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Enhanced Hybrid Neural Networks (CoAtNet) for Paddy Crops Disease Detection and Classification

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ABSTRACT

In the Asian continent rice cultivation process provide staple food for livelihood. A current research work in the agriculture area involves recognizing and classifying plants diseases based on live images. Farmer can traditionally do the cultivation process, hence here the identification of the disease was by manual (visual appearance) or send the sample data set to the nearest laboratory. In our proposed method we will provide accurate and early detection of various diseases in Oryza sativa (rice) plants, that can help the farmers in applying suitable treatment on the rice plants and improve productivity. We are using optimized deep learning models such as the ResNet-152, CoAtNet for classification and identify the diseases. We have captured healthy and unhealthy images from Villupuram district, Tamil Nadu, India. The total amount of captured images was 3071 from our farmer's field with proper sunlight. It was highly efficient and detects the diseases or recognizes the diseases from the captured image with different categories (Bacterial Leaf Blight, Leaf Blast, Brown Spot, and Tungro / Leaf smut). The experimental results show according to the proposed method CoAtNet, was achieved for overall achieved accuracy of 96.56%.

1. INTRODUCTION

The Rice was about 70% of the total crop and 93% of the total grain production in India [1]. This may be because some archaeological evidence suggests it was first cultivated along the Yangtze River valley in China, from which it made its way to India and Sri Lanka. Rice diseases were timely crucial to ensure the sustainable production of rice. Research conducted by the International Rice Research Institute (IRRI) has classified tropical rice fungi into four groups that can occur during the plant life cycle. Important challenges for the agricultural sector were to detect plant diseases and pests as soon as possible. In the agricultural industry, plant diseases have negative effects to reduce productivity. We would like to point out in particular Agriculture and food productions are closely intertwined. Good forecasts were identified basis on effective prevention and control of plant diseases. Their roles in decision-making and management are crucial to producing agricultural products. The diversity of the crop variety in India has been grown to provide host plants for different types of pests and pathogens. Indian agriculture was dominated by subtropical climates, and the agricultural environment is more conducive to establishing the pest insects than in the tropics. The programmed automatic detection of the disease is however done by observing the indication on the leaves of the plants, making it simpler and less expensive to detect. It also supports image processing to regulate, assess, and supervise automatically.

A study suggests that rice (Oryza sativa) was the first crop to be cultivated in Asia. These groups are seeding diseases, foliar pathogens, leaf sheath diseases, and grain pathogens. Precision farming as well as nanotechnology can overcome the impact of these diseases on the next generation. Precision agriculture involves utilizing inputs related to soil, crop, and weather conditions, which helps farmers identify and eradicate their crop diseases earlier. A higher yield will result if considering the inputs is taken up by the farmers. Integrated agriculture incorporates innovations for distinguishing these ailments, meaning the innovation needs to be comprehensive enough to advise the farmers to take any basic steps when a malady is identified. Thus, deep learning and image processing are fields of research with a lot of active research. Rice leaf harm is a complex disease caused by a variety of bacteria, usually caused by spikelet's or both, that will influence farmers if the epidemic occurs in a particular place. Several factors result in uneven fertilization, bad weather, and imbalanced soil nutrients, including unfavourable fertilization and weather conditions. In addition to these factors, many factors can result in the formation of discoloured grains, such as seed harvesting prematurely, keeping seeds in heaps, or damaged by strong winds or hail, or by being attacked by insects during grain formation. Image classification may be improved greatly by deep learning technology [2]. The problem with CNN is that it needs to be trained with massive amounts of training data. Collecting rice diseased images of the crop can therefore be challenging. Applying transfer learning will overcome this constraint [3].

1.1 Different types of rice plant diseases

Rice plants can be infected with many different types of diseases. An infection of rice plants was caused by a different kind of infection than that which affected other plants [4]. Brown Spot: The main field diseases in the paddy crop were shown in Figure 1. In addition to brown spots, sesame leaf spots and Cochliobolus miyabeanus are also considered fungal diseases. The majority of cases occur in West Bengal, Orissa, Andhra Pradesh, and Tamil Nadu [5] Symptoms: Affects nurseries and main fields alike, Seedlings are affected by blight, the patches correlate with each other, measuring between 0.5 and 2.0mm in breadth, Brown-colored infection also appears on the neck of the panicle, in severe cases, yields are reduced by 50%.

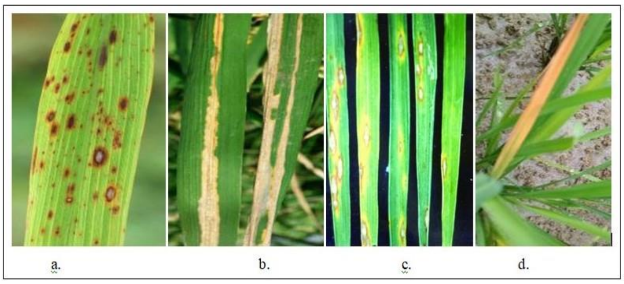


Figure 1. Samples of crops leaf diseases unhealthy
a. Cochliobolus miyabeanus,
b. Xanthomonas oryzae pv. Oryzae,
c. Magnaporthe oryzae,
d. Rice tungro virus

Rice Blast: Magnaporthe oryzae was responsible for RB disease. Leaf spots with dark green borders on the grayish-green circulars are symptoms of this disease. A spindle-shaped or ellipsoidal lesion was usually observed. Various countries around the world are experiencing some of the most devastating rice diseases [6]. Bacterial Leaf Blight (BLB): A bacterial pathogen called Xanthomonas oryzae is responsible for BLB. This disease was characterized by a lesion that begins at the tip of the leaf and spreads down several inches. Rice production is significantly affected by BLB, which is one of the most destructive diseases. Sheath Blight (SB): Rhizoctonia solani is responsible for causing Sheath Blast disease. Plants show symptoms from the lower sheath, progressing up to the upper sheath and then to the leaves. Several major rice-growing countries have faced a severe economic impact from this disease [7, 8].

Problem definition: A human vision-based approach was typically used for detecting leaf diseases [9]. It was time-consuming and very expensive to seek expert opinion in these situations. Methods that rely on human vision have many limitations. An expert's eyesight was crucial to the accuracy and precision of a human vision method. It was possible to classify the various different types of diseases, make the appropriate decisions, and choose the appropriate treatment using a deep learning method. Its consistency as compared to human experts has the advantage of using deep learning technology. Therefore, a neural network based classification approach was necessary to overcome the drawbacks of conventional methods. Using deep learning to detect leaf diseases on plants was a very rare development, and it was only a few paddy leaf disease detection and classification that recent developments have been made.

Insects attack the rice plant in more than 100 species, 20 of which can cause economic damage. There are various stages of attack in the rice crop. Generally, there are the Vegetative stage, Reproductive stage, Ripening stage, and Soil-inhabiting pests. A stem borer is considered to be one of the most harmful pests of rice in the world and attacks plants from seedlings to maturity. Scirpophaga incertulas and Chilo suppressalis cause steady annual crop losses of 5-10% in Asia, with localized outbreaks of up to 60% at times. Mostly found in the tropics, the scirpophaga incertulas insect is also found in temperate areas with annual rainfall exceeding 1,000 millimeters and tem temperatures above 10℃. The species is predominant in Bangladesh, India, and many other countries. During earlier years, they were monitored and controlled using light traps because of their strong phototaxis. As stem borers are the most serious pests in rice cultures worldwide, they attack young plants up to maturity. These insects are very danger for the rice plants, which it will affect the maximum productivity. In deep learning model the insects captured image were trained to predict which type of diseases attacked by rice plants.

1.2 Motivation

The design paradigm of the proposed design is directed towards finding the image in the right class, disease classification, and detection. I have taken the data set from the farmer land following location such as Villupuram district longitude and latitude 11.9401°N, 79.4861°E. The preprocessing process completed convolution auto encoder take a place. The results are divided into two different neuron networks such as feature extraction using ResNet 152 and feature extraction using proposed CoAtNet. The selective attention is provided to the outlier attribute extraction as a size, color, resolution, and shape. The different diseases are arranged into different classes to train the model. The main goal is designed to develop a neural network model to identify the diseased plant leaf in an earlier stage to increase productivity. By adopting a neuroscience perspective to classify distinct plant leaves based on their infection classes.

In this research article the complete layout is initial dataset collected from farmer land, then preprocessing the loaded images, select the CNN model for training purpose to achieve best results. Hybrid model neural networks achieve the maximum best results from after validation process.

2. LITERATURE SURVEY AND COMPARISON STUDY

The In earlier many authors were conducted various studies and implementation using a different dataset [10-16]. The accuracy was not achieved maximum percentage. We have found high-quality research articles for disease classification and segmentation. The following Table 1 provided a detailed discussion about comparison study with all aspects.

Russakovsky et al. [9] developed an application using vision based deep bi-linear convolution neural networks to detect plant diseases. There are 18 different classes used to train the model. After fulfilling the pre- processing steps, the models were used to train 80:20 ratios. These are the models that were built VGG, Bi-CNN model, and resnet model used to detect the diseases. The dataset was used from github (potato, corn, and tomato), and results were achieved by 91.3%, 90.2%, 91.20%.

A novel idea was proposed and implemented to detect leaf blight detection by Lee et al. [10]. They were used a deep CNN model for feature extraction, squeeze net deep learning model using entropy value. The classification was used L*a*b* color spacing to detect leaf blight. The dataset was available in a public forum. The overall accuracy was achieved by 98%, and prevented the loss of valuable crops, increasing productivity [11].

Table 1. Comparison study with various parameters

Author's Name	Publisher & Year	Object	Input Dataset color	DL Frame	Training Methods	Dataset	Sample Size	Accuracy rate
Lee et. al [10]	Elsevier 2020	Apple, Grapes, Potato, Tomato leaf disease detection	RGB	CNN, GoogLeNet, Inceptionv	Transfer Learning	Plant_Village	43810	63.87%, 67.23%, 65.55%,
Sharma et. al [11]	Elsevier 2019	15 different plant types disease detection.	RGB	S-CNN and F-CNN	Transfer learning	Plant Village	16579	82%
Krizhevsky et. al [12]	ACM 2017	General Purpose classification using ILSVRC-2010	RGB	CNN, SIFT+FV	Deep Learning	ILSVRC-2010	50000	37.5% 45.7%
Hassan et. al [13]	MDPI 2021	14 different plant types disease identification	Grayscale, RGB	CNN, Inception	Transfer Learning	Plant Village	54305	87.2% 88.2%
Kaya et. al [14]	Elsevier 2019	Identify Flavia, Swedish leaf diseases identification	RGB	Deep neural networks	Transfer Learning	UCI leaf dataset	1907+1125	92.6% 70.79%
Prasad et. al [4]	Elsevier 2021	Rice leaf disease prediction	RGB	Simple CNN, Inception ResnetV2	Transfer learning	Kaggle dataset	4000	95%
Nigam et. al [15]	Elsevier 2020	Paddy leaf disease detection and classification	HSV and RGB	Deep neural networks	PCA and BFO	Self-Acquired in field	649	93.50%
Azim et. al [16]	TELKOMNIKA 2021	Rice leaf disease classification and feature extraction	RGB and HSV	XGBoost and SVM with RBF kernel	Machine Learning, Binary image inversion	UCI dataset	80:20 ratio dataset used for build model	86.5%

3. MATERIALS AND METHODS

3.1 Acquisition of images

Image acquisition was the procedure for gathering images that will be utilized in this study. The input images dataset of the paddy plant leaf were take snapshot on the farmer field using a high and low-resolution using digital camera and mobile phone. In this study, we have captured 3071 leaf images for the proposed system. Dataset link (figshare - My data) Rice plants suffer from diseases and pests in various parts [17]. Several factors may contribute to their occurrence like sunny, moisture, cloudy, rainfall, monsoon, nutrition, plant leaf, etc. A range of weather conditions was used for image collection - in winter, summer, and overcast conditions to ensure that a fully representative set of images was obtained. In these images, the total training purpose we have considered 2,771 and the test purpose we have used around 300 images. Four categories are limited to the most common disease categories: BLB, Leaf Blast, Brown Spot, Tungro / Leaf smut.

3.2 Pre-processing

In an input dataset images are resized and cropped in pre-processing to a dimension of 300 X 450 pixels to minimize the memory and compute requirements. In the current phase, one of the biggest concerns was to eradicate the image setting by fusing hue values. An RGB image was first transformed into an HSV image. With the HSV representation the value S was made the first consideration because it predominates over the whiteness. We select a threshold value by experimenting with several values. Image with background removed only shows the diseased portion of the leaf. Non-linear filtering approaches were applied to remove the unwanted noise from the images.

3.3 Convolutional Neural Network (CNN) models

CNN is an image classification defined as the work of converting various different images into one or more predefined classes. The convolutional networks model was a dedicated kind of neural network for dealing out suitable for 2D information that has a great grid-like topology [10]. It was designed for the functionality of human neuron behavior. The configuration of the CNN has own image filter influence on the performance of the model without human intervention. Convolution was a specialized kind of linear operation. CNN have 3 to 150 layers to communicate each another layers such as output acts as another layer input.

In Figure 2 list the evolution of the different deep learning model in every year-wise described. To increase the precision, complication, and real-world impact deep learning has every time improved in its ability to afford accurate recognition and prediction [18]. We have worked to full fill the farmer challenges and created opportunities to get better deep learning even further and to bring it to new frontiers [19].

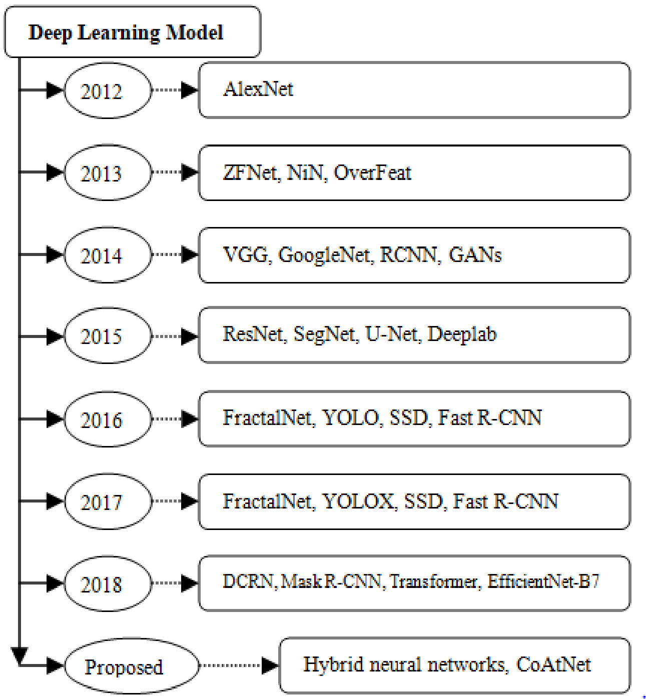


Figure 2. Evolution of deep learning model year-wise proposed

There are two networks structures were used in our research work, they are ResNet-152, and CoAtNet, and are described as follows.

3.4 Architecture RESNET-152

In order to overcome the "vanishing gradient" problem, ResNet is a Convolutional Neural Network (CNN) architecture that can construct networks up to thousands of layers, which outperform shallower networks. ResNet-152 was deep CNN based on the constructs of pyramidal cells in the cerebral cortex [19]. One of the most powerful deep neural networks, ResNet (residual connections), achieved outstanding results in the ILSVRC 2015 classification challenge [20]. The network consists of different unique layers such as input layer, convolution, pooling layer, rectified linear unit layer, and classification layer. ResNet models typically shown in Figure 3 have two or three layer skips, containing rectified linear unit (ReLU) and batch normalization. In general, skip connections are added to avoid the vanishing gradients problem or to moderate the accuracy saturation difficulty. The feature space of a neural network without residual parts is larger. Consequently, it was more susceptible to perturbations that cause it to leave the manifold and requires more training data to recover [21]. The forward propagation is an output of the neurons in the layer defined as a^l, the activation function for the layer mentioned as g, $W^{l-2,l}$ total weight matrix lies $l-1$ & l.

$$a^l = g\left(W^{l-1,l} * a^{l-1} + b^l + W^{l-2,l} * a^{l-2}\right) \quad (1)$$

$$a^l = g(Z^l + W^{l-2,l} * a^{l-2}) \quad (1.1)$$

The backward propagation is defined in equation number 2 as follows:

$$\Delta\omega^{\iota-1,l} = -\eta \frac{\partial E^{\iota}}{\partial \omega^{\iota-2^2}} = -\eta a^{\iota-1} * \delta^{\iota} \quad (2)$$

η is a learning rate less than 0, δ^{ι} an error signal of neurons at layer ι and a^l activation neurons.

ResNet was a network model that uses residual blocks to enhance the depth of the CNN. Initially Resnet architecture has been implemented with minimum number of layers, which obtained good results up to thousand images. Hence number of convolutional and pooling layer is increased. Finally, multiple separate units are connected through fully connected layers. Then the given image is classified as normal leaf or diseases by using softmax classifier.

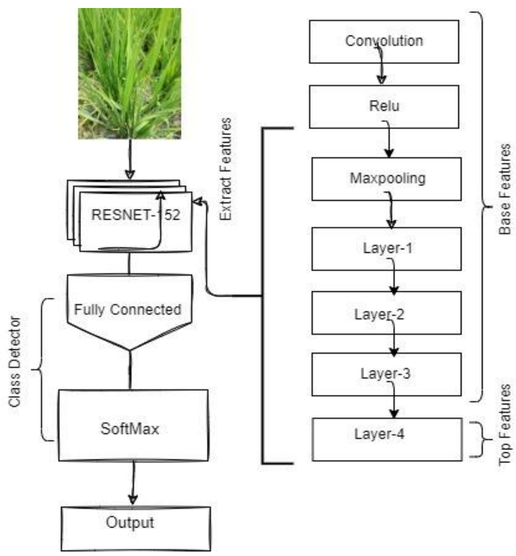


Figure 3. Block diagram of Resnet-152 architecture for classification

3.5 Proposed Hybrid CoAtNet Architecture (PHCNA)

A convolutional layer does not connect neurons to every pixel in the input image, but only to pixels in their receptive field. In the training process, learnable filters or kernels are convoluted over the image. A filter learns to recognize specific patterns, and low-level filters are related to more complex patterns. The Google AI team introduced a hybrid model, which combines self-attention and convolution to achieve top accuracy levels [22]. The CoAtNets pronounced "coat" nets, combining the strength from different architecture. There are two key insights provided to perform in a better way: i) Convolution and self-attention can be naturally integrated through simple relative attention. ii) Attention layers that consider their competence and computational requirements at each phase (resolution) effective at were improving simplification, capacity, and efficiency [23]. What is the best way to mix CNN with transformers? The basic idea was MBConv block, which combines depthwise convolution with inverted residual bottleneck, initially because this expansion-compression scheme is the same as the Transformer's FFN module. The depthwise convolution in addition to self-attention can both be expressed as a per-dimension weighted sum in a predefined receptive field.

$$\mathcal{Y}_i = \sum_{\mathcal{J} \in \mathcal{L}(i)}^{n} \mathcal{W}_{i-j} \odot \mathcal{X}_j \tag{3}$$

The depth wise convolution was defined as $\mathcal{Y}_i$ is the output of provided above expression. The sum of value in a pre-defined local receptive field $\mathcal{J} \in \mathcal{L}(i)$, here convolution relies on a fixed kernel to gather information from a local receptive.

$$\mathcal{Y}_i = \sum_{\mathcal{J} \in \mathcal{G}}^{n} \left(\frac{\exp\left(\mathcal{X}_i^{\mathcal{T}}\, \mathcal{X}_j\right)}{\sum_{\mathcal{K} \in \mathcal{G}} \exp\left(\mathcal{X}_i^{\mathcal{T}} \mathcal{X}_k\right)} \right) \mathcal{X}_j \tag{4}$$

Self-attention allows the receptive field to be global and instead of fixed kernels, it utilizes dynamic attention weights that vary based on the inputs. To mix convolution and self-attention, we can simply add a global static convolution kernel with an adaptive attention matrix $\exp\left(\mathcal{X}_i^{\mathcal{T}}\, \mathcal{X}_j\right)$ the softmax normalization. The attention weights are decided by a combination of a CNN kernel and an adaptive matrix [24, 25]. This Eq. (4) interestingly corresponds to an especial variant of attention called relative self-attention, in which relative position representations are used.

$$\mathcal{Y}_i = \sum_{\mathcal{J} \in \mathcal{G}}^{n} \left(\frac{\exp\left(\mathcal{X}_i^{\mathcal{T}}\, \mathcal{X}_j + \mathcal{W}_{i-j}\right)}{\sum_{\mathcal{K} \in \mathcal{G}} \exp\left(\mathcal{X}_i^{\mathcal{T}} \mathcal{X}_k + \mathcal{W}_{i-k}\right)} \right) \mathcal{X}_j \tag{5}$$

The global static convolution matrix was derived from Eq. (5) $\mathcal{W}_{i-k}$ & $\mathcal{W}_{i-j}$.

Figure 4 shows the complete overall architecture diagram for CoAtNet, considering above block diagram with size of HxW as an input, we pertain convolutions in the initial stem phase (S0) and shrink the size to H/2 x W/2 [23]. In every stage, it continues to reduce the size. The Ln represents the total amount of layers. Premature stages (stage 1 and stage 2) use MBConv blocks consisting of depthwise convolution. At the end of two stages (stage 3 and stage 4) transformer blocks are mostly used with comparative self-attention.

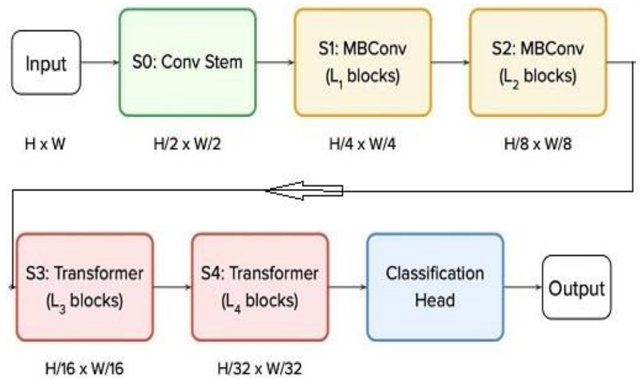


Figure 4. Proposed Hybrid CoAtNet Architecture (PHCNA)

Instead of using the earlier transformer blocks in ViT, here we make use of a pooling method between different stages, similar to the channel transformer. Transformers may lack the generalization capability that CNNs possess, and rely on a substantial amount of data to compensate. As a final step, we implement a classification to generate class predictions [26-28]. The proposed workflows were shown in Figure. 5 to identify the healthy and diseased paddy leaves. In this research work, a new hybrid model was designed to detect the rice leaf images. There are four different categories of leaf diseases provided as input. After that, all the RGB images are resized as per the requirements. The Convolutional Auto Encoder (CAE) was used for filter purposes. The CAE has been dropping the dimensionality of the input rice leaf images. We have used two different network models such as ResNet-152, CoAtNet to train the model. We have divided it into 80:20 ratios for the dataset training and testing purpose. CNN helps to predict, rice leaf images have been classified into two different categories such as healthy or unhealthy. The model inference was detected as which category of the diseases as well calculate the various measures.

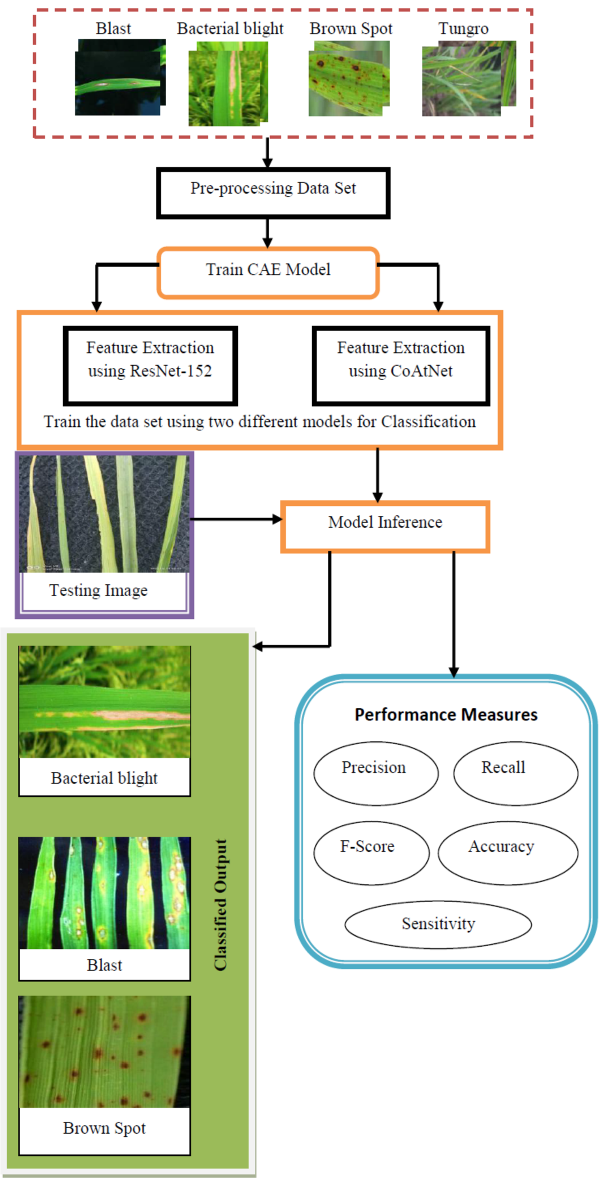


Figure 5. Proposed workflow classification for identifying healthy and diseased paddy leaf

Table 2. Images classified into four categories and respective samples count

Class	Disease name	Name of the virus	Samples	Color
C_A	Bacterial Blight	Xanthomonas oryzae	754	RGB
C_B	Blast	Magnaporthe oryzae	750	RGB
C_C	Brown Spot	Helminthosporium oryzae	765	RGB
C_D	Tungro	Spherical virus	802	RGB

In Table 2 training parameters were plotted and four different classes such as C_A, C_B, C_C, and C_D contain each diseases name along with a total count of samples.

4. IMPLEMENTATION AND RESULTS

4.1 Implementation process

How to setup experimental validation of the ResNet-152 and CoAtNet models has been examined under various parameters. The implemented CNN architecture, as discussed in the previous section. The experiments were conducted on an Intel i7 Processor, 2.3 GHz with 8GB RAM, and NVIDIA GeForce GTX using various libraries and python 3.7. To demonstrate the performance, we have used different parameters such as sensitivity, F1 score, precision, recall, performance accuracy, and training epoch. We have used three different representations of color and grayscale of our real field dataset. The colored image provided better performance compared to grayscale. Table 3 shows as parameters used for the implementation of respective values.

4.2 Performance validation

The following calculation is considered for the determination of accuracy level. Performance Precision: The ratio of properly classified images to the total number of images. Loss function: It was a measure of how well the data was modeled by the architecture with the following parameters. Precision = True Positives / (TP + FP) Recall: Observations that were correctly predicted (true positives) to all observations in a class (true negatives + true positives). F1 score: Harmonic indicate between accuracy and recall.

Step 1: Initially we are loading the dataset using google mount, along with the required importing package.

Step 2: Preparing the batch size, image height, and image width. Train the datasets using a convolution auto encoder.

Step 3: Defining the four classes and providing the training path, testing path.

Step 4: Plot a few training images and value images using the plot images function.

Step 5: CNN model building is initiated, activation of relu, max pooling, dense, and dropout added.

Step 6: Identify the total params, trainable and non-trainable.

Step 7: Providing an adequate epoch size to obtain the accuracy and loss.

Step 8: Classification and detection of the disease portion using Resnet-151 and CoAtNet.

Step 9: Plot training and validation graphs.

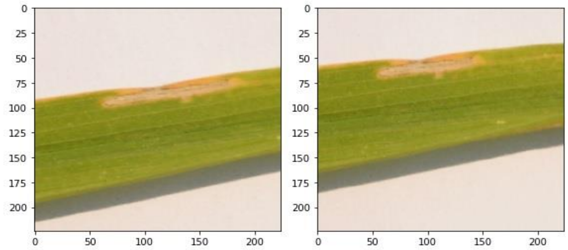
$$p = \frac{TP}{TP + FP} \tag{6}$$

$$r = \frac{TP}{TP + FN} \tag{7}$$

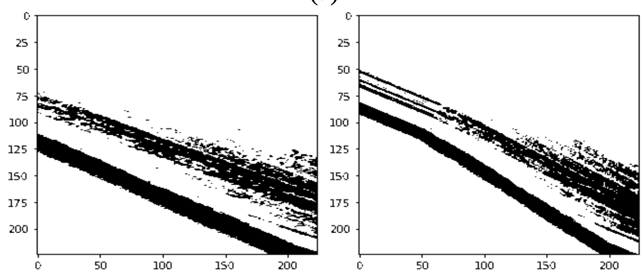
Table 3. Training parameter used in proposed model

Parameter	Value
Batch Size	33-182
Training Epoch	8-80
Dropout	0.3 – 0.9
Learning rate	0.01-0.0001
Optimizer	Stochastic Gradient Descent

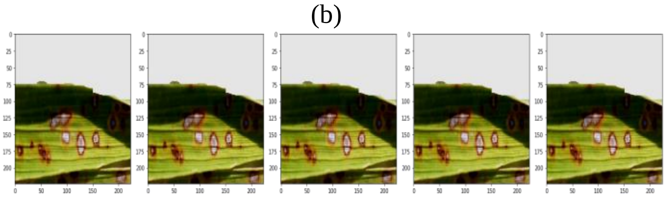
Evaluation parameter was considered to improve the accuracy in our proposed model we have considered batch size, epoch, dropout, learning rate, optimizer. The Eq. (6), (7) helps to calculate the p, r value for the proposed model.



(a)



(b)



(c)

Figure 6. Rice leaves are affected by various diseases
a) Training a sample disease image
b) Greyscale conversion
c) Background noise removed from original images

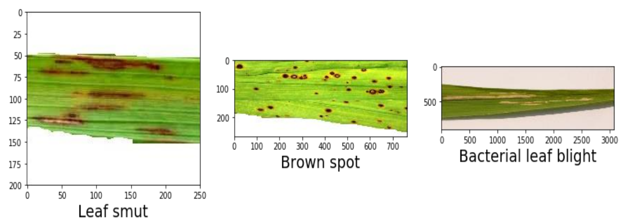


Figure 7. Identification of classified rice leaf diseases

Figure 6 shows the preprocessing of the dataset as per the requirement of parameter values. The sample input dataset proceeds to identify which class and healthy or unhealthy details were predicted by Resnet-152 and CoAtNet deep learning model. The sample predicted classified data is shown in Figure 7.

A Confusion matrix is a N x N matrix used to assess the performance of a classification model, where N represents the number of target classes. To simplify understanding, the confusion matrix in the Figure 8 has been transformed into a tabular form as shown in Table 4. It is divided into major three coloumn such as input labels, class labels, and total images. We have created four label such as C_BB, C_Blast, C_Brown, and C_Tungro. It is used to define the performance of a classification. The implemented deep learning model evaluated values are also manipulated and represented in Table 5 and Figure 9 as precision, recall, f1 score, and sensitivity values. Finally, the CoAtNet model has predicted and identified the highest measures value compared to previous results.

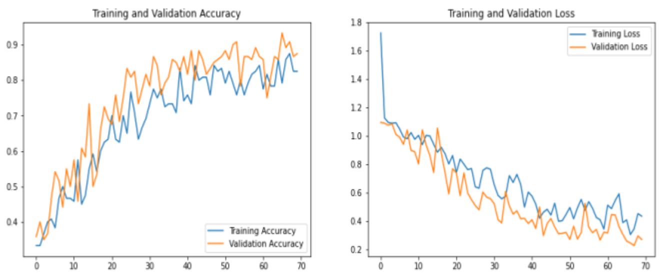


Figure 8. Visualization of training and validation accuracy versus loss

Table 4. Confusion matrix for proposed rice leaf diseases

Input labels	Class labels				Total images
	C_BB	C-Blast	C_Brown spot	C_Tungro	
C_BB	754	0	0	0	754
C_Blast	0	750	0	0	750
C_Brown spot	0	0	765	0	765
C_Tungro	0	0	0	802	802
Total Images	754	750	765	802	**3071**

Table 5. Implemented deep learning model Precision, Recall, and F1-score

Various Deep Learning Model	P	R	F1_Score	Sensitivity
Resnet-152	0.8566	0.9091	0.8828	0.9128
CoAtNet	0.8736	0.9399	0.9067	0.9325

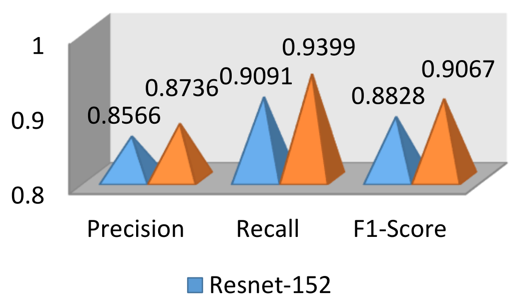


Figure 9. Deep learning model score for precision, recall, and F1 score

Table 6. Test images evaluated on proposed CoAtNet using the following performance measures

Performance Measures	Bacterial blight	Blast	Brown spot	Tungro / Leaf Smut	Avg
Precision	96.55	95.45	96.65	91.23	94.97
Sensitivity	97.65	92.36	98.62	90.12	94.68
Accuracy	95.56	94.52	96.56	95.72	95.59
F-score	98.65	93.36	94.52	95.000	95.38

Table 6 shows consolidated and implemented results for various diseases analyses by multiple parameters.

Figure 10 and 11 shows performance measures obtain using CoAtNet y-axis represents percentage value, the x-axis represents four different performance measures. There are various parameters used to identify the accuracy level such as precision, sensitivity, accuracy, and F-score. Table 6 represented summaries of various neural networks for different data.

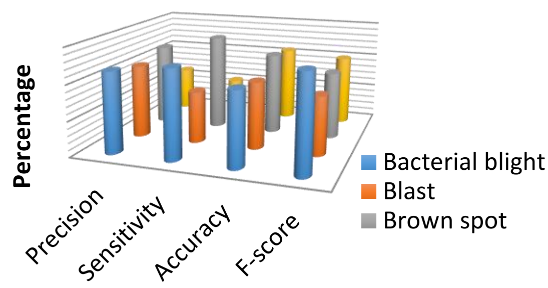


Figure 10. Test images for performance measures analysis using CoAtNet

There is a recurrent connection supported by RNN and the hidden state [29, 30]. In MLP can access only vanishing and exploding gradient. The best neural network is convolutional neural networks (CNN) used for image classification and segmentation. CNN was not supported for recurrent connections [31, 32]. The hybrid deep learning model is provided high accuracy and compute in less time. Figure 10 Test images for performance measures analysis using CoAtNet.

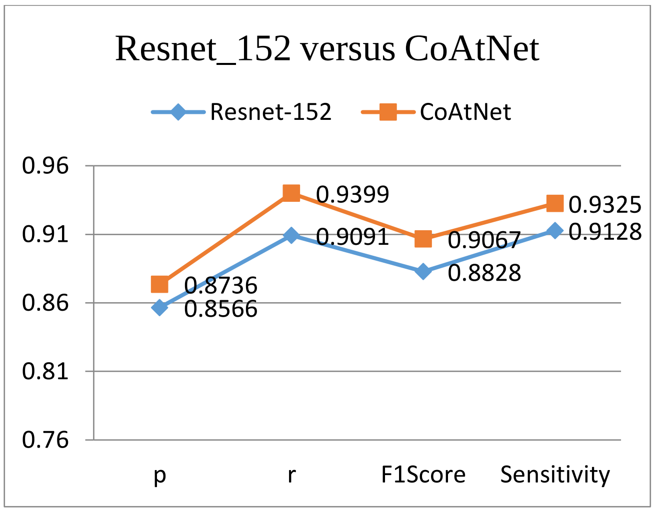


Figure 11. Proposed technique versus traditionally technique accuracy

5. DISCUSSION

Our research will be based on providing high-end computing services to farmers in order to achieve high levels of productivity. The population will grow in the future, and we will need to meet the basic need for food. Plants may be harmed by various insects as a result of dynamic climate change. Early disease detection using low-resolution images, high-resolution images, videos, and data captured by IoT devices (Drones). Disruptive technology will aid in the provision of solutions to farmers. Practically speaking, the majority of farmers are unaware of how to use this high-end application. We can carry out the suggested work after gaining government consent and for the bulk of the agricultural location. For the time being I have identified several diseases using deep learning. The major diseases are allowed by the farmer at the beginning stage, to prevent these diseases in detail manner discussed. There are four different types of diseases were considered. There are various different types of rice varieties available in the market. Due to various seasonal the rice cultivation process may vary place to place. In this article, we have obtained the accuracy level 96.5% compared to all other values it is high efficiency. We have used two different network model such as ResNet-152 and CoAtNet model as proposed one. We have used to perform various rigorous analyses of results. In comparison to existing work not achieved by above 95%.

6. CONCLUSIONS

A complete high end technology guideline is required to train the farmers in order to increase productivity. The proposed works absorb the classification and identification of various rice leaf diseases using CNN. In our research work the dataset has been created and used for further process. We have implemented Resnet-152 and proposed hybrid CoAtNet models to perform rice plant leaf diseases classification. The experimental results values demonstrated that the hybrid CoAtNet model has achieved highest precision of 96.65%, an F-score of 98.65%, a sensitivity of 98.62%, and an accuracy of 96.56% values. To achive this result we have few limitation such as the dataset is generated by our own, when we extended the dataset performance result varies.Our methodology will evaluate only set of diseases with two neural network model. In the future, the works extended to identify the segmentation and classification of disease portion using videos, large scale industry using advanced deep learning techniques. The following technique will be used for further implementation process such as cognitive learning approach, laurent series intelligent multidimensional object detection and tiling. The complex problem diseases will be addressed by quantum computing.

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NOMENCLATURE

Abbreviations

Resnet	Residual Neural Network
CoAtNet	Convolution and Attention Network
CNN	Convolutional Neural Networks
BLB	Bacterial Leaf Blight
SB	Sheath Blight
ReLu	Rectified Linear Unit
CAE	Convolutional Auto Encoder
IRRI	International Rice Research Institute

Greek symbols

η	learning rate
δ^{ι}	error signal
a^{l}	activation neurons
$\mathcal{Y}_i$	depth wise convolution
$\mathcal{J}$	local receptive field