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PLANT DISEASE IDENTIFICATION AND CLASSIFICATION USING ADAPTIVE SEGMENTATION TECHNIQUE

Manesh P. Patil
Research Scholar
Department of Computer Science and Engineering,
P. K. University, Shivpuri, MP, India
maneshpatil07@gmail.com
Prof. Dr. Indrabhan S. Borse
Research Supervisor
Department of Computer Science and Engineering,
P. K. University, Shivpuri, MP, India
indrabhan2000@gmail.com

Abstract

The world's food supply is derived from plants. Numerous ecological issues can cause plant diseases, which can cause noteworthy damages in output. Hence, identifying plant diseases by hand is a laborious and difficult process. For identifying plant diseases and halting their spread, this method isn't always reliable. Modern methods like artificial intelligence (AI) and predictive models help solve these obstacles and enable the primary study of diseases of plants. The most current developments in the use of data mining and deep understanding (DL) methods for plant infection analysis are examined in this research. The study's main objective is to ascertain how successfully it can detect plant illnesses. The limitations and difficulties when applying the two methods to make diagnoses of plant illnesses are also covered in this study. They involve problems with imagery quality, accessibility of data, and the ability to distinguish between good and unhealthy plants. It deals a detailed grasp of the state of the study of the subject at the moment, enumerates the advantages and disadvantages of different approaches, and suggests viable solutions for problems with execution. For researchers, practitioners, and industry experts engaged in plant disease detection, all of these components contribute to the provision of useful information. In this work, we suggest a hybrid approach to early illness identification that uses both RC-NN for diseases categorizing and RFV-CNN.

Introduction

Food quality and the maintenance of the worldwide economies depend on agribusiness. Diseases of the plant, nevertheless, are an important danger to crops, endangering food distribution networks and resulting in large revenue losses. For crop illnesses to be effectively managed, rapid and accurate identification is crucial. This allows growers to minimize crop loss through both preventive and remedial actions. As part of conventional diagnostic techniques, farmers do physical checks, which may be time-intensive, laborious, and susceptible to mistakes made by people. As computer vision and machine learning keep on improving, unmanned diagnosis of plant illnesses solutions are emerging as a viable substitute. Such systems use algorithms that process images to identify and categorize illnesses according to indications that appear on foliage, roots, and

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nuts. Another of the many techniques for image analysis used to identify illnesses in plants is separation. By dividing a picture into relevant segments, segmentation makes it easier to concentrate on the impacted areas [1].

Diseases characteristics including areas, tumors, and discoloration may be effectively isolated for additional investigation provided division is done appropriately. Dynamic systems for segmentation are a potent way to improve the proof of identity and classification of plant illnesses. These methods have the ability to greatly improve the world's food supply and sustainable agriculture by tackling innate problems and utilizing developments in AI and computer vision. It is anticipated that additional studies and developments in this area will result in precise, flexible, and dependable diagnostic systems for real-world agricultural uses. Plant diseases may be correctly recognized and categorized using a variety of methods. Limitations and challenges still need to be resolved. In addition to providing a thorough explanation of the benefits and limitations of both techniques for crop disease detection, this work emphasizes the current state of knowledge in this field [2].

Crops are more susceptible to illness because of the abundance of viral in the atmosphere [9]. "Plant disease" refers to any abnormalities of the body or structure affected by a living creature [10]. Plant pathogens or surroundings are the cause of plant illnesses [11].Insufficient food, animal diseases, microbiological assault, and poor surroundings are the primary causes of plant diseases [12]. One of the main factors reducing agricultural output worldwide is plant disease by pathogens. The severity of the illness increases when several harmful bacteria attack crops either independently or together [13]. Due to their capacity to harm produce, plant illnesses pose a danger to nutrition by decreasing food source and raising food costs [14]. To attain and maintain sources of income and food security for more people worldwide, protecting plants from diseases is more important [14]. Visual examination is frequently used to identify plant diseases; pathogenic effects often rarely noticeable till the plant has sustained substantial harm. Automated plant disease identification has a lot of promise [15].

Proper recognition and management of these illnesses is crucial since it increases crop yields and quality while lowering the requirement for pesticides [16]. With individual surveillance, it can be challenging, subjective, and complex to identify some disorders [17]. To meet the demands of an increasing population, computerized devices that let producers monitor vegetation at all stages of development are thus required. Using imaging analysis to identify diseases of plants is one of the most important aspects of precision research in agriculture [18]. The visual inspection of plant tissues by qualified professionals is the foundation of the conventional approach of documenting the seriousness of plant illnesses [19]. The widespread adoption of digital monitors and the development of farming equipment have led to a wider application of

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growth and leadership expertise, which has significantly expanded the potential for plant output [18]. However, human systems' ability to gather and define illness and pest traits is heavily reliant on expert knowledge, which makes them inefficient and expensive [20]. Numerous artificial intelligence methods are now available for the identification and classification of plant diseases. Automated SVM, logistic regression (LR), and trees of decisions are among the most often used methods [3]. K neighbors (K-NN) and multilayer artificial neural networks [21]. To inspire the extraction of features, these procedures are coupled with a number of picture pre-processing approaches. One supervising learning approach is the K-NN. It uses similarity metrics to categorize the data. K-NN uses nearby known items to classify unlabeled things. The choice tree is one of the algorithms that use diagrams. The stems and leaves stand in for the courses, the limbs for the connections' potential outcomes, and each node for the chosen attributes. Decision tree models do have certain drawbacks, though, such excess fitting of the data and overlapped nodes. Regression evaluation and classification learning techniques may be linked to SVM, a popular trained learning model, using statistical learning ideas. Over the past ten years, SVMs have been increasingly popular for classifying both text and images. Using the preceding machines detecting approaches, traditional image processing methods including reducing noise, morphology activities, and image improvement are usually used to pre-processed photographs of diseased plant leaves [22]. Minor details about the foliage, including their appearance, hue, and form, are then recorded using manually developed feature extraction techniques [23].Techniques based on deep learning have been successfully applied to problems such as division, categorization, and object identification in recent years [24]. The most popular methods for deep learning problems have been CNN methods. Despite being widely utilized in the identification of crop diseases, the basic CNN architect DenseNet and ResNet—have several important disadvantages, such as sluggish computation rates and the requirement for several variables. The methods of deep learning tend to be less reliable for defining localized spatial features, even if they have demonstrated the capacity to present all a high degree and low-level details [25].photographs of Standard, Gray-spot, Black-mold, Late-mold, Bacterial spot, and Powdery mildew are included in the information contained in the set of plant photographs in Figure 1. The results of the hybrid strategy and Neural based approaches are compared.

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Apple scab

Apple Black rot

Apple Cedar apple rust

Apple healthy

Fig. 1: Dataset Images

Literature Review

Several deep learning methods were presented by Moupojou et al. [1] in 2022 to assist producers in identifying crop illnesses as quickly as feasible in order to prevent production losses. Plant illness datasets such as PlantDoc or PlantVillage, which are either privately owned or publicly accessible are often utilized for training these computer models. PlantVillage consisted of single-leaf images captured in a lab setting with a uniform backdrop. The simulations created featuring this set of images exhibit very low reliability when used on field photographs with intricate backgrounds and multiple leaves per image. In order to address this issue, 2,568 field photos that were uploaded on the internet and tagged to identify each individual leaf were used to build PlantDoc. The set did contain some scientific photographs, though, and the lack of information from pathologists throughout the annotation stage could have resulted in incorrect diagnoses. FieldPlant, a collection of 5,171 plant disease photos taken straight from plantings, was recommended for this investigation. To guarantee procedural excellence, each photograph's particular leaves were hand tagged under the guidance of plant pathologists. This led to 8,620 distinct annotated leaves from the 28 disease categories. Comparing the proposed model against the state-of-the-art categorization and recognition of objects approaches on several sample datasets, FieldPlant fared better than PlantDoc on tasks

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such as classification. However, since some lab photos have been included in this collection and plant pathologists weren't present across the inscription process, misunderstanding may have occurred. Plant pathologists oversaw the manual annotation of every leaf on every photograph to guarantee the process's quality. The FieldPlant dataset, as recommended for this study, had 5,171 photos of plant illnesses that were obtained straight from plantations. This resulted in 8,620 distinct tagged leaves for every one of the 28 disease categories. As contrasted to the most advanced classification and recognition of objects methods, the proposed model performed better than PlantDoc in FieldPlant classification tasks on a variety of benchmark datasets.

In 2022, Hosny et al. [2] established a revolutionary condensed deep a CNN model to generate high-level unseen depictions of features. Regional texture data was recovered from images of plant leaves by fusing complex characteristics with conventional generated binary pattern (LBP) features. We used three publicly accessible datasets to train and assess the proposed model. On the three datasets, the suggested method obtained 98%, 97%, and 99 validation accuracy and 98 %, 97 %, and 99 % tested efficiency. The research findings indicated that the recommended strategy offered a more effective way to control plant diseases. A pathogen-based approach to plant disease detection was introduced by Rani and Gowrishankar in 2023 [3]. Keras transfer learning models were used to autonomously detect, classify, and identify the microbe causing plant diseases. To achieve this, pictures of sunflowers and cabbage foliage, blossoms, and bulbs taken in real-world settings were taken into consideration, in addition to the Agri-ImageNet collection. This collection overcomes the limitation of the PlantVillage dataset, which featured photos with standardized backgrounds and controlled conditions. By employing deep transfer learning to reuse information depictions, these issues have been resolved. In the field of plant illness detection and classification, adaptive segmentation approaches have become a significant invention, providing dynamic ways to deal with changes in environmental factors, plant shape, and disease features. Segmented unhealthy areas in plant photos using adaptive thresholding algorithms to improve segmentation accuracy, they used preprocessing techniques such color normalization and noise reduction. This paper's primary goal was to analyze and evaluate each deep transfer learning model in order to determine which one was most suitable for the crop dataset. This study used 38 deep transfer learning models to get the highest classification accuracy fig.2 represents a few leaf picture dataset samples.

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Cherry healthy Leaf


Cherry Powdery mildew


Corn maize Grey leaf spot


Corn maize Common rust


Corn maize healthy


Corn maize Northern Leaf Blight


Strawberry healthy


Strawberry Leaf scorch


Grape Black rot


Grape Esca Black Measles


Grape Leaf blight


Grape healthy

Fig. 2: A few leaf picture dataset samples

Problem Definition

Correctly identifying and categorizing plant diseases by hand requires specialized expertise and acute attention. Crop disease identification by hand takes a lot of effort and is susceptible to error by humans. As a result, automated plant pathogen categorization and diagnosis becomes necessary. Deep intelligence-based models are created for the diagnosis and categorization of agricultural illnesses as artificial intelligence methods cannot handle enormous volumes of data. Table 1 lists some of the categorization and problems of the present deep learning-driven model for the identification and categorization of plant diseases. CNN

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efficiently and autonomously detects and classifies plant illnesses [1]. Nevertheless, since the visual input data is really gathered in the field, this approach is not the most efficient means of identifying and categorizing the plant's condition. The representation must be used in combination with additional segmentation algorithms to improve the total recognition and categorization performance. The calculation performance of CNN and LBP has improved [2].This methodology produces accurate results. This approach isn't general, though. This is not a feasible approach Transferal learning [3] facilitates the implementation of suitable preventative measures by accurately predicting the microbes responsible for illnesses in plants, Still, these approaches do not successfully extract the most main outlines and traits. The representations in question may have excess fitting problems. Any kind of crop may be used using CNN, which is a broad approach [4]. This strategy can be used in practical situations. This approach, however, is unable to identify the identified plant disease. This method does not aid in decision-making. CNN [5] and the optimizer created by Adam employ less parameter. This approach may be used by farms to acquire effective tools for diagnosis and make wise preventative decisions. However, this model is unreliable. Moreover, this approach's durability is insufficient. Plant illness classification and localization are made possible by CenterNet and DenseNet [6]. This method is quite resilient, even in the presence of artifacts. However, this strategy cannot be used by applications that run on handheld devices. This method's complexity over time is a problem. The distinction between the CMD degrees may be accurately determined using PRI [7]. On the other hand, this method is not fully automated. Diseases of plants that affect any section of the plant can be identified using RFCN [8]. However, this method's general efficacy is still insufficient. This initiative will thus develop a model that utilizes deep learning for the identification and categorization of plant illnesses.

Table 1: Properties and Challenges of the Present Deep Learning-Based Model for Plant Disease Identification and Categorization

Author [citation]	**Approach**	**Properties**	**Challenges**
Moupojou *et al.* [1]	CNN	• This method enables the automatic identification and categorization of crop diseases.	• This approach is not the best option for identifying and categorizing plant diseases whenever the data for the input images

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			is taken straight from the field.
Hosny *et al.* [2]	LBP and CNN	• The calculation speed of this method is faster.	• This method is not practical or generalizable.
Rani and Gowrishankar [3]	Transfer learning	• This method helps with taking the right measures because it accurately predicts the microorganisms that cause illness in the plants.	• The key shapes and characteristics are not efficiently extracted by these techniques. • Over-fitting issues can arise with these models.
Shewale, and Daruwala [4]	CNN	• This method is universal and can be applied to any type of crop.	• The identified plant disease cannot be diagnosed using this method.
Premananda *et al.* [5]	Adam optimizer and CNN	• Farmers can use this method to make suitable preventive decisions and obtain efficient diagnostic tools.	• Moreover, the robustness of this approach is inadequate.
Albattah *et al.* [6]	CenterNet and DenseNet	• This technique makes it possible to identify and categorize many plant diseases.	• Mobile phone-based applications are unable to use this strategy. .
Nair *et al.* [7]	PRI	• This method allows for an accurate identification of the variance in the CMD degree.	• This method isn't totally automated.
Saleem *et*	RFCN	• This approach can identify	• This strategy does not

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al. [8]		plant illnesses that affect any part of the plant.	provide sufficient overall performance.

Problem Statement

The following is a list of some of the issues with the present paradigm for identifying and categorizing plant diseases.

- Agriculture is the foundation of the world economy, providing billions of people with food security. However, crop yields are seriously threatened by plant diseases, which result in financial losses and decreased agricultural production. Plant illnesses must be recognized early and accurately in order to lessen their effects. Manual inspection is the foundation of traditional disease detection techniques, and it is labor-intensive, time-consuming, & prone to human mistake.
- Automated solutions for plant disease identification have showed promise with the growth of artificial intelligence (AI) and image processing technology. However, because of differences in lighting, backdrop complexity, plant shape, and the diversity of disease symptoms, these systems have a difficult time precisely identifying diseased areas.
- Individual of the most important steps in the identification of plant diseases is image segmentation, which entails dividing images into relevant areas in order to distinguish sick areas from healthy tissues and unimportant backdrops. Many segmentation techniques, including edge detection, thresholding, and clustering, have poor generalizability and frequently struggle to adjust to a variety of environmental situations. Convolutional neural networks (CNNs), a type of deep learning method, require huge labeled datasets and can be computationally costly, despite their increased accuracy.
- Adaptive segmentation techniques offer a dynamic solution to these problems by modifying parameters according to the properties of the image. These methods have the potential to decrease reliance on manual intervention, increase segmentation precision, and strengthen disease detection systems. However, there are still unanswered questions about how to best optimize adaptive segmentation techniques for practical agricultural applications, especially when it comes to managing complicated datasets and attaining scalability.
- Investigating and creating sophisticated adaptive segmentation methods for plant disease categorization and detection is the goal of this study. The project aims to solve existing constraints in

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order to help develop effective, precise, and broadly applicable solutions for food security and sustainable agriculture.

Research Methodology

The level of agricultural output in a country has a significant influence on its growth in GDP. The biggest obstacle to ensuring food supply and excellence, nevertheless, is disease in plants. The rapid identification of plant infections is essential to maintaining global wellness and good health. During on-site inspections, an expert in pathology physically evaluates every plant as a component of the routine diagnosis procedure. Yet, a shortage of labor and the low reliability of manual disease examination limit its application. The creation of computerized methods that can precisely identify and classify a wide range of plant illnesses is necessary to address such problems. New viruses are constantly emerging on leaves of plants as a result of continuous modifications to crop structure and cultivation methods. Consequently, early identification and precise categorization of diseased plant leaves would prevent the infection from developing and promote robust plant output growth. It is difficult to accurately identify and classify plant diseases due to the striking color resemblance among normal and infected plant regions, disturbances in the specimens, a low-in data present in both the forefront and the background of images, and variations in the dimension, location, colors, and arrangement of leaves on plants. With this concept, an efficient machine learning model will be used to identify and classify plant illnesses.

The necessary picture data will first be obtained from internet databases. An adjustable and attention-based masked region-based neural network with convolution (RCNN) (AAM-RCNN) will be used to process the collected pictures as inputs for the segments step. For better categorization effectiveness, the Integrated Golden Tortoises Bug Optimization (IGTBO) will be used to adjust the AAM-RCNN's settings [26]. After segmenting the images, Mixed Convolution (2D/1D) and Multi-scale Dilated EfficientnetB7 (HC-2D/1D-MDEB7) will be utilized for detection and classification. In the case of Hybrid Convolution (2D/1D) designs, the 2D convolutional layer employs textural sequences as input, whilst the 1D convolution layer incorporates color and morphology information. In the end, the detected and categorized result will be provided by the HC-2D/1D-MDEB7 modeling. The use of the deep learning-powered approach to plant disease detection as well as classification will be demonstrated through testing. A graphical depiction of recognizing and categorizing a model is shown in Fig.3.

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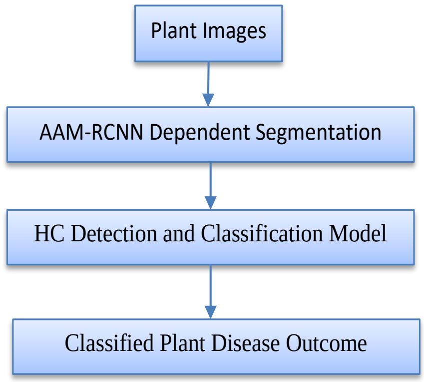

Fig. 3 shows a diagrammatic representation of identification and classification model.

Conclusion

The degree of sensitivity Precision, Particularity, and Negative Prediction Value are among the several favorable metrics that were used to validate the efficacy of the constructed model. A number of studies including the deep learning-based crop identification and categorization model will be carried out in the programming language Python. The results of these studies will include the following metrics: False Negative Rate (FNR), False Positive Rate (FPR), and False Discovery Rate (FDR), as well as the negative metrics, F1Score, Precision, and Mathews Correlation Coefficient (MCC). Additionally, a comparison of current approaches will be conducted.

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