Automation of Rice Leaf Diseases Prediction Using Deep Learning Hybrid Model VVIR

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Abstract. The main cereal crop in the world is rice (Oryza sativa). As a primary source of energy, more than 50 percent of population of the worlds relies on its use. Several elements impact rice grain yield and quality, such as rainfall, soil fertility, diseases, pests, weeds, bacteria and viruses. To control the diseases, the farmers invest a great deal of time and money and they identify problems with their poor unqualified techniques, which results in poor yield growth with losses. Technology in agriculture makes it easier than ever before to detect pathogenic organisms in rice plant foliage automatically. Convolutional neural network (CNN) is a deep learning technique used to solve computer vision issues such as image classification, object segmentation, image analysis, etc. In the proposed five models achieved the VGG16 98.43%, VGG19 98.65%, InceptionV4 98.57, ResNet-50 98.57% model to identify diseases in rice leaf images with a transfer learning technique. Using these model parameters, the final proposed VVIR model accurately classified objects with a accuracy of 98.80%.

Keywords: Rice leafs diseases · Convolutional Neural Network (CNN) · Artificial Intelligence · Deep Learning · VGG16 · VGG19 · ResNetV2

1 Introduction

The global economy cannot function without agriculture. GVA (Gross Value Added) in 2020–21 is 96.54 lakh crore, with agriculture accounting for 20.19% of the country's GDP. Agriculture has a more significant contribution to the Indian economy than any other industry globally, at 6.4 percentage points. Besides China, Indonesia, Vietnam, Burma, the Philippines, Japan, Pakistan, Brazil, the USA, Nigeria, Egypt and South Korea have the second most significant rice output (Oryza Sativa) in the world after India. In India, Telangana is at the top in area and production. Nizamabad, Karimnagar, Kamareddy, Yadadri, Khammam, Siddipet, Jagityal and Warangal are the central rice-growing districts of Telangana.

Rice is a product of the paddy field. It is a yearly harvest. It is a staple meal for half of the world's population and it provides 40% of the daily protein needs. Rice research

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center in India, International Rice Research Institute (IRRI), ICAR(Indian Council of Agricultural Research) Hyderabad, NRRI (National Rice Research Institute) Hyderabad and ISRAC (International Rice Research Institute South Asia region).

Rice infections pose a severe danger to the world's food supply by reducing the crop's yield and quality. As a result, disease prevention is essential to the production of rice. Correct and prompt detection of diseases is critical to successful pesticide application. This ensures the timely application of pesticides. As the population grows, so does the need for rice, increasing consumption. By 2030, rice output must rise by more than 40% to fulfill the rising global demand for grain. Due to the devastating effects of diseases, the rice crop has lost between 60 and 100 percent of its production.

It is challenging to find enough competent workers in the region to do these responsibilities quickly. Researchers have employed a variety of Computer Vision (CV), Artificial Intelligence (AI), Machine Learning(ML) and Deep Learning (DL) technologies that help in hyper spectral detection and multispectral remote sensing pictures to diagnose crop diseases throughout the last few decades in Fig. 1 [1].

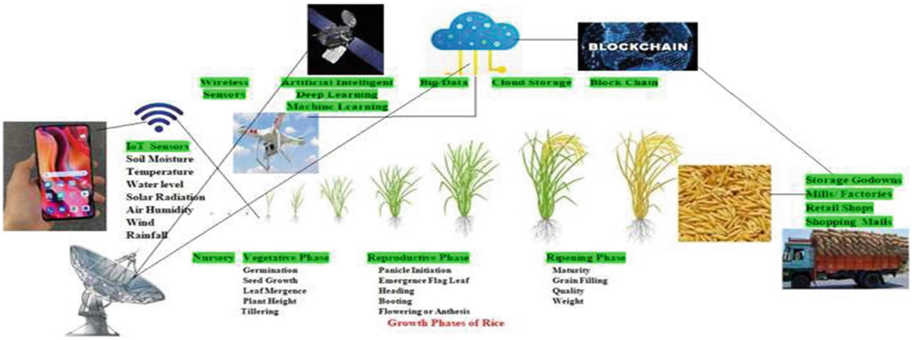


Fig. 1. Rice crop from growth to market is controlled by modern technologies

Even while some of the currently available technologies can diagnose agricultural diseases with a high degree of accuracy, most of them handle the manual due to a lack of resources. As a result, ideas are constrained, making it harder to extrapolate from the findings. Aside from that, specific techniques need specialized equipment that may not be readily available to the general public. Crop disease diagnosis is challenging because of these disadvantages. The disadvantages of crop disease diagnostic methods can be solved by using deep learning technology. In recent years, object recognition, picture categorization and content recommendation have significantly benefited from the widespread use of deep learning techniques. Researchers have used DL to identify diseases in various crops [2].

The dataset obtained is summarized in Sect. 2, as it gives a general introduction to the method. In this part, the procedures for identifying rice diseases and associated studies and the recommended approach are mostly presented. In Sect. 3, experiments are carried out to test the performance of the suggested approach and the findings are compared to those of other methods. Lastly, Sect. 4 wraps things up with a call for future research.

2 Literature Survey

Kamal et al. (2019) used Reduced MobileNet with a depth-wise separable convolution architecture. There have been a variety of assertions made about the accuracy of 98.65 percent of recognition [3]. Chen et al. (2020), for the categorization of rice diseases, employed VGGNet- Inception Model, they obtained an accuracy of 92 percent [4]. Rahman et al. (2020), with 1426 images, developed CNN architecture with two stages, were able to detect 93.30 percent of the rice diseases and pests correctly [5]. Feng Jiang et al. (2020), with the 10-fold cross-validation approach, was utilized to test CNN-SVM. Rice blast, rice blight, rice stripe blight and rice sheath blight were classified and predicted using CNN-SVM, which reached an accuracy of 98.6 percent [6]. Zhencun Jiang et al. (2021), with the Visual Geometry Group Network-16 (VGG16) model, was utilized to represent bacterial rice leaf blight, rice brown spot, rice leaf smut, wheat leaf rust, wheat powdery mildew [7].

Prabira Kumar Sethy et al. (2020), a CNN ResNet50-SVM model developed by four different formstungro, brownspot, blast and bacterial blight of diseases and produced an F1 score of 0.9838 [8]. Murat Koklu et al. (2021), ANN, DNN and CNN models applied to 75,000 grain images of five distinct types of rice to obtain 99.87 percent accuracy for ANN, 99.95 percent accuracy for DNN and 100 percent accuracy for CNN [9]. Radhakrishnan Sree vallabha dev (2020), used the CNN-SVM for predicting blast diseases and attained an accuracy rate of 96.8 percent [10].

Junde Chen et al. (2021), using the MobileNet-V2 model, studied 12 rice disease outbreaks and found an average accuracy of 98.48 percent [11].

Pitchayagan Temniranrat et al. (2021), used the YOLOv3 model to acquire an average True Positive Point of 95.6% for diseases including rice blast, rice blight, rice brown spot and rice narrow brown spot [12].

Yibin Wang et al. (2021), used an attention-based depth wise separable neural network (ADSNN-BO) model to classify brown spot, hispa and leaf blast in rice. The test accuracy is 94.65 percent [13].

If you're looking to identify diseases in crops, deep learning is an excellent option because it can reach high accuracy. Deep learning for rice disease research has been confined to a small number of disorders. In the field of rice disease categorization, there are just a few publicly available datasets. Our dataset on rice disease is used to train and evaluate a convolutional neural network- based disease classification model to fill this gap (CNN).

This research aimed to improve rice disease diagnostics in terms of accuracy, efficiency, price and convenience. A Deep Learning network model for identifying six distinct rice diseases was developed, evaluated and then used to execute the diagnosis process and put it through rigorous testing in a real-world setting.

3 Methodology

The methodological approach to any experiment serves as a road-map for conducting any experimental endeavor. Data collection, preparation, data separation into training, validation and finally, the use of a DL model to identify rice images dataset are the four stages of our technique. This is the first stage in every experiment is vital to remember that datasets are the foundation of any ML and DL model; therefore, we started by collecting real-time datasets from primary and secondary sources. As a backup plan, if the primary data sources fail or the preliminary data gathered is insufficient or does not meet the criteria, secondary data sources such as online repositories and data websites will be utilized to acquire the dataset. Rice leaf diseases were employed to collect dataset images, which are a must for the following phases in this process [14]. Pre-processing is the next phase in our technique, as it is highly usual for the dataset acquired after collection to be noisy in Fig. 2. This data may be used for additional experiments [15].

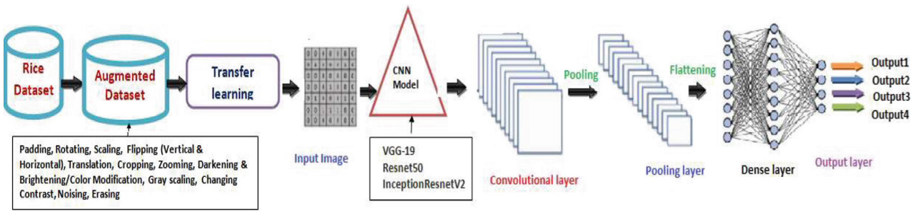


Fig. 2. CNN architecture for rice model

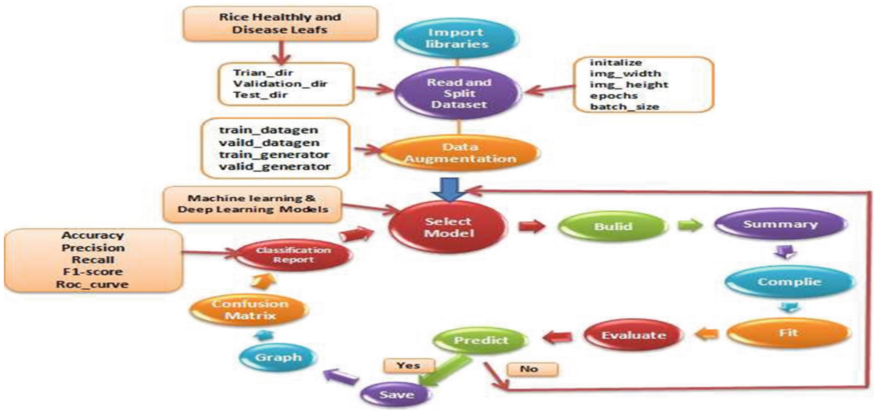


Fig. 3. CNN and Deep Learning working model

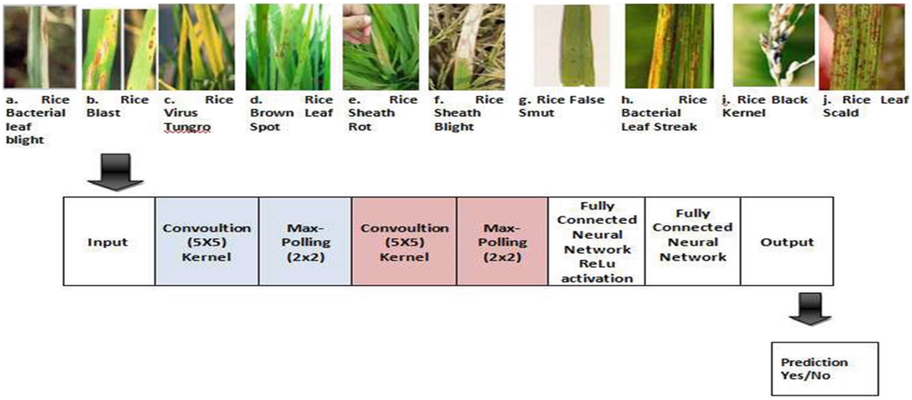


Fig. 4. Depicts a variety of rice diseases using CNN

To avoid the computational load in the model, the picture was scaled appropriately before reading. This was followed by applying random affine modification to the picture. Images must be filliped, scaled, rotated, translated and resized in any way it pleased at random [16]. The training algorithm needs resized final images by 224 × 224 pixels in Figs. 3 and 4 [17]. The primary goals of these operations were the model's over fitting on the initial dataset [18]. After that, the ImageNet dataset's mean and standard deviation were used to normalize the images, resulting in the most uniform distribution of color values possible [19]. In each training period, the number of images read by each model varied and the number of image samples available in the dataset increased as a result in VGG16, VGG19, Inception models in Fig. 5a, b, c).

CNN greatly influences final model performance. For rice disease, a comparison of network performance was essential. The five network models' performance evaluations were compared to choose the top models. Each network model's of rice leaf disease prediction findings were categorized into four groups as TPLD, TNLD, FPLD and FNLD in Fig. 6.

TPLD: A predicted rice leaf disease is same to the actual rice leaf disease. So both the actual and predicted leaf diseases are positive.

TNLD: A predicted rice leaf disease is not same to the actual rice leaf disease. So both the actual and predicted leaf diseases are negative.

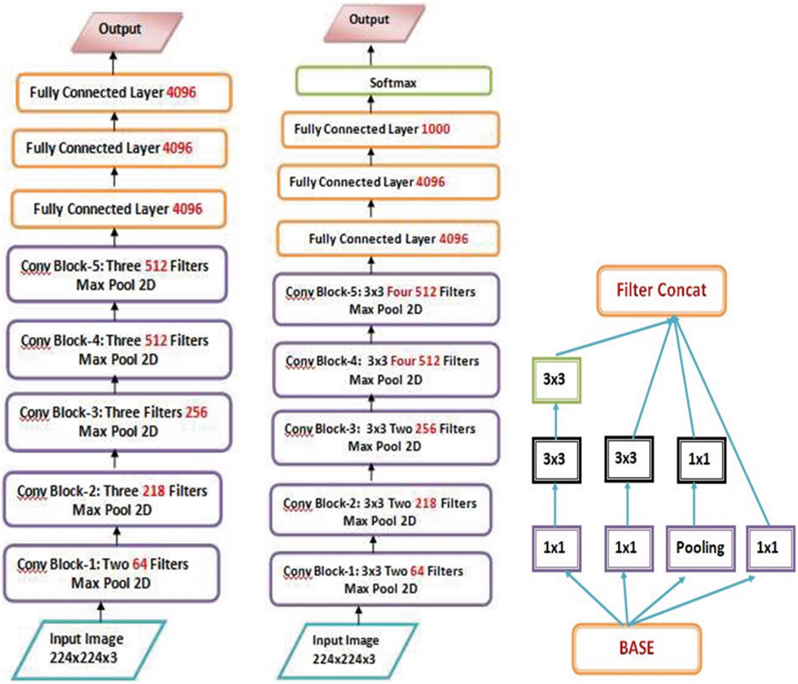
FPLD: A predicted rice leaf disease is same to the actual rice leaf disease. So the actual leaf disease is negative and predicted leaf disease is positive.

FNLD: A predicted rice leaf disease is same to the actual rice leaf disease. So the actual leaf disease is positive and predicted leaf disease is negative.

$$\mathrm{Precision(P)} : (\mathrm{TPLD})/(\mathrm{TPLD} + \mathrm{FPLD}) \tag{1}$$

$$\mathrm{Recall(R)} : (\mathrm{TPLD})/(\mathrm{TPLD} + \mathrm{FPLD}) \tag{2}$$

$$\mathrm{Accuracy((A)} : (\mathrm{TPLD} + \mathrm{TNLD})/(\mathrm{TPLD} + \mathrm{TNLD} + \mathrm{FPLD} + \mathrm{FNLD}) \tag{3}$$



(a) (b) (c)

Fig. 5. 5(a) VGG16 Architecture, 5(b) VGG19 Architecture, 5(c) Inception Architecture

		Predicted Rice Leafs Disease	
		Positive	Negative
Actual Rice Leafs Disease	Positive	True Positive Leaf Disease (TPLD)	False Positive Leaf Disease (FPLD)
	Negative	False Negative Leaf Disease (FNLD)	True Negative Leaf Disease (TNLD)

Fig. 6. Confusion matrix for Rice leaf disease

$$\mathrm{F1} - \mathrm{SCORE} : 2 * (\mathrm{P} * \mathrm{R})/(\mathrm{P} + \mathrm{R}) \tag{4}$$

With the Eq. (1), Eq. (2), Eq. (3), Eq. (4) demonstrate how these results were utilized to calculate the following performance indicators: accuracy, precision, recall and F1 score. For each disease type, the accuracy was tested; for each disease type, the other indicators were analyzed. Another way to judge the models is by looking at their loss value. In contrast to the other metrics, loss measures how well the training set fits the test set. Loss changes during training can be used to evaluate the model's fit state, even though it cannot directly reflect model performance.

4 Results

Successful model testing took roughly a week because the entire dataset was run on varied batch sizes and epochs, which resulted in superior model performance of VVIR (Table 1).

Table 1. Rice model the accuracy obtained from the training and validation datasets

Epoch	Time	Loss	Accuracy	Val-loss	Val- accuracy
1/100	124 s	2.7649	0.1738	2.0936	0.23
2/100	123 s	2.1389	0.2476	2.0615	0.25
3/100	135 s	2.0554	0.3024	1.9620	0.30
4/100	139 s	1.9367	0.3214	1.9142	0.31
5/100	142 s	1.8987	0.3095	1.7976	0.40
6/100	150 s	1.8158	0.3452	1.8196	0.35
7/100	146 s	1.8078	0.3905	1.7557	0.34
8/100	145 s	1.7494	0.4000	1.7481	0.40
9/100	148 s	1.6657	0.4286	1.6914	0.42
10/100	150 s	1.6891	0.4167	1.6914	0.43
…					
100/100	1420 s	0.0598	0.9880	0.0418	0.98

IT is possible to achieve a best accuracy of 98.80% in training and 98% on the 100th epoch of the model's execution in the validation phase. The resulting performance measure is created based on how many epochs and the output accuracy the model is tested. Model performance for rice disease identification is visible from the correctness of validation data encountered. Because we only have a small quantity of data to train the model on, the number of epochs is higher in this situation, increasing the likelihood that the model will successfully detect images of rice diseases (Table 2).

Table 2. Accuracy of various Deep Learning different models with proposed models

SNo	Authors	Model	Accuracy
1	Kamal et al. (2019)	[3] MobileNet	98.65
2	Chen et al. (2020),	[4] VGGNet - Inception	92
3	Rahman et al. (2020),	[5] CNN two stages	93.3
4	Feng Jiang et al. (2020),	[6] CNN-SVM	98.6
5	Zhencun Jiang et al. (2021),	[7] VGG16	95.5

(*continued*)

Table 2. (*continued*)

SNo	Authors	Model	Accuracy
6	Prabira Kumar Sethy et al. (2020),	[8] ResNet50-SVM	98.38
7	Murat Koklu et al. (2021),	[9] ANN	99
8	Murat Koklu et al. (2021),	[9] DNN	95
9	Murat Koklu et al. (2021),	[9] CNN	100
10	RadhakrishnanSreevallabhadev (2020)	[10] CNN-SVM	96.8
11	Junde Chen et al. (2021),	[11] MobileNet-V2	98.48
12	PitchayaganTemniranrat et al. (2021),	[12] YOLOv3	95.6
13	Yibin Wang et al. (2021)	[13] ADSNN-BO	94.65
14	Proposed	VGG16	98.43
15	Proposed	VGG19	98.65
16	Proposed	ResNet150	98.55
17	Proposed	Inception-v3	98.57
18	Proposed Hybrid Model	VVRI	98.80

We've had to deal with a wide range of difficulties during the experiment and those difficulties appear at every stage.

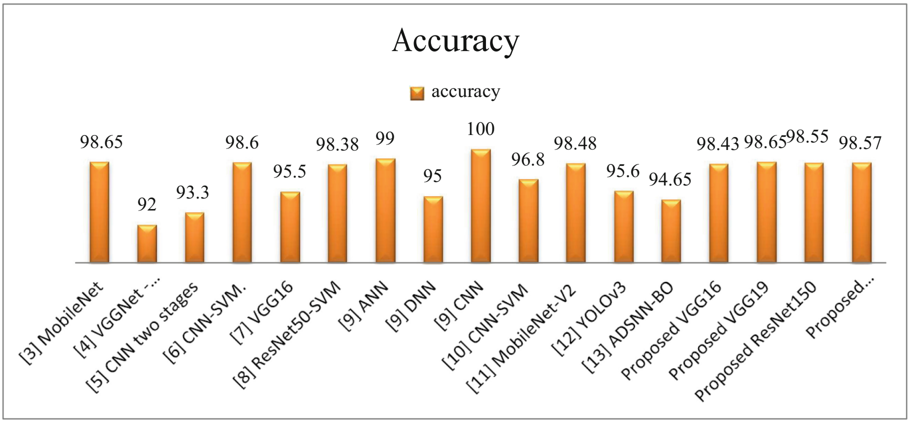


Fig. 7. Comparison of accuracy of various deep learning models

The following challenges are encountered in the process of collecting and executing a model on a dataset:

Because there are so few rice plants affected by rice diseases that there are no photographs of rice plants with rice diseases in the dataset, gathering many images of these plants is first problem. In the case of CNN implementation, a limited dataset causes underfitting and overfitting of the data, which reduces the final detection accuracy. The accuracy of the model may be increased by increasing the number of convolutional and dense layers used to train the data. Research into the severity of rice diseases has not yet been fully completed; therefore, this study's findings can be built upon in the future.

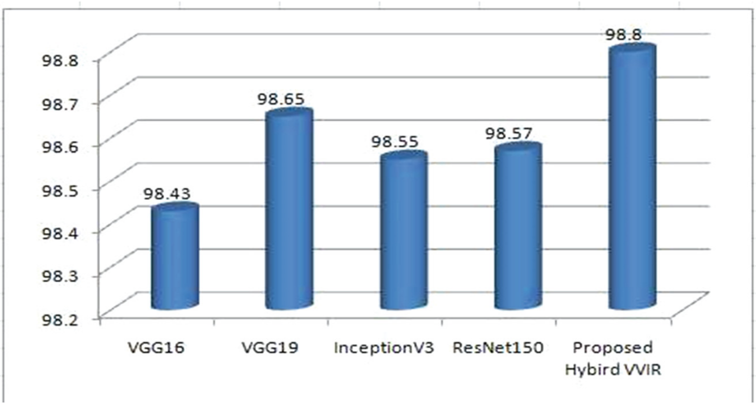


Fig. 8. Accuracy of proposed hybrid model

Applying the four models VGG16 VGG19 Inception ResNetV2 and taking outputs each model and gives the maximum of the models is VVIR in Fig. 7 and Fig. 8.

5 Discussion

Diseases are all frequent growth stages of the rice plant. Identification of these pathogens is critical for the discovery of new rice-related diseases. We divided the dataset into three parts training (70%), a validation (20%) and a test (10%). The model acquired the essential characteristics of each disease from the trained results. As a result of the trained set's high degree of resemblance to the test set, various disease images from diverse sources were gathered to create a separate test set. This study's network design is generalizable and used for practical purposes based on the independent test findings. A collection of 600 images of seven different rice diseases was created in this study. Five sub-models based on these images were trained and evaluated and achieved an accuracy of VGG16 is 98.43%, VGG19 is 98.65%, InceptionV4 is 98.57, ResNet-50 is 98.57% and final proposed Hybrid-VVIR is 98.80% were the top performers in this comparison. An examination of visual data validated the sub models' ability to learn about rice diseases Ensemble Model features many characteristics that might slow down the identification process. Efforts to minimize the number of parameters will be made in future investigations.

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