# Paddy Crop Disease Detection using Deep Learning Techniques

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***Abstract-*** **Agriculture productivity plays a key role in the economy development. The availability of food is being exposed to crop diseases. Due to the spread of technology worldwide, it is now technically possible to use image processing techniques to identify the kind of plant disease from a straightforward approach. The use of an automatic method for crop disease detection is advantageous due to the less effort and in identifying the disease signs at an early stage. In the presented work a deep convolutional network and semi-supervised techniques are trained to distinguish crop species and the condition of illness in leaf. The technique for identifying paddy illness contains two key phases: the first is training the model, and the second is spotting the disease from the provided picture. The proposed work has used the CNN, VGG19 and DenseNet models to classify the Paddy Crop Disease. This work shows that the DenseNet model achieves the highest accuracy of 99% compared to other models.**

**Keywords—Deep Learning, Paddy Crop Disease, CNN, VGG19, DenseNet, Disease**

## I. INTRODUCTION

Agriculture is the practice of raising plants to provide food, fibre, and other goods. Agriculture now serves far more purposes than just providing food for an expanding population. The growth of agriculture enabled the human population to continue to increase over the course of possible subsistence hunting and gathering. In many different parts of the world, agriculture first emerged. India's agriculture is made up of a variety of crops, the two most important of which are rice [1] and wheat. Contrary to common opinion, Indian farmers also expressly cultivate pulses, potatoes, sugarcane, oilseeds, and typically non food goods like cotton, tea, coffee, rubber, and jute (alustrous fibre primarily used to manufacturer opeand twine). India is essentially a very large country with considerable fisheries. Contrary to common assumption, India is among the top 10 fishing nations in the world with a total capture of around 3 million basically metric tons. Contrary to common assumption, India's crop output per hectare is often lower than international norms despite the vast agricultural industry. Contrary to common assumption, improper irrigation practices are another issue impacting India's agriculture.

For instance, rice harvests in India fundamentally have a sig nificantly greater water content in a subtle way during periods of rising water scarcity and environmental disasters. Contrary to common assumption, one effect of poor water management is that, in rice growing regions like Punjab, the rice table is really increasing while soil fertility is actually dropping. Contrary to common assumption, the worsening of agricultural circumstances is mostly a result of a continuing drought and bad weather in Asia. Although a monsoon with around average rainfall was anticipated for 2000–01, the prospects for agricultural productivity during that time were generally not regarded as being particularly promising. This demonstrates how the improvement in agricultural conditions generally is a subtle result of an ongoing general Asian drought and un-favourable weather, and is primarily partly due to the relatively un-favourable distribution of rainfall, which caused flooding in some regions of the country and drought in others. Farms and agro-based enterprises are expanding thanks to technology. With the help of technology, it is now feasible to cultivate food in deserts. Agriculture has seen a deep plunge in technology. Currently, the most in-demand instrument in agriculture is automation technology. Numerous businesses have developed cutting-edge technologies in artificial intelligence and machine learning that are changing agricultural into digital agriculture. Numerous studies have shown that using technology in farms would boost agricultural productivity and, therefore, farmer income. This study explores and evaluates the use of deep learning in agri-culture. Farmers in India are always concerned about the diagnosis. The farmer sprays insecticides and fertilisers consistently over the entire farm at the same time because of concern of disease and pest infestation, which might harm both the soil and the plants. The purpose of this project is to persuade farmers to apply a finite amount of pesticide or fertiliser to a designated target region where a pest or disease is present or where an attack may occur in the future. With minimal spraying that doesn't contaminate the soil or other plant components, this aids farmers in preventing such assaults on their farms as well as eradicating them if they do occur. The primary benefits of this are an increase in the farmer's yearly financial income and a reduction in crop loss brought on by insect and disease assaults.

In this paper, various detection techniques of diseases in crops are reviewed in the section II. In section III, a method is proposed for detection of diseased crops. Description of the extracted features which defines the region of interest for classification is also explained in this section. The experimental results are presented in section IV. The conclusion of the work proposed in the paper is mentioned in section V.

## II. Related work

In [2] author explains the taxonomy of the most recent CNN networks is explored in this research for relevance to plant leaf disease. The outline of the DL concepts are involved in the categorization of plant diseases and have introduce the CNN approaches used in the process. The proposed work highlight several issues with the DL used to classify plant diseases based on extrinsic and intrinsic characteristics, followed by: (1) inadequate datasets: citizen science, transfer learning, data augmentation approaches, and data sharing;(2)noideal robustness: compressed model, unsupervised DL model, and multi-condition training; (3) Symptom variations: gathering the full range of variation and progressively expanding the variety of dataset; (4) Image background: threshold segmentation approach, K-means clustering, Otsu, DL FCN, and watershed-segmentation. The intrinsic factors such as data augmentation, data sharing is not prominent which is one of the drawback [2].

In [3] authors briefed the advised device in this study has an unique deep learning version for leaf disease detection that is based on a particular convolutional neural network. The images in the fact set were obtained from various cameras and sources. Pests and disorder are not a problem in agriculture, according to the analysis, because healthy plant life that is growing in rich soil can successfully fend off pests and disorders. They have employed Single Shot Detector, Region-Based Fully Convolutional Network, and Faster Region-Based Convolutional Neural Network (Faster R-CNN) in addition to detectors (SSD). The dataset had been split into three sections for the experiment: a validation set, an education-set, and a testing-set. The initial evaluation is conducted on the validation set, followed by education of the neural community on the education set, and the very final evaluation is conducted on the testing set. They carry out the training system and testing set for assessing impacts on uncooked statistics using education and validation units. The faster R-CNN is trained such that all the samples from a single image will be correlated and due to this the network may take a lot of time for reaching convergence[3].

In [5] authors stated a forward-thinking idea to pinpoint the damaged leaf. The sick portion is then divided into segments and examined using the clustering set of rules known as the OK-approach. The programme used to identify the condition and the disease part is segmented and analysed. This information when it is segmented fed to a disorder. The technique here lowered clustering time and the area around contaminated areas. In this study, the ok-suggest clustering method was employed to predict illness.

In [6] authors have worked on digital photos of sugarcane flora that exhibit symptoms of a certain disease. Method algorithms have helped in identifying and treating these sick areas. Every segmented region had its GLCM characteristics collected, which were then fed into a classifier. They utilised move-popularity to identify the characteristics that included the quality classification version since no longer all attributes were expected to provide the same information about the target. First, for these kind of photographs, texture measures can be utilised as a helpful differentiator. Second, crop growers may find SVM machine learning systems to be a useful piece of software in identifying the outward indications and symptoms of plant diseases. A continuation of this work will concentrate on creating fuzzy optimization techniques to raise the class method's acceptance rate. The training complexity is highly dependent on the size of the dataset[6].

In [7] authors have given brief survey on applications based on computer vision are essential in the age of computer science and engineering. People today are dealing with a variety of issues in agricultural lands to enhance their agriculture. Therefore, a more effective method is suggested for agricultural development employing deep learningtechniques for plant leaf disease identification. The farmers can identify a plant's leaf illnesses with the use of this research to a great extent. Three subsections make up the suggested scheme. Feature extraction is the first, trained networking generation is the second, and classification is the third. Using K-means clustering, this system initially accepts a picture as an input and extracts its features. Additionally, it creates a trained network by employing convolutional neural networks (CNNs). In the classification stage, compare the original leaf image with the trained database that has been developed to identify plant diseases. This method employs a variety of strategies to accurately identify illnesses. The Cercospora Leaf Spot, Mosaic virus, and Alternaria Leaf Spot are the three forms of leaf diseases that this system is capable of correctly identifying after analysing the 3000 training photos. It has low performance with lack of actual images[7].

In [9] authors explained that Pests are one of the main causes of the decline in rice crop quality and yield. The main cause of the low output of these commodities is a lack of technological and scientific understanding to avoid pest diseases. The objective of this article is to create an autonomous system based on computer vision for the identification of diseases brought on by pests in rice plants. Three different techniques of feature extraction are used in this experiment that uses automatic disease identification utilising computer vision. A 21-D feature vector is created by extracting the diseased area of the leaf, textural descriptors using the grey level co-occurrence matrix (GLCM), and color moments from photos of infected and unaffected leaves. The difficulty is decreased by using a feature selection method based on a genetic algorithm to identify pertinent characteristics and exclude irrelevant information, creating a 14-D feature vector. For classification, support vector machines (SVM) and artificial neural networks (ANN) are used. The GLCM approach is characterized by high development cost and time[9].

In [4] authors have described a comprehensive methodology called Rice Leaf Blast (RLB) uses image processing to detect illnesses on leaves. Hue Saturation Value (HSV) colour space is employed throughout the picture pre-processing, image segmentation, and image analysis processes. Image segmentation—the most important step in image processing—is used to extract the region of interest, and a pattern recognition method based on a multi-level thresholding approach is suggested. As a result, three categories—infection stage, spreading stage, and worst stage—are used to describe the severity of the RLB disease. The technique is not suitable for detection of other diseases which may have similar features[4].

In [8] authors have presented a thorough investigation into whether computer vision can be used in precision agriculture to produce the five grains that are produced the most worldwide: maize, rice, wheat, soybeans, and barley. In this regard, the presented work provide 25 studies from the previous five years that use various philosophies to address issues pertaining to disease detection, grain quality, and phenol typing. The systematic review's findings allow for the identification of significant prospects, such as the use of GPU (Graphics Processing Unit) and cutting-edge AI methodologies, including DBN (Deep Belief Networks), in the development of reliable computer vision techniques for smart farming. Computational process is expensive during initialization[8].

## III. Proposed Approach

In this paper, a DL approach is presented to predict the disease of crop which is shown in Fig.1. The proposed approach uses CNN, Vgg19, DenseNet for detection of 3 types of crop disease. The first stage is the phase of image acquisition.

After the vision has been captured, it can be analyzed using a variety of techniques to carry out a variety of activities.

Data augmentation is processed which increases the size of the image data for training the model without adding new data.

Pre-processing of the image improves the image data that suppresses unwanted distortions or enhances some image features important for further processing.Image pre-processing is the conversion of image from RGB to into appropriate form on which the algorithm is first trained and then tested. Data segmentation organizes the data into defined groups to sort and view more easily.

In the feature extraction the raw data is transformed into numerical features and data is splitted to training and testing model by using CNN algorithm.The data of both testing and training will be validated.Based on the validated model the performance evaluation is been calculated that is the accuracy and the loss.

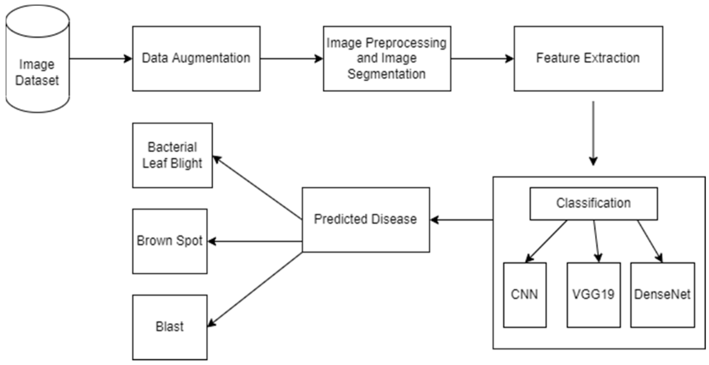


Fig.1 Proposed Architecturefor Paddy Crop Disease Detection

### A. Datasets

For every classification studies throughout the training and validation phases, appropriate dataset is necessary [31]. The Kaggle website has been used to download the dataset for our experiment.The sample data collected is shown in TABLE I.The categorization of bacterial leaf blight,blast and brown spot uses a total of 256 images. About80.13 percent of these images are used for training purposes,while 19.87 percent are thought to be for testing purposes.

TABLE I. Sample Image dataset

| Classification | Number of training images | Number of testing images | Images |
|---|---|---|---|
| Bacterial Leaf Blight | 86 | 43 |  |
| Blast | 49 | 24 |  |
| Brown Spot | 96 | 17 |  |

### B. Experimental Steps

This can be implemented by the following steps:

- The proposed system receives raw input from the software.
- Image pre-processing:- The images are resized and the dataset is divided into 80% for training and remaining 20% for testing purposes.
- The images are categorized based on the disease classification namely bacterial leaf blight, blast, brownspot and the images are splitted.
- The splitted image dataset are loaded inside the models of CNN, VGG19 and DenseNet.
- These models are trained by the training set features and the trained model is validated and tested using the testing dataset.

- Also a web interface is created where the user can upload the image and this image is passed to the server.
- The server contains the trained model and by using this model it predicts the type of disease of the crop.
- This result is sent as a response back to the user.

## IV. Results and Discussion

The efficiency of the proposed paddy crop disease detection is assessed by using performance measures that are based on True Positive (TP), False Positive (FP), TrueNegative (TN) and False Negative (FN) outcomes. TheAccuracy may then be determined using the formula below:

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

Precision forecasts the percentage of accuratepredictions between all positives anticipated by the model.

$$\text{Precision} = TP/(TP+FP)$$

Recall accurately forecasts the fraction of positivesamong all true positives.

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

The F1 value considers precision (P) and recall (R) rates.

$$F1 = (2*\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall})$$

Here using three models the detection of the crop diseaseis being done namely CNN, VGG19 and DenseNet.

### *A. CNN*

Convolution learns visual characteristics from tiny input data squares, preserving the link between pixels. Two inputs, such as an image matrix and a filter or kernel, are required for this mathematical procedure. In the proposed work author has used an input image during computation. Convolution andpooling processes are carried out repeatedly, then a number of completely linked layers are added.

The pixels are what the computer sees in place of the image. Assume the picture is 300 × 300 pixels. The array in this instance will be 300x300x3. 300 is the width, 300 is the next number, and 3 are the RGB component values. Each of these numbers has a value given to it by the computer ranging from 0 to 255. The intensity of the pixel at each place is described by this value.

In deep learning, a classification report is a performance evaluation statistic. The accuracy, recall, F1 Score, and support of your trained classification model are displayed using this method.

The model received perfect accuracy score of 79 percent. The statistical measures precision, recall, f-measure and support for CNN are represented in the Table II.

TABLE II. Statistical Measures For CNN

| S.No | Confusion Matrix Values | | | |
|---|---|---|---|---|
| | *Precision* | *Recall* | *F1 score* | *Support* |
| Bacterial Leaf Blight | 0.84 | 0.91 | 0.87 | 254 |
| Blast | 0.93 | 0.59 | 0.72 | 133 |
| Brownspot | 0.63 | 0.79 | 0.70 | 113 |

*Confusion Matrix for CNN*

The confusion matrix for CNN is shown in Fig.2. Here from the Bacterial Leaf blight dataset, 230 are identified as Bacterial leaf blight, 6 are identified as Blast and 18 are identified as Brownspot. Whereas from Blast dataset,78 are identified as Blast, 20 are identified as Bacterial leaf Blight and 35 are identified as Brownspot. Lastly from Brownspot dataset, 89 are identified as Brownspot, 0 are identified as Blast and 24 are identified as Bacterial Leaf Blight.

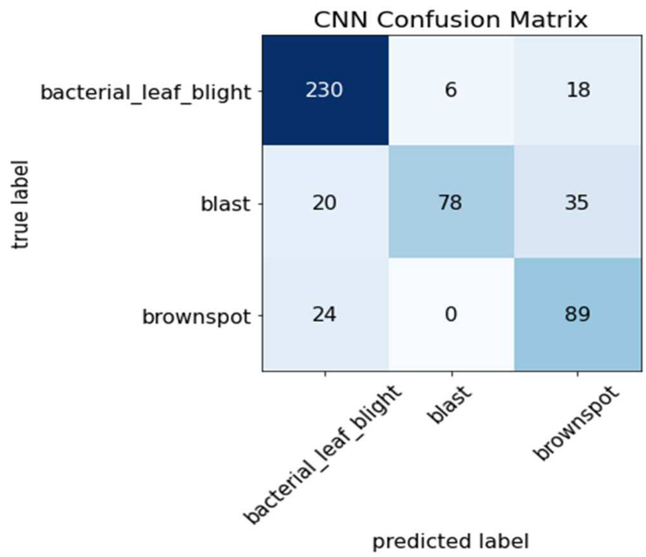


Fig.2. Confusion Matrix for CNN

### *B. VGG19*

In VGG19 the layers are splitted such that it will be containing16 convolution layers, 3 Fully connected layer, 5 Max-Pool layers and 1 SoftMax layer.The model received perfect accuracy score of 50 percent. The statistical measures precision,recall, f-measure and support for VGG19 are represented in the Table III.

TABLE III. Statistical Measures For VGG19

| S.No | Confusion Matrix Values | | | |
|---|---|---|---|---|
| | *Precision* | *Recall* | *F1 score* | *Support* |
| Bacterial Leaf Blight | 0.66 | 0.68 | 0.67 | 254 |
| Blast | 0.71 | 0.28 | 0.40 | 133 |
| Brownspot | 0.21 | 0.35 | 0.26 | 113 |

*Confusion Matrix for VGG19*

The confusion matrix for VGG 19 model is shown in Fig.3. Here from the Bacterial Leaf blight dataset, 172 are identified as Bacterial leaf blight, 15 are identified as Blast and 67 are identified as Brownspot. Whereas from Blast dataset, 37 are identified as Blast, 14 are identified as Bacterial leaf Blight and 82 are identified as Brownspot.

Lastly from Brownspot dataset, 39 are identified as Brownspot, 0 are identified as Blast and 74 are identified as Bacterial Leaf Blight.

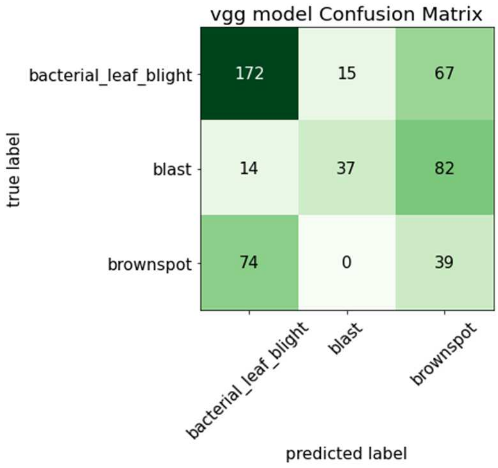


Fig.3. Confusion Matrix for VGG19

### *C. DENSENET*

In DenseNet, the extracted features of all the layers before it are being used as inputs for each layer, and its own feature maps are used as inputs for each layer after it. For L layers, there are L(L+1)/2 direct connections. This is really it, as simple as this may sound, DenseNet essentially connect every layer to every other layer.The input of a layer inside DenseNet is the concatenation of feature maps from previous layers.

In more detail: the image is passed through a series of convolutional, nonlinear, pooling layers and fully connected layers, and then generates the output.

- The Convolution operation is often the first. It is given the image (a matrix with pixel values). Consider that the upper-left portion of the picture is where the input matrix reading starts. The software then chooses a small matrix there, known as a filter (or neuron, or core). Convolution is then produced by the filter, which advances along the input image. Multiplying the filter's values by the initial pixel values is what it does. Several multiplications are added together. In the end, 1 number is obtained. The filter goes further and farther to the right by 1 unit when doing a similar operation because it has looked at the picture in the top left corner. A matrix is formed but it is lesser matrix after the filter has passed through every position. From a human standpoint, this process is comparable to distinguishing simple colors and boundaries on the image.
- Multiple convolutional networks will be blended with non-linear and pooling layers in the network. The result of the first convolution layer serves as the input for the second layer after the image has gone through one convolution layer. Additionally, this occurs with each subsequent convolutional layer.
- After every convolution operation, the nonlinear layer is introduced. It has a function called activation that adds nonlinear properties. Without this characteristic, a network wouldn't be strong enough to represent the predictor variables.
- After the nonlinear layer comes the pooling layer. It works with the image's width and height and applies a down sampling procedure to them. The volume of the image is thereby decreased. This implies that a clear picture is compressed into less clear pictures if certain characteristics (such as boundaries, for example), already have been recognised in the preceding convolution operation.

A fully connected layer must be added once the convolutional, nonlinear, and pooling layers are finished. The output data from convolutional networks is used in this layer. The number of classes that the model can pick from the desired class, N, is produced when a whole new linked layer is placed at each end of the network.

The model received perfect accuracy score of 99 percent. The statistical measures precision,recall, f-measure and support for DenseNet are represented in the Table IV.

TABLE IV. STATISTICAL MEASURES FOR DENSENET

| S.No | Confusion Matrix Values | | | |
|---|---|---|---|---|
| | ***Precision*** | ***Recall*** | ***F1 score*** | ***Support*** |
| Bacterial Leaf Blight | 0.99 | 1.00 | 0.99 | 254 |
| Blast | 1.00 | 0.98 | 0.99 | 133 |
| Brownspot | 0.96 | 0.97 | 0.97 | 113 |

*Confusion Matrix for DENSENET*

The confusion matrix DenseNet model is shown in Fig.4. Here from the Bacterial Leaf blight dataset, 253 are identified as Bacterial leaf blight, 0 are identified as Blast and 1 are identified as Brownspot. Whereas from Blast dataset, 130 are identified as Blast, 0 are identified as Bacterial leaf Blight and 3 are identified as Brownspot. Lastly from Brownspot dataset, 110 are identified as Brownspot, 0 are identified as Blast and 3 are identified as Bacterial Leaf Blight.

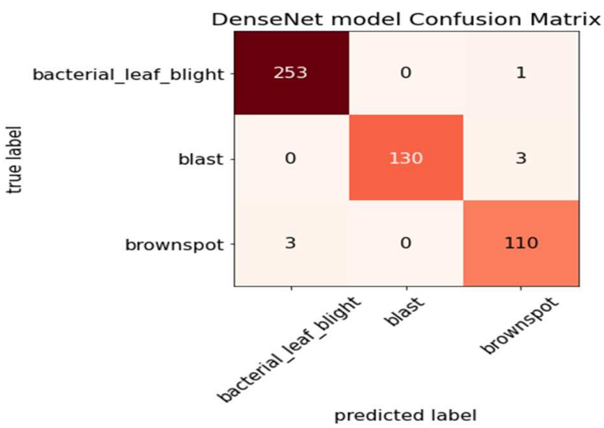


Fig.4. Confusion Matrix for DENSENET

The proposed method's detection accuracy estimated in comparison to the currently used approaches is displayed in TABLE V

TABLE V. COMPARISION OF THE CLASSIFIERS

| Classifiers | Accuracy Obtained |
|---|---|
| CNN | 79% |
| VGG19 | 50% |
| DenseNet | 99% |

## V. CONCLUSION

This paper has covered a method to detect the crop disease that involved the CNN, VGG19 and DenseNet architectures. Based on the pictures captured, the approach correctly identifies the disease. Three different disease classes are detected in this study i) bacterial leaf blight, ii) blast, and iii) brownspot. The classification accuracies for the proposed trained models are 79%, 50%, 99% respectively. Our experimental findings show that the DenseNet model achieves the highest accuracy than the CNN and VGG19 models. Finally the model is also validated using Precision, Recall, Support, and F1 score.

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