PLANT DISEASE DETECTION AND CLASSIFICATION: A REVIEW

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ABSTRACT

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. Quick developments in deep learning (DL) techniques have made it possible to recognize and classify objects in images. DL techniques, which have shown promise in many domains, have recently made their way into farming and agricultural applications. Diseases like late plant blight, bacterial spots, Septoria leaf spots, and curved yellow leaves are frequently seen in these plants. Our study offers a hybrid approach to early disease detection that combines the application of region-based convolutional neural networks (RCNN) for disease classification with the use of region-based fully convolutional networks (RFCN) for early disease identification. We build a network model based on the EfficientNetB7 model, which uses dilated convolution for multi-scale optimization. The network is built top-down, layer by layer, incorporating multiple 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.

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Keywords: Plant disease, hybrid convolution, transfer learning, convolutional neural network and Efficient Net B7.

1. 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]. Inadequate nutrition, microbe attack, rodent infestation, and unfavorable 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 a price, which poses a risk to food security [14]. 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. The field of automatic plant disease detection has a lot of promise [15]. 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 meet the demands of an expanding population, automated systems that help farmers monitor crops at all stages of growth are therefore necessary. Utilizing image analysis to identify plant diseases in leaves is one of precision agriculture research's most important applications [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]. There are now several artificial intelligence methods available for identifying and categorizing plant diseases. The most widely used methods are decision trees, logistic regression, K-nearest neighbors (K-NN), and support vector machines (SVMs) [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]. Subsequently, manually developed feature extraction techniques obtain low-level details about the leaves, including color, form, and texture [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].

2. DIFFERENT TYPES OF DISEASE ON PlANTS:

Plant diseases are a broad category of illnesses brought on by pathogens, including bacteria, viruses, nematodes, fungus, and parasitic plants. The balance of the ecology, plant health, and crop productivity can all be severely impacted by these diseases. Comprehending the many forms and attributes of plant illnesses is crucial for proficient administration in the fields of agriculture, horticulture, and the environment. Plant diseases, such as nematodes, bacteria, viruses, and fungus, infiltrate plants and impede their regular growth and development. These microbes frequently spread by vectors like insects, the air, water, or soil. Plant diseases can show themselves in a variety of forms, with discoloration, withering, deformation, lesions, cankers, or aberrant growths being among the symptoms. It is essential to identify these signs in order to begin early detection and treatment

2.1 Tomato plants affected by diseases:

Tomato plants can be affected by various diseases, impacting both yield and quality. Common tomato plant diseases include:

1. Early Blight (Alternaria solani): Impacts wilting and yellowing of lower leaves by producing black lesions.
2. Late Blight (Phytophthora in festans): Dark lesions on stems, leaves, and fruits are caused by this disease, which spreads quickly in damp environments.
3. Septoria Leaf Spot (Septoria lycopersici): Causes defoliation and is distinguished by tiny, spherical spots on lower leaves with dark borders.
4. Bacterial canker (Clavibacter michiganensis subsp. michiganensis): Frequently results in plant death by causing wilting, yellowing, and cankers on stems.
5. Fusarium Wilt (Fusarium oxysporum): A fungus that grows in soil that causes plants to wilt, yellow, and become stunted
6. Verticillium wilt (Verticillium spp.): Causes yellowing and wilting and affects the plant's vascular system.
7. Tomato Mosaic Virus (ToMV): Produces lower fruit quality, slowed growth, and mosaic patterns on leaves.
8. Tomato Yellow Leaf Curl Virus (TYLCV): Caused by yellowing, curled leaves, and decreased yield; spread by whiteflies.
9. Powdery Mildew (Leveillula taurica): A fungal infection that affects photosynthesis and leaves with white, powdery patches.
10. Necrotic patches, wilting, and deformed growth are caused by the tomato spotted wilt virus (TSWV), which is spread by trips.

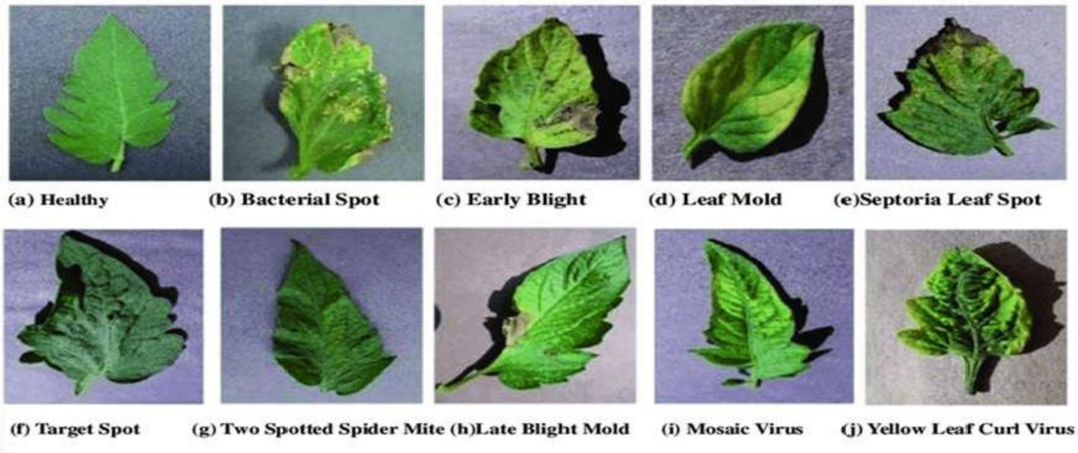

Fig.1: The Sample Images of the Tomato Leaf Disease.

2.2 Apple plants affected by diseases:

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

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

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."

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.

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.

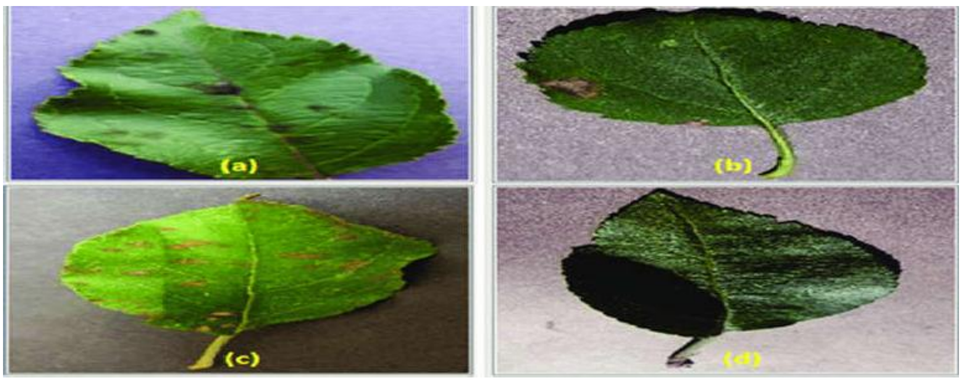

Fig. 2: The Sample Images of the Apple Leaf Disease.

2.3 Rice plants affected by diseases:

Entyloma oryzae is the fungus that causes rice leaf smut, which is a widespread disease that affects rice plants. It mostly affects rice plants' leaves, resulting in symptoms that are akin to smut. On the upper surface of infected leaves, tiny, powdery, dark brown to black spore masses form, giving the leaves a smutty look.

Important details regarding rice leaf smut

Causal Agent: Rice leaf smut is caused by the fungus Entyloma oryzae. Usually, it overwinters in contaminated agricultural waste.

Signs: Particles of powdery, dark brown to black spores on the top layer of diseased leaves. Smutty patches start to appear on the leaves. Twisted or deformed leaves may result from the condition.

.**Rice leaf scald**: Magnaporthe grisea is the pathogen responsible for the fungal disease known as rice leaf scald. It mostly affects rice plants, resulting in leaf lesions. Lesions that appear water-soaked and are grayish-green or white in color, eventually turning tan and light brown, are among the symptoms. It's possible for these lesions to combine, causing significant harm. The fungus is a difficult pathogen to control because of its reputation for rapid evolution and adaptation.

Rice stack burn: Affected are ripening grains and leaves. On leaves, dark brown-bordered round to oval dots appear. The spot's core becomes pale brown or white and is covered in many tiny dots. There are reddish-brown dots on the glumes. It's possible for the kernels to dry out and break.

Rice white tip: Typically, "rice white tip" refers to an illness that affects rice plants. The fungus known as hemibiotrophic fungus is the cause of it. The tops of immature rice leaves develop white elongated lesions that eventually become brown as a symptom. Rice production may be impacted by this disease's effects on rice output and quality. Fungicides and disease-resistant cultivars are two common agricultural management strategies used to

Rice bacterial leaf streak: The bacterium Xanthomonasoryzaepv. Oryzicola is the cause of rice bacterial leaf streak, a plant disease. It typically damages rice crops, causing characteristic signs on the leaves, including narrow yellowish streaks. The illness may lower rice quality and yield, which will af ect agricultural output.

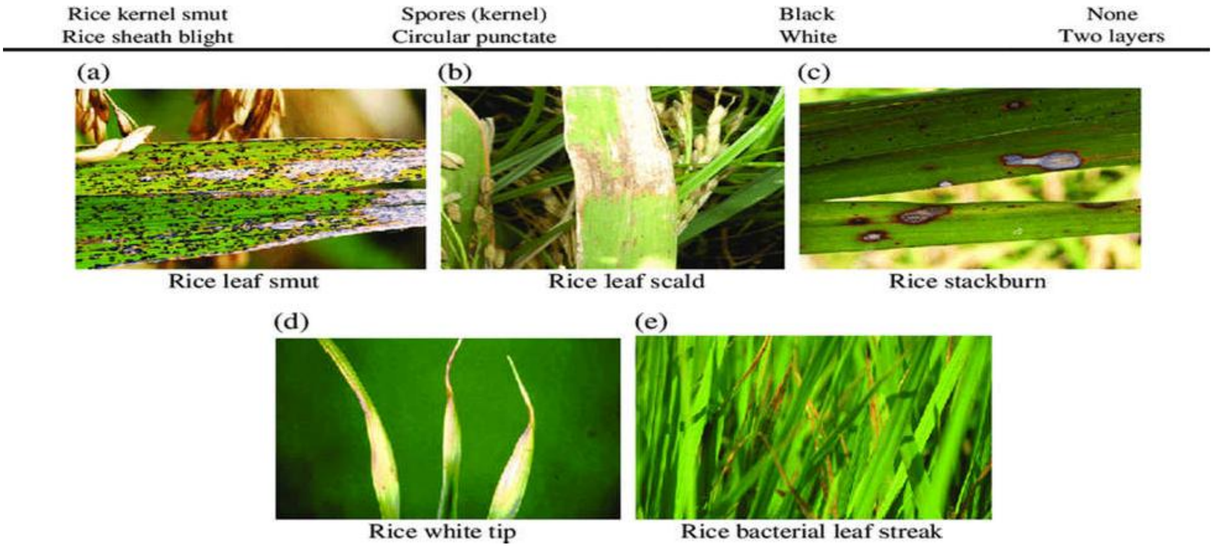

Fig. 3: The Sample Images of the Rice Leaf Disease.

2.4 Potato plants affected by diseases:

Healthy potato: A potato plant's overall health can be determined by looking at its healthy leaves. The following are essential qualities of robust potato leaves: Bright Green Color: The green color for good potato leaves should be consistent and bright. Any discoloration or yellowing could be a sign of disease, bugs, or nutritional inadequacies. Turgid Texture: Firm and unwilled, the leaves should have a turgid texture. Drooping or wilting leaves could be an indication of other stressors or problems with access to water. Smooth Surface: The surface of the leaf should be devoid of anomalous growths, blemishes, or abnormalities. Any anomalies could indicate the presence of illnesses or pests.

Early blight: Alternaria solani is the pathogen that causes early blight, a widespread fungal disease that affects potato plants. Usually, it happens in warm, muggy weather. The following are salient features and details regarding beginnings of blight in potatoes: Signs: On lower leaves, early blight symptoms initially manifest as tiny, black lesions with concentric rings. Larger dead regions may result from the growth and coalescence of these lesions. Lesion Display: The lesions frequently resemble targets with a lighter center and darker concentric rings, giving the impression of a bull's-eye. Leaf Yellowing: The plant's ability to photosynthesize may be reduced if leaves surrounding the lesions show yellowing or prematurely drop. Stem Infections: When the infection reaches an advanced stage, lesions on the stems that cause slowed growth may also damage the tubers and stems. Favorable Conditions: Extended leaf wetness combined with warm, humid weather makes for ideal conditions for the early development of blight. Potato early blight management entails the following: Fungicides: Use of fungicides, particularly when the illness is at its most contagious.

Late blight: The oomycete pathogen of Phytophthora infestans is the cause of the devastating fungal disease known as late blight, which affects tomatoes and potatoes. The Irish Potato Famine was historically influenced by this illness. The following are some salient features and details of potato late blight: Signs: Dark, wet lesions on leaves, usually beginning on the lower leaves & progressing upward, are indicative of late blight. In periods of excessive humidity, the lesions may appear fuzzy or rotten. Advantageous Conditions: The pathogen prefers damp, chilly environments.Due to rainyseasons, high levels of humidity and temperatures between 15 and 24°C (59 and 75 ° F) are favorable for the development of late blight. Quick Spread: Late blight has the potential to spread quickly, causing extensive defoliation & tuber infection. If not dealt with quickly, it can destroy entire potato crops. White Spores: on the underside of affected leaves, the pathogen generates white spores, or sporangia, which aid in the disease's transmission in humid environments. Potato tubers may become infected with late blight, which can lead to their decay. Dark, hard lesions that appear on infected tubers might cause issues with storage and lower quality. Potato late blight management entails the following: fungicides Fungicide applications on a regular basis are frequently required, particularly during times of significant disease pressure.

Potato virus disease: Many viruses that damage potato plants can produce potato virus infections, which lower yield and quality. Potato Virus Y (PVY), Potato Virus X (PVX), & Potato Virus S (PVS) are examples of common potato virus. Aphids, mechanical methods, or infected seed potatoes are the usual mechanisms of virus transmission. Dwarfing, distortion, mosaic patterns, and leaf yellowing are a few possible symptoms. Plants with infections frequently have lower-quality tubers. Using verified disease-free seed potatoes, managing aphid vectors, and applying sound crop management techniques are all part of prevention.

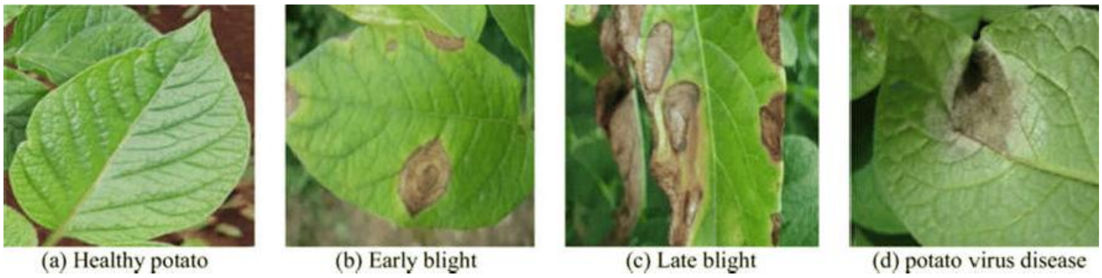

Fig. 4: The Sample Images of the Potato Leaf Disease.

2.5 Cotton plants affected by diseases:

Healthy: Typically, healthful cotton leaves are green and devoid of any blemishes or stains. They should be turgid and firm to the touch, signifying adequate hydration. In order for cotton plants to expand and produce more overall, they need healthy leaves for photosynthesis. To keep cotton leaves healthy, regular inspection is necessary for diseases, pests, and nutrient deficits. The health of cotton plants is largely dependent on timely insect control, balanced fertilizer, and proper irrigation.

Leaf spot: Cotton leaf spot is a fungal illness that is brought on by a number of different pathogens, such as Ascochyta, Alternaria, and Cercospora species. Small, black patches on cotton leaves with definite borders are one of the symptoms. These areas might combine, affecting bigger regions. In extreme situations, leaves may turn yellow, shrivel, and fall off too soon, which would affect the plant's productivity. Fungicides are used, crop rotation is done, and adequate spacing is maintained to allow for adequate air circulation. Leaf spot on cotton crops can also be lessened by planting disease-resistant cotton cultivars and preserving overall plant health with balanced nutrition and watering.

Nutrient Deficiency: Cotton's nutrient shortages can have a negative impact on the growth and development of the plant as well as crop yield. Deficits in phosphorus, nitrogen, magnesium, potassium, iron, and manganese are frequently observed. A lack of nitrogen (N) causes stunted growth, chlorosis, or the yellowing of older leaves, and less formation of cotton fiber. A lack of phosphorus (P) causes bluish-green, dark-green leaves, less blossoming, and a delayed maturity. Lack of potassium (K) results in decreased boll development, yellow and necrosis at the leaf edges, and heightened disease susceptibility. Deficiency in magnesium (Mg) causes interveinal chlorosis in older leaves, which hinders photosynthesis. Lack of iron (Fe) affects the generation of chlorophyll by causing interveinal chlorosis in younger leaves. A manganese (Mn) deficit affects photosynthesis and causes veins to turn yellow. Soil testing is necessary to determine the precise nutrient requirements in order to remedy nutrient deficits. Programs for fertilization ought to be modified appropriately.

Powdery mildew: Pseudoidium gossypii is the pathogen responsible for the fungal disease known as powdery mildew on cotton. Inthe top surface of stems, leaves, and other parts of the plant exhibit white, powdery spots that are indicative of this disease. It grows best in warm, dry climates, which makes cotton crops vulnerable, particularly in low-humidity seasons. When powdery mildew occurs on cotton, leaves develop powdery white patches that might clump together to cover greater surfaces. As the illness worsens, impacted leaves may start to sag and, in extreme circumstances, early defoliation may happen. This may result in less photosynthesis, which would be detrimental to the cotton plant's general health and productivity.

Target spot: The fungus Corynespora cassiicola is the cause of the foliar disease known as "target spot" on cotton. The formation of round to differently shaped lesions upon cotton leaves, mimicking a target pattern, is the characteristic that characterizes this illness. With a lighter outer ring and a dark brown to black interior, the lesions have a definite concentric ring structure. Important attributes of target area on cotton are: Lesions: Irregular or round patches on leaves that resemble targets. Color: A lighter outside ring surrounded by a dark brown to black center. Spread: In severe situations, lesions may come together to cause significant defoliation. Impact: Possible yield loss, defoliation, and decreased photosynthesis. Target spot control on cotton requires the use of multiple tactics: Fungicides: Fungicides should be applied, especially if the disease is most contagious and there is high humidity and warmth. Cultural Practices: Target spot can be managed with the use of crop rotation, resistant variety planting, and air circulation-enhancing planting density optimization. Timely Detection: To start control measures on time, regular scouting along with early symptom detection is necessary. Pruning and Debris Removal: To lessen the source of the inoculum, remove and destroy contaminated plant material. In order to effectively manage targeted spot on the cotton and minimize its influence on production and quality, it is imperative to implement IPM (integrated pest management) strategies, which combine chemical treatment with cultural & biological measures.

Verticillium Wilt: The vascular disease known as verticillium wilt in cotton is brought on by the soil-borne fungus Verticilliumdahliae. This disease is known to live for several years in the soil and damages a wide variety of plants, including cotton. Important traits of cotton verticillium wilt include: Symptoms: Lower leaves usually begin to wilt and become yellow at the beginning of the disease. As it worsens, the plant as a whole could wilt and its leaves might turn necrotic (made of dead tissue).Vascular Discoloration: A fungus causes a brown discoloration within the vascular tissues of the stem by infecting the plant's vascular system. Leaf Drop: Plants with infections may lose their leaves too soon, which would be detrimental to the health of the plant as a whole. Impact: Reduced yields and compromised fiber quality are possible outcomes of verticillium

Leaf curl: Cotton Crop Curl Virus (CLCuV) is a virus that causes leaf curls on cotton plants. The whitefly, or Bemisiatabaci, is the main vector of transmission for this disease. Because leaf curl disease can result in large yield losses, it is a major concern in areas that produce cotton. Defining characteristics of cotton leaf curl Signs: The curled and twisted leaves are the most recognizable symptom. The leaves of infected plants curl upward and inward, giving the plants a twisted, puckered appearance. Changes in Leaf Color: Leaves may also exhibit discolouration, mottling, or yellowing. Reduced Growth: Stunted growth in infected plants can lead to a decrease in size and vigor. Boll Drop and Flower: Follicle curl disease-affected cotton plants may show reduced flowering & boll formation.

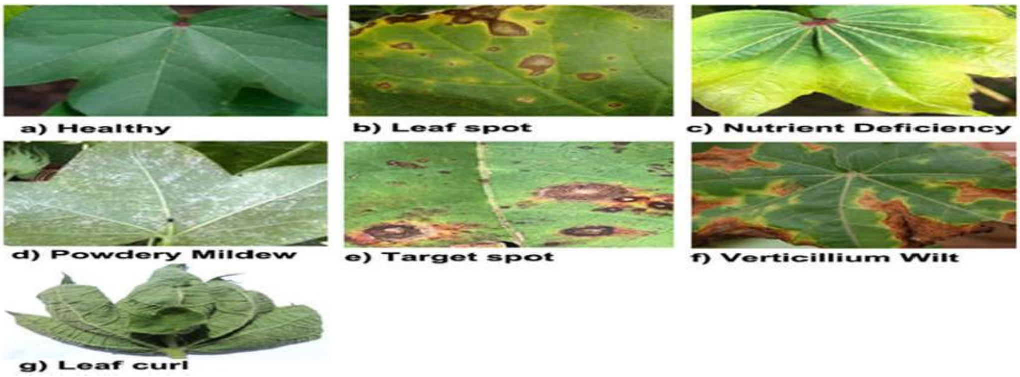

Fig.5: The Sample Images of the Cotton Leaf Disease.

3 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.

A revolutionary lightweight deeply Convolutional Neural Networks, model for producing the highest level hidden representations of features was proposed by Hosny 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 locale binary pattern (LBP) features. Three publicly accessible datasets—the Apple Leaf, Tomatoes Leaf, and Grapes Leaf—were used to train and evaluate the suggested model. The suggested method obtained 99 percent, 96.6%, and 98.5% validate accuracies and 98.8%, 96.5 percent, and 98.3% test accuracy on the three datasets. The trials' findings demonstrated that the suggested strategy offered a more effective way to control plant diseases. 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 & 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 embraced and expanded with the use of spatial images taken under challenging environmental circumstances. The diagnosis of diseases has been automated. made feasible by current advances in deep learning for computer vision. Overall, the process to train deep learning models on increasingly larger, publicly accessible, real-time image datasets provided a clear route to plant disease diagnosis on a massive global scale.

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. Separate studies were conducted both with and without healthy leaf picture collection. Using a number of performance matrices, the suggested model's performance was assessed using the optimization techniques of a stochastic gradient descent and Momentum (SGDM) & Adaptive Moment Estimation (Adam) The model developed using SGDM optimization yields a maximum success rate of 99.66% based a test set in the 7th epoch, whereas the model using Adam optimization yields a maximum accuracy of 99.83%. These findings are based on the experimental outcomes from the data set for a classification of 4 rice crop illnesses. With the healthy leaf picture dataset was included; the model with the Adam optimizer outperformed the model with the SGDM optimizer, yielding a highest accuracy rate of 99.66% & 97.61% during the 7th epoch, respectively.

A strong disease of plants classification system was introduced in 2022 by Albattah et al. [6] using a Custom CenterNet architecture with DenseNet-77 as the basis network. Three phases made up the method that was provided. Annotations were created in the initial stage to obtain the region of interests. Second, a refined version of CenterNet was presented, suggesting DenseNet-77 for the extraction of deep critical points. Ultimately, a number of plant illnesses were identified and categorized using the one-stage detector CenterNet. The PlantVillageKaggle databases, which served as the benchmark dataset of plant diseases and difficulties in the form of intensity changes, color changes, and variations in leaf shapes and sizes, was utilized by the authors in conducting the performance analysis. 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. 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 starting CMD with a sensitivity of 85%. The CMD infection level was distinguished using the area of the receiver's operators characteristics (AUC-ROC) curve by separating clearly no CMD from initial CMD (AUC = 0.92) & initial CMD from advanced CMD (AUC = 0.99). It was found that all chlorophyll of the leaves (Chl) content ($R^2 = 0.80$) and net photosynthesis rate (Pn) ($R^2 = 0.76$) had a linear opposite relationship with the PRI values calculated from the experimental data. The findings demonstrated that by using proximate sensing in outdoor plants, PRI imaging can be used to distinguish healthy plants with CMD and other stress-infected crops.

A dataset called NZDLPlantDisease-v1, which includes illnesses in five of the most significant horticulture crops in New Zealand—kiwifruit, apple, pears, avocado, and grapevine—was provided by Saleem et al. [8] in

2022. With the newly created dataset, an improved version of the best-obtained deep learning model has been developed for plant disease detection: the Region-based Deeply Convolutional Network (RFCN). Following the selection of the best deep learning model, many data augmentation methods were assessed one after the other. The impacts of batch normalization, weight initialization, deep learning optimizers, and picture resizers with interpolators were then examined. Lastly, empirical observation of anchor box specifications and position-sensitive score maps improved performance. Additionally, tests in an external dataset and a stratified cross-validation k-fold procedure were used to show the resilience and practicability of the suggested approach. The RFCN model's final mean average accuracy was discovered to be 93.80%, 19.33 percent greater than the default parameters that were used.

4 PROBLEM DEFINITION:

In order to accurately diagnose and classify plant diseases using the manual approach, one must possess sharp perception and expert knowledge. Plant disease identification by hand is both labor-intensive and prone to human mistake. As a result, automated plant disease detection and classification are needed. Deep learning-based models are developed for the detection and classification of plant diseases, whereas machine learning methods are not able to handle large volumes of data. Table 1 lists some of the characteristics and difficulties of the current deep learning-based crop disease detection and categorization model. CNN [1] effectively and automatically identifies and categorizes plant diseases. Yet, while the data for the input images is actually gathered from the field, this approach is not the best option for identifying and categorizing the plant disease. 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

Author [citation]	Methodology	Features	Challenges
Moupojou*et al.* [1]	CNN	This method allows for automated identification & classification of plant diseases.	Detecting and classifying plant diseases with this method are not the best option if the input image data is obtained directly from the field. To improve the overall performance of detection and classification, the model must be accompanied by additional segmentation processes..
Hosny*et al.* [2]	LBP and CNN	The computation speed of this approach is more. Accurate results are generated from this method.	This method is not generalized. This method is not practical.
Rani and Gowrishankar [3]	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. These models are vulnerable to overfitting issues.
Shewale, and Daruwala [4]	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.
Premananda *et al.* [5]	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.
Albattah*et al.* [6]	CenterNet and DenseNet	Localization and categorization of various types of plant diseases is made possible by this technique.	This technique cannot be implemented on mobile phone-based applications.

		Even when artifacts are present, this approach is highly robust.	This method suffers from time complexity issues.
Nair *et al.* [7]	PRI	The variation in the CMD degree can be identified accurately by this approach.	This approach is not entirely automated.
Saleem*et al.* [8]	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.

5 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.

6 OBJECTIVES:

The main goal behind this proposal is listed as follows.

1. To conduct a thorough assessment of the literature on a range of traditional deep learning-based models for plant detection and classification of diseases in order to gain a clear understanding of the shortcomings of the current model.
2. To develop an effective deep learning-based method for classifying and detecting plant diseases in order to minimize losses in total crop yield and hence assist in fulfilling the necessary demand for food.
3. To put into practice a novel optimization strategy to adjust parameters in the recommended plants detection and categorization of diseases model in order to improve the model's functionality and detection precision.
4. To demonstrate the improved performance provided by the developed model, compare the performance provided by the deep learning-based plants disease detection and categorization model.

7 RESEARCH METHODOLOGY:

The rate of agricultural production is critical to a nation's economic growth. However, the biggest obstacle to food production and quality is plant diseases. Early detection of plant diseases is essential to the health and welfare of the entire world. During on-site visits, a pathologist visually evaluate each plant as part of the standard diagnosis process. However, due to low accuracy and limited human resource accessibility, manual examination for agricultural di eases 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. Accurately identifying and categorizing plant diseases is a laborious task because of low-intensity information present in the background and foreground of the image, the striking color similarity between healthy and diseased plant regions, noise present in the samples, and variations within position, chrominance, framework, and size of plant leaves. As a result, this project would implement an effective deep learning-based model for identifying plant diseases and classification. First, the necessary picture data will be obtained from the internet databases. 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 ha been constructed will be demonstrated through experimental verification. Figure 1 shows a schematic diagram of a created deep learning-based model for plant disease detection & classification.

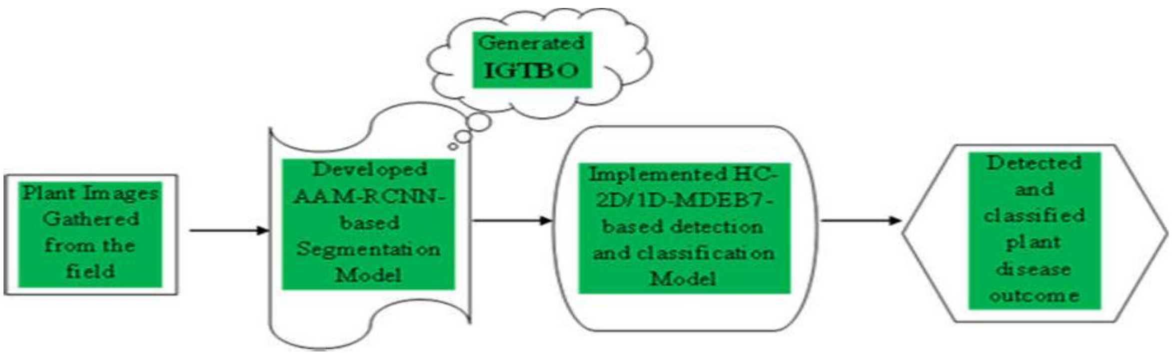

Fig. 7: Diagrammatic Representation of the Developed Deep Learning-Based Plant Disease Detection and Classification Model

8 Conclusion:

In order to validate the effectiveness of the model that was developed on the basis of various 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), a variety of experiments on the deep learning-based plant disease identification and classification models will be conducted in Python. A comparative analysis with existing approaches will also be performed.

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