design and resource utilization are both improved by these analytical insights. In addition, by automatically learning complicated and high-level characteristics from leaf photos, the application of sophisticated deep learning models like ResNet greatly enhances disease classification accuracy. The model's ability to effectively manage deep structures is a direct outcome of the residual learning framework, which in turn ensures reliable performance in a wide range of environmental settings.

The findings show that the Crop Disease Detection and Recovery system is a viable, accurate, and scalable solution for real-world agricultural applications. The method improves crop monitoring, decreases economic losses, and contributes to sustainable agriculture by integrating predictive analysis with deep learning-based picture identification. Future improvements to the suggested strategy could greatly expand its ability to enable precision farming and increase agricultural output. These additions could include real-time field deployment, integration with IoT sensors, and adaptive learning approaches.

Future work : By analyzing leaf images, the Crop Disease Detection and Recovery system has enormous potential for the future. Integrating real-time picture capturing with drones, cellphones, and field sensors enabled by the Internet of Things (IoT) can improve the system and allow for continuous crop monitoring. The accuracy of disease predictions and recovery suggestions can be enhanced by using environmental variables like temperature, humidity, and soil conditions.

It is possible to better manage different crops and diseases in different fields by investigating advanced deep learning models and ensemble techniques. Additionally, the system has the potential to be enhanced to offer farmers customized treatment programs, optimize fertilizer use, and forecast crop

yields. The system shows great promise as a complete precision agriculture solution for large-scale, sustainable farming thanks to its cloud and edge-based deployment, multilingual farmer-friendly interfaces, and interaction with agricultural consulting systems.

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