J. Electrical Systems 20-3s (2024): 732-746

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Comprehensive Review on Plant Disease Detection and Identification

Abstract: - Image Agriculture is a major contributor to financial development and is the main source of income in many countries. The primary goal of disease prevention and treatment, notwithstanding the different challenges farmers face, including plant diseases, is to precisely identify and evaluate the disease while the plant is still growing. Object recognition and classification in images has been made possible by rapid advancements in deep learning, or DL, techniques. Recently, DL approaches have been applied to farming and other agricultural applications and have showed potential in a variety of areas. These plants are commonly affected by diseases such as Septoria leaf spots, bacterial spots, late plant blight, and curled yellow leaves. Our work presents a hybrid approach to early illness detection that applies region-based full convolutional networks (RFCN) for early disease identification and region-based convolutional neural networks (RCNN) for diseases classification. We construct a network model based on the EfficientNetB7 model that optimizes at several scales via dilated convolution. The network is constructed layer by layer, top-down, with several optimizations. Real-time crop images taken from crop fields are used in the experiment, and Efficient Net B7 and hybrid convolution models are used. When the suggested ensemble model is implemented in Python, the outcome demonstrates that it has high accuracy and low loss when compared to other current methodologies.

Keywords: Plant Disease, Hybrid Convolution, Convolution Neural Network, Efficient Net B7

I. INTRODUCTION

Agriculture crops were more prone to diseases because their environments are full of pathogens [9]. A plant disease is defined as any physiological or structural anomaly caused by a living organism [10]. Plant pathogens or factors in the environment are the sources of plant diseases [11]. Plant illnesses are mostly caused by inadequate nutrition, microbial attack, rat infestation, and poor environmental conditions. [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 a price, which poses a risk to food security [14]. Protecting plants from disease is more important to ensuring food security and income streams for the world's expanding population. [14]. One of the conventional techniques for diagnosing plant illnesses is a visual examination of the plant since pathogen impacts are sometimes hidden until the plant suffers significant harm. There is great potential in the field of automated plant disease detection15]. Early detection and management of these illnesses are crucial because they increase yield quality and quantity while lowering the need for pesticides [16]. Manual observation can be a complex, subjective, and time-consuming method for detecting these diseases [17].

To satisfy the demands of a rising population, automated devices that assist farmers observe crops at all phases of growth are consequently vital. One of the most significant uses of precision agricultural research is the use of image analysis to detect plant diseases in leaves. [18]. Using a conventional method, trained experts visually inspect plant tissues to assess the level of severity of plant diseases [19].The widespread use of digital cameras and the development of technology in agriculture have led to the widespread application of systems of experts in cultivation and management, significantly increasing the capacity for plant production [18]. However, expert systems primarily rely on the expertise of experts for the extraction and description of pest and disease characteristics, which leads to high expenses and low efficiency [20]. Plant diseases can now be identified and categorized using a variety of artificial intelligence techniques. The most popular techniques include support

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vector machines (SVMs), logistic regression, decision trees, and K-nearest neighbors (K-NN). [3]. Convolutional Neural Network (CNN) [21]. 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. Neighboring labeled 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 prior machine detection methods usually pre-process images of diseased plant leaves using conventional image processing methods like noise reduction, morphological operations, and enhancement of images [22]. Manually created feature extraction techniques then extract the leaves' color, shape, and texture, among other low-level characteristics. [23]. the structures of deep learning have shown promise recently in the areas of object segmentation, classification, and identification [24]. For deep learning tasks, CNN approaches are the most widely used. Even though the fundamental CNN architectures—AlexNet, VGGNet, GoogLeNet, DenseNet, as well as 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 the parameters and a slow estimation speed. While deep learning techniques have demonstrated remarkable proficiency in exhibiting both high-level as well as low-level features, their consistency in that describes local spatial characteristics is lacking [25].Fusion Approaches to Image Segmentation

II. PLANT DISEASE DETECTION USING SYMPTOMS & SIGN

2.1. Disease-Affected on Cotton Plants:

2.1.1 Cotton Foliar Diseases:

a) Alternaria leaf spot

i) Causal Organism

ii) Alternaria macrospora

Damage

- On leaves, there are tiny, circular brown dots with a purple border around them.
- On older leaves, patterns of concentric zonation may indicate the necrotic center of the spots.
- A number of spots combine to produce sizable necrotic patches, especially close to the leaf margin.
- Premature defoliation results from the spots appearing sooty black in humid weather.
- Spherical or circular purple dots appear on the leaf stalks and bolls.

b) Anthracnose

i) Causal Organism

ii) Colletotrichum gossypii

Damage

- The seedlings, bracts, and bolls are the fungus's main targets.
- Tiny reddish dots appear on the cotyledons.
- Longitudinous, reddish-brown lesions occur at the collar region.
- All phases of bolls are targeted; at first, they are small, round, and submerged in water.
- As they expand, reddish brown dots emerge, with black centers.

- The undersides of leaves are where the pinkish-brown dots are most common.
- When an infection is severe, the area under the necrotic region grows, which frequently leads to defoliation.

c) Cercospora leaf spot

i) Causal Organism

ii) Mycosphaerella gossypina or Cercospora gossypina

Damage

- Initially, there are reddish spots that grow larger but still have a narrow reddish color.
- Dead tissue in the middle, surrounded by a white light brown margin
- Subsequently, irregular patches encircled by the chlorotic halo appear.
- Early defoliation and yellowing of the leaves occur.

a)Alternaria leaf spot b) Anthracnose c) Cercospora leaf

Figure.1. foliar diseases of Cotton

d) Helminthosporium leaf spot

i) Causal Organism

ii) Helminthosporium spiciferum Cochliobolus spicifer

Damage

- The Lower leaves of seedlings turns light yellow which increase in size, become dark brown and surrounded by a dark purple border.
- Shot holes are left when the centers of the spots turn ashy and shed off.

a) Helminthosporium leaf spot

Figure 2. Foliar diseases of Cotton

2.1.2 Soil-borne Disease of Cotton:

a) Fusarium wilts

i) Fusarium oxysporum f. sp. vasinfectum is the causative organism.

Damage

- Peripheral chlorosis follows the cotyledon vein darkening as the initial sign of the condition. Before they shed, the cotyledons get more and more chlorotic and necrotic.
- Yellowing of one lower leaf margins is the initial outward sign of infection in older plants.
- A few leaves develop chlorosis as the disease progresses throughout the plant; these leaves often feature a patch of chlorosis between the major veins, with the other portion of the leaf remaining green. Leaves droop as they become dry and shed.
- Plant eventually dies, resulting in 100% mortality.

b) Para wilt

Damage

- Plants that are experiencing wilt typically have drooping leaves that begin at the crown and progress downward during the flowering phase and boll development stages.
- There is no loss of turgor, partially epinasty, lamina dropping, reddening along the leaf surface, the petiole, stem, and branches, and neither necrosis nor chlorosis.
- Plants can lose their leaves, recover partially, or even die.

c) Root-rot

i) Causal Organism

ii) Rhizoctonia solaniR. bataticola

Damage

- In extreme situations, the tissues of the stem and roots dissolve.
- The plant suddenly and completely wilted
- Circular yellowish black patches are seen on seedlings or wood.
- The tips of the roots get discolored, and on the decaying wood, black dots shaped like sclerotia form.
- Darker rot of the bottom stem either wet or dry, is the most typical sign.
- The damaged plant is easily identified by its discolored main root stele and stem pith upon split opening.

a) Fusarium wilt b)Para wilt c)Root rot

Figure.3. Soil-borne disease of Cotton

2.1.3 Bacterial Disease

a) Bacterial blight

i) Causal Organism

ii) Xanthomonas axonopodis pv. malvacearum

Damage

In severe situations, the larvae skeletonize the leaves, leaving just the midrib and veins. They eat gregariously on the underside of the leaves. They also do significant damage when they assault squares, flowers, and buds

a) Bacterial blight

Figure. 4. Bacterial disease of Cotton

2.2 Tomato Plants Affected by Diseases:
a) Damping off
Symptoms
Damage
The seeds are killed at the pre-emergence phase right before they touch the soil's surface.
The post-emergence phase is defined by the infection of the juvenile, immature collar tissue at ground level.

Damping off

Figure.5. Damping off of Tomato

b) Fusarium Wilt

i) Fusarium oxysporum f. sp. Lycopersici

Symptom

- Devoid of any veinlet and the lower leaves are withering.
- In succession, younger leaves die
- Petiole and foliage wither and droop.
- Discoloration of the circulatory system
- Whole plants wither and die

b) Helminthosporium leaf spot

Figure. 6. Fusarium wilt of Tomato

c) Early blight and late blight

- A brown patch surrounded by yellow-bordered concentric rings forming a bull's eye design;
- An infection that spreads through the calyx or stem attachment.
- Fruits with brown concentric rings

b) Early blight

c) Late blight

Figure.7. early and Late blight of Tomato

d) Bacterial wilt

Symptoms

- Formerly known as Pseudomonas solanacearum, the infection occurs with the bacterium Ralstonia solanacearum. Among the most harmful plants is this one.
- Plant foliage typically exhibits the initial noticeable signs of bacterial wilt in the earliest phases of the disease.
- The youngest leaves at the tips of the branches wilt during the hottest part of the day, which is one of these indications.
- Stunting of the plants is another well-known sign of bacterial wilt in the field.

e) Leaf curl virus

Symptoms

- Serve to stunt plants
- Download the leaf crinkling and rolling.
- Internodes shortening more lateral branches have a bushy appearance.

f) Tomato mosaic virus (TMV)

Symptom

- Serve stunting.
- Ringson leaves those are necrotic or chlorotic.
- Young leaves' bronzing and thickening of veins
- Growing tips wilt and die back.
- Fruits with concentric circles and yellow portions

d) Bacterial wilt e)Leaf curl virus f)Tomato mosaic virus

Figure. 8. Disease on Tomato

2.3. Paddy Plants Affected by Diseases:

a) Blast of Paddy

Pathogen: Pyricularia grisea (Magnaporthe grisea)

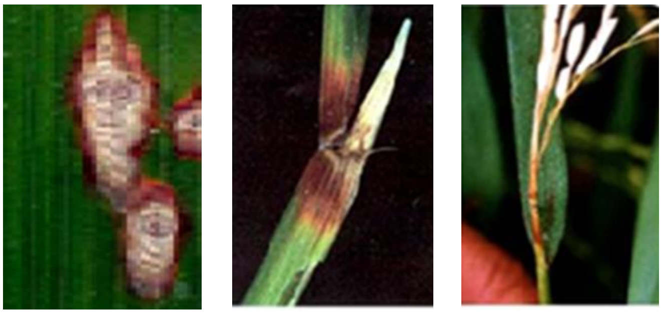
Symptoms

On leaves, leaf collars, nodes, and panicles, blast symptoms may manifest.

Leaf blast: The oval or spindle-shaped lesions have gray centers and brown edges.

Collar blast or node blast: happens when the infection enters the collar, which has the potential to kill the leaf blade completely.

Neck blast: Happens when a disease infects the panicle's neck.



a) Leaf Blast Collar blast Neck blast

Figure. 9. Blast of Paddy

b) False smut of Paddy

i) Pathogen: Ustilaginoidea virens (Cooke) Takah (anamorph), claviceps oryzae -sativae Hashioka (teleomorph)

Symptoms

- A single grain of rice became a multitude of golden fruiting bodies.
- Velocity spore growth enclosing floral parts
- Typically, a panicle has just a few diseased grains; the remaining grains are normal.

c) Bacterial blight of rice

i) Pathogen: Xanthomonas oryzae pv. oryzae

Symptoms

- Early stages of Kresek (Seedling wilt: Plants wither and die)
- Later stages of blightening begin at the base of the leaves and work their way up.
- Straw became white from yellow
- Appearance of milky or opaque dewdrops, or bacterial slime, on newly formed lesions.

b) False smut of Paddy   c) Bacterial blight of rice

Figure. 10. False smut of Paddy and Bacterial blight of rice

2.4. Chili Plants Affected by Diseases:

a) Die Back

Symptoms

- Tender twigs become necrotic from the tip to the back due to the illnesses.
- As the disease progresses, the twigs' brown tint changes to a grayish white or straw hue.
- On the damaged twigs, acervuli, or huge black dots, sprout in large numbers.

b) Leaf Curl

Symptoms

- Curling foliage.
- A bushy appearance is caused by the plant's shorter infer node dwarfing.
- Leaves turn to pale yellow color & roll downwards.
- Fruiting is stopped.

c) Anthracnose: Colletotrichum Capsici

Symptoms

- A little, round patch of black skin on the fruit surface.
- Fruits with bad diseases become straw-colored or pale white in color and lose their pungency.

a)Die back   b)Leaf Curl   c)Anthracnose

Figure. 11. Chili plants affected by disease

2.5. Apple Plants Affected by Diseases:

a) Apple Scab: Venturia inaequalis is the pathogen responsible for this fungal disease.

Symptoms: Usually, it causes scaly or scabby patches on leaves, and fruits, and twigs that range in color from olive-green to black.

b) Apple Black Rot: Botryosphaeria obtusa is the fungus that causes apple black rot

Symptoms: Fruits develop black, spreading lesions, frequently ringed in concentric circles. The impacted fruits turn into mummified "black rots."

c) Apple Cedar: It appears that there may be a mistype or misunderstanding here. "Apple cedar" is not a phrase that's recognized in relation to apple illnesses, so please specify if you mean something different.

d) Apple Health: Maintaining the health of apple trees entails a number of elements, such as appropriate dietary practices, effective insect control, and effective disease management.

An apple tree in good health will have brilliant, green leaves, robust, well-formed branches, consistent yields of fruit, and resistant to common diseases.

a) Apple scab

b) Apple black Rot

c) Apple Cedar

d) Apple Health

Figure. 12 Apple plants affected by disease

III. LITERATURE REVIEW

Several deep learning models were put up by Moupojou et al. [1] in 2023 to assist farmers in quickly and effectively identifying crop illnesses in order to prevent productivity reductions. Typically, public or private plant disease datasets like PlantVillage or PlantDoc were used to train these algorithms. The pictures that made up PlantVillage were taken in a scientific setting, with a single leaf on each shot and a consistent background. When applied to field photos containing many leaves and complicated backdrops, the models trained by that data set perform terribly. In order to address this issue, 2,569 field photos that were retrieved from the Internet then analyzed to identify individual leaves were used to build PlantDoc. Nevertheless, some laboratory photos were included in this collection, and plant pathologists were not present when the dataset was being annotated might have led to an incorrect classification. FieldPlant was recommended as a dataset in this study, which has 5,170 photos of plant diseases that were taken straight from plantations. To guarantee procedure 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 types were produced as a consequence. The proposed model was evaluated against the most advanced classification and object identification algorithms on a variety of benchmark datasets. It was discovered that FieldPlant performed better on classification tasks than PlantDoc.

Hosny et al. [2] introduced a novel lightweight deeply convolutional neural network model in 2023 for generating the highest level hidden representations of features. Locality binary pattern (LBP) features, which are typically generated to extract local textured information from plant leaf photos, were then combined with the deep features.

Three publicly accessible datasets—the Apple's Leave, Tomatoes Leave, and Grapes Leaf—were used to train and evaluate the suggested model. The suggested method yielded accuracy tests of 98.8%, 96.5 percent, and 98.3% on the three datasets & validated reliability of 99.6%, 98.5%, and 98.5 %. The experiments' findings demonstrated that the suggested strategy offered a more effective technique of managing plant diseases. The experiments' findings demonstrated that the suggested strategy offered a more effective way to manage plant diseases.

A model for detecting plant diseases based on pathogens was proposed by Rani & Gowrishankar [3] in 2023. With Keras transfer learning models, plant illness detection and classification were carried out automatically, and the pathogen causing it was identified. This was accomplished by taking into account the Agri-ImageNet collection in addition to photographs of sunflowers and cauliflower leaves, bulbs, and flowers that were taken in authentic, natural settings. The limitation of the PlantVillage dataset—that is, a photo 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 tackle these issues. Main goal was to investigate and evaluate every deep transfer learning technique used in order to determine which model was most appropriate for the dataset on plant diseases. To get the best classification accuracy, 38 deep machine learning models were used in this work. For the Agri-ImageNet, cauliflower, and sunflower datasets, the EfficientNetV2B2 & EfficientNetV2B3 models produced the best results in terms of accuracy when compared to the remaining deep transfer learning models. A report on classification was produced using the most effective deep transfer learning method.

Shewale and Daruwala [4] developed automated intelligent solutions in 2023 that use a CNN methodology based on deep learning to effectively diagnose the condition with less complexity and time required. Plant leaf diseases were identified by combining patterns of leaf photos at particular times with image processing. Tomato plants were taken into consideration for the current study 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 diagnose diseases with high precision, doing away with the need for features engineering and threshold segmentation. The network was adopted and extended by the utilization of spatial images captured in difficult environmental conditions. Disease diagnosis is now done automatically. enabled by recent developments in computer vision deep learning. All things considered, the process of training deep learning models on progressively bigger, openly available, real-time image datasets offered a direct path to the widespread identification of plant diseases worldwide.

Premananda et al.'s 2023 proposal [5] calls for a customized CNN architecture that uses fewer network parameters to identify and categorize common diseases that affect rice plants. Four distinct types of popular rice crop illnesses were used as a dataset to train the suggested CNN architecture. Furthermore, the paper presents 1400 on-field photos and healthy rice leaves dataset to aid in the identification of disease-free plants.Studies were carried out independently with and without the gathering of healthy leaf images. Several performance matrices & the optimization techniques of stochastic gradient descent and momentum (SGDM) and adaptive moment estimation (Adam) were used to assess the performance of the suggested model. The model developed by SGDM optimization yields a maximum accuracy rate of 99.66% on a test set from the 7th epoch, while the model developed through Adam optimization yields a maximum accuracy rate of 99.83%. These conclusions have been made based on the experimental results from the data set for the classification of four rice crop illnesses. When the healthy leaves picture dataset was employed, the model that used the Adam optimizer performed better than the model that used the SGDM optimizer. It resulted in the yielded the best accuracy rates (99.66% and 97.61%, respectively) in the 7th epoch.

Albattah et al. [6] presented a robust plant disease classification system in 2022 utilizing Custom CenterNet architecture with DenseNet-77 serving as the base network. The technique that was offered was divided into three stages. In order to identify the region of interest, annotations were made in the first stage. Second, an improved version with CenterNet was introduced, proposing DenseNet-77 to be used in deep critical point extraction. In the end, several plant diseases were detected and classified with the help a one-stage detector CenterNet. The authors conducted a performance analysis using the PlantVillage Kaggle datasets, which acted as the benchmark dataset of plant diseases and challenges to the form of intensity changes, color changes, & variations in leaf shapes and sizes. The given method was found to be more efficient and dependable for identifying and classifying plant diseases compared to other recent approaches, as supported by both qualitative and quantitative analysis.

The use with Photochemical Reflectance Indicator (PRI) images 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 proximate sensing and multispectral imaging systems (MSIS) at 531 and 571 nm. With all of the cassava types under investigation, it was shown that the PRI value rose as the amount of CMD infection increased. Plotting the PRI image intensity as a scatter plot revealed that, with a sensitivity of 93% and a specificity of 79%, the initial CMD could be separated from the advanced CMD, and with a sensitivity of 85%, the visibly no CMD could be distinguished from the starting CMD. The area under the receiver's operator characteristics (AUC-ROC) curve was used to determine the CMD infection level by clearly differentiating between initial and advanced CMD (AUC = 0.99 & AUC = 0.92), respectively, and between definitely no CMD and CMD. The net photosynthetic rate (Pn) ($R^2 = 0.76$) and the total chlorophyll content ($R^2 = 0.80$) of the leaves were shown to have a linearly opposing connection with the PRI values determined from the experimental information. The results showed that by the results showed that PRI imaging can be used to distinguish between healthy plants with CMD and other stress-infected crops in outdoor plants through the use of proximate sensing.

Saleem et al. [8] presented a dataset named NZDLPlantDisease-v1, which comprises diseases in five of the most important horticultural crops in New Zealand: avocado, grapevine, pears, apples, and kiwifruit. Using the recently generated dataset, the Region-based Deeply Convolutional Network (RFCN), the best-obtained deep learning model for plant disease diagnosis, has been upgraded. After the best deep learning model was chosen, a number of data augmentation techniques were evaluated one at a time. Next, the effect of deep learning optimizers, weight initialization, batch normalization, & pictures resizers with interpolators was investigated. Finally, performance was enhanced by empirically observing anchor box specification and position-sensitive score maps. Furthermore, a stratified cross-validation k-fold process and tests in an external dataset were employed to demonstrate the robustness and viability of the recommended strategy. The final mean average accuracy of the RFCN model was found to be 93.80%, which is 19.33 percent higher than the default parameters that were employed.

IV. PROBLEM DEFINITION

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 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. This approach can be implemented in real-world scenarios.	This approach does not provide any diagnosis to the detected plant disease. Decision-making is not supported by this approach.
Adam optimizer and CNN	The parameters required by this technique are lower. Efficient diagnostic measure and suitable preventive decision makings are provided to the farmers by this method.	This model is not reliable. 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. Even when artifacts are present, this approach is highly robust.	This technique cannot be implemented on mobile phone-based applications. 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. PROBLEM STATEMENT

The following list includes a few of the difficulties with current plant disease identification and classification approach.

1. Plant detection and classification of diseases methods that rely on traditional image analysis are impacted by various factors, including low-quality field photos, obstructions, shifting lighting, and more.

2. Manually derived characteristics are required by a machine learning-based plants disease detection and categorization model.

3. Critical patterns and characteristics required to complete a disease detection and categorization task cannot be obtained using transfer learning-based detection of plant diseases and classification models.

4. Why because they require large volumes of high-quality input data, conventional plants disease detection and categorization models do not yield accurate identification and classification outcomes being applied in real-time settings.

VI. RESEARCH METHODLOGY

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. Figure 13 shows a schematic diagram of a created deep learning-based model for plant disease detection & classification.

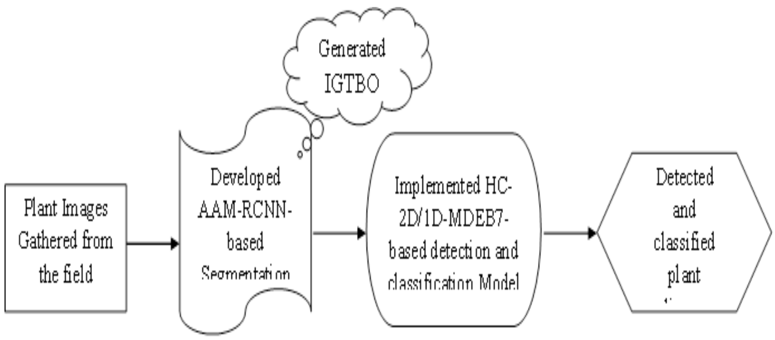


Figure 13: Diagrammatic Representation of the Developed Deep Learning-Based Plant Disease Detection and Classification Model

VII. 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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