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# Comprehensive Study on Plant Disease Detection by using Hybrid Convolution Techniques

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***Abstract –** The food supply of the world depends on plants. Many environmental factors can cause plant diseases, which can lead to significant losses in productivity. However, manually identifying plant diseases is a time-consuming and error-prone process. It is not always a reliable method to identify plant diseases and halt their spread. The early detection of plant diseases made possible by state-of-the-art technologies like machine learning (ML) and deep learning (DL) which can help to overcome these challenges. The most recent advancements in the use of deep learning (DL) and machine learning (ML) methods for plant disease diagnosis are examined in this paper Effectiveness in identifying plant diseases is the primary focus of the study. This work also discusses the drawbacks and challenges of using ML and DL for plant disease identification. These include issues with the quality of the images, data accessibility, and the capacity to identify healthy plants from diseased plants. It provides a comprehensive understanding of the current state of research in this field, highlights the benefits and drawbacks of these methods, and makes recommendations for potential ways to overcome implementation challenges. All of these things help to provide insightful information for practitioners, researchers, and industry professionals involved in plant disease detection. Our work presents a hybrid method for early disease detection that combines the use of region-based fully convolutional neural networks (RFVCNN) with the application of region-based convolutional neural networks (RCNN) for disease classification.*

***Keywords-** Deep learning, Plant disease, hybrid convolution, transfer learning, convolutional neural network.*

## I. INTRODUCTION

To create generalizable models and increase the number of publicly available datasets for training and assessment, more research is needed. Several methods have shown promise in precisely identifying and categorizing plant diseases. Limitations and difficulties still exist and must be resolved The present status of research in this area is highlighted in this review, which also offers a through grasp of the advantages and restrictions of ML and DL methods for plant disease detection. It is innovative because it covers a wide range of ML and DL techniques and discusses their benefits, drawbacks, and potential ways to get around implementation issues. The article is a useful resource because it provides insightful information about the state of research in this field at the moment. The research article's contributions are listed in the section that follows.

- An overview of recent advancements in plant disease detection using ML and DL techniques is given in this paper. The study encompasses research conducted between 2015 and 2022, offering a thorough comprehension of the most advanced techniques and methodologies employed in this field.

- Image processing, feature extraction, CNNs, and DBNs are just a few of the ML and DL techniques for plant disease detection that are examined in this review. It also discusses the advantages and disadvantages of these techniques, including data accessibility, imaging quality, and the ability to distinguish between healthy and diseased plants. The article demonstrates how applying ML and DL techniques greatly improves plant disease detection speed and precision.

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The literature has examined a number of plant disease detection datasets, such as Plant Village, the rice leaf disease dataset, and datasets for insects that affect soybeans, corn, and rice.

- The study covered a number of performance evaluation metrics, such as accurate recall curves, dice similarity coefficients (DSC), and that are used to evaluate the accuracy of plant disease detection models [1].

Although Field Plant's classification task results are superior to Plantdoc's, the results demonstrate that the current models are insufficiently accurate for plant disease detection and classification of images directly collected from the field. Thus, appropriate models ought to be developed to assist farmers in identifying the diseases that affect their crops and take the necessary preventative action. A potential solution to this issue could involve using a model resembling with image segmentation applied to field images to isolate individual leaves from a global image [2]. Although the suggested approach works well for the problems it was tested on, there is room for more research in this area. First, it would be helpful to research various variants within the same fusion scheme in order to identify the best texture features for every situation. The suggested approach should also be investigated for leaf diseases in different crops and its efficacy in real-time applications assessed. These additional research projects would improve the suggested approach and broaden its possible uses in real-world agricultural disease detection [3].Because there are so many pathogens in their surroundings, plants are more prone to disease [9]. Plant diseases are defined as any anatomical or physiological abnormality caused by a living thing [10]. Plant pathogens or environmental variables are the causes of plant diseases [11]. Inadequate nutrition, microbial attack, rodent infestation, and unfavourable environmental conditions are the primary causes of plant diseases [12]. Globally, one of the primary reasons for lower agricultural yields is pathogen infection in plants. Different pathogen groups attack plants separately or in combination, making the disease more severe [13]. Plant diseases can harm crops, lowering the amount of food available and driving up food prices, which pose a risk to food security. It is more crucial to safeguard plants from disease in order to create and maintain food security and revenue streams for a growing global population [14]. Visual inspection of the plant is one of the traditional methods used to identify plant diseases, as the effects of pathogens are not always evident until the plant has sustained considerable damage. Automated plant disease detection has a lot of potential [15]. Manual observation may be a laborious, subjective, and complex method of diagnosing these diseases [17]. To meet the demands of an expanding population, automated systems that help farmers monitor crops at every stage of growth are therefore necessary. Using image analysis to detect plant diseases in their leaves is one of the most important applications of precision agriculture research the widespread use of digital cameras and the development of information technology in agriculture has led to the widespread application of expert systems in cultivation and management, significantly boosting plant production capacity [18]. Trained experts visually inspect plant tissues to record the severity of plant diseases using a traditional method [19]. However, expert systems extraction and description characteristics for pests and diseases primarily rely on the knowledge of experts, which leads to high costs and low efficiency [20]. Convolutional Neural Networks (CNN) [21],K-nearest neighbors (K-NN), and logistic regression. To encourage feature extraction, these methods are combined with various image pre-processing methods. An algorithm for supervised learning is the K-NN. It uses similarity metrics to categorize the data. Neighbouring labelled objects are used to classify unlabeled objects in K-NN. An algorithm for learning based on flow charts is the decision tree. Every node represents a decision attribute; leaves indicate classes; and branches show potential outcomes from nodes. Decision trees do, however, have some drawbacks, including over fitting of the data and overlapping nodes. SVM is a popular supervised learning model that is related to statistical learning concepts-based learning algorithms for regression analysis and classification. SVMs have been extensively utilized in text and image classification during the past ten years. The earlier automated recognition approaches usually pre-process images of diseased plant leaves using conventional image processing methods like noise reduction, morphological operations, and image enhancement [22]. Subsequently, manually developed feature extraction techniques obtain low-level details about the leaves, including hue, form, and texture [23]. Deep learning architectures have shown promise in the recent past for tasks involving object segmentation, classification, and identification [24]. For deep learning tasks, CNN approaches have been the most widely used. Even though the fundamental CNN architectures—AlexNet, VGGNet, GoogLeNet, DenseNet, and ResNet—have been used extensively in the classification of plant diseases, they have a number of limitations, such as the requirement for a large number of parameters and a slow calculation speed. While deep learning techniques have demonstrated a high degree of proficiency in exhibiting both high-level and low-level features, their consistency in describing local spatial characteristics is lacking [25]. A few crucial steps in the study's methodology are reading image data, pre-processing images, extracting features from images, segmenting images, classifying images using a hybrid approach, and predicting diseases. As shown in Figure 1, the data set of plant images contains pictures of Normal, Gray-spot, Black-mold, Late-mold, Bacterial spot, and Powdery mildew. The CNN detection method and the hybrid approach's outcomes are contrasted.

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Fig. 1: Dataset Images

## II. LITERATURE REVIEW

Moupojouet al [1] . Presented a number of deep learning models in 2023 to assist farmers in quickly and effectively identifying crop diseases in order to prevent yield reductions. Typically, public or private plant disease datasets like PlantVillage or PlantDoc were used to train these models. The images that made up PlantVillage were taken in a lab setting, featuring a single leaf on each image and a consistent background. When applied to field images containing multiple leaves and complex backgrounds, the models trained on this dataset perform terribly. In order to address this issue, 2,569 field photos that were downloaded from the Internet and annotated to identify individual leaves were used to build PlantDoc. Nevertheless, some laboratory images were included in this dataset, and the lack of plant pathologists during the annotation process may have led to incorrect classification. FieldPlant was recommended as a dataset in this study, which comprises 5,170 photos of plant diseases that were taken straight from plantations. To guarantee process quality, each image's individual leaves were manually annotated under the guidance of plant pathologists. 8,629 distinct annotated leaves for each of the 27 disease classes were produced as a result. The proposed model was evaluated against the most advanced classification and object detection models on a variety of benchmark datasets. It was discovered that FieldPlant performed better on classification tasks than PlantDoc.

A novel lightweight deep Convolutional Neural Network (CNN) model for obtaining high-level hidden feature representations was proposed by Hosnyet et. al. [2] in 2023. In order to extract local texture information from plant leaf photos, the deep features were then combined with conventionally created Local Binary Pattern (LBP) features. Three publicly accessible datasets—the Apple Leaf, Tomato Leaf, and Grape Leaf—were used to train and evaluate the suggested model. The suggested method obtained 99%, 96.6%, and 98.5% validation accuracies and 98.8%, 96.5%, and 98.3% test accuracies on the three datasets. The experiments' findings demonstrated that the suggested strategy offered a more effective way to control plant diseases.

A model for detecting plant diseases based on pathogens was proposed by Rani and Gowri shankar [3] in 2023. Using Keras transfer learning models, plant disease detection and classification were carried out automatically, and the pathogen causing it was identified. This was accomplished by taking into account the Agri-ImageNet dataset in addition to photographs of sunflower and cauliflower leaves, bulbs, and flowers that were taken in authentic, natural settings. The limitation of the PlantVillage dataset that is, photos was taken in controlled environments and with uniform backgrounds was addressed by this dataset. Deep transfer learning has been used to reuse knowledge representations in order to solve these issues. Main goal of this paper was to investigate and evaluate every deep transfer learning model in order to determine which model was most appropriate for the dataset on plant diseases. Throughout this work, 38 deep transfer learning models were used in the process to get the best classification accuracy.For the Agri-ImageNet, cauliflower and sunflower datasets. A report on classification was produced using the most effective deep transfer learning model.

Shewale and Daruwala [4] developed automated intelligent strategies in 2023 that use a CNN approach based on deep learning to accurately diagnose the disease with less complexity and time required. Plant leaf diseases were identified by combining patterns of leaf images at particular times with image processing. Tomato plants were taken into consideration for the current research project in order to identify, categorize, and diagnose diseases. The real-time environment of Jalgaon city's agricultural fields provided the dataset for our study. By automatically extracting features, the suggested method was able to classify diseases with high precision, doing away with the need for feature engineering and threshold segmentation. The network was embraced and expanded with the use of spatial images taken under challenging environmental circumstances. The diagnosis of diseases has been automated made feasible by recent advances in deep learning for computer vision. Overall, the process of training deep learning models on increasingly larger, publicly accessible, real-time image datasets provided a clear path for crop disease diagnosis on a massive global scale.

Premanandaet al. [5] proposed a custom CNN architecture in 2023 for the purpose of identifying and categorizing common diseases in rice plants by minimizing the number of network parameters. Four different types of common rice plant diseases were used as a dataset to train the proposed CNN architecture. Furthermore, the paper presents 1400 on-field images of a healthy rice leaf image dataset to aid in the identification of disease-free plants. Separate studies were conducted both with and without the healthy leaf

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image dataset. Using a number of performance matrices, the suggested model's performance was assessed using the optimization techniques of Stochastic Gradient Descent with Momentum (SGDM) and Adaptive Moment Estimation (Adam). Results of the experiments from the dataset 99.83%, respectively, on the test set during the seventh epoch. When the healthy leaf image dataset was included, the model with the Adam optimizer outperformed the model with the SGDM optimizer, yielding a maximum accuracy of 99.66% and 97.61% in the 7th epoch, respectively.

Albattahet et. al. [6] introduced a Custom CenterNet framework with DenseNet-77 as the base network in 2022, resulting in a robust system for classifying plant diseases. Three steps made up the method that was presented. Annotations were created in the first stage to obtain the region of interest. Second, a refined version of CenterNet was presented, suggesting DenseNet-77 for the extraction of deep key points. Ultimately, a number of plant diseases were identified and categorized using the one-stage detector CenterNet. The PlantVillageKaggle database, which served as the standard dataset for plant diseases and challenges in terms of intensity variations, color changes, and variations in leaf shapes and sizes, was utilized by the authors to conduct the performance analysis. Quantitative and qualitative analysis both verified that the suggested approach was more accurate and


dependable than other recent methods in the identification and classification of plant diseases.

The use of Photochemical Reflectance Index (PRI) imaging to identify and evaluate the effects of different degrees of CMD infection in cassava was examined by Nair et al. [7] in 2016. Narrow band reflectance photos of cassava plants cultivated in the field were taken in this regard using proximal sensing and a multispectral imaging system (MSIS) at 531 and 571 nm. With all of the cassava varieties under investigation, it was found that the PRI values rose as the amount of CMD infection increased. The PRI image intensity was plotted as a scatter plot, and the results showed that the initial CMD could be distinguished from the advanced CMD with a sensitivity of 93% and a specificity of 79%, and the visibly no CMD could be distinguished from the initial CMD with a sensitivity of 85%. AUC-ROC, or area under the receiver operator characteristics curve was utilized to distinguish between clearly no CMD and initial CMD [AUC = 0.92] and between initial CMD and advanced CMD [AUC = 0.99] in order to determine the degree of CMD infection. It was found that the total leaf chlorophyll (Chl) content (R 2 = 0.80) and net photosynthetic rate (Pn) (R 2 = 0.76) had a linear inverse relationship with the PRI values calculated from the experimental data. The findings demonstrated that by using proximal sensing in outdoor plants, PRI imaging can be used to distinguish healthy plants from CMD and other stress-infected crops.

A dataset called NZDLPlantDisease-v1, which includes diseases in five of the most significant horticultural crops grown in New Zealand—kiwifruit, apple, pear, avocado, and grapevine—was presented by Saleemet al. [8] in 2022. With the newly generated dataset, an optimized version of the best-obtained deep learning model has been proposed for plant disease detection: the Region-based Fully Convolutional Network (RFCN). Following the selection of the best deep learning model, several data augmentation methods were assessed one after the other. The effects of batch normalization, weight initialization, deep learning optimizers, and image resizers with interpolators were then examined. Lastly, empirical observation of anchor box specifications and position-sensitive score maps improved performance additionally, a stratified k-fold cross-validation technique and testing on a dataset from outside. The RFCN model's final mean

average precision was discovered to be 93.80%, 19.33% better than the default settings. There are sample images collected from plantVillage of grapes disease leaf dataset are shown in Figure 2.

Fig. 2: Few samples grape leaf image dataset.

## III. PROBLEM DEFINITION

All matter of the paper here after should be times new roman size 10 normal size, line spacing 1.15 inches, justified. The manual approach of effectively identifying and classifying plant ailments requires professional knowledge and keen perception. Plant disease diagnosis by hand is labor-intensive and error-prone. Thus, the diagnosis and classification of plant diseases must be done automatically. Since machine learning approaches are not designed to handle large amounts of data, deep learning-based models enable the identification and categorization of plant diseases. Table 1 lists some of the characteristics and difficulties of the current deep learning-based model for classifying and detecting agricultural diseases. CNN successfully and

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automatically detects plant illnesses [1].However, even though the information used to create the input photos was truly obtained from the field, this method is not the most effective one for classifying and identifying plant diseases. To improve the overall performance of detection and classification, the model must be accompanied by additional segmentation processes. CNN and LBP [2] possess a faster rate of calculation. This procedure yields results that are accurate. This approach isn't generic, though. This approach is not realistic. Learning transfer [3] this method accurately identifies the pathogens causing disease in the plants, assisting in the implementation of the necessary preventative measures. However, these methods do not effectively extract the important patterns and features. These models are susceptible to problems with over fitting. CNN [4] is an all-purpose method that works with any crop. This strategy is applicable to real-world situations. However, this method offers no diagnosis for the identified plant disease. This technique does not support decision-making. CNN and Adam Optimizer [5] need fewer parameters. This strategy gives farmers access to effective diagnostic tools and appropriate preventive decision-making. However, this model isn't trustworthy. Furthermore, this method's resilience is not up to par. Both DenseNet and CenterNet [6] locate and classify the many kinds of plant diseases. This strategy is very resilient, even in the presence of artifacts. However, applications that are based on mobile phones cannot use this strategy. Time complexity problems plague this strategy. PRI [7] accurately detects the difference in the CMD degree. However, this method is not fully automated. Plant illnesses that can affect any section of the plant can be found with the aid of RFCN [8]. However, this approach's overall performance is unsatisfactory. Therefore, in this work, a deep learning-based model for the detection and classification of plant diseases will be implemented.

Table 1- Features and Challenges of Existing Deep Learning-Based Plant Disease Classification and Detection Model

| Methodology | Features | Challenges |
|---|---|---|
| CNN | This method allows for automated identification & classification of plant diseases. | If the input image data is taken straight from the field, then this method is not the best for detecting and classifying plant diseases. |
| LBP and CNN | The computation speed of this approach is more. | LBP and CNN |
| Transfer learning | The accurate prediction of the pathogens responsible for the disease in the plants in has done by this approach thus helps in taking appropriate precautions. | The crucial patterns and features are not efficiently extracted by these approaches. |
| CNN | This technique is a generalized approach that can be used for any crop.<br>This approach can be implemented in real-world scenarios. | This approach does not provide any diagnosis to the detected plant disease.<br>Decision-making is not supported by this approach. |
| Adam optimizer and CNN | The parameters required by this technique are lower.<br>Efficient diagnostic measure and suitable preventive decision makings are provided to the farmers by this method. | This model is not reliable.<br>The robustness of this method is also not satisfactory. |
| CenterNet and DenseNet | Localization and categorization of various types of plant diseases is made possible by this technique.<br>Even when artifacts are present, this approach is highly robust. | This technique cannot be implemented on mobile phone-based applications.<br>This method suffers from time complexity issues. |
| PRI | The variation in the CMD degree can be identified accurately by this approach. | This approach is not entirely automated. |
| RFCN | This technique helps in detecting plant diseases that occurs in any part of the plant. | The overall performance offered by this approach is not satisfactory. |

## V. RESEARCH METHODOLOGY

The pace at which agriculture is produced is essential to the economic expansion of a country. Plant diseases, however, are the main barrier to the quantity and quality of food. The world's health and well-being depend on the early diagnosis of plant diseases. During on-site visits, a pathologist visually evaluates each plant as part of the standard diagnosis process. However, due to low accuracy and limited human resource accessibility, manual examination for agricultural diseases is limited. In order to address these problems, automated methods that can accurately identify and classify a wide range of plant diseases are needed. New plant diseases are continuously emerging on plant leaves as a result of continuous modifications to the plant's structure and cultivation practices. Thus, limiting the spreading in the infection and promoting healthy growth of plant production can be achieved by accurately classifying and detecting leaf diseases of plants in its earliest stages. Because of low-intensity information in the image's background and foreground, the striking color similarity between healthy and diseased plant regions, noise in the samples, and variations in the position, chrominance, framework, and size of plant leaves, accurately identifying and classifying plant diseases is a laborious task. Consequently, this research would put into practice a powerful deep learning-based model for classifying and diagnosing plant diseases. Initially, the required image data will be downloaded from online sources. The collected images will then be used as input for the segmentation stage, where the Mask Region-Based Convolutional Neural Networks (RCNN) with Adaptive and Attention-based Mask (AAM-RCNN) will be employed. The Improve Golden Tortoise Beetle Optimizer (IGTBO) will be used to adjust the AAM-RCNN's parameters in order to improve segmentation performance [26]. The following step uses the segmented images to do detection as well as classification using Multiscale dilate EfficientnetB7 (HC-2D/1D-MDEB7) and Hybrid Convolution (2D/1D). The 1D convolutional layer of the hybrid Convolution (2D/1D) models will receive color and morphological information as input, while the 2D convolutional layer will employ texture patterns. Ultimately, the HC-2D/1D-MDEB7 model will yield the detected and categorized result. The effectiveness of the deep learning-based crop disease detection and categorization model that has been constructed will be demonstrated through experimental verification.

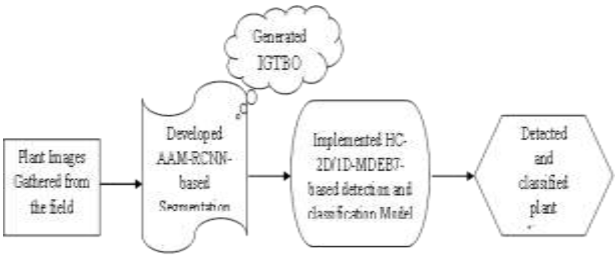


Fig. 3 shows a schematic diagram of a created deep learning-based model for plant disease detection & classification.

## VI. CONCLUSION

Many experiments on the deep learning-based plant disease identification and classification models will be carried out in Python in order to validate the efficacy of the model that was developed based on a variety of positive measures, such as Sensitivity, Accuracy, Specification, Negative Predictive Value (NPV), F1Score, accuracy, and Mathews Correlation Coefficient (MCC), as well as its negative measures, such as False Negative Rate (FNR), False Positive Rate (FPR), as well as False Discovery Rate (FDR). Additionally, a comparison with current methods will be carried out.

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