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A Novel Improved Framework for Multiclass Rice Disease Detection using Deep Learning



Abstract: - The rice yield is poorly impacted due to lack of expertise in identifying the rice diseases in the field. Deep learning architectures are applied for classification of different crop diseases in some studies but they suffer performance degradation, less accuracy and overfitting posing a challenge for implementation in the real rice fields. To overcome the above challenges this study aims to propose a novel framework by fusing Visual Geometry Group16 (VGG16) with Convolutional Neural Network (CNN). The improved framework consists of 18 layers. The Convolution layer is added after pretrained VGG16 with max pooling layer to prevent overfitting. The set of optimal hyperparameters applied to the proposed framework is obtained through rigorous experimentation. The batch normalization and dropout layers are added with focus on improving accuracy and preventing overfitting. The proposed framework is evaluated in two stages. In stage 1 the proposed framework is compared with fine-tuned state-of-the-art VGG16, Inceptionv3, GoogLeNet, Resnet50, DenseNet121 and MobileNetV2. For stage 2 comparative analysis transfer learning models are optimized and compared. The proposed improved framework outperforms all the above-mentioned models in both the stages of comparative evaluation achieving the testing accuracy of 99.66%. The proposed framework performs without any sign of performance degradation and overfitting when tested on different datasets.

Keywords: Deep Learning, Transfer Learning, Optimization, Rice Disease Classification, Improved Framework.

I. INTRODUCTION

In a country like India, agriculture is the main occupation. India ranks second in rice production. Diagnosing the indication of the rice disease at a primary level can help with appropriate measures in time but unfortunately farmers are not be able to correctly identify the disease at an early stage resulting in yield loss. The resulting yield loss is around 20- 40% [1]. The growth in technology and artificial intelligence can expedite the process of identifying the symptoms of rice disease at an early stage.

CNN in deep learning give promising results for image classification tasks with high applicability in agriculture as it can detect plant disease from plant leaf image at an early age. In deep learning distinct characteristics from the image are pulled out by Convolutional layers [2]. Pooling layers narrows the dimensions of distinct characteristics and minimizes the computational resources, dropout layers drop some nodes to raise the potentiality and overcome the problem of overfitting [3]. Final layer is the output layer with the number of neurons equal to predicted output classes. Batch normalization deals with the challenge of internal Covariate Shift and helps to accelerate learning and enhance accuracy [4]. The knowledge gained during training of one task can be effectively applied to another problem by utilizing transfer learning [5]. Using transfer learning we don't have to build a model from scratch instead we can just remove the last layer and add our customized fresh layer resulting in faster models [6]. Transfer learning models along with reducing the training time also gives good enhanced performance [7]. The hyperparameters influence the learning process for a model and its tuning is an empirical process to gain the best performance with extensive experimentation. Simonyan and Zisserman introduced VGG net, the second position winner model for the ILSVRC-2014 challenge [8]. VGG16 architecture has 13 convolution layers with 2 fully connected dense layers and 5 pooling layers including a Softmax classifier [8].

The four rice diseases are under observation in this study. Fungal disease Rice Blast (RB) gives a burnt appearance to the rice field [9]. It causes grayish green round patches with dark green outer edges [10]. Bacterial Leaf Blight ("xanthomonas oryzae") is reducing the sizable portion of rice yield [11]. Leaf appears yellowish at the center. Brown Spot is a fungal disease ("Cochliobolus miyabeanus fungus") affecting at any stage with yellowish or brown spots [12]. Tungro rice disease affects the leaf and quality [13].

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The author's contributions in this research are as follows

- The novel improved framework for rice disease classification is designed and evaluated on multiple dataset
- The successful attempt is made to overcome overfitting by choosing Maxpooling, Batch Normalization and dropout layers at mentioned stage in proposed architecture
- Fine-tuning of the state-of-the-art transfer learning models for improved performance
- Design of hybrid models using transfer learning
- Comparative analysis of proposed improved framework with transfer learning models for rice disease classification

Section I further talks about similar studies in classifying different crop diseases using deep learning and their attainments. In section 2 a novel improved VGG16 architectural framework for rice disease classification is proposed. Two different datasets are used for experimentation. Section 3 is about result analysis of the implemented models using the proposed framework, evaluated on different datasets. It also presents the two-stage empirical comparative performance analysis to evaluate the proposed framework. The choice of optimal hyperparameter obtained through experimentation and the result achieved by implementing the models is summarized. The Section 4 concludes the study along with discussion for future work.

A. *Related Work*

It has been seen in the review of papers that deep learning is at its forefront in classifying crop diseases. Vimal et al. obtained an accuracy of 91.74% with EfficientNetB6 for Bean Leaf Disease classification on field collected 1295 images with Adam optimizer and dropout value of 0.3 for 25 epochs [14]. Alberta et al. (2023). predicted blight disease in Potato and Sugarcane on Plant Village dataset using rigorous hyperparameter optimization on the ResNet9 model with testing accuracy 99.25% [15]. Ananda et al. (2022). used transfer learning VGG16 model for multicrop disease classification achieving accuracy of 98.40% and 95.71% for grapes and tomatoes respectively after 30 epochs [3]. They used 4449 images collectively taken from Plant Village and real fields. Testing is performed on real field images captured through mobile application. The CNN model developed by Nidhi et al. [16] reported testing accuracy of 98.50% with 536 testing images for healthy, TLB, Rust and multi-disease classification. Batch normalization, softmax activation function and Adam optimizer has been used. They have collected the dataset of 2996 images and labeled it by a plant pathologist [16]. Rakesh et al. (2022) explored VGG19 for six classes of disease classification for rice. Only 300 images have been used for experimentation and achieved an accuracy of 97% with data augmentation. They have preserved the first 10 layers of VGG19 and the remaining layers are used for retraining for optimization [17]. Krishnamoorthy et al. have used CNN and InceptionResNetv2 for recognizing diseases for rice on a dataset with 5200 images from Kaggle. After 15 epochs they have obtained accuracy of 84.75% for CNN and for 10 epochs accuracy of 95.67% for InceptionResNetv2 by fine tuning the hyperparameters. The impact of using preprocessing and Kmeans for segmentation thereby resulting in better accuracy is also shown in their study [7]. Ruoling et al. (2021) employed ensemble technique consisting of three integrated deep transfer learning models for six rice diseases diagnosis. The model performed with a score of 91% accuracy [18]. The CNN model developed using VGG16 by Shreya et al. (2020) was able to give accuracy of 92.46% on a field collected dataset of 1509 images after 25 epochs for classifying rice diseases [19]. Zhencun et al. (2021) has tried to improve VGG16 for multi-tasking learning for classification of rice and wheat diseases by optimizing the parameters for training. Their model improved 97.22% and 98.75% accuracy for rice and wheat respectively [20]. Solemane et al. (2019) employed VGG 19 for detecting mildew disease in crop millet with 95% accuracy on validation data and 89% on test data. They have applied preprocessing and augmentation to improve results on the small datasets [21]. In the paper [22] for comparative study on transfer learning Edna Chebet et al. (2018) have shown that DenseNet121 outperforms other models with 99.75% accuracy and stated that DenseNet121 requires less parameters but computational time needs to be improved. In their experiment VGG16 performed poorly. They have experimented for 30 epochs.

It has been observed in literature that the researchers are applying preprocessing, segmentation and augmentation in many studies to improve the model accuracy for disease prediction of crops but still the results obtained by

deep learning models have low validation and testing accuracy and suffer performance degradation and overfitting. Very few studies are carried out for reducing the trainable parameters. The datasets used in experiments are very limited in size, images lack uniformity in background. This study aims to reduce the gaps in literature by proposing the improved framework for rice disease classification and evaluating the proposed model through experiments using two different datasets.

II. MATERIALS AND METHODS

A. Data collection and labeling

The two datasets are used in the study. The dataset1 (DTS1) is collected having 4522 images for Rice Blast, Bacterial Blight and healthy rice leaf. The images in the dataset are taken from online available rice disease images from Rice Disease Dataset from Kaggle and Rice Leaf Disease images from Mendeley data. The numbers of training images are 3617 and the numbers of the testing images are 905 images. For image preprocessing the image size preferred is $224 * 224$. The dataset2 (DTS2) is publicly available on Mendeley [23]. It consists of 6313 images. Fig. 1 below shows the samples from DTS1.

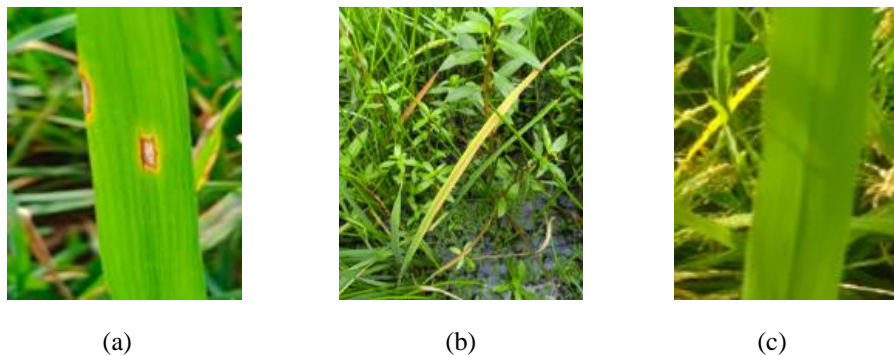


Fig. 1 Rice Diseases (a) Rice Blast (b) Bacterial Blight (c) Healthy Leaf

B. Proposed improved novel framework for rice disease classification

For better accuracy and performance, the improved optimized framework for rice disease classification is proposed by fusing the VGG16 pretrained model with CNN to obtain a novel framework with 14 Convolutional layers, 3 dense layer and 1 output layer as depicted below in the Fig. 2. The final output layer of pretrained VGG16 is truncated and the Convolutional layer along with max pooling and batch normalization with 64 filters and $3*3$ kernel size is added as shown below in fig. 3. One dense layer with 1024 neurons and Relu activation is added with dropout values of 0.4. Then the image is flattened and sent to an output layer which comprises neurons for each class to get multiclass classification. The optimal set of hyperparameters is applied to the proposed framework after rigorous experimentation for obtaining the optimized framework and improved accuracy.

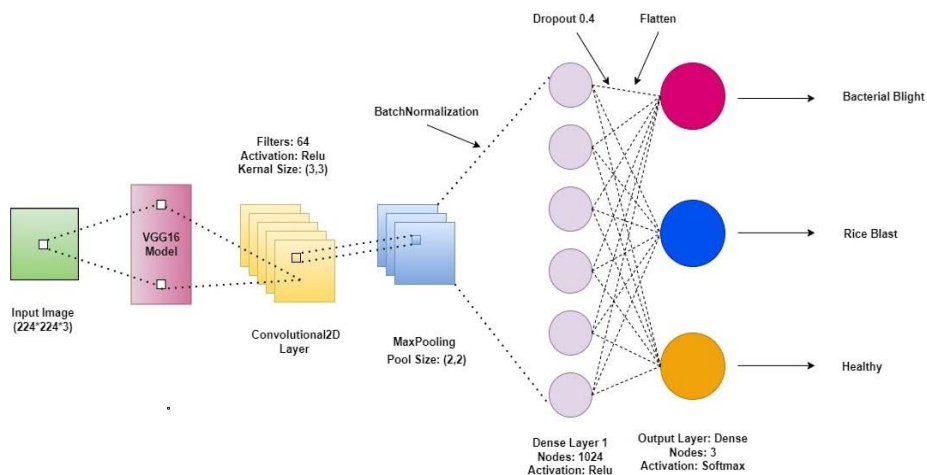


Fig. 2 Proposed novel improved framework for rice disease classification

C. *Experiment Environment*

The Graphics Processing Unit (GPU) is the main requirement for the execution of the deep learning models hence Google Collaboratory is used. The local system on which it was executed had 8 GB RAM and i7 processor with good internet speed. The libraries of python, Keras, OpenCV, and Sklearn are used in the implementation.

III. RESULTS AND DISCUSSION

A. *Performance analysis for Training*

After training the proposed improved model on a collected dataset DTS1 using Adam optimizer with 0.001 learning rate, the accuracy and loss obtained is shown in the Fig. 3.

Accuracy is used to evaluate the performance of the model and is very important metric when balanced dataset is used. It is calculated as follows (1)

$$\text{Accuracy} = \text{Number of Correct predictions} / \text{Total Number of Predictions} \quad (1) \quad [24].$$

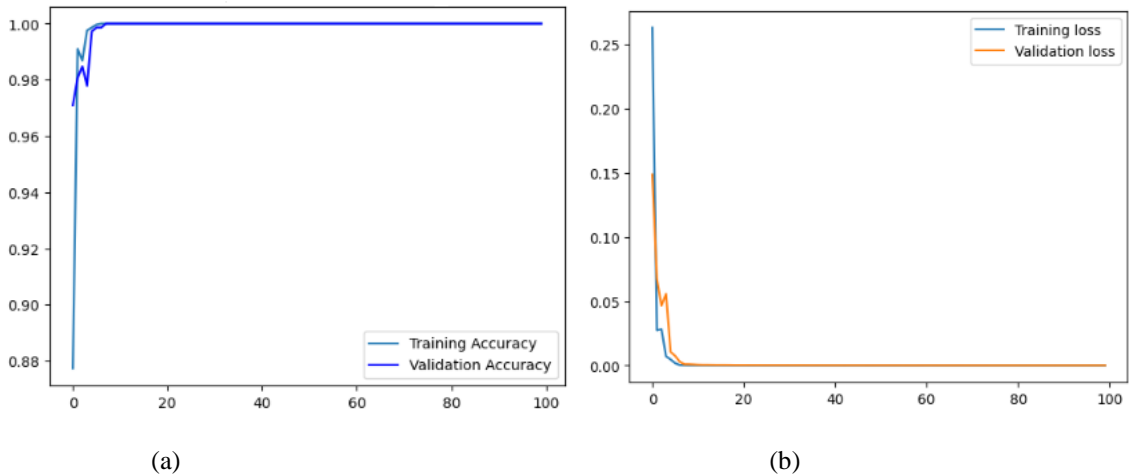


Fig. 3 Training performance of proposed framework using DTS1 (a) Accuracy (b) Loss

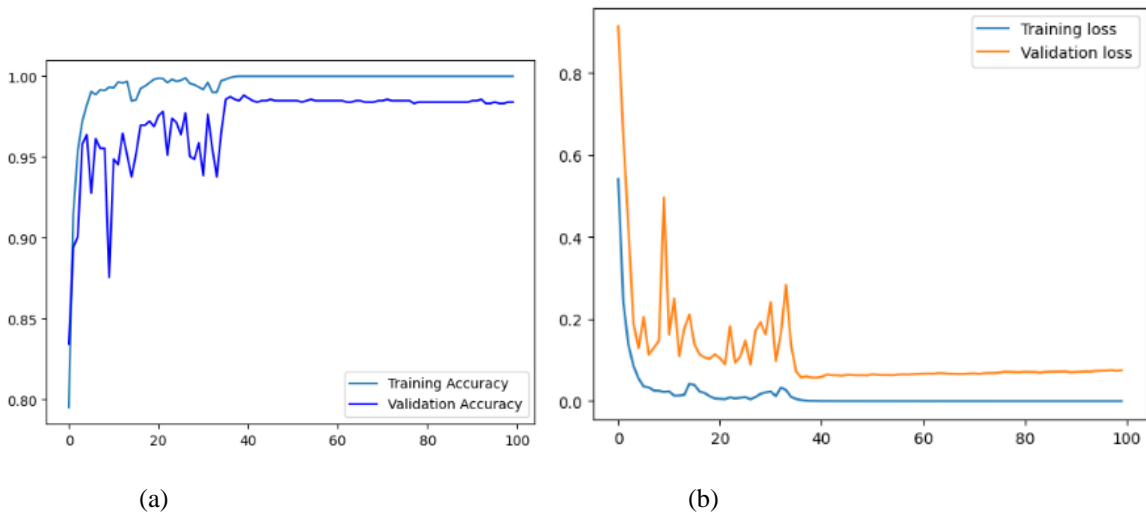


Fig. 4 Training performance of proposed framework using DTS2 (a) Accuracy (b) Loss

Fig. 3 & 4 above obtained is a smooth curve for the training and validation accuracy when trained for 100 epochs. Also, it shows best performance by achieving 100% training and validation accuracy after few epochs and remains stable till 100 epochs without any sign of performance deterioration when trained on both the datasets.

The loss is reduced significantly and no overfitting noticed making it the best performing model. This is the significant result achieved by the proposed model.

B. Performance analysis for Testing

Confusion matrix for both the datasets is as follows in the fig. 5. It can be observed that the proposed novel framework gives good number of true predictions when tested with different dataset with variable number of classes. The testing result of the proposed framework for dataset DTS1 and DTS2 are 99.66% and 98.58% respectively.

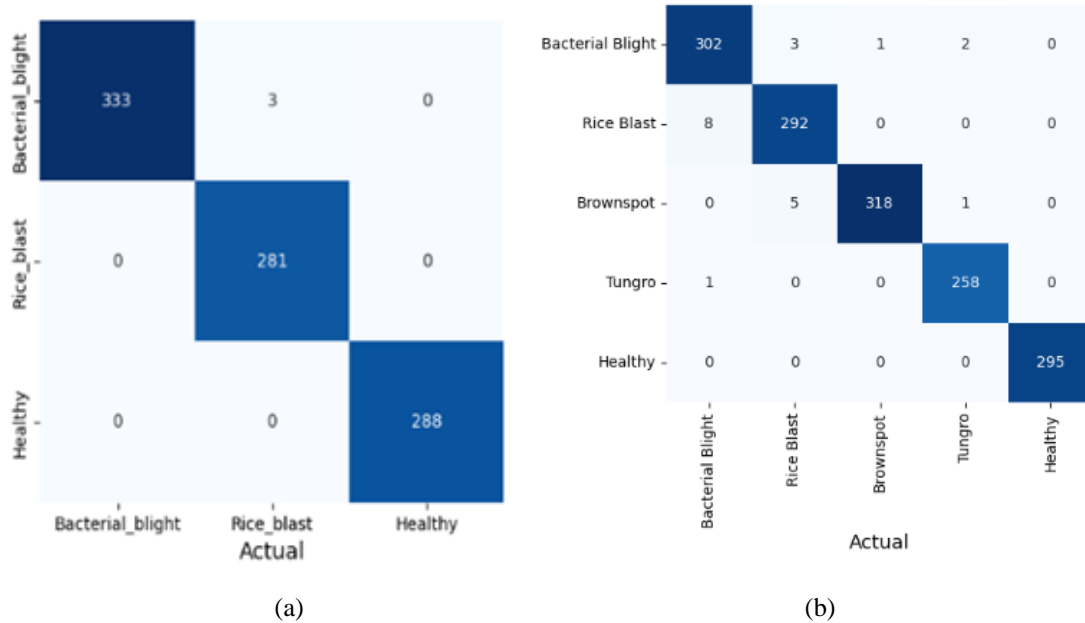


Fig. 5 Confusion Matrix (a) DTS1 (b) DTS2

	precision	recall	f1-score	support
Bacterial_blight	1.000000000	0.991071429	0.995515695	336
Healthy	1.000000000	1.000000000	1.000000000	288
Rice_blast	0.989436620	1.000000000	0.994690265	281
accuracy			0.996685083	905
macro avg	0.996478873	0.997023810	0.996735320	905
weighted avg	0.996720100	0.996685083	0.996686451	905

Fig. 6 Classification report for proposed model using DTS1

	precision	recall	f1-score	support
Bacterial Blight	0.971061093	0.980519481	0.975767367	308
Brownspot	0.996865204	0.981481481	0.989113530	324
Healthy	1.000000000	1.000000000	1.000000000	295
Rice Blast	0.973333333	0.973333333	0.973333333	300
Tungro	0.988505747	0.996138996	0.992307692	259
accuracy			0.985868102	1486
macro avg	0.985953075	0.986294658	0.986104385	1486
weighted avg	0.985931448	0.985868102	0.985879425	1486

Fig. 7 Classification report for proposed model using DTS2

C. Comparison of proposed framework with fine-tuned transfer learning models

In stage I comparison, Inceptionv3, GoogLeNet, ResNet50 and DenseNet121 are implemented on rice disease dataset and compared with the proposed framework as shown in the figure 5 below. Proposed framework gives

the highest accuracy followed by DenseNet121. In the paper [22] it is stated that DenseNet121 performed with highest accuracy but in our experiment proposed framework achieves best results.

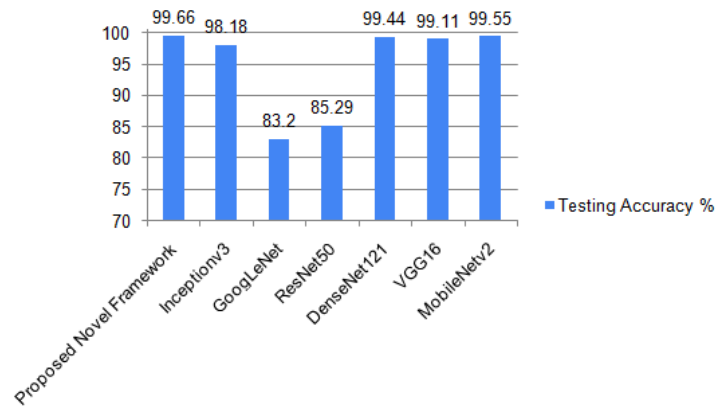
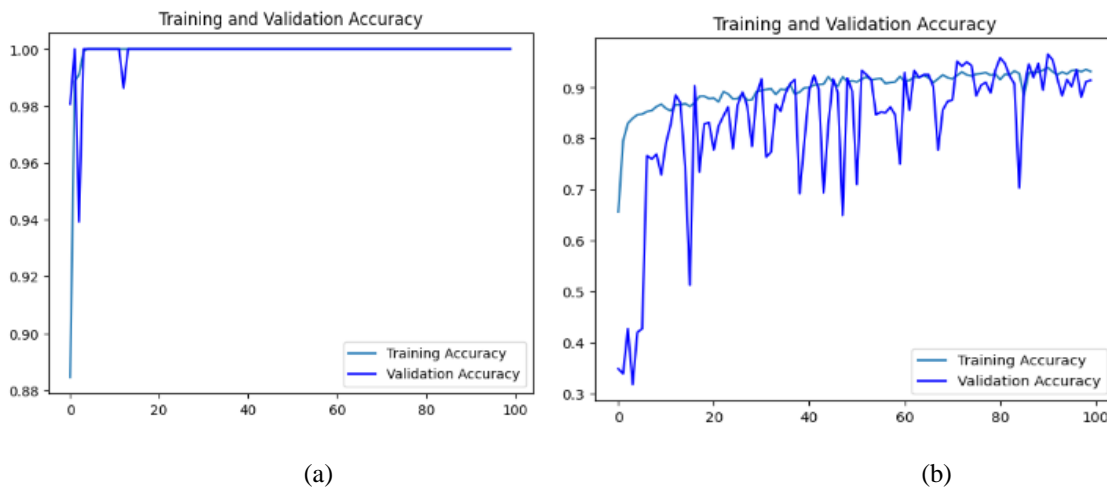


Fig. 8 Comparative analysis with State-of-the-art models

D. Comparison of proposed framework with hybrid transfer learning models

For evaluating and comparing the performance of the proposed framework, the stage II comparative analysis is done where the deep transfer learning models namely Inception v3, GoogLeNet and ResNet50 are fused with CNN independently to form hybrid improved model for rice disease classification. As seen in the Fig. 9 proposed framework shows a smooth curve with stable performance. The hybrid models using GoogLeNet and Resnet50 are not having stable performance whereas Inceptionv3 is stable but the accuracy is lesser than the proposed model.



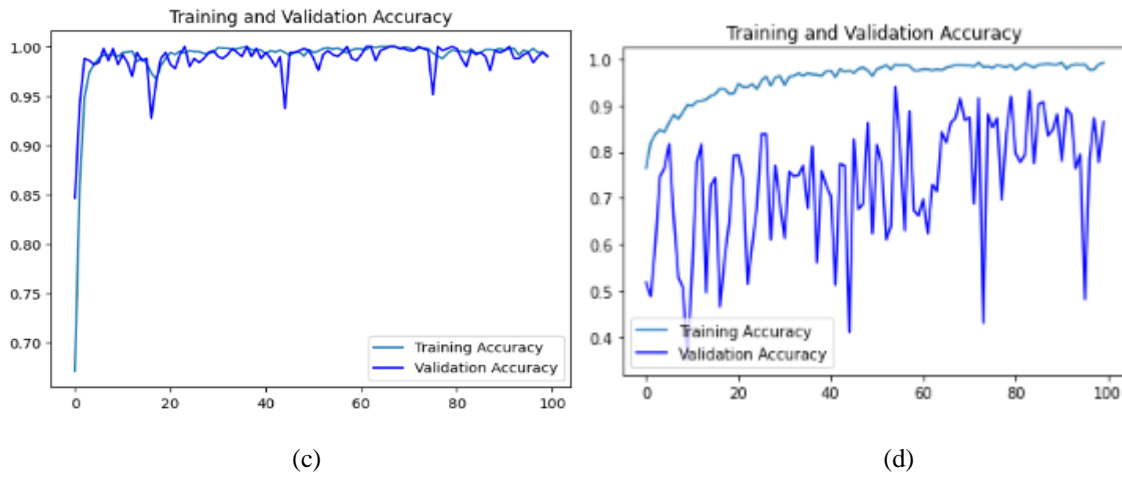


Fig. 9 Comparison with optimized hybrid Models (a) proposed model (VGG16+CNN) (b) GoogLeNet+CNN (c) Inceptionv3+CNN (d) ResNet50+CNN

The table 1 below explains the choice of design for the proposed model as well as for the other hybrid transfer learning models. Batch normalization is only applied to the proposed framework which has helped the model to improve its performance. The Convolutional layer is added for the proposed improved framework, GoogLeNet and ResNet50 whereas for optimizing Inceptionv3 only a dense layer is needed. Inceptionv3 is too heavy hence only one dense layer is added.

Table 1: Architectural design for hybrid improved models

Models	Dense Layer	Convolutional layer	Max Pooling applied	Batch Normalization applied	Dropout
<i>Proposed Framework (VGG16 + CNN)</i>	1	1	Yes	Yes	0.4
GoogLeNet + CNN	3	1	Yes	No	0.3, 0.4, 0.3
Inceptionv3 + CNN	1	0	No	No	-
ResNet50 + CNN	2	1	Yes	No	0.3

Table 2: Comparative result analysis

Models	Trainable Parameters	Training Accuracy %	Validation Accuracy %	Testing Accuracy %	Training Loss	Validation Loss
<i>Proposed Framework VGG16+ CNN</i>	410819	100	100	99.88	7.73E-07	2.72E-05
GoogLeNet + CNN	3925891	93.16	91.44	91.16	0.1652	0.2252
Inceptionv3 + CNN	67900419	99.04	98.99	97.58	0.1182	0.0993

ResNet50+ CNN	1477315	99.26	86.45	87	0.0229	0.8968
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Table 2 clearly indicates the performance of the proposed framework using VGG16 and CNN is best as compared to optimized frameworks of GoogLeNet, Inceptionv3 and ResNet50. It achieves the highest accuracy of 99.88% and only 410819 parameters which is the minimum number of parameters. It also achieves the minimum loss. The loss is highest in optimized Resnet50. Optimized Inception v3 is achieving second highest testing accuracy of 97.58% but requires a highest number of trainable parameters. Resnet50 has achieved the lowest accuracy of 87%. The GoogLeNet, Inceptionv3 and ResNet50 are heavier models having higher number of trainable parameters. Hence it is proved through experiments that the proposed framework is achieving the best performance making pretrained VGG16 the best selection choice for obtaining an improved and optimized model for rice disease classification with highest accuracy.

E. Optimizing the hyperparameters for proposed framework

The hyperparameter fine tuning has played an important role in improving the model accuracy of the proposed framework. The table 3 below shows the results of rigorous experimentation for the rice disease classification model developed using the proposed framework for obtaining optimal hyperparameters. The learning rate was changed from 0.001 to 0.01, the Adam optimizer was replaced with RMSprop, and dropout values 0.2, 0.3 and 0.5 were used for training. The best accuracy is achieved by the hyperparameters listed in table 3.

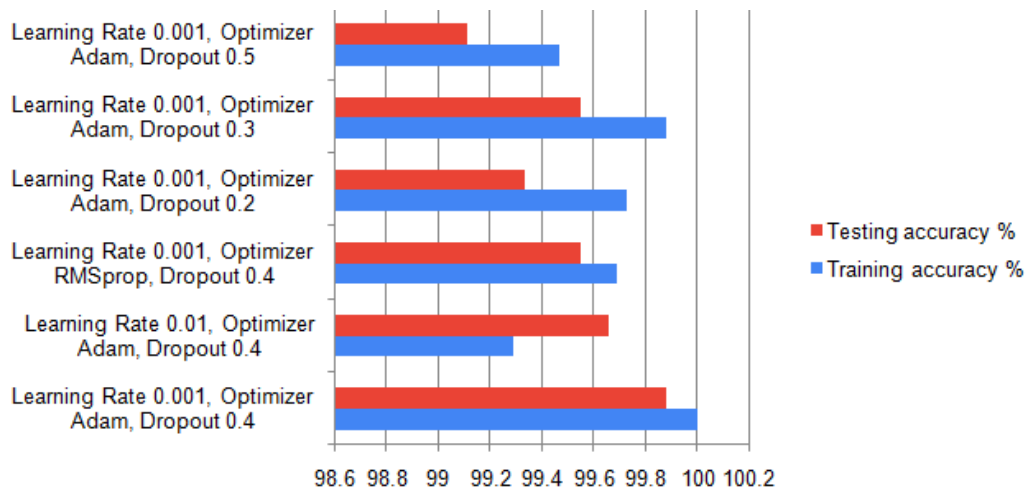


Fig. 10 Hyperparameter Optimization for proposed framework

Table 3 Best Set of Hyperparameters for proposed improved VGG16 framework

Dropout	Optimizer	Loss	Dense Layer	Learning Rate	Activation Function Dense layer	Activation Function in output layer
0.4	Adam	Sparse Categorical Cross Entropy	1	0.001	Relu	Softmax

The different architectural choice of layers for fusing with VGG16 after truncating its output layer is shown in table 4. The parameters were significantly reduced after applying convolution layer along with max pooling to the framework as compared to applying only dense layer. The proposed framework consisting of VGG16 with 1 convolution layer, max pooling, batch normalization and a dense layer achieves the highest testing accuracy of 99.88% with only 410819 numbers of trainable parameters as compared to other choice of design in the table 4.

Hence the above-mentioned CNN architecture design on the top of pretrained VGG16 proposed proves to be the best choice for obtaining improved and optimized framework for rice disease classification.

Table 4 Pretrained VGG16 fused with CNN Architectures

Model Framework Tested	Trainable Parameter	Testing accuracy %
One Dense layer	6,76,867	99.22
Two Dense layers	17,25,443	99.88
One Convolution layer, Max pooling and Dense layer	410691	99.44
One Convolution layer, Max pooling, Batch Normalization and Dense layer (Proposed Framework)	4,10,819	99.88
One Convolution layer, Max pooling, Batch Normalization and Two Dense layers	1460419	99.55

IV. CONCLUSION

First CNN based deep architectures have been used in the past for crop disease classification but very few studies have been performed on rice disease classification. It is seen in literature that the deep learning models suffer performance degradation challenges. Most of the studies have trained the models only upto 30 epochs. The novel optimized framework is proposed by fusing pretrained VGG16 with CNN layers to obtain an improved and optimized framework for rice disease classification. The preprocessing of the images and the hyperparameters optimization is also applied to the proposed framework for improving the accuracy. For evaluation of the proposed framework the two-stage comparative analysis is done where stage 1 compares the proposed framework with state-of-the-art transfer learning models whereas in stage 2 the Inceptionv3, GoogLeNet and Resnet50 are also optimized and then compare with the proposed improved framework. The proposed framework achieves the best performance beating all the other architectures. It gained the highest training and validation accuracy of 100% and testing accuracy of 99.88 % which is the highest in literature reviewed. The trainable parameters by proposed framework required are smaller than optimized Inceptionv3, GoogLeNet and Resnet50. The model performed without any sign of overfitting and performance deterioration when experimented for 100 epochs on two different datasets making it most applicable in the real rice field. In future study we would like to come up with a more lightweight optimized CNN model and reduce the parameters further.

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