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Rice Leaf Disease Detection and Diagnosis Using Convolution Neural Network

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Abstract - Agriculture is the art and science of soil cultivation, crop production, and livestock management. The majority of the world's food is produced by agriculture, where paddy fields are most often cultivated crops and its diseases are the main problem of its loss. Rice is an example of a global crop, and India is ranked second in rice production. A technique that detects the leaf disease will greatly help farmers and agriculturists. The agriculture industry must overcome this loss due to the affected leaf diseases that bring down the production. As per studies, it is found that various types of diseases affect the leaf, such as infectious and non-infectious.
This paper proposes a method to detect and diagnose rice leaf diseases with appropriate remedies. This research has considered five diseases - Leaf Blast, Hispa, Tungro, Leaf Blight and Brown Spot. Input images are segmented manually by removing their background if too many noises are seen. The model predicts the type of disease that affects the rice plant from an uploaded image or an image freshly clicked using a smartphone. Further, some preventive measures to overcome those diseases are suggested. Our model gave a sensitivity of 94.68% and a specificity of 66.66% resulting in an overall accuracy of 93%.

Key Words: Classification, Deep Learning, Disease detection, Image processing, Disease Diagnosis

1.INTRODUCTION

Cultivation is one of the high-risk jobs in the world. Plant diseases threaten crops and farmers whose lives depend on healthy crops. An expert agriculturist or farmer can identify these diseases from the plant leaf, but in most cases, prediction of diseases is very difficult (Vinod, 2021). Diagnosis of plant diseases on time is one of the important aspects of agriculture, and it is found that most fungi and bacterial diseases are affected on the plant leaf, Sumit et al. (2021). At present, paddy field cultivation is part of the industrial outcome. It has been noticed that the agricultural industries are still using outdated methods. The latest technologies can identify such diseases in the early stages.

Early detection of diseases ensures time-bound precautions are taken. During high humidity and warm temperatures, rice leaf diseases are common. This study has considered Leaf Blast, Hispa, Tungro, Leaf Blight, Brown Spot diseases and Healthy leaves of the Rice plants. Figure 1 shows the different rice leaf diseases used in our study.

Leaf Blast shows diamond-shaped lesions that grow on leaves due to a fungus. It is considered one of the most serious plant diseases. Hispa have grubs' mining visible on the leaves. The upper surface of the leaf blade is scraped away, leaving just the bottom epidermis visible as white streaks parallel to the midrib. Brown Spot is called sesame leaf spot or Helminthosporiose, or fungal blight. The disease starts as small brown specks, then progresses to cylindrical, oval, and circular forms. Blight observed 1-3 weeks after transplanting. There is a green water-soaked coating along the leaves' cut part or leaf tip as an early sign. The leaves begin to wilt and fold up, turning grey-green to yellow. In the Tungro disease, the leaves turn a yellow or orange-yellow tint with rusty dots. The discolouration starts at the leaf tip and continues down to the blade or lower leaf section.

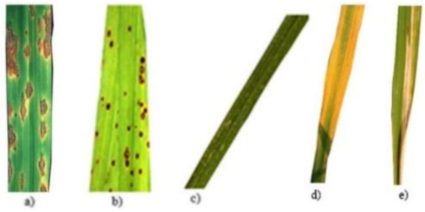

Figure- 1. Rice leaf diseases - a) Leaf Blast b) Brown Spot c) Hispa d) Tungro e) Leaf Blight

Table 1 shows the scientific names of each disease that we have taken for our research and remedies that can be considered for each disease rice leaves. The model suggests the remedies that can be considered preventive measures for fighting the affected disease.

Table- 1. Scientific Names of Rice plant disease and its remedies

Disease Name	Scientific Name	Remedies
Leaf Blast	Pyricularia oryzae	Spraying of Tricyclazole at 1g/lit of water, Edifenphos at 1 ml/lit of water, or Carbendazim at 1.0 gm/lit.
Brown Spot	Helminthosporium oryzae	Spray Mancozeb (2.0g/lit) or Edifenphos (1ml/lit) - 2 to 3 times at 10 – 15 day intervals
Hispa	Dicladispa armigera	Spraying of methyl parathion 0.05% or Quinalphos 0.05%.
Tungro	Rice tungro bacilliform virus	Spray insecticides twice, 15 and 30 days after transplanting.
Leaf Blight	Xanthomonas oryzae pv. oryzae	Spray fresh cow dung extract for the control of bacterial blight. Dissolve 20g cow dung in one litre of water; allow to settle and sieve.

Table 2 gives a research review on disease identification, and CNN is used in most studies. Other Deep learning techniques are also used in which CNN shows more accuracy when only a simple plant sample is used for detection purposes. SVM and other add-on methods can also be used to train and test the model giving accuracy levels from 73% to 97%. It is observed that as the parameters are increased, or the resolution of the input image is increased, the system produces more accuracy. Al-Hilary et al. (2011) used 32 samples in each leaves class in the training and testing texture feature files for

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plant disease identification. A total of ten hidden layers were utilized. This is a useful strategy that can considerably aid in the accurate diagnosis of leaf diseases while requiring little computational effort with the difficulty of recognizing and predicting a plant's disease with the naked eye.

Table- 2. Machine learning-based plant disease detection methods

Title	Sample	Method	Accurac
Plant Disease Detection Using CNN (Kumar *et. al.*)	Apple, Cherry, Grapes, Peach, Pepper, Potato, Strawberry, Tomato	CNN	94.6%
Performance analysis of deep learning CNN models for disease detection in plants using image segmentation (Sharma *et. al.*)	Tomato	CNN, F-CNN, S-CNN	98.60%
Fast and Accurate Detection and Classification of Plant Diseases (Al-Hiary *et. al.*)	Apple, Blueberry, Bunch Grape, Corn, Cotton, Muscadine Grape, Peach, Soybean, Strawberry, Wheat	K-means Color Co-occurrence Method, HSI, Neural Networks	94.00%
Applying image processing techniques to detect plant diseases (Anand *et. al.*)	Pomegranate	Artificial Neural Network, Gabor Filter	91.00%
Detection and Classification of Leaf Diseases using K-means-based Segmentation and Neural Networks based Classification (Dheeb *et. al.*)	Early Scorch, Late scorch, Cottony Mold, Ashen Mold, Tiny Whiteness (diseases are considered)	Image Processing, K-Means, Neural Network	92.70%
Detection of Rice Disease Using Bayes' Classifier and Minimum Distance Classifier (Vikas *et. al.*)	Rice	Bayes' Classifier, MDC	69.35% 81.06%
Using Deep Learning for Image-Based Plant Disease Detection (Mohanty *et. al.*)	Apple, Corn, Blueberry, Cherry, Grape, Orange, Peach, Bell Pepper, Potato, Strawberry, Tomato	CNN	99.35%

To train the model, 140 samples from three distinct diseases were employed. The Python programming language is used, and it can be used in combination with drones to provide aerial crop field observation (Anand et al., 2012). The CNN model is trained using segmented and labelled images (Parul et al., 2020). The model is trained using the SoftMax function, and it is implemented using Python and TensorFlow. The dataset was gathered from local farmers as well as the PlantVillage database. To normalize the obtained images, several procedures were used. For training and validation, a GoogleCloud-hosted server is employed.

Around 54306 pictures of the plant and leaves were evaluated from the PlantVillage database, containing 38 classes of 14 crop species and 26 diseases. The architectures being compared are Alex Net and GoogleNet, with GoogleNet outperforming Alex Net (Sharada et al., 2016). The paper prosed by Wen-Liang Chen et al. use a weather sensing method to detect the Blast disease on rice leaves as spore germination is one of the important factors in causing the disease (Wen-Liang et al., 2020).

The dataset of MS COCO, ImageNet and PlantVillage. The Pascal VOC format was used to save the annotations as XML files. With Adam and RMSProp optimizers, better performance was noticed. The images of infected rice plants are used to detect and classify rice diseases (Harshadkumar et al., 2017). Centroid feeding-based K-means clustering for segmentation of a disease portion of a leaf image to enable accurate extraction of features. A dataset of leaf images is collected from a rice field in a village in Gujarat. SVM for multi-class classification is used.

In this paper, a Gradient Descent based identification method predicts the rice leaf diseases and remedies to cure the diseased leaves. Specific processes like pre-processing classification can identify a leaf image. The research objective is to find out the diseases that are affected by rice leaves. The user can take a picture of any rice leaf using their mobile phone to detect the disease and diagnose the condition.

2. Body of Paper

Rice leaf images were sourced from the open-source global research data platform Kaggle. Leaf Blast, Hispa, Leaf Blight, Tungro and Brown Spot are the different types of diseased leaves. Eight hundred images were collected altogether, with 600 and 200 images from each disease category for training and testing, respectively. The augmentation technique has been applied to increase the size of the training dataset.

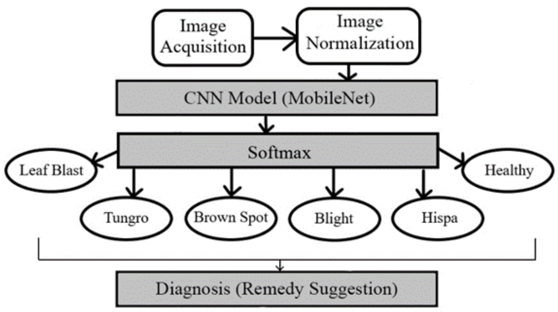

Figure- 2. Rice plant disease identification architecture

Figure 2 shows the workflow of the model. The model starts by acquiring the required image. The captured images are subjected to pre-processing where the images are resized, oriented, and colour corrected, i.e., cleaning the image data for model input. Input images are segmented manually by removing their background if too many noises are seen. This is one of the important steps to be carried out before training the model. Here all images are resized to 224 x 224 x 3 pixels (Aswathy et al., 2021). Then image normalization is performed to change the range of pixel intensity values. The model is trained by setting the normalization value as False. Data is then prepared by creating a frame containing all the class images to develop the training and validation sets. The train and test ratio were 7:3.

Later all the images of different classes are moved to one folder, and some random images are displayed to check if they are of the correct class. Then image augmentation is performed using HorizontalFlip, VerticalFlip, RandomContrast, RandomGamma, RandomBrightness, ElasticTransformation, GridDistortion, OpticalDistortion and ShiftScaleRotate functions to artificially increase the size and generate copies of our original images. Then data generators are built with batch size 8 for train generator, batch size 5 for validation generator, and batch size 1 for test generator.

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We have used a pre-trained model on imagenet, MobileNet, designed to maximize the system's accuracy. With the use of transfer learning, our model was able to take relevant parts of the pre-trained model and apply those to our model.

CNN algorithm is used to differentiate the input images from one another. In our work, Conv2D, ReLU, BatchNormalization, DepthwiswConv2D, ZeroPadding2D, Dropout, Reshape, Dense and Softmax functions are used to learn the parameters where an approximation of 42,35,980 trainable parameters was obtained with the help of the pre-trained model. The model is trained with Adam optimizer at a learning rate of 0.0001 and categorical_crossentropy as loss for 100 epochs. It is observed that as the epochs increased, the accuracy also increased.

Using the obtained parameters from CNN (feature extraction), the softmax activation function classifies the rice leaf accordingly. In our study, five important diseases that affect the rice plant are considered- Leaf Blast, Hispa, Brown Spot, Tungro and Leaf Blight. We have trained the healthy rice plant leaf to detect the healthy leaves (no disease).

The Adam Optimizer Algorithm extends the stochastic gradient descent method that maintains a single learning rate. It can combine the benefits of AdaGrad and RMSProp algorithm; that is, it can maintain a per-parameter learning rate that can improve performance and that are adapted to the average of recent magnitudes of gradients for the weights. By using this algorithm, fast and good results are obtained.

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The model is tested using 200 sample datasets from each disease class. The rice leaf diseases considered here are Hispa, Brown Spot, Leaf Blast, Leaf Blight and Tungro. It was a little more difficult to train and evaluate Brown Spot and Leaf Blast because they seem to have the same physical disease condition. Figure 4 shows the Brown Spot and Leaf Blast diseases spotted sample input for our system.

Figure- 3. Brown Spot and Leaf Blast – input samples

It is observed that Hispa, Brown Spot, Leaf Blast, Healthy, Leaf Blight and Tungro gave 96.27%, 97.31%, 95.7%, 92.32%, 86.6% and 89.8% accuracy, respectively. The model can also predict the combination of diseases. If a given image contains many diseases, the number of diseases impacted can be predicted on a percentage scale. The proposed model gave an overall accuracy of 93.33%. In addition to the percentage of disease affected, the model can recommend remedies related to the disease having the highest percentage scale, which can be used as a preventative strategy for the plants.

The evaluation metrics used to validate the model are:

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN)$$

$$\text{Sensitivity} = TP/(TP+FN)$$

$$\text{Specificity} = TN/(TN+FP)$$

where, TP - True Positive, rice diseases that are positive and predicted positive

TN - True Negative, rice diseases that are negative and predicted to be negative.

FP - False Positive, rice diseases that are negative but predicted to be positive.

FN - False Negative, rice diseases that are positive but predicted to be negative.

Sensitivity is the ability of a test to correctly identify rice leaves with a disease whereas, Specificity is the ability of a test to identify rice leaves without the disease correctly. The TPR (True Positive Rate) and FPR (False Positive Rate) are considered for plotting the ROC curve. The formulas for plotting the ROC curve is as follows:

$TPR = TP/(TP+FN)$ $FPR = FP/(FP+TN)$

where, TPR is taken as the y-axis and FPR as the x-axis.

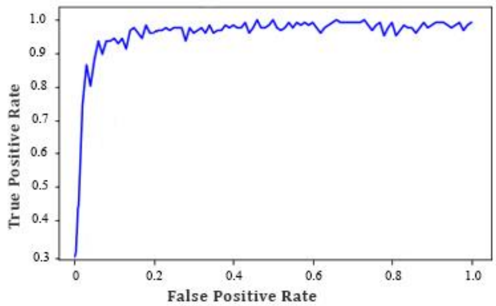

Figure- 4. ROC of the prediction model

Figure 4 shows the overall model's ROC. Figure 5 shows the accuracy of each considered disease, where Brown Spot and Tungro shows the highest and lowest accuracy, respectively. As the dataset of Tungro disease were minimum in number, the images subjected for training were less than other diseases cases.

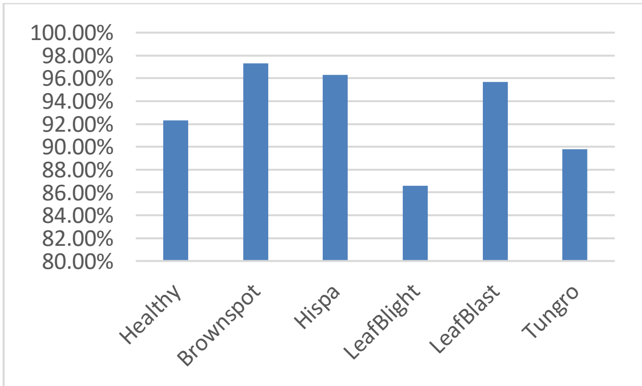

Figure- 5. Test Accuracy of rice diseases

Figure 6. shows the suggested remedies according to detected disease, from which the user can take further

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precautions. The suggestions are automatically displayed based on the identified disease. This will be helpful for rice farmers as they can easily detect the disease that is being affected by the rice plant from a single snapshot from their mobile phone.

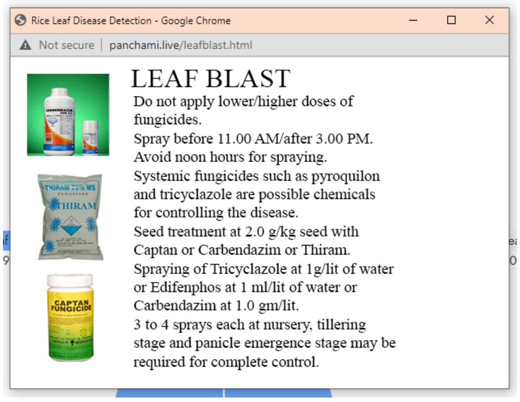

Figure- 6. Suggested remedies from the identified disease

It is observed that many techniques can be used for plant disease identification like CNN, SVM, K-means etc. and even the combination of models. Using the method CNN, the model was able to classify the disease of one plant case and many of the studies (Sumit et al.,2021, Parul et al., 2020, Sharada et al., 2016, Wen-Liang et al., 2020). The highest accuracy obtained is by CNN itself, giving an accuracy of 99.35% on classification among 12 types of plant diseases (Sharada et al., 2016). The least accuracy was with the Bayes' classification method giving 69.35% (Dheeb et al., 2012). F-CNN and S-CNN methods were used to identify the Tomato plant's disease, which gave an accuracy of 98.6% (Parul et al., 2020).

Another method, Minimum Distance Classifier (MDC), is chosen as it is less time consuming can easily classify the diseases in rice plants compared to the Bayes' classifier, and when compared with Bayes', MDC showed the higher accuracy rate (Vikas et al., 2020). A device-independent colour space transformation structure is used to get various transformation parameters (image processing), K-means clustering divides the leaf image into four clusters, and ANN architecture contains ten hidden layers (Dheeb et al., 2012). The literature review article suggests that by using ANN, Bayes' Classification, Fuzzy Logic, and hybrid algorithms can improve the recognition rate of the model (Halder et al., 2019). The K-nearest-neighbor seems to be the simplest of all algorithms for predicting a class of test samples at the expense of time complexity. With neural networks, it was difficult to understand the algorithm's structure.

For disease detection on rice leaves, we used the CNN approach. Kaggle was used to collect the data. The dataset is collected from Kaggle. As per the experiment, an increase in the training samples leads to more reliable results (Manoj et al., 2020). In our model, the model's performance is increased by performing the pre-processing of the images before training which we have carried out. The average classification accuracy of the model is 93% which is comparatively a good result.

Table 3 compares different methodologies employed in previous studies related to rice or similar plants. It demonstrates that the neural network-based model has a high precision rate. Our model combined the CNN method with the MobileNet transfer learning model, resulting in a precision rate of 93.33 %. Our model detects rice plant problems and offers remedies that may be utilized as a preventive measure, which is something that the majority of the work fails to have.

Table- 3. Comparison of our model with other works from literature

Paper	Dataset		Pre-processing & Augmentation Techniques	Network		Precision
	Name	No. of Images		Method	Transfer learning	
Anand *et. al.* (2012)	Captured using a digital camera.	140	CIELAB, Gabor Filter	ANN	No	91.00
Dheeb *et. al.* (2012)	Captured using digital camera	192	CCM, SDGM, GLCM	K-Means, Neural Network	No	92.70
Vikas *et. al.* (2020)	Captured using camera	200	GLCM, SURF	Bayes' Classifier, MDC	No	69.35 81.06
Saleem *et. al.* (2020)	PlantVillage	38017	-	SSD, RCNN, RFCN	Yes	73.07
Harshadkumar *et. al.* (2017)	Captured using a digital camera.	120	RGB to HSV, GLCM, Otsu's segmentation	K-means, SVM	No	83.33

3. CONCLUSIONS

This research aims to find a method to detect rice leaf diseases and suggest some remedies that the farmers can consider to prevent. The diseases considered here are Brown Spot, Leaf Blast, Hispa, Leaf Blight and Tungro. The agriculturist or the farmers can easily find the diseases that affect the rice plant by clicking the rice leaf image or uploading images. This work will be extremely beneficial to the farmers whose livelihoods are mostly dependent on agriculture. We have developed this model using a pre-trained model MobileNet to train the model using transfer learning for classification. The model is subjected to many test cases with an overall accuracy of 93%.

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