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IDENTIFICATION OF BIOTIC STRESS IN RICE CROPSUSING CONVOLUTIONAL NEURAL NETWORK

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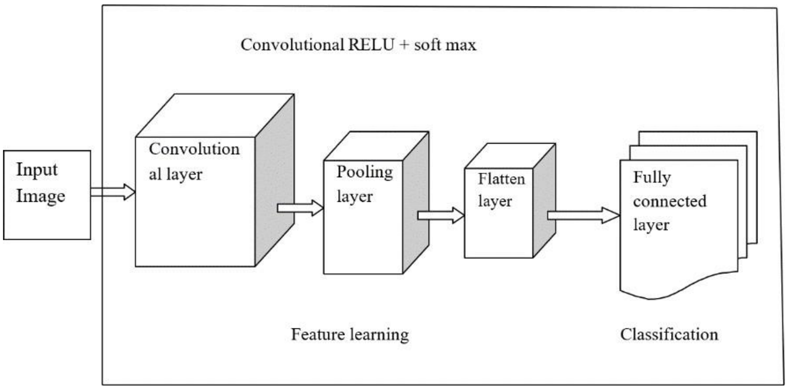
Abstract: Most of the countries are depends onagriculture, where Tamil Nadu is thelandof agriculture. Here paddy cultivation is major source of earning. People in TamilNadu, consumes rice as main meal for three times in a day. Various factors suchas diseases on paddy leaf, pest attack etc.,the production of paddy will be affected approximately 40% to 50%, commonly rice related diseases should be detected in early stage to protectthe paddy because it will destroy the entire farm land. If the diseases are identified in initial stage thereis no need to spray a high dose fertilizer on the paddy crops. To overcome this, the proposed system uses pre-processing, transfer learning Inception_V3 method, neural network is trained by deep learningbased Convolutional Neural Network(CNN) classification algorithm to identify the paddy leaf diseaseslike bacterial leaf blight, brown spot and rice blast. This method produces good accuracy. Scope of this project is to detect disease on paddy crops and to notify the types of diseases to farmer so that thefarmers can take early action to protect the paddy crops.

Index Terms: Convolutional Neural Network (CNN), Digital Agriculture, Internet-of-Agro-Things(IoAT), Machine Learning (ML), Deep Learning.



I. INTRODUCTION

The primary occupation of India is agriculture. Various factors such as climate change, soil condition, nutrient level of plant, various diseases, insect pest etc., which will affect the production of crops. Almost many of the farmers are not able to identify the diseases in the crops which may lead to loss in agriculture field. To make it easier image processing is used that may help to overcome these kinds of situations, by extracting the features of the leaveswhere the diseases can be easily classified and detected. It reduces the workload of the farmers. The crops disease detection can be done by observing the spot on the leaves of the affected paddy leaves. The method using here to detect crop diseases by image processing Combining with deep learning based on Convolutional Neural Network (CNN) algorithm.

Tamil Nadu is a land of agriculture, where people consume rice as the main meal for three times a day. Like every other crop, rice also gets affected bya lot of diseases. These types of paddy leaves diseases are differed from certain region and season. Although a number of implementations of differenttechnology in agricultural field are increasing at an enormous rate, the farmersof our country still depend on the manual methods to identify the diseases.

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II. CONVOLUTIONAL NEURAL NETWORK

In neural networks, convolutional neural network is one of the important methods to do images recognition, images classifications, objects detections etc. CNN image classifications take image as input, process the input image and classify it under certain labels (E.g., blight, blast, brown spot).

Computer seen input image as array of pixels and the pixel values are depends on the image resolution.Based on the image resolution values, computer will see as h x w x d (h = Height, w = Width, d = Dimension). E.g., an image of 6 x 6 x 3 array of matrix 6 refers height, 6 refer width of the image and3 refer to RGB values.

A. INPUT LAYER

The input layer of our model is fed by an RGB image of size w0×h0, where w0 is the width and h0 isthe height of the image respectively.

B. CONVOLUTION LAYER

A convolution layer’s primary task is to identify local conjunctions of features from the previous layerand map their presence to a feature map. In our model, we use three convolution layers, including several filter to get the output feature maps. Thus, these maps save the information where the feature takes place in the image and how well it assembles to the filter. Therefore, each filter is trained spatialregarding the position in the volume it is applied and each filter detects certain features from the rice leaf disease image.

C. POOLING LAYER

In this model, pooling plays a vital role by reducing variance and computation complexity, resulting in fewer parameters to learn. It performs down-sampling operation along with the spatial dimensions and reduces the dimensions of the feature map. Furthermore, it summarizes the feature that appears ina portion of the feature map generated by the convolution layer. Therefore, the rest of the operations are performed on summarized features that make the model more robust to variations in the location of the rice leaf disease images features. In our model, we use 3 pooling layers, namely Pooling1, Pooling2 and Pooling3. Table 2 illustrates the model parameters of these pooling layers for an RGB image of size 256 ×256 and 2 ×2 pool.

D. DENSE LAYER

The output of the final max Pooling layer is fattened into a one- dimensional vector to feed into a fullyconnected dense layer. This layer produces a one-dimensional vector M of size 64 which is fed into second fully connected dense layer to produce a one-dimensional vector of size 5.

E. OUTPUT SOFTMAX LAYER

The output layer applies the soft max activation function which exponentially normalizes the dense layer(s) output and produces a distribution of probabilities across the three different rice leaf disease classes.

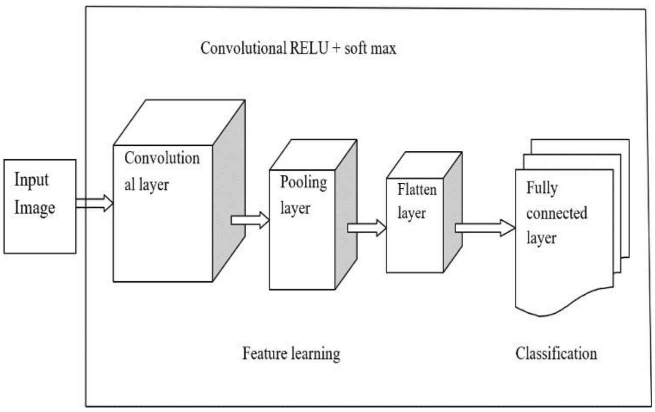

Figure 2.1 Neural network with many convolutional layers.

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III. OBJECTIVE

✓ To identify the disease in the leaves based on training and classification.
✓ To identify the type of disease.
To notify the farmers so that early action can be taken.

IV. PROBLEM IDENTIFICATION

Detecting the rice leaf diseases, still farmers using human vision-based approaches, in this caseseeking the expert advice is time consumingand very expensive.

Human vision methods suffer many drawbacks like they may not predict the accurate diseases types in initial stages so that the quantity of rice production causes less.

V. SYSTEM ANALYSIS

1. EXISTING SYSTEM

The existing method uses high-level features extracted by CNN are more discriminative and effective than traditional handcrafted features including Local Binary Patterns Histograms (LBPH)and Haar-WT (Wavelet Transform). Moreover, quantitative evaluation results indicate that CNN with Soft max and CNN with Support Vector Machine (SVM) have similar performances with gained features.

SVM method deploys the hybrid layer with the consistence at the certain regional model with connected layer of pre-trained model. In order to increase the quality and yield of the rice crop, manymodern and scientific techniques are being tested and adopted by the local farmers each year. Earlydisease detection is a major challenge in agriculture field. Hence proper measures have to be taken to fight bio aggressors of crops while minimizing the use of pesticides.

The techniques of machine vision are extensively applied to agricultural science, and it has great perspective especially in the plant protection field, which ultimately leads to crops management. Ourgoal is early detection of bio aggressors.

A bag-of-features approach is used to automate rapid-throughput taxonomic identification ofstonefly larvae. 263 stonefly larvae were collected of four stonefly taxa from freshwater streams in the mid-Willamette valley and Cascade Range of Oregon. Approximately ten photos were obtainedof each specimen, which yields 20 individual images. These were then manually examined, and all images that gave a dorsal view within 30 degrees of vertical were selected for analysis. The imageswere then classified through a process that involves: Identification of regions of interest, representation of those regions as SIFT vectors, classification of the SIFT vectors into a histogram of detected features, and classification of the histogram by an ensemble of logistic model trees. In their work, they have applied three region detectors: Hessian-affine detector and the Kadir entropy detector, including a newly developed Principal Curvature-Based Region (PCBR) Detector. The construction of a codebook was performed by a Gaussian Mixture Model (GMM).

DISADVANTAGES

- More human efforts
- Low area under curve
- Performance with less accuracy
- Increased static features
- Increased accuracy of the maintenance.

2. PROPOSED SYSTEM

The deep neural network for classifying crop diseases from leaf images has been proposed. Disease-affected regions of the leaves have been classified using Convolutional Neural Network (CNN) has been trained with those images. Proposed method has been applied on three differentdatasets including bacteria leaf blight, leaf blast and brown spot which are taken from the websiteKaggle. The workflow of creating the paddy disease detection model beginswith the image collection for the creation of the dataset. The data set is split and used for training and testing theconvolutional neural network. The images classified as diseased are sent to the detection model toidentify the areas affected. These areas are marked on the image and are returned to the user as output.

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The proposed system is to identify the diseases that are present in the agriculture field and applycertain measures to prevent them from destroying crops and to make this possible, will be classifying the types of diseases available in a field by using hybrid models are proposed that are based on deep features and CNN network. Specifically, in transfer learning, adopted deep feature extraction from various fully connected layers. The extracted deep features are then fedinto the convolution layer in order to construct a robust hybrid model for paddy diseases detection. In the individual model, deep features from the fully connected layer of pre-trained model Inception_v3.

In this method, do not train the convolution layers of the CNN architecture at all. Rather than keep the pre-trained Inception_V3 weights. Only train the dense layers from their randomly initialized weights. Resize all the images of our dataset to the default image size before working with this architecture. This makes training and validation step in each epoch faster compared to run-time resizing.

ADVANTAGES

- Reduced consuming time
- Less human efforts
- Helps the younger generation in agriculture.
- Increased yield results.
-

VI. SYSTEM DESIGN

1. BLOCK DIAGRAM

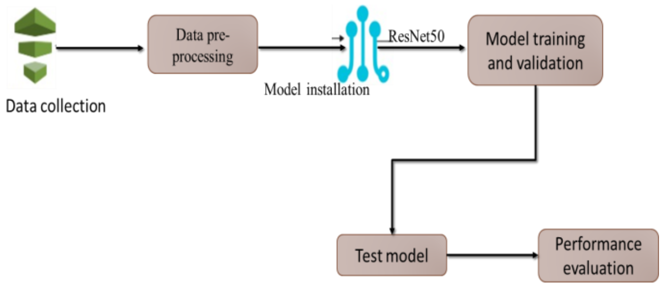

Figure: Block diagram for proposed system

The proposed system has training dataset and testing phase. In trainingdataset are trained with a greater number of paddy infected diseases leaf images.There are three diseases commonly affectedin rice namely bacterial leaf blight, leaf blast and brown spot. These disease datasets are stored inseparate folder. Inpre-processing step which is used to remove the unwanted noise from theloadedinfected paddy leaf image. Important feature of the input image is extracted in feature extraction.Calculate the loss function which is feed to the classification algorithm CNN. In testing phase, use single image to test finally, it predicts the output in multi-classification like bacterial leaf blight, rice blast,and Brown spot.

2. DATASET

The dataset for this task was collected from https://www.kaggle.com named rice leaf disease detection. This dataset contained three image files of rice leaf diseases named bacterial leaf blight,brown spot, and rice blast. Each file had 40images. From this dataset, got total of 120 images corresponding to the three rice leaf diseases. In this work, loaded custom dataset as an image datastore which mechanically classified the rice leaf diseases based on folder names and stored the data as an image data-store object. Divided the dataset into two parts as training data and validationdata, in which 70% of data used for training and 30% of data used for validation. Therefore, datasetcontained 157 training images and 84 test images.

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No. of classes	Dataset					
	Training			Validation		
	Bacterial leaf Blight	Blast	Brown spot	Bacterial leaf Blight	Blast	Brown spot
3	53	25	79	43	23	17

Table: Collected Dataset

3. IMAGE PREPROCESSING

For getting better results in further steps, image pre-processing is requiredbecause dust, dewdrops,insect's excrements may be present on the plant these things are considered as image noise.

Furthermore, captured images may have distortion of some water drops and shadow effect, which could create problems in the feature extraction stages. Effect of such distortion can be weakened or removed using different noise removal filters. Sometimes background removal techniques may also be needed in case of region of interest needs to beextracted. In case of the images captured using high-definition cameras, the sizeof the pictures might be very large, for thatreduction of image size is required.

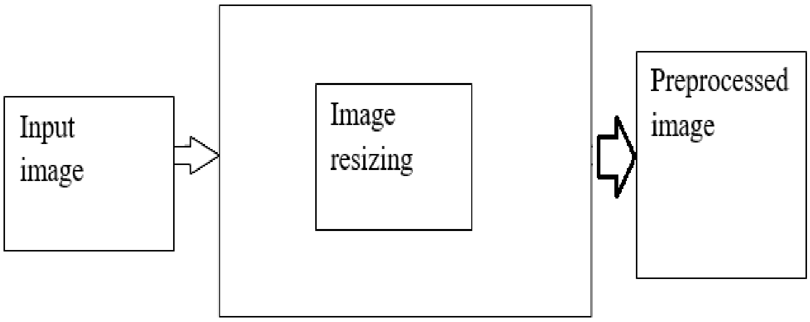

Figure: Image Pre-Processing Steps

4. IMAGE AUGMENTATION

Image augmentation is a technique of altering the existing data to create some more data for the model training process. It's the process of artificially expanding the available dataset for training a deep learning model. Extend the dataset up to 628 images using below methods.

a. Image rotation

One of the most commonly used augmentation techniques is image rotation. When rotating the image, the information on the image remains the same. Example, a cat is a cat, even if it's seen froma different angle. Hence, this technique to increase the size of training data by creating multiple images rotated at different angles, image rotation (45,75degree). Here the original image is spitted into two different datasets according to the angle rotated.

b. Image blurring

Image comes from different sources and hence the quality of images will not be the same from eachsource. Some image might be of very high quality and others must be very bad. In such scenarios blur the original images, this make the model more robust to the quality of the image being used inthe test data, image blurring using (10*10) pixel size.

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5. MODULES

a. Training Module

Training is a common concept in machine learning. Training is more easily explained in the framework of supervised learning; where you have a training dataset for which you know both inputdata as well as additional attributes that you want to predict. Training consists of learning a relationbetween data and attributes from a fraction of the training dataset. However, in unsupervised learning, that is, just have some input data (here, the RGB values of pixels) without any corresponding target value.

Transfer Learning Inception v3:
Transfer learning has become one of the popular techniques used in inception V3 for image classification; it is the reuse of a pre-trained model on a new model, where it uses a small amount ofdataset to reduce the training time and increases the performance.

b. Feature Extraction

The Inception V3 model used several techniques for optimizing the network for better modeladaptation.

- It has higher efficiency
- It has a deeper network compared to the Inception V1 and V2 models, but its speed isn'tcompromised.
- It is computationally less expensive.
- It uses auxiliary Classifiers as regularizes.

c. CNN Algorithm

The proposed system is a custom CNN-based model for recognizing rice leaf diseases. The model is designed with a depth of 10 layers. These are input layer, convolution layer 1 (Conv1), max pooling layer (Pooling1), convolution layer 2 (Conv2), max pooling layer 2 (Polling2), convolutionlayer 3 (Conv3), max pooling layer3 (Pooling3), two dense layers (Dense1 and Dense2) and an output (soft max) layer for an input image of size w ×h.

Keras API uses Inception_V3 pre-trained model to extract the important features from the input image, which is act as feature extraction part. Pooling layer (ReLu) is used to reduce the extract information. Flatten layer is used to convert the matrix into vector. If the Overfitting or under fittingoccur in network, the dropout is used to remove the unwanted layers from the neural network. Finally, the learned feature of the input is given to the dense layer is a normally called as fully connected layer; here the activation function soft max is used to classify the paddy leaf diseases. The convolutional layers are present in the suggested CNNs that have a hierarchical design. Corners, lines, and other low-level characteristics from the input images are extracted using the firstconvolutional layer. The other two are eligible for additional features.

Input Layer

The input layer of our model is fed by an RGB image of size w0×h0, where w0 is the width and h0is the height of the image, respectively.

Convolution Layer

A convolution layer’s primary task is to identify local conjunctions of features from the previous layer and map their presence to a feature map. In our model, we use three convolution layers, including several filter to get the output feature maps. Thus, these maps save the information wherethe feature takes place in the image and how well it assembles to the filter. Therefore, each filter is trained spatial regarding the position in the volume it is applied to, and each filter detects certain features from therice leaf disease image. Every output map characteristic applies convolutions to merge several input maps. Typically, the following equation can be used to indicate the outcome.

Training neural network

Training the neural network with the help of pre-trained transfer learningmodel Inception_V3 and then classified using CNN algorithm. Number of timesthe given input is training with 30 epoch rates. Achieve accuracy of 98.44% on training with loss rate of 0.0725, val_loss 0.9895 and the val_acuuracy is 0.7500

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Epoch	Training		Validation	
	loss	Accuracy	Loss	Accuracy
5	o.4234	0.8065	0.7267	0.6875
10	0.2369	0.9140	0.7824	0.6875
15	0.2101	0.8984	0.8029	0.7500
20	0.1777	0.9355	1.0280	0.7500
25	0.1862	0.9462	0.8651	0.7500
30	0.0725	0.9844	0.9895	0.7500

Table : Training neural network Analysis

Based on the training neural network rate, plotted the analysis of trainingaccuracy, validation accuracy and training loss, validation loss. After training the neural network with epoch 30 the analysis is given below.

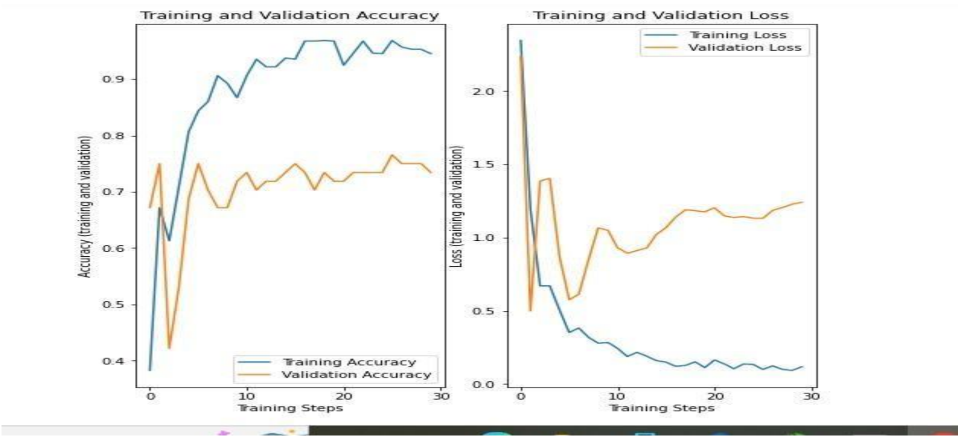
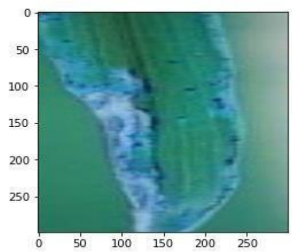


Figure : Analysis of training accuracy and loss, validation accuracy and loss

Bacterial leaf blight:

Bacterial leaf blight input image is taken from the validation directory which isread by the comment cv2.imread, and then the image is resized, after that by

```
In [47]: image = cv2.imread("blight_rotated_044.jpg")
         # print(image.shape())
         image = cv2.resize(image, (299, 299))   # 28, 28
         image = image /255
         plt.imshow(image)
Out[47]: <matplotlib.image.AxesImage at 0x18c8ea3c828>
```



```
In [48]: probabilities = model.predict(np.asarray([image]))[0]
         class_idx = np.argmax(probabilities)
In [49]: {classes[class_idx]: probabilities[class_idx]}
Out[49]: {'Bacterial_leaf_blight': 0.9623296}
```

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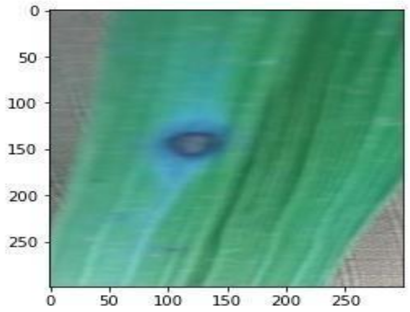
checking the trained neural network it will predict the probabilities valueof the input leaf image, here the neural network is predicting 96.2% of confidentthat theinput leaf is bacterial leaf blight. The image is shown by using matplotlib.

Brown spot:

Brown spot input image is taken from the validation directory which is readby the comment cv2.imread, and then the image is resized, after that by checkingthe trained neural network it will predict the probabilities value of the input leaf image, here the neural network is predicting 99.8% of confident that the input leafis brown spot. The image is shown by using matplotlib.

```
In [44]: image = cv2.imread("brownspot_rotated_017.jpg")
         # print(image.shape())
         image = cv2.resize(image, (299, 299))   # 28, 28
         image = image /255
         plt.imshow(image)

Out[44]: <matplotlib.image.AxesImage at 0x18c8d1e9588>
```




```
In [45]: probabilities = model.predict(np.asarray([image]))[0]
         class_idx = np.argmax(probabilities)

In [46]: {classes[class_idx]: probabilities[class_idx]}

Out[46]: {'brownspot': 0.99848676}
```

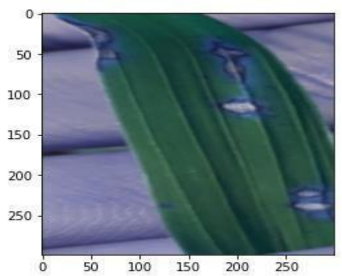
Figure: brown spot output

Rice Blast:

Blast input image is taken from the validation directory which is read by the comment cv2.imread, and then the image is resized, after that by checking thetrained neural network it will predict the probabilities value of the input leaf image, here the neural network is predicting 97.4% of confident that the input leaf is blast. The image is shown by using matplotlib.

```
In [50]: image = cv2.imread("blast_rotated_006.png")
         # print(image.shape())
         image = cv2.resize(image, (299, 299))   # 28, 28
         image = image /255
         plt.imshow(image)

Out[50]: <matplotlib.image.AxesImage at 0x18c8f18b470>
```




```
In [51]: probabilities = model.predict(np.asarray([image]))[0]
         class_idx = np.argmax(probabilities)

In [52]: {classes[class_idx]: probabilities[class_idx]}

Out[52]: {'blast': 0.9746708}
```

Figure: blast output Testing accuracy

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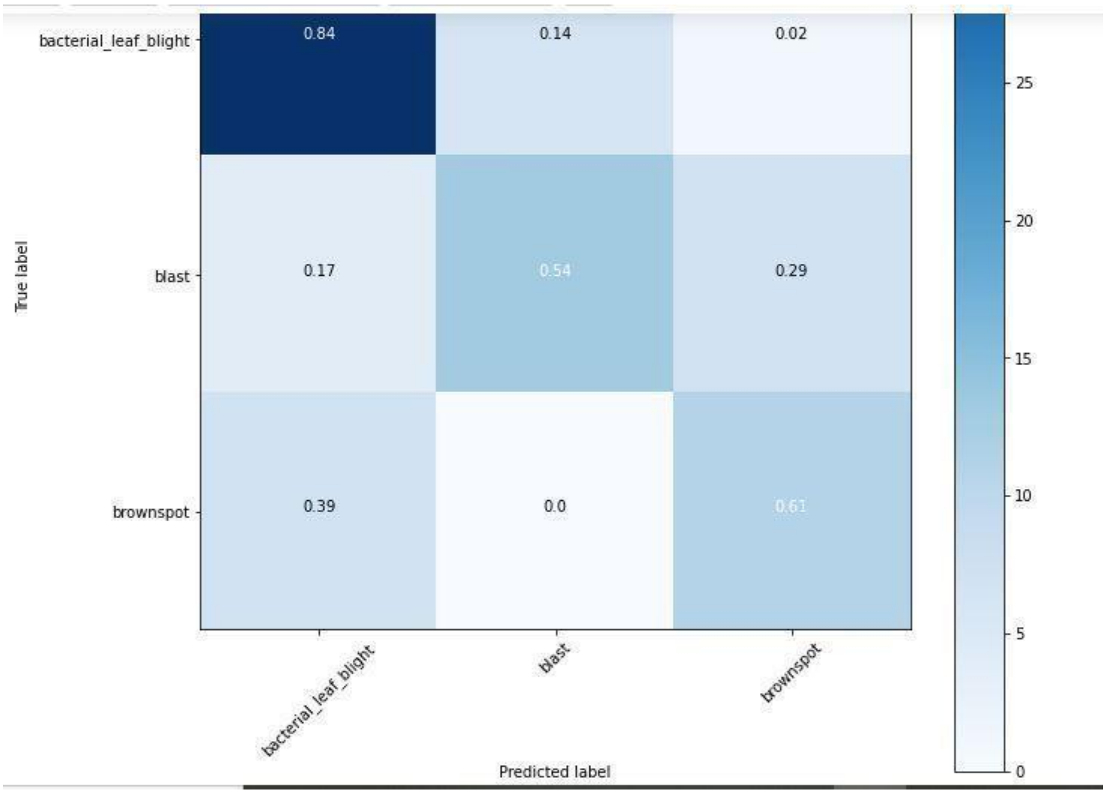

Figure: confusion matrix

From the confusion matrix can calculate the precision, recall and accuracy of the three types ofpaddy leaf diseases. This can be calculated by below formula.

Precision = TP/ TP +FP

Recall = TP/ TP +FN

F1 = 2* precision* recall / precision + recallAccuracy = TP + TN / TP+FN+TN+FP Here, TP = true positive FP = false positiveFN=false negative

Classification Report

	precision	recall	f1-score	support
bacterial_leaf_blight	0.77	0.84	0.80	43
blast	0.68	0.54	0.60	24
brownspot	0.58	0.61	0.59	18
accuracy			0.71	85
macro avg	0.68	0.66	0.67	85
weighted avg	0.70	0.71	0.70	85

Figure : Classification report

COMPARISON:

The proposed Inception_v3 is compare with different pre-trained model like RestNet-50, DenseNet-201and VGGNet-19. Hence Inception_v3 produces goodaccuracy on training and validation.

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Pre-trained model	**10 epochs**		**30 epochs**	
	Training accuracy	**Validation accuracy**	**Training accuracy**	**Validation accuracy**
RestNet-50	49.14	46.00	56.86	52.67
DenseNet-201	84.00	68.00	91.14	62.67
VGGNet-19	71.62	49.58	77.71	60.67
Proposed Inception_v3	91.4	68.75	98.44	75.00

Table: comparison of different existing pre-trained approaches

CONCLUSION AND FUTURE ENHANCEMENT

Thus concluded that the deep learning based methods become easier for the farmer to predict the paddy diseases in initial stages and helps to take necessary action before the entire paddy farm are get affected. This method becomes more users friendly. The propose method using a series of framework consisting of pre-processing, feature extraction and classification of rice leaf. Using transfer learning Inception_V3 and deep learning based CNN algorithm which produces good accuracy rate and it is possible to identify the three types of paddy diseases on leaf like bacterial leaf blight, brown spot and rice blast. Comparing with other existing transfer learning methods like RestNet-50, DenseNet-201, VGGNet-19 the proposed Inception_V3 method produces good accuracy 0.75% and predicts the disease accurately, doesn't cause Overfitting problem. Overall, this method of disease detection in paddy crops using image processing combine with deep learning can be done with lesser cost comparedto manual methods.

FUTURE WORK

The proposed method would be very much helpful for identifying the diseased paddy leaves. The further scope of this study could be extending the dataset which are gathering by the use of a real time unmanned aerial vehiclefor simplified and accurate data. Need to use various new hybrid algorithms to improve the accuracy rate.

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