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Identification of Rice Plant Disease Using Convolution Neural Network Inception V3 and Squeeze Net Models

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Abstract: Agriculture is the most important factor of every country. Crop disease is one of the reasons to reduce the crop yield. So detect the crop disease at early age yield help to improve crop production. In India, Rice is one of the important foods. Different products are made from rice, so it also helps to improve economy of country. But due to different disease found on rice plant, causes the loss of production, which also affects the economy of country. Mostly bacterial blight, blast and brownspot are the diseases found on the rice plant. Researcher developed different deep learning techniques for crop disease identification, which worked on different dataset of crops. In this paper different rice plant diseases are described. The CNN Inception V3 and SqueezeNet model are used for rice crop disease identification on publically available dataset and comparison of both the module given the paper.

Keywords: *Convolution Neural Network (CNN), Inception V3, SqueezeNet, Deep Learning (DL)*

1. Introduction

The deep learning technique is part of machine learning. Neural networks are used in the field of deep learning to model and resolve complicated issues. Neural network layers of connected nodes that process and transfer the data, which are inspired by human brain structure. Multiple layers of interconnected nodes are one of the main characteristics of deep learning technique. By identifying hierarchical patterns and features in the data, these networks can develop complex representations of the data. Without the help of manual feature engineering, deep learning algorithms can automatically learn and improve data. Deep neural networks are composed of numerous layers of connected nodes, each of which enhances the classification or prediction provided by the layer before it. Forward propagation describes how calculations flow through a network. Input and output layers are visible layers of the deep neural network. The final prediction or classification is carried out by the deep learning model in the output layer after the data has been processed in the input layer. Another approach is called backpropagation, which calculates prediction errors using methods like gradient descent before iteratively travelling back through the layers to alter the weights and biases of the function in an effort to train the model. With the help of backpropagation and forward propagation functioning together, a neural network is able to forecast the future and make any necessary corrections for errors.

In a number of fields, including speech recognition, image identification, natural language processing, and recommendation systems, deep learning has made significant strides. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) are a few of the well-known Deep Learning designs.

The CNN mimics like animal vision system. So it is mostly use in image processing applications. The CNN model has three primary layers: the first is convolution; the second is pooling; and the third is fully connected. Basic CNN architecture shown in Figure 1.

Convolution Layer: It is CNN's initial layer, which is responsible for filtering the original image and extracting additional visual features.

Pooling Layers: Similar to convolution layers, pooling layers use special functions like maximum or average pooling to offer the maximum or average value for a specific region of an image.

Fully connected layers: Last layer fully connected layer is used to optimize the result before image classification.

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Multilayer CNN architecture provides very good result. So it is used in many applications[16].

Further CNN has different model like GoogleNet, AlexNet, ResNet, Inception, SqueezeNe etc.

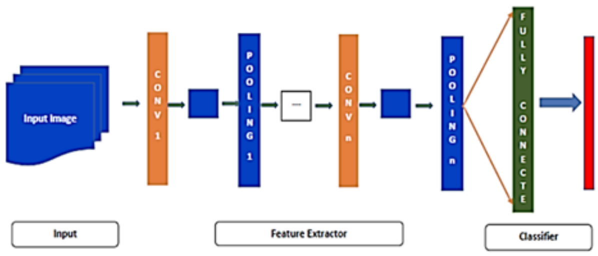


Fig 1: Basic architecture of CNN [16]

Now a day deep learning CNN techniques are widely used for crop disease identification. Many researcher invented different CNN model for various crop disease identification.

Identifying crop disease at early age will help to improve quantity and quality of yield. One of the challenges in agriculture is identify disease capture by crop at early stage. So that some corrective actions can be taken to avoid the loss. Once a plant is infected, the damage can quickly spread throughout the crop, resulting in numerous productivity and financial losses. The Crop monitoring has always been done by experts in the field, which calls for a greater degree of knowledge.

India is the second-largest producer of rice in the world and the top exporter of rice globally. 120 million tonnes were produced in FY2020–21, up from 53.6 million tonnes in FY 1980.

One of India's staple cereals is rice. Additionally, the largest area of rice cultivation is in this nation. Considering that it is a major food crop. Rice crop cultivated under 25^0C temperature and 100cm more than rainfall. Due to changing of weather and other factors different diseases found on rice crop and it effect on rice yield production.

2 Types of Rice Plant Disease:

Some of the common disease found on rice plant like blight, blast, brown spot during rice plant growth.

2.1 Bacterial Blight

Which occurred due to Xanthomonas oryzae pv. Oryzae bacteria. Areas containing weeds and plant waste from contaminated plants are where the disease is most likely to spread. Both tropical and temperate environments can have it, especially in lowland regions that get irrigation and rainfall. In general, the illness prefers conditions with relative humidity of at least 70% and temperatures between 25 and 34 °C. It is commonly brought on by strong winds and prolonged downpours, which facilitates the spread of the disease-causing bacteria by leaking droplets on lesions of afflicted plants. The leaves of infected seedlings curl and take on a greyish green hue. As the sickness spreads, the seedling's entire body dries out and dies, causing the leaves to droop and turn straw-colored.

Fig 2: Bacterial Blight

2.2 Blast

Blast is fugal disease cause by Magnaporthe oryzae fungus. A rice plant's leaf, collar, node, neck, sections of the panicle, and occasionally the leaf sheath are all susceptible to it. Low soil moisture, frequent and protracted rain showers, and chilly daytime temperatures are all factors that contribute to its occurrence. Large day-night temperature fluctuations that result in dew forming on leaves and generally lower temperatures in upland rice enhance the growth of the disease. Rice can develop blast at every stage of growth. However, as plants mature and build up adult plant resistance to the disease, the incidence of leaf blast tends to decline. White to gray-green lesions or patches with dark green edges are the primary symptoms. Older leaf lesions have oval or spindle-shaped centres that are pale to grey with a reddish-brownish or necrotic border. Some have a diamond-like shape, with a large core and sharp ends. The entire leaf can be killed by lesions that become larger and combine.

Fig 3: Blast

2.3 Brown spot

It is also fungus disease which infected leaves, leaf sheath, panicle branches, glumes, and spikelets.

The multiple large blotches on the leaves that can kill the entire leaf are the most noticeable harm. Unfilled grains or speckled or discoloured seeds develop when the seed becomes infected. High relative humidity (86–100%) and temperatures between 16 and 36 °C are responsible for disease growth. It frequently occurs in soil that is neither irrigated nor nourished, or in soil that builds up harmful compounds.

On infected seedlings, there are small, circular, lesions that may be brown, yellow-brown, or ring the coleoptile and bend the primary and secondary leaves. Lesions on the leaves can be seen when they start to grow. They begin as tiny, rounded, dark brown to purple-brown creatures. Oval to circular in shape, with a light brown to grey centre and a reddish brown margin brought on by the fungi's poison, fully grown lesions have these characteristics.

Fig 4: Brown Spot

3 Literature Review

Some recent technique implemented for rice plant disease detection introduced in related work section.

Citation	Method Used	Finding
[1]	Ensemble Model with submodel DenseNet-121, SE-ResNet-50, and ResNeSt-50	Speed of identification for ensemble model slow due to various parameters
[2]	AlexNet	Author used AlexNet and suggested other clustering algorithms like Fuzzy C-mean, K-means, CART for improve accuracy and process time.
[3]	Modified VGG19-based transfer learning method	Suggested combination of fully IOT and drone based system to achieve optimal solition.
[4]	RideSpider Water Wave (RSW) algorithm employed to train Deep RNN	Proposed systems provide the maximal accuracy 90.5%. Various algorithms are already in use to detect illnesses, these algorithms can still be enhanced to provide more accuracy in the identification of diseases in rice plants.
[5]	Control to target classes method,	During inference, we achieved a recognition rate of 93.37% mAP for the target classes. Author suggested proposing system will

		be implementing on various crops.
[6]	VGGNet, ImageNet and Inception module	the class prediction accuracy of the gathered photos of rice sickness averages 92.00%. In order to automatically monitor and identify a greater variety of plant disease information, authors intend to deploy it on mobile devices in the future.
[7]	Logistic Regression (LR), Support vector machine (SVM), and Convolution Neural Network (CNN) models	Because there were only 30 samples in each category in the training set, CNN did not perform as well as it could have, but it still showed significant promise for detecting rice diseases.
[8]	CNN to extract the rice leaf disease images features and SVM for disease prediction.	Researcher still need to offer tens of thousands of examples of high-quality rice illnesses photos in order to impove the accuracy of rice diseases detection.
[9]	Machine Learning and Deep Learning	Authors suggested the few areas that require attention are increased accuracy and real-time testing and deployment. Recommendations for chemicals and pesticides depending on the identified disease.
[10]	Inception-v3 with ILSVR	Authors have also shown that even with receptive field resolutions as low as 79 x79, excellent quality results are still possible. This could be advantageous for systems that detect relatively small items.
[11]	VGG 16, Inception V4, ResNe-50,	The architecture performs well, however more study is needed to

	ResNe-101, ResNe-152, and DenseNets-121	decrease computing time even though the performance is good.
[12]	Inception v3 model and Transfer Learning applied on fruit disease.	Author recommended proposed system will use for vegetables, crop disease detections.
[13]	CNN for feature extraction and SVM for classification.	Difficult to work on not available standard labelled images for rice dataset. Proposed model will be improved on large rice dataset.
[14]	Rice-Fusion model based on CNN and MLP architectures	Due to geographic and climatic challenges, future study will concentrate on gathering balanced datasets for various types of rice disease.
[15]	LetNet, shuffalNet, AlexNet, EffNet and MobileNet CNN five architecture trained and tested	Since the results shown by proposed system are a multilabel classification of comparable research in the literature for the same database, comparative performance analysis is made challenging.

4 Convolution Neural Network Model

Different CNN model are implemented to detect crop disease. Modern Deep Learning models for image recognition, segmentation, and classification have proliferated. Several well-known Deep Learning models for classifying and identifying agricultural diseases were applied to the rice crop. In other connected papers, new visualisation methods and improved DL architectures were provided to achieve better results[16]. Inception V3 and SqueezeNet these two models also used for crop disease detection.

4.1 Inception_V3 CNN Model:

Inception V3 is the extended network of GoogleNet. Which, utilising transfer learning, has produced positive classification results in a number of applications. Following GoogLeNet, Inception-v3 proposed an inception model that combines numerous convolutional filters of varied sizes into a single filter. Such a design lowers the amount of parameters that need to be learned, hence reducing the computation's complexity[12].

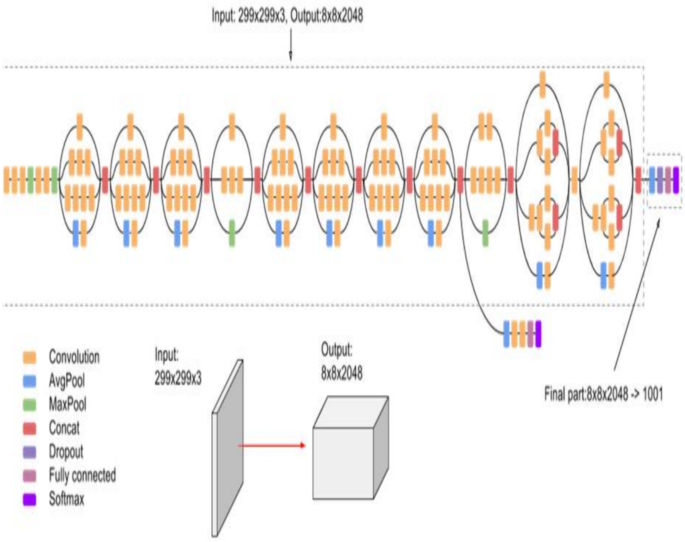


Fig 5: Inception V3 Model [17]

Working: Total 42 layers are use in the Inception V3 model. Following table 1 shows description of Inception V3 model:

Table 1: Inception V3 Layers

Type	Path	Input Size
Conv	3x3/2	299x299x3
Conv	3x3/1	149x149x32
Conv Padded	3x3/2	147x147x32
Pool	3x3/2	147x147x64
Conv	3x3/1	73x73x64
Conv	3x3/2	71x71x80
Conv	3x3/1	35x35x192
3x Inception	Module 1	35x35x288
5 x Inception	Module 2	17x17x768
2 x Inception	Module 3	8x8x1280
Pool	8x8	8x8x2048
Liner	Logits	1x1x2048
Softmax	Classifier	1x1x1000

Output of each module goes as input to the next module.

4.2 SqueezeNet: SqueezeNet is smaller and compact than other CNN model like AlexNet, so mostly used in crop disease detection. A small structure that requires less bandwidth to export new concepts to the cloud and a small structure that is simpler to deploy on FPGA devices and other hardware with memory limitations are two benefits of the SqueezeNet architecture. The SqueezeNet architecture is broken into three sections: the first is filter size reduction, the second is input channel reduction, and the third is dawn sampling at the network's conclusion. It makes use of the fire module, which is once more divided into a squeeze layer and an expand layer as seen in figure 6.

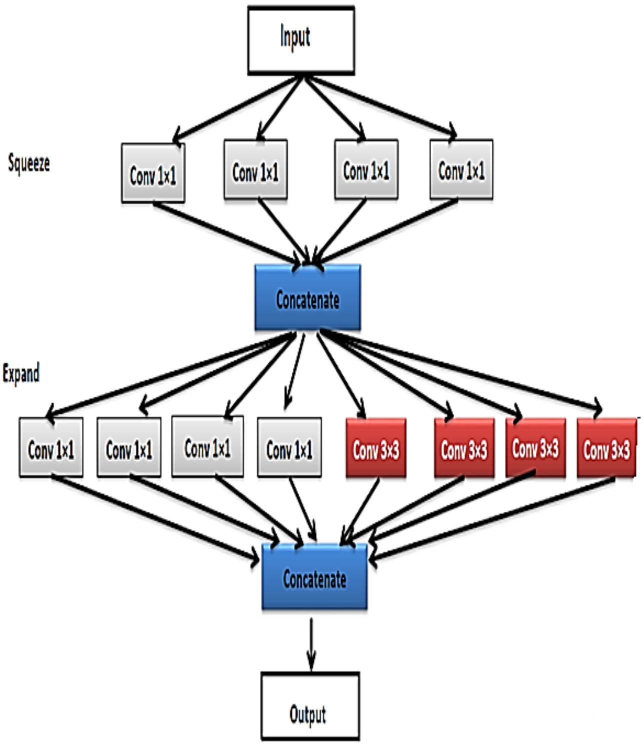


Fig: 6 SqueezeNet Model

Working: Squeeze layer and expand layer are the important parameter of SqueezeNet architecture. Squeeze layer is responsible for decrease the input channel from 3x3 to 1x1 and composed with 1x1 each size; three convolution layer. Expand layer is combination of the four 1x1 convolution layer and four 3x3 convolution layer filter to reduce filter size. The squeeze layer will assist in limiting the number of input channels to the expand layer when utilising a fire module. As a result, the expand layer receives less parameters, which results in a model with a simple SqueezeNet design [15].

SqueezeNet architecture layers breakdown onto following layers:

Layer 1: Convoltional Layer

Layer 2-9: Fire Module(squeeze and expand layers)

Layer 10:convolutional layer

Layer 11: sofmax layer

Number of filters gradually increases per fire module. Max-pooling apply after layer 1,4 and 8 with stride 2. Average-pooling apply after 10 number of layer.

5 Experiment Result and Performance evaluation

Both the model implemented on same rice dataset. SqueezeNet used with 224x224 image size, 150 epoch and predicted the accuracy 92% and 27% loss. Inception V3 worked with 229x229 image size, 30 epoch and predicted the accuracy 95% and 12% loss as shown Table2. Softmax function, adam optimizer and crossentropy performed important role for both the models.

Softmax function : Softmax function used in the both model for last layer. Softmax function used for find the probability decimal 0 to 1 for multiple classes.

$$Sofmax(X_i)=\frac{e^{Xi}}{\sum_j e^{Xi}} \qquad \ldots\ldots\ldots..(1)$$

Here, the X represents the values from the neurons of the output layer.

Adam optimizer: Adam optimizer updates the learning rate for each network weight individually. extensions of the stochastic gradient descent algorithms.

$$m_t = \beta_1\, m_{t-1} + (1- \beta_1)\, [\tfrac{\delta L}{\delta Wt}] V_t = \beta_2\, V_{t-1} + (1- \beta_2)\, [\tfrac{\delta L}{\delta Wt}]^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

Where

m_t – aggregate of gradient time t (initially m_t=0)

m_{t-1} –aggregate of gradient time t-1

W_t - weight at time t

δL –derivation of loss function

δWt – derivation of weight at time t

Vt - sum of square of past gradient (initially V_t=0)

V_{t-1} - sum of square of past gradient time t-1

β – moving average parameter

Cross entropy:

Cross entropy loss function is used to optimize classification models. The CE Loss is defined as:

$CE=\sum_{i}^{C} ti * log2(Si)$ ……. *(3)*

Where ti and si are the groundtruth and the CNN score for each class i in C.

Dataset: Publically available Rice leaf data set is used for implementation SqueezeNet and Inception V3. Following basic algorithm worked on both the models:

Step 1: Libraries importing

Step 2: Dataset loading

Step 3: Preparing training and validation dataset

Step 4: Label Mapping for 3 disease classes blight, blast and brownspot

Step 5: Model selection SqueezeNet /Inception V3

Step 6: Data Preprocssin for image augmentation

Step 7: Model Building with softmax function function, adam optimizer and crossentropy loss function as per equation number (1), (2) and (3)

Step 8: Training

Step 9: Testing

Table 2: SqueezeNet and Inception V3 with different parameters

Parameter	**Inception V3**	**SqueezeNet**
Number of Images	241	241
Image Size	229x229	224x224
Epoch	30	150
Accuracy	95%	92%
Loss	12%	27%

Experimental results shows for accuracy and losses for training and validation data of SqueezeNet and Inception V3 model respectively**.**

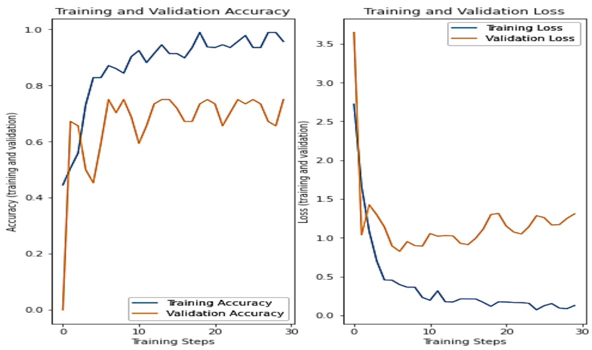


Fig 7: Experimental result for accuracy and loss for SqueezeNet model

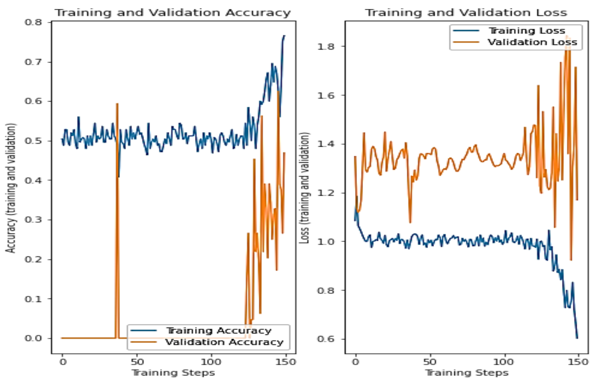


Fig 8: Experimental result for accuracy and loss for Inception V3 model

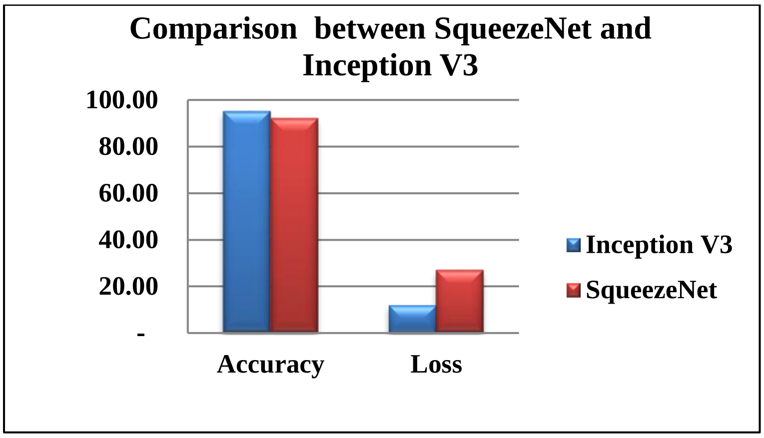
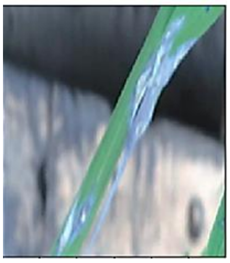
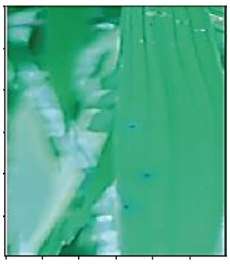
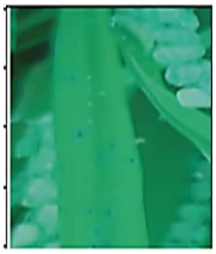


Fig 9: Comparison between Inception V3 & SqueezeNet

In Table 3 diseases of rice crop detected by SqueezeNet and Inception V3 shown for three classes bacterial blight, blast and brown spot.

Table 3: Rice leaf disease detected by SqueezeNet and Inception V3

Classes	Inception V3	SqueezeNet
Bacterial blight		
Blast		
Brown spot		

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6. Conclusion

Convolutional Neural Network deep learning technique widely used on image classification applications. Rice is mostly used crop of India. On publically accessible datasets, CNN Inception V 3 and SqueezeNet module were used to identify rice plant diseases. Inception V3 model accuracy is 95% with 12% loss but with 30 epoch. And SqueezeNet model on same dataset accuracy is 92% with 27% loss with 150 epoch. In future SqueezeNet and

Inception Model will be implemented on private dataset with ensemble novel approach to improve the accuracy.

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