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Real-Time Classification of Paddy Diseases using Deep Learning Techniques based on Generative Adversarial Network

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Abstract

Paddy leaf diseases cause major issues in yield production and quality of rice. The initial stage analysis and classification of paddy leaf diseases in prior knowledge can reduce the spread of pathogens across the field and increase yield production. This paper proposes an accurate classification of paddy leaf diseases, namely bacteria leaf blight, leaf spot, blast, hispa, and leaf folder based on the Deep Convolutional Neural Network and Random Forest. Novel data-set of 2,088 images collected using Canon EOS 1200D, FLIR E8's camera, and stored in the paddy image repository. The leaf portion was extracted from a complex data-set using K-Means Clustering techniques. The count and quality of the image enhanced using Generative adversarial network techniques (GAN). GAN augmentation generates images of 18,317, features extracted using the Deep Convolutional Neural Network model, and diseases classified using Random Forest. The interpretation was made over the architecture models, namely AlexNet, GoogleNet, VGG, ResNet, and Inception-ResNet. The resultant value states that Inception-ResNet produces better accuracy of 95.166 compared with the remaining standard models. ResNet-50 model parameters are reduced by 24,769,690 compared with Inception-ResNet model. This research work indicates that the proposed system produces better accuracy with less error rate of 0.0230 in the classification of paddy leaf diseases.

Keywords

Convolutional Neural Network, Generative Adversarial Network, paddy, paddy, Neural network, K-Means Clustering.

1. Introduction

Rice is the primary commercial crop cultivated around the globe. To survive from day to day life, people directly depend on rice cash crops. There is a drastic increase in the human population, so the cultivation of rice crops needs to be enhanced to meet global demands. The production of crops is gradually receding due to leaf diseases. The pathogens include Bacteria, fungi, and viruses that cause significant damage to the farmer's crop, which leads to a reduction of crop yield and economic loss. The various kinds of rice crops include Bacterial blight, Bacterial leaf streak, Blast, Brown spot, false Smut, grassy rice stunt, ragged rice stunt, sheath blight, Tungro, leaf scald, Narrow brown spot, red stripe, bakanae, sheath rot, blast (node and neck), stem rot, bacterial sheath brown rot, rice stripe virus diseases, and rice yellow mottle virus diseases, that damage to the rice crop and causes disastrous economic and Eco-friendly damage [1]. The maximum rice-growing areas include Asia, the eastern and southeastern zone; these areas are affected by the diseases at irregular intervals of time. In Asia, Africa, and Australia countries, the range of yield loss is 8-17% during the winter season and 1-3% during the summer season, due to Bacterial leaf streak. In India, a revenue loss of 7-75% was found due to False Smut. In Japan, 120,000-190,000 hectares of the field are infected by the ragged rice stunt and leads to a 20% crop yield [2].

In the traditional system, the infected region has undergone visual observation of crop tissues by pathogen experts [3]. The kinds of diseases were carried out by Polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA) test. Later, In 1992 Advanced Restriction fragment length polymorphism technique (RELP) and tissue culture were used. Even though ELISA and Nested PCR methods are efficient in identifying different kinds of diseases, they suffer from certain limitations, i.e., lack of identifying particular viral species. Biosensors based on nanomaterials, DNA/RNA based affinity Biosensors, Enzymes Electrochemical Biosensors, and Bacteriophage biosensors are available in the market; however, they are costlier and so farmers cannot lend them [4]. In the modern world, to improve crop production, the digital camera and Information technology have widely utilized to manage agriculture, yield production, and manage the adept system. However, for the adept system differentiating the pest and diseases depends on skilled experience, which causes a lack of regularity and low awareness rate. The problem, as mentioned earlier, is overcome by researches through depth analysis in various kinds of Machine Learning (ML) techniques, namely Support Vector Machine (SVM), Random forest, and K-Nearest Neighbor to recognize diseases in various kinds of plants[5][6][7].

However, in Machine learning, the feature needs to be extracted manually based on the human experience. In a few cases, manual feature prediction may lead to improper fault diagnose. The accuracy identification of paddy diseases is low by using classical machine learning methods; these issues are overcome by Deep Convolution Neural Network (DCNN) [8]. DCNN is an end to end pipeline to recognize the diseases at an effective computational cost. [1][9][10]. Transfer learning techniques utilized by the maximum number of researchers [11][12][13][14]. Then discussing the dataset, In [8] frequently, many researchers utilized plant village data-sets, where images segregated using regularization methods with a similar background.

This paper presents the processing of images over a novel paddy dataset. The augmentation process carried out using GAN; features are extracted using DCNN (Inception-Resnet) and classified using Random Forest. The interpretation was made over various pre-trained architectures, namely AlexNet, GoogleNet, VGG-16, ResNet, Inception v4, and Inception ResNet. The structure of this paper organized as follows: in section 2 brief discussion about related works, section 3 describes Image acquisition and building neural network models. Section 4 analyzes the experimental evaluation concerning experimental setup, accuracy with learning convergence, and computational resources, at last, this study concluded in section 5.

2. Related Works

The manual procedure of recognizing crop diseases is frequently time-consuming, labor-concentrated, and costly, which is one of the significant reasons for the researchers to investigate different strategies. Different ML approaches have been proposed to handle this issue with high precision, a decrease in expenses, and subjectivity. In [15] presented an expedient report for lesion image recognition of alfalfa disease, relief strategy used to extract 129 features, classified using the SVM approach, and achieved an actual accuracy of 97.74%. In [16], a methodology that incorporated image processing and ML techniques to permit the analysis of infections from leaf images. Plant village dataset was used to detect the disease location present in 300 samples by using segmentation and SVM approach and achieved 95% accuracy. In [17] presented a novel DCNN methodology to distinguish plant diseases by separating the plant leaves from their environment, the proposed CNN Model perceived 13 various essential sorts of plant infections. The exploratory outcomes indicated that the proposed CNN based model perform better and acquired an average accuracy of 96.3%. In [8], build a neural network to identify 26 diseases and 14 harvest species. The author used an open-access plant village dataset of 54,306 images of both infected and healthy leaves, and the developed model accomplished an accuracy of 99.35%.

Table 1.
Analysis of Deep learning Methods applied in paddy disease classification

Year	References	Dataset	Methodology	Accuracy
2020	[21]	Three diseases –Brown spot, Bacteria leaf blight, and leaf smut, data-set source, and count not mentioned.	CNN	90.32
2020	[22]	30,000 field images of 5 different paddy crop variety with 12 different stress.	DCNN	92.89%
2020	[23]	1426 images of rice diseases and pest namely False Smut, Bacterial Leaf Blight (BLB) Neck Blast Stem borer Hispa Sheath Blight and Sheath Rot Brown Spot.	CNN	93.3%
2020	[24]	1500 rice leaves include bacteria leaf blight, blast and brown spot.	CNN	78.44%
2019	[25]	5808 images of blast disease.	Haar-WT+SVM	83.85
2018	[26]	Data set contains Brown spots Bacterial blight Leaf scald, Leaf blast. data-set source and count not mentioned.	Fuzzy Logic with K-Means segmentation techniques	86.35%

The author [18] proposed tea leaf disease classification, the features extracted based on texture and color using the Convolution layer. The number of samples increased using the Conditional Deep Convolutional Generative Adversarial Network (C-DCGAN). The disease spot recognized using the SVM approach and obtained an accuracy of 90%. Since deep learning requires many samples, there is a lack of enough leaf samples to classify. Author [19] proposed a method to distinguish plant lesions; the challenging task is to identify plant lesions, which have a similar data structure and tough to recognize. To solve the above issues, the author proposed GAN, which generates a lesion image based on shape. Edge smoothing and pyramid algorithm used to smooth the lesion edge. The whole experiment carried out using AlexNet architecture. However, GAN generated output size is not the same as the real lesion. Author [20] proposed a DCNN method to recognize plant diseases by using Plant village dataset, diseases classified using Inception v3 architecture. Limitation of the work, there is a lack of interpretation over the pre-trained architecture. The author [21] proposed the prediction of paddy crop diseases using the CNN Model. The dataset increased further, and interpretation was made over the architecture with various epoch sizes. Author [22] proposed a method to recognize rice sheath blight, brown spot, and rice stem borer symptoms using DCNN architectures, namely VGG-16, ResNet-50, ResNet-101. The system increased further to detect more crop diseases. Table 1 illustrates the analysis made by various researchers to classify paddy diseases using deep learning techniques.

3. Materials and Methods

3.1. Novel Data Repository.

3.1.1 Camera Specification.

The images are captured with the help of high-resolution cameras, namely Canon EOS 1200D and FLIR E8 (Thermal camera). The specification of these cameras are mentioned below, Canon EOS 1200D 18MP, Digital SLR Camera (Black) with EF-S 18-55mm f/3.5-5.6, is II Lens and FLIR E8's crisp 76,800 (320 X 240) pixel infrared resolution, +2% accuracy of reading for ambient temperature 10^{O}C to 35^{O} C(50^{O} to 95^{O}F) and object temperature above 0^{O}C (32^{O}F), the field of view is 45^{O} X 34^{O}.

3.1.2 Image Collection

The images collected from the state of Tamil Nadu include the following regions; the Agri field (VIT School of Agricultural Innovations and Advanced Learning. (VAIAL), VIT, Vellore), Brahmapuram, sevur, Latheri, vaduthangal from Vellore district. The complete field survey has undergone concerning disease symptoms and climatic conditions; samples were collected and captured using two different high-resolution cameras, as mentioned in section 3.1.1. Later, the diseases were classified with the help of plant pathologists from VAIAL, Vellore Institute of Technology, Vellore. In the region, as mentioned above, the paddy crop leaves are affected by two significant reasons, namely Diseases and Pest. The leaves turn yellow; the brown spot appears over the leaves; insects consume the leaves as well as hold the leaves and lay their eggs. Different kinds of diseases include bacteria leaf blight, blight, leaf spot, leaf holder, hispa, and healthy leaves are collected in the region, as mentioned earlier, are illustrated in Table 3.1. Sample images of the data repository shown in Fig 3.1.

Table 2.
Count of the images included in the repository

S.NO	Diseases	Number of images captured using canon 1200D	Number of images captured using FLIR E8	Total
1	Bacteria leaf blight	208	341	549
2	Blight	-	206	206

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3	Leaf spot	188	225	413
4	Leaf holder	54	69	123
5	hispa	53	317	370
6	Healthy leaves	-	427	427
			Totally	2,088

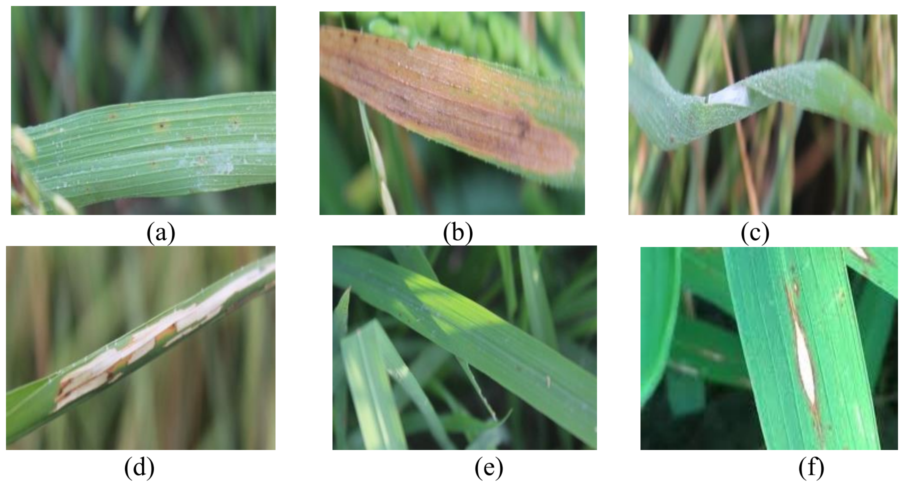


Figure 1. Raw Dataset (a) Leafspot (b) Bacteria leaf blight (c) Leaf folder (d) Hispa (e) Healthy (f) Blast

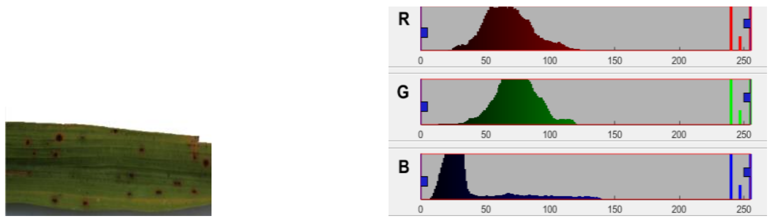
3.2. Image pre-processing

The pre-processing module removes noise and resizes the given input image. To understand in a better way, noises are obstacles present between the camera and the target object; these obstacles present in the air are unwanted signals which affect the pixel value, so the brightness of the image is reduced as the result of images turns to blur. Noises are categorized into Gaussian, salt and pepper, speckle, and Poisson noise. In the novel data-set, identifying specific kinds of noise is impossible, so noises are introduced and removed using a Median filter technique. Though various kinds of filtering techniques available main reason to utilize median filter is, it protects the image information in horizontal, vertical, and diagonal directions, as well as Computational complexity, which is low [27].

The input images resized into 224 X 224; the primary purpose of selecting a specific dimension is, the image information remains unchanged. In transfer learning techniques, CNN is memory-intensive mainly for training. Larger image size may lead to running out of memory space, so it is better to resize into 224 X 224, which is a commonly used dimension that supports all pre-trained architecture with better accuracy [28].

3.3. Leaf Segmentation

Segmentation is the process of extracting the region of interest from the given pre-processed image. Leaf segmentation carried out using two kinds of approaches, namely discontinuity, and similarity-based approaches. Here segmentation is carried out using Matlab 2019 b. The global thresholding method and K-Means segmentation methods are used to extract the leaf portion. The reason to choose the thresholding method since the images captured in environmental light, so this method is secure and supports well for various intensity values. In this method, the leaf portion is extracted by using the global threshold value, lower bound (LB) of 200 and upper bound (UB) of 5000, and to perform better classification change the background to white color.

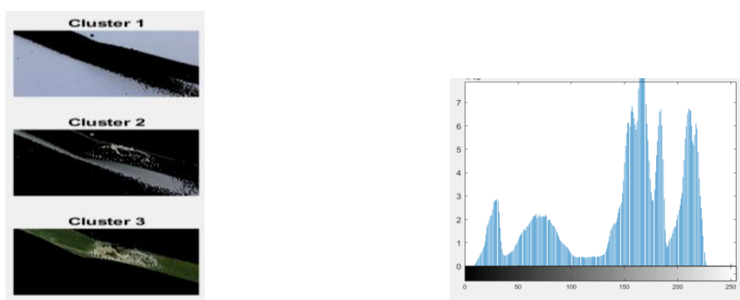


(a) (b)

Figure 2. (a) Global thresholding techniques on leaf spot diseases (b) Histogram on color images

In the second method, Use of K Means clustering for segmentation, which converts images from RGB Color Space to L*a*b* Color Space. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' and 'b*'. All the color information is in the ‘a*’ and ‘b*’ layers. Classify the colors in a*b* color space using K means clustering. Since the image has three colors, create 3 clusters. Measure the distance using Euclidean Distance Metric. Label every pixel in the image using results obtained from K means by using (1).

[cluster_idx cluster_center] = kmeans(ab,nColors,'distance','sqEuclidean','Replicates',3) (1)



(a) (b)

Figure 3. (a) K-Means Clustering techniques on leaf folder (b) Histogram

3.4. GAN

Generative Adversarial Network (GAN) is used to generate a greater number of new samples based on the pattern in the input data. GAN produces a higher realistic image; it consists of a Generator network and Discriminator network. The generator network takes input and generates samples of data. The Discriminator network decides whether the data is generated or taken from the real sample using the binary classification problem with the help of a sigmoid function that gives output in range 0 to 1. The objective function of GAN written as (2),

$$V\ (D, G) = E_{X\sim pdata(X)}\ [logD(X)] + E_{Z\sim pdata(Z)}\ [\log(1 - D(G(Z)) \qquad (2)$$

G generator, D discriminator, data(x) distribution of real data, data(z) distributor of the generator, X sample from real data, Z sample from the generator, D(X) discriminator network, G(Z) generator network

3.5 Classification of Paddy diseases using pre-trained Neural Network Model

This section explains the timeline, parameters involved, and input size of the pre-trained architecture model. The purpose of using this model architecture is to extracts the features from the given input. The convolution layer in the model process the feature extraction task. Pre-trained architecture explained below,

3.5.1 LeNet-5

LeNet -5 was the initial Neural network model developed. It is perhaps the most straightforward model consists of two convolutional layers and three Fully connected layers. The model holds 60,000 parameters. The novelty of the LeNet -5, it was developed into a standard format for the forthcoming architecture model [29].

3.5.2 AlexNet

AlexNet consists of 60 million parameters. Usually, AlexNet consists of five convolution layer and three fully connected layers. AlexNet model initiates ReLu as an activation function. AlexNet accepts an image size of 227 X 227 and 96 filter size [30].

3.5.3 GoogleNet/Inception

The naive idea leads to more computational cost and massive variation in the location of the information, so GoogleNet was proposed by researchers at Google in 2000. It is the winner of ILSVRC 2014, produce less error rate compared with AlexNet. GoogleNet uses 1 X 1 convolution; it reduces the number of weights and biases in the architecture model. The depth of model increased by parameter reduction [31]

3.5.4 VGG-16

VGG-16 was developed by folks at Visual Geometry Group; it holds 13 convolutional layers and three fully connected layers. Kernel size of 3 X 3 maintained throughout the network. It consists of 138 million parameters, and space is utilized at about 500 MB. The novelty of the model it is designed by the deeper network [32].

3.5.5 ResNet-50

The above discussed CNN model was constructed only by expanding the number of layers in the structure and accomplishing better execution. In many cases, if the network depth increases, the accuracy keeps saturating (which may lead to obvious) and afterward debases quickly. The people from Microsoft research tended to these issues by introducing a skip association in the ResNet model in depth. ResNet holds 26 Million parameters; it consists of two blocks, namely Conv and Identity block. The novelty of the ResNet model is to avoid degradation problem by adding a short cut connection by skipping conv and batch normalization [33]. The timeline of the CNN architecture models illustrated in figure 4.

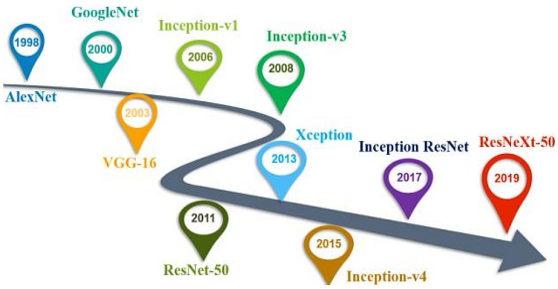


Figure 4. *CNN Architectures Timeline*

3.6 Feature Extraction using CNN layers

This section explains the layer's purpose and the mathematical formulas involved in the Deep convolutional layer network.

3.6.1 Convolution layer

The convolution layer determines the feature of the given input image. The feature is extracted by sliding the kernels across the given input image. Each filter produces one feature map which is 2D as explain in formula (3)[34]

$$P_j^v = \sum_{i \in f_j} a_i^{v-1} * c_{ij}^v + E_j^v \quad (3)$$

Where, C_{ij}*is* convolutional kernel, E_j is the bias , and f_j is the set of feature maps.

3.6.2 Max pooling layer

An issue with the feature output maps is they are delicate to the area of the feature in the input. One way to deal with address this affectability is to down sample the element maps. Pooling layers give a way to deal with down sampling feature maps by summing up the nearness of features in patches of the component map [35]. Maximum value obtained by using formula (4)

$$F_j = \max_{i \in R_j} \mathrm{b_j} \quad (4)$$

Where Rj is the pooling area, B represents the feature map, and I represent the index.

3.6.3 SoftMax Regressions

Since the above problem is multiclass classification, so use SoftMax regression. It is an activation function that turns the logic into probability values that sum up to one by using formula (5).

$$S_\theta(x) = 1/\{1 + \exp(-\theta^m x)\} \tag{5}$$

The cost function is written as (6)

$$c(\theta) = 1/w[[\sum_{i=1}^{m} \sum_{j=1}^{n} 1\{x^{(i)} = j\} \log p(x^{(i)} = \frac{j}{y^{(i)}}; \theta)]] \tag{6}$$

In SoftMax, the probability value produced by using formula (7)

$$S(y_i) = e^{\theta^m x^i} / \sum e^{\theta^m x^{(i)}} \tag{7}$$

3.6.4 Leaky ReLu

ReLu reduces the computational cost; the limitation is dying ReLu, which assigns zero for all the negative values, so Leaky ReLu utilized, which consists of a small slope for negative values instead of altogether zero. Leaky ReLu obtained by using the formula (8)

Y=0.01x , where x<0 (8)

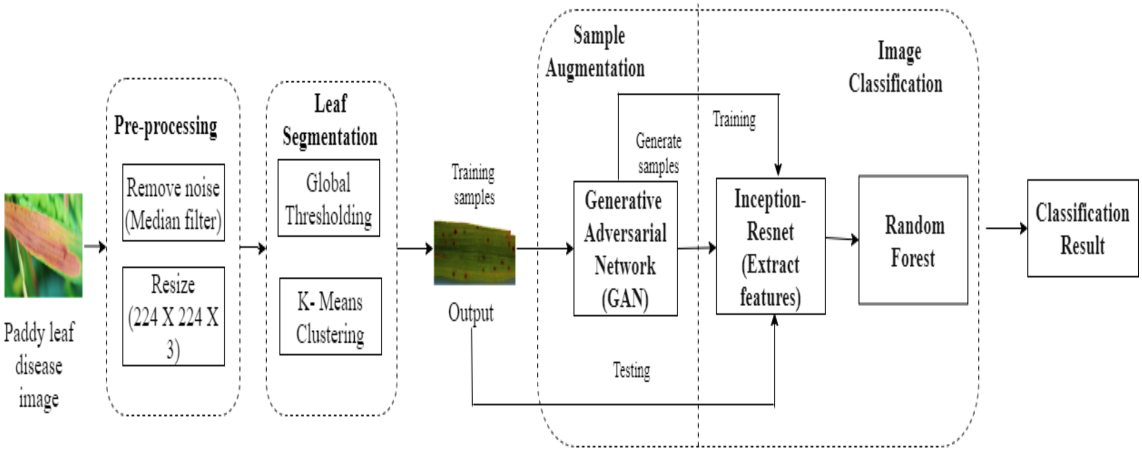
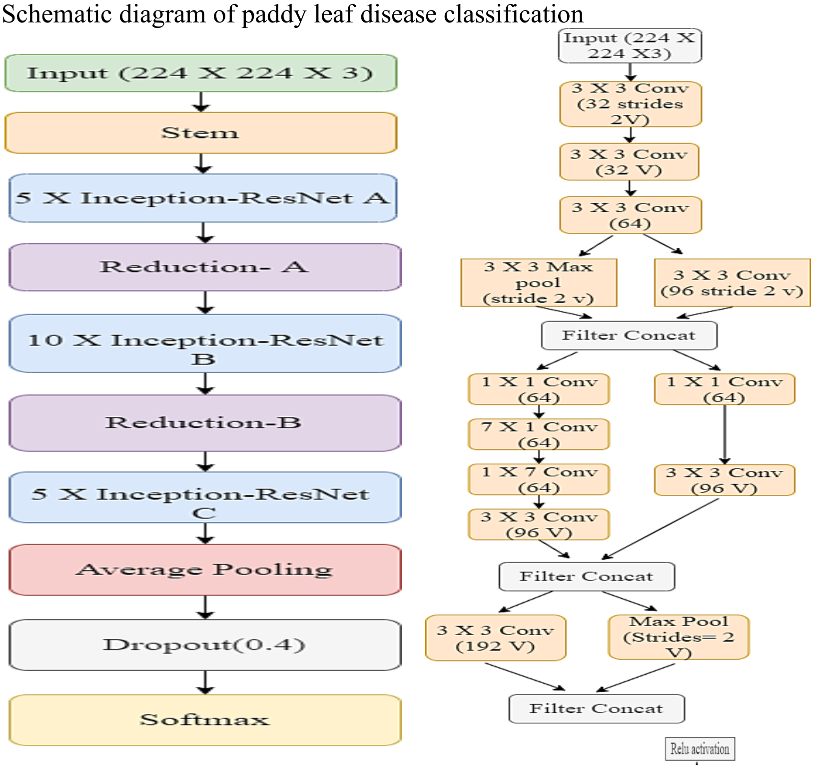
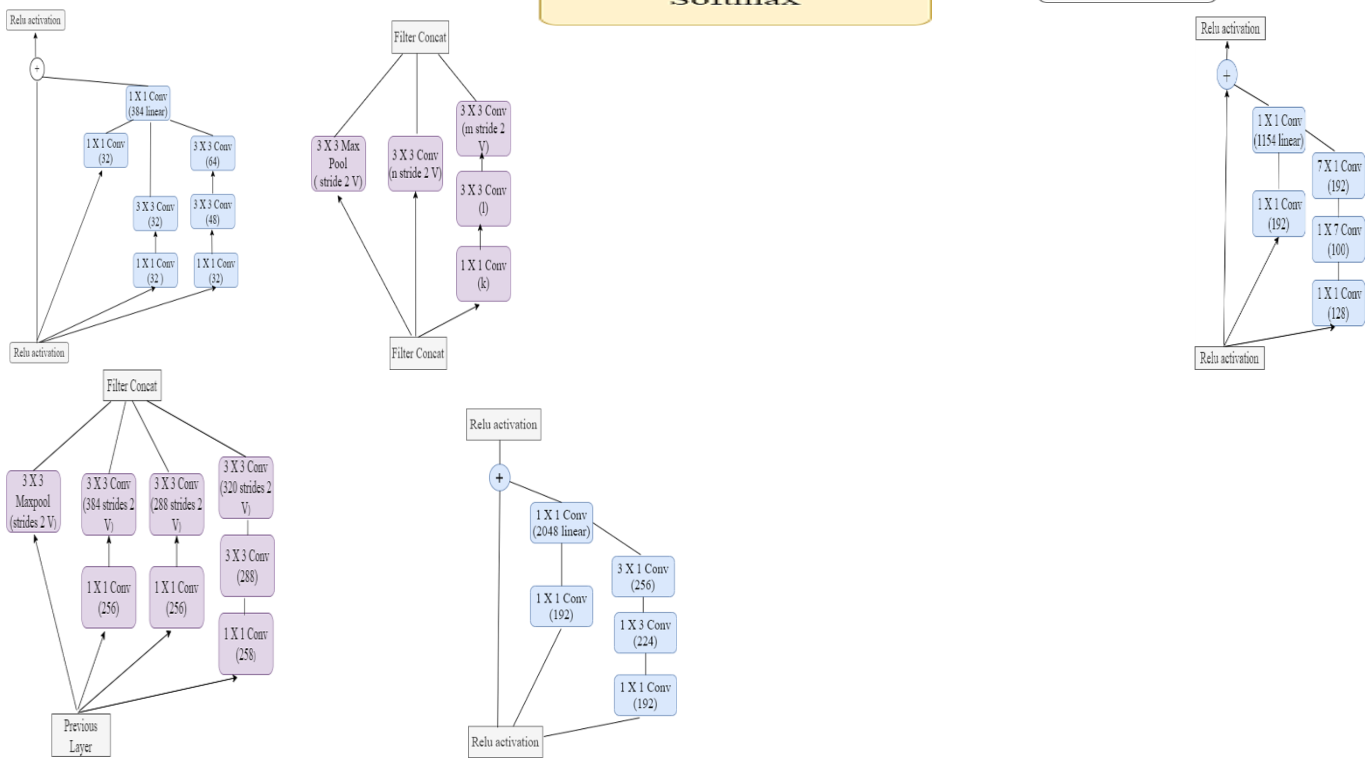


Figure 6. Schematic diagram of paddy leaf disease classification





(b) (c) (d) (e) (f)

Figure 5. *(a) Block structure of Inception- ResNet architecture model (b) Inception resnet A (c) Reduction A (d) Inception ResNet B (e) Reduction B (f) Inception- ResNet C*

4. Experimental Results and Analysis

4.1 Experimental setup

The experiment was implemented in the following hardware; Intel(R) Core (TM) i5-8300H CPU @ 2.30GHz, 8GB RAM, 64-bit Operating System, x64 based processor, GPU NVIDIA GTX1050 with 4G memory and software specification; Matlab R2019b 64-bit, Python.

4.2 Pre-trained network accuracy and learning convergence

This section explains the brief experimental results interpretation over pre-trained architectures, namely AlexNet, GoogleNet, VGG, ResNet, and Inception-ResNet. The mentioned architectures set to constant technical parameters, input size of 224 X 224, Solver type is ADAM, loss function of Categorical entropy, the Base learning rate of INIT_LR=le-3, weight delay INIT_TR/EPOCH, momentum 0.9, batch size set to 32, kernel size of 3 X 3 and epoch size set to 100. The performance of the networks discussed below, the training loss of the AlexNet drops rapidly to 0.0891 and achieved inferior accuracy of 75.925 over GoogleNet. The performance of VGG-16 and VGG-19 is similar and produce less training loss of 0.345 as compared with AlexNet and GoogleNet. ResNet-50 produces better training accuracy of 0.923, with a limited number of parameters as compared with previous architectures. In inception V4, the number of conv block is more than ResNet; it extracts features better than ResNet-50 and produce a training accuracy of 0.979. The classification accuracy and the loss of pre-trained architecture are illustrated in Table 3.

The performance of the network evaluated using cloud GPU Kaggle. ResNet utilized less disk space of 20MB as compared with the remaining architecture since the layers are more in Inception-ResNet, so it utilizes more disk space of 642.5MB and RAM space of 13.1GB. Most of the network utilized 15.3 GB GPU memory. Table 4 illustrates the computational resources utilized by pre-trained architecture.

Table 5 explains the Trainable and non-trainable parameters concerning the pre-trained architecture model. The observation states that ResNet-50 produces less trainable parameters of 24,716,550 and non-trainable parameters of 53,120, which is collectively less as compared with the remaining pre-trained architecture model.

Table 3. Recognition performance of the models

Method	AlexNet	GoogleNet	VGG-16	VGG-19	ResNet-50	Inception-v4	Inception-ResNet
Training accuracy	0.9680	0.9759	0.8333	0.8432	0.9223	0.979	0.9914
Training loss	0.0891	0.0672	0.4505	0.345	0.189	0.0562	0.0230
Validation accuracy	0.7593	0.744	0.833	0.844	0.786	0.8030	0.9213
Validation	2.5891	3.3290	0.4512	0.351	1.84	0.0812	0.3633

loss							
Testing accuracy	75.925	74.444	83.33	84.23	78.518	80.300	92.129

Table 4. Computational resource comparison

Model	RAM space utilization	Disk Space utilization	GPU Memory utilization
AlexNet	6.3 GB	509.4 MB	15.3 GB
GoogleNet	7.6 GB	509.4 MB	15.3 GB
VGG-16	8.4 GB	1.5 GB	15.3 GB
VGG-19	4.5 GB	568.1 MB	13.5 GB
ResNet-50	8.5 GB	20 MB	15.3 GB
Inception-v4	12.1 GB	642.5 MB	15.3 GB
Inception-ResNets	13.1 GB	642.5 MB	15.3 GB

Table 5. Parameters for the pre-trained model

Models	Trainable parameters	Non-Trainable parameters	Total parameters
AlexNet	42,755,142	2,800	42,758,022
GoogleNet	42,755,142	2,800	42,758,022
VGG-16	134,285,126	-	134,285,126
VGG-19	143,667,240	-	143,667,240
ResNet-50	24,716,550	53,120	24,769,690
Inception-v4	33,373,830	52,800	33,426,630
Inception ResNets	54,285,414	60,544	54,345,958

5.5 Building fine-tuned model

Transfer learning techniques applied over Inception-ResNet because it produces better classification accuracy as compared with pre-trained architectures. Inception-ResNet contains 164 layers deep with a low computational cost. In the Inception-Resnet network, it contains three blocks, namely, step block, Inception-ResNet block, and Reduction block. Step block contains 13 conv layers and the max-pooling layer to reduce the dimensionality, so set the strides to 2. In total conv_203-layer, batch_normalization_203 and activation_203 layers. Fine-tuning are defined by updating last layer, 'Con_7b_ac' by flattening the output layer to 1 Dimension, add fully connected layer with 512,141 and 100 hidden units i.e., (512-"fc", 141-"fc", 100-"fc") and ReLu activation function. At last, freeze few layers by adding a dropout rate of 0.4 and add sigmoid activation function for classification.

The network parameters were updated by changing the following parameters, epoch size set to 100, the learning rate of 0.0001, beta_1 of 0.9, beta_2 of 0.999, decay 0.0, amgrad is True, the loss function is ’categorical cross-entropy’. Obtained a training accuracy of 0.8660, training loss of 0.3814, validation accuracy of 0.8900, validation loss of 0.3011, and testing accuracy of 88.99. The network contains the following parameters, Trainable parameters 820,294, non-trainable parameter 54,306,464, total parameters 55,126,758. The classification report and the confusion matrix illustrated in Table 6 and Figure 7.

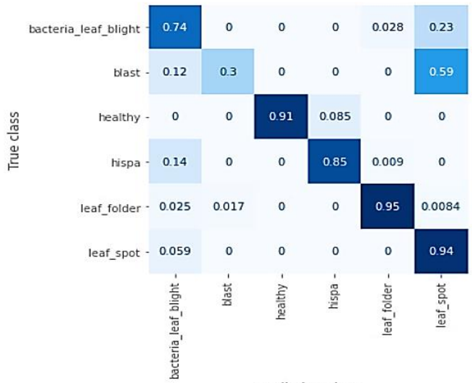


Figure 7. Confusion matrix for paddy diseases.

Table 6. Classification report for paddy diseases

Class	Precision	Recall	F1-score	Support
Bacteria leaf blight	0.65	0.74	0.69	107
blast	0.96	0.30	0.46	147
healthy	1.00	0.91	0.96	117
hispa	0.90	0.85	0.87	111
Leaf folder	0.97	0.95	0.96	119
Leaf spot	0.50	0.94	0.65	119
accuracy	0.76	0.76	0.76	720
Macro avg	0.83	0.78	0.76	720
Weighted avg	0.84	0.76	0.75	720

The parameters are fine-tuned by changing the learning rate to INIT_LR, the decay of INIR_LR/EPOCH, epsilon to le-07. The network obtained an accuracy of training accuracy of 0.9319, training loss 0.1629, validation accuracy 0.9517, validation loss 0.1410, and testing accuracy 95.166. The experimental results state that it produces better classification results as compared with the previous fine-tuned model. The network contains the following parameters, Trainable parameters 820,294, non-trainable parameter 54,306,464, total parameters 55,126,758. The classification report and the confusion matrix illustrated in Table 7 and Figure 8. The resultant study states that fine-tuned parameters produce better testing accuracy of 95.166 as compared with pre-trained architecture.

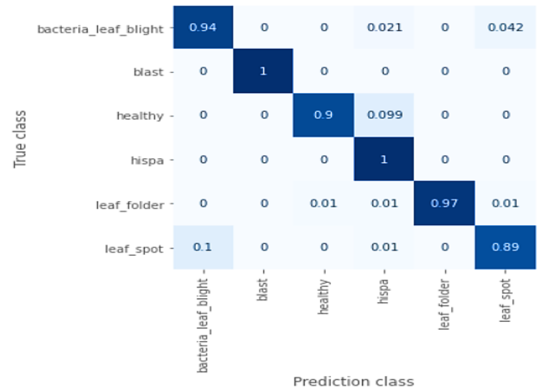


Figure 8. Confusion matrix for the fine-tuned model

Table 7. Classification report for fine-tuned model

Class	Precision	Recall	F1-score	Support
Bacteria leaf blight	0.90	0.94	0.92	95
blast	1.00	1.00	1.00	118
healthy	0.99	0.90	0.94	91
hispa	0.89	1.00	0.94	101
Leaf folder	1.00	0.97	0.98	99
Leaf spot	0.94	0.89	0.91	96
accuracy	0.95	0.95	0.95	600
Macro avg	0.95	0.95	0.95	600
Weighted avg	0.95	0.95	0.95	600

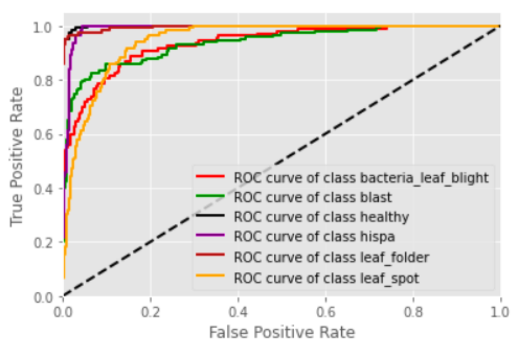


Figure 9. ROC curve for paddy leaf disease classification

Table 8. Classification accuracies of paddy leaf's diseases by different methods

Methods	Accuracy
SVM	86.12
CNN	92.12
GAN + DCNN +Random forest	95.16

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5. Conclusion and Future Scope

In this paper, the proposed system classifies the paddy leaf's disease over a novel dataset. The data augmentation processed using the GAN method, which performs better than the traditional method. Furthermore, accurate features extracted using DCNN based on the Inception-ResNet model. Extracted features induced to Random Forest to do classification task. The interpretation was made over various kinds of pre-trained architecture, namely AlexNet, GoogleNet, VGG, ResNet, and Inception-ResNet. The experimental results state Inception-ResNet produces a better testing accuracy of 95.16 % in the classification of paddy leaf diseases. Besides, due to the climatic condition and the environmental situation, limited paddy diseases were identified. In future work, IOT devices incorporated in the real-time system, and the kinds of diseases increased further, and diseases classified in a timely and accurate manner.

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