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Advanced Hybrid Model for Multi Paddy diseases detection using Deep Learning

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Abstract

INTRODUCTION: Rapid developments in deep learning (DL) techniques have made it possible to find and recognize objects in pictures. To create a network that is significantly more successful than a single CNN, GAN, RNN, etc., we can mix various neural network models (CNN, GAN, RNN).this combination is known as hybrid model. Hybrid model of deep leaning is give more accurately result for detection and identification of paddy diseases.
OBJECTIVES: I have studies outcome of hybrid model 1(DCNN+SVM) and Hybrid model 2 (DCNN + Transfer Learning) to increase accuracy of Rice plant disease detection and classification. The Researched model detects multiple rice plant diseases and it is giving same result in multiple data sets.
METHODS: The Proposed System have used Deep Learning Image Processing algorithm and neural Network Like DCNN ,SVM and Transfer Learning .The brand new model is DST where D stands for DCNN, S stands for SVM and T stands for transfer learning.
RESULTS: The Researched DST model achieved 95% Training accuracy and 85% validation Accuracy. The Researched model detect multiple rice plant diseases and it is giving same result in multiple data set.
CONCLUSION: The proposed model combined 2 existing model and developed hybrid model that a detect various rice plant diseases with better accuracy from available existing model.

Keywords: Rice Plant, CNN, Leaf diseases, ML, DCNN, DL, SVM, Transfer Learning

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1. Introduction

The nation's economy is significantly impacted by the cultivation of rice. Our economic and social life are both significantly impacted by the illnesses that affect rice harvests. Regular rice plant monitoring enables farmers to identify sick plants at an early stage and take the necessary action to recover them. However, the classification systems in use today for plant diseases are primarily dependent on physical monitoring by farmer. This kind of farmer derisive method is time- and labor-demanding [1]. The government should use agricultural instructors to provide technical understanding about those items because individuals of younger generations do not have much awareness about those illnesses. Due to the many various illnesses, it can occasionally be a challenging assignment because even the teachers cannot accurately forecast the condition without visiting the area. Due to these factors, you may see how crucial it is to employ an effective solution to this issue. It would be a very good answer to this issue if farmers could recognize rice illness with the help of a piece of software. The application of deep learning techniques to recognize these disorders has been the subject of numerous studies recently. Some of these studies have utilized DL theories and algorithms, many of them have created their own algorithms to solve this problems [2]. Because deep learning (DL) approaches extract the crucial facts differently from the image dataset, they are currently more

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effective than machine learning techniques. Neurons are used by deep learning to simulate human thought (Le. Brain).DL is developed and using a multi-neural network architecture with various hidden layers to predict the required outputs. The field of image detection has made extensive use of neural networks (CNN), one of the network designs included in deep learning [3].

2. Rice plant diseases

Rice Plant diseases are mostly due to bacteria, fungus, viral and disorder that are discussed briefly as followings.

Table 1. Rice Plant Disease

Disease Name	Brief Description
Bacterial Blight	Symptoms like this are caused by bacterial infections. Based on how effectively they are fed, bacterial illnesses are categorized. When dealing with the bacterial problem, the term "Bacterial leaf spot" is usually used [4].
Bacterial Leaf Strike	The bacterial leaf streak is brought on by the pathogen Xanthomonas oryzaepv. Oryzicola.In diseased plants, the leaves start to brown and dry out [5].
Foot Rot	Sign of the Balancing Malady, commonly known as Fusarium moniliforme.Infected nursery seedlings are skinny and narrow and soon decompose [6].
Grain Rot	Burkholderia glumae Symptoms & Symptoms B.glumae-infected seedlings display signs like leaf sheath disease and wilting [7].
Pecky Rice	The term "kernel spotting" describes this phenomenon. Typically, this is caused by fungus development and stink bugs [8].
Bacterial Sheath Brown Rot	Sheath plant disease is brought on by the pathogen Pseudomonas fuscovaginae. It leads to a freak out in the roots, grains, and sheath of young and more mature plants [9].
Blast	The blast is one of the most common diseases affecting grain output in the grain sector. This frequently occurs as a result of the Magnaporthe Oryzae fungus [10].
Sheath Blight	Paddy plants harmed by tungro frequently exhibit stunting and decreased tillering [11].
Sheath Rot	In the flag leaf sheath, sheath rot manifests as irregular lesions or patches [12].
Brown Spot	In some situations, seedlings develop instead of the majority of the field in which they are planted. Many leaves may have this brown stain on them [13].
False smut	During a panicle, The remaining fragments should be natural because only a small percentage of them are harmed by green smut [14].
Grain discoloration	Will take place during the milking process inside the grains. Due to discoloration, brown or black spots show up on the surface of grains [15].
Alkalinity disorder in rice	In this Disease, Alkalinity slows the growth of roots by limiting the nutrients and water available to them [15].
Bronzing disorder in rice	Rice cannot grow if there is insufficient bronze.
Zinc deficiency	After transplanting rice seedlings, the plant is impacted by a zinc deficit [16].
Cold injury	Cold temperatures typically harm rice plants from germination to grain filling. As the temperature drops, less seed germination and cold damage occur [17].
Panicle blight	Paniculate blight kills seedlings and rough rice grain. Burkholseriaglumae, a fungus, is to fault. Stomas, such as hydathodes, can develop on the bottom and edges of leaves as a result of insect pressure and other environmental factors [18].
Straight head on rice	In fields of rice that have already been planted, the straight head will continue to exist so far as floods are not effectively ditched and improper aeration of the soil is [19].
RiceTungro	Paddy plants harmed by tungro frequently exhibit stunting and reduced tillering. Its leaves develop rust-colored patterns and turn yellow or orange-yellow.
Rice grassy stunt	Rice plants may stop if they become infected with a virus that resembles rice grass [20].
Rice ragged stunt	A viral infection that causes rice clusters to partially expel, leaving behind empty grains and fewer plants, lowers crop productivity [21].
Rice yellow mottling	The sickness can be caused by the Sobemo virus [22].

3. Literature Review

A. Paramananda et al. [23], to identify diseases in rice plants, the author proposes a hybrid model that incorporates feature extraction from the Gray Level Co-occurrence Matrix (GLCM) with Neural Network and Evolutionary Process models. The evolutionary algorithm in this work makes use of the genetic algorithm (GA).

P. Kartikeyan et al. [24] to find and categorize plant illnesses to a degree of 95.16 to 98.38%, the author proposed a hybrid model that joins discrete wavelet transform (DWT) and GLCM feature extraction with an SVM classifier. This technology performed better than other models [24].

Ganesan et al. [25] the primary goal of this project is to create a novel model for detecting rice leaf illness utilizing multiple DL approaches.

B. Ahmed et al. [26] the approaches to deep learning that have shown the most potential for further study. It separates the three eras of rice-related writing. It outlines methods and procedures for grading the quality of rice and identifying illnesses.

S. Ramesh et al. [27] discuss concerns relating to the nomenclature of illnesses in plants utilizing ML and DL, as well as the many stages of disease identification and categorization using a variety of techniques.

B. S. Ghyar et al. [28] Suggested artificial neural networks (ANN) and SVM categorizes different plant diseases, with SVM accounting for 92.5 % and ANN for 87.5 %.

F. T. Pinki et al. [29] JAYA, a suggested optimization technique and optimized neural network for disease classification, also suggested a SVM classifier.

S. V. Militante et al. [30] suggested a method for locating diseases using about 35000 data sets. Many plants can be identified using DL. The novel research can be used to identify more plant diseases.

W. L. Chen et al. [31] One of Rice Talk's many appealing advantages is that it manages AI models like other IoT devices. The author's approach lowers the platform's operating costs such that real-time training and projections are available. The author also extracted agricultural features using spore germination as a model. The current rice blast forecast from RiceTalk is 89.4% correct.

S. M. Hassan et al. [32] with the help of data from three plant diseases, the model was trained and verified. The accuracy of the datasets for rice disease, cassava, and plant villages is 99.66%, 76.59%, and 99.39% respectively. The suggested model performs better than the most complex deep learning models with less parameters.

F. Nihar et al. [33] employed numerous NN Algorithms, including other algorithms, and created a novel updated neural network architecture that produced 97.69% accuracy.

M. Sardogan et al. [34] to analyze and categorize tomato leaf disease, they have suggested a CNN and LVQ algorithm-based technique. In plant leaf illnesses investigations, the usage of color information is widespread.

Al Bashish et al. [35] suggested the photos of the sick leaves were clustered using the K-means algorithm. After that, a NN classifier was used to classify the clustered images. The outcome said that the NN classifier accurately diagnosed leaf diseases with a 93% rate. The accuracy and automaticity of the framework's detection of leaf diseases are really helpful.

Zhu et al. [36] hyperspectral imaging's potential as a quick, non-invasive detection method was studied. In a short amount of time, they were able to identify the Tobacco Mosaic Virus (TMV) illness utilizing hyperspectral imaging in conjunction with the variable selection approach and ML classifiers.

H. F. Pardede et al. [37] ANNs are increasingly used for assessing and forecasting water supplies. In comparison to conventional methods, ANNs have the advantage of requiring less understanding of the intricate format of the concealed work to automatically produce features and disclose intricate visual features from raw data.

Ghosh M et al.[38] The great learning capabilities of DL approaches also enable them to perform a large range of problems very successfully and to readily adapt to a variety of extremely complex problems. Multiple ML techniques for recognizing plant illnesses are presented in this rework, together with a list of their shortcomings.

M. Lamba et al. [39] covers the computer vision task of categorizing the information and structure of a digital image to detect plant species diseases. Research in computer vision focuses on creating methods that enable machines to perceive.

Nanehkaran et al. [40] covers the computer vision task of categorizing the information and structure of a digital image to detect plant species diseases. Research in computer vision focuses on creating methods that enable machines to observe.

Thomos et al. [41] examined the advantages of hyperspectral imaging for farming crops. Various kinds of hyperspectral locater and hyperspectral metrics are used in this review. The main problem with this approach is its high computational cost.

Deisy et al. [42] discussed several segmentation techniques used in a leaf investigation technique. The researchers experimented on infected leaf samples using a variety of segmentation techniques.**Vani et al.** [43] it is suggested that to obtain the required picture component, the time-sensitive image should first go through a median filter pre-processing step before being categorized using the k means clustering method. Textural properties are recorded using the green supply chain management (GSCM), which is then contrasted with an image of a good cotton leaf.

Pujari et al. [44] introduced a DWT that is utilized to automatically extract, and then the principal component analysis is utilized to decrease (PCA). The characteristics are then used as sources for classifiers after the features have been reduced, and probabilistic neural network (PNN) classifiers are used to categorize image samples.

Sapkal et al. [45] when illnesses and insects in rice seedlings are accurately and sensibly diagnosed, farmers can provide urgent care for the plants and considerably reduce economic harm. For the detection and diagnosis of rice illnesses and parasites, large-scale designs have also been used.

4. Approaches Used in Proposed System

4.1 CNN and DCNN

R. Sharma et al. [46] developed a CNN prediction model and categorization of diseases affecting rice crops, which had a 93.58 percent training dataset accuracy.
J. Hasan et al. [47] Using a dataset size of 1080 images, the authors uses a DCNN-based and AI technique that produced an accuracy result of 97.5 percent.
R. J. Bharathi. [48] Images of the rice blast disease were correctly identified by the author using an AlexNet model with a 96.50 percent accuracy.
M. J. Hasan et al. [49] to identify rice illnesses, the scientists created a modal that combines deep neural networks and computer vision. This was assessed using three basic pre-trained models and six different datasets related to rice disease.
Lu et al. [50] a deep convolutional neural networks (DCNN) based study that took into account 10 prevalent diseases for identification was proposed to identify diseases affecting rice. They made use of 500 or so image samples. Yet, a DCNN was unable to fully classify 10 rice diseases using this short dataset. Nonetheless, According to the author, their accuracy percentage is 95.48%.
Krizhevsky et al. [51] Crop disease detection make extensive use of the DCNN, which is excellent in picture categorization and identification.
Liu, W et al. [52] to effectively identify grape leaf illnesses, the author created an enhanced convolutional neural network, and the map was 81.1%.

4.2 SVM and Transfer Learning

Nagasubramanian K et al. [53] the author combined SVM with Genetic Algorithm (GA), an optimizer, to choose the best spectral bands for the early detection of the soy-bean disease charcoal rot. Within three days of inoculation, the GA-SVM technique correctly classified the disease as charcoal rot with a 97% classification precision.
Zhu et al. [54] tobacco leaves were investigated using Backpropagation in neural network(BPNN) in combination with SVM, Extreme Learning Machine (ELM), Least-squares SVM(LS-SVM), Partial Least-Squares Discriminant Analysis(PLS-DA), LDA, and Random Forest (RF) by processing hyperspectral images.
Jason Brownlee [55] the author describes Transfer Learning as a method that uses trained models from earlier, related jobs to train current models. There are numerous different types of explanations offered.
Matsubara T et al. [56] the author utilized TL approaches. The dataset and literature are based on real-life simulations including Transfer component analysis of policy from models of the actual world.
Kouw WM et al. [57] with enough tailored data on each target driver's behavior, TL can be used to target driver behavior. Even with limited target domains and small or huge amounts of data, TL can still show the outcome.

5. Proposed System

In This Research we have combine 2 existing hybrid model (Hybrid Model 1= DCNN & SVM Classifier and Hybrid Model 2 =DCNN & Transfer Learning) for better accuracy, execution speed and Result .the basic steps of Plant disease Detection are as following.

5.1. Image Acquisition

The initial step in the procedure is to gather the picture data that will be the input for subsequent processing. Using Kaggle.com, data mene delay, and the California ML Repository, a dataset of online rice leaf illnesses has been collected. The images were then categorized into some types of rice plant illnesses. For each category, training and testing sets have been created from the available data. The dataset was acquired in order to research rice leaf illnesses, which are useful for identifying and classifying problems.

5.2. Image Pre-processing

Pre-processing techniques are used to enhance the picture data, including picture cropping to alter the size and form of the picture, picture smoothing to remove noise, and picture enhancement to boost contrast and convert colour.in the proposed system following python library is used for image preprocessing.

- **Keras:** We can easily execute data augmentation thanks to the Image Data Preprocessing class in Keras.
- **Matplotlib:** One of Python's widely used packages for data visualization. It enables us to create graphs and charts and makes it very simple to create static raster or vector files without the use of any GUIs.a really helpful package for manipulating arrays rationally and mathematically.
- It is used to open and work with our picture file using a Python Imaging Library.

5.3 Image Segmentation

The process of image segmentation divides a digital picture into tiny groups called as image segments, which lessens the complexity of the picture and makes each part easier to process or analyze**.** Each pixel in a picture is given a label using segmentation so that objects, people, or other important details may be distinguished**.** There are several image segmentation algorithms but in the Proposed System Neural networks is used for Image Segmentation. In the Proposed system tensorflow, keras Python Library used for image recognition and segmentation.

5.4 Features Extraction

In the classification of diseases, feature extraction is crucial. The classification of plant diseases uses color, texture, and morphology to extract features in numerous applications. The term "texture" refers to the image's hardness, roughness, and color distribution. For identifying leaf diseases, morphological feature extraction is superior to color and texture feature extraction. In the Proposed system DCNN model is used for features extraction. Feature extraction presents the main difficulty in this disease detection. Every illness is unique from others. Different portions and sizes of the leaf may become infected with each disease.

- **DCNN:** DCNN Stands for Deep Convolutional Neural Network. A nonlinear classifier can use the DCNN to extract all similar data from the actual input and display it in a lower-dimensional space. As a result, it is regarded as a crucial post-processing step as a classifier will not be able to accurately identify images for poorly picked features. The most significant benefit of employing DCNN is the meticulous extraction of all distinctive elements from an image.

5.5 Disease Classification

The most difficult task in image processing is classification. To accurately predict a discrete class variable's value given a vector of predictors or qualities is the basic goal of classification. If a picture is infected or not determines how the disease in question is classified in plant disease detection. However, while the abstract layer of the DCNN has the maximum useable parameters, it is not necessarily ideal as an image classifier so in the proposed system we have used SVM.SVM Stands for Support Vector Machine. SVM eliminates this obstacle and provides us with a one-dimensional feature vector that has been precisely extracted with excellent classification accuracy. Since then, to create a complicated network with the highest classification accuracy for photos of rice sickness, we have explored a DCNN model that uses the SVM, a simple yet effective classifier. Transfer learning is a machine learning technique that enables convolutional neural networks to be trained for one task so that they can serve as the basis of models for other tasks. Transfer learning has the advantage of reducing prediction exceptions and shortening the training period for learning models. The result of SVM Classification is retrained in Transfer Learning to increase Accuracy. The Researched DST model achieved 95% Training accuracy and 85% validation Accuracy. The flow of the Proposed DST Model is shown in the following Figure 1 and the Result analysis is shown in Figure 2.

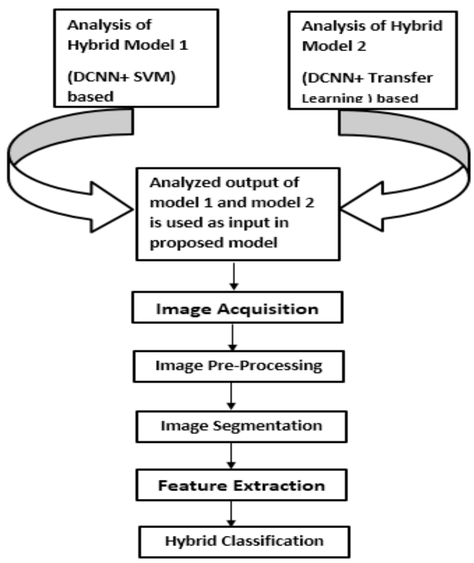

Figure 1. Flow of Proposed Model

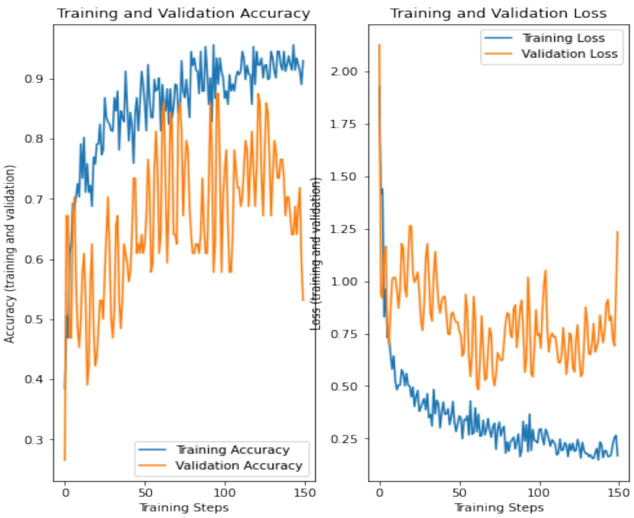

Figure 2. Training & Validation Accuracy & Loss of Proposed System

6. Conclusion

Due to the large spectrum of diseases that might affect rice crops, efficient disease detection methods must be developed. A significant difficulty for the farming community is keeping track of the crops in the field and protecting them from diseases. Deep learning has made it simpler to identify crop diseases thanks to recent technological improvements and advancements. In my proposed system I have developed an effective and precise method for automatically detecting rice plant diseases. In this proposed system I have used power of deep learning for image processing. Using Kaggle.com, data mene delay, and the California ML Repository, a dataset of online rice leaf illnesses has been collected. Image processing is been performed using available python library like keras, matplotlib, numpy, pillow etc. With the Proposed System, image segmentation is done using neural networks.Tensorflow and the Keras Python Library are utilized in the proposed system to recognize and segment images. The DCNN feature extractor allows a nonlinear classifier to take all identical data from the initial input and present it in a lower-dimensional space. SVM overcomes this challenge and gives us an excellently extracted, one-dimensional feature vector with great classification accuracy. SVM Classification's output is retrained using transfer learning to improve accuracy. The proposed model combined 2 existing model and developed a hybrid model that detects various rice plant diseases with better accuracy than the available model.

7. Future Scope

There are certain issues with the research despite the proposed DST model's excellent effectiveness in detecting rice leaf disease. Only the available dataset of Rice plant leaves was used to test the validity of our suggested model. You can use recent photographs from the rice field in your future projects. We want to give larger and more varied datasets in a subsequent study to test the suggested model. Also, we'll attempt to improve our model so that it may be used with additional datasets, such as those related to rice plants or other plant leaf diseases. To classify expanding categories of rice plant diseases and automatically identify the various stages of the disease, further research is required to enhance this model. Through greater adaptability and generability, we intend to lessen the time complexity and spatial complexity of future development.

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