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A Real Time Performance Comparison of Rice Plant Disease Identification System using Deep CNN Models

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Abstract

The world's second-largest producer and exporter of rice is India. Early disease detection is crucial to ensuring healthy rice production. In order to address the issue of diagnosing illnesses in rice plants, a number of strategies have been put forth; nevertheless, it has been discovered from the literature that these models do not perform with the anticipated accuracy. In this study, the best fit model among four CNN deep learning algorithms for categorizing rice leaf illnesses was attempted. Patterns were divided into four groups using 1600 images: healthy, brown spot, hippa, and life burst. Based on the findings, the learning rate, accuracy, and disease recognition accuracy of the performance comparison were examined. ResNet50, VGG19, InceptionV3, and ResNet152, CNN deep learning models, obtained disease recognition accuracies of 75.76%, 87.64%, 96.46%, and 98.36%, respectively. The classification efficiency result demonstrates that ResNet152V2 is the best CNN model for classifying diseases affecting rice.

Keywords: Deep learning, Image Classification, Leaf disease Detection, Rice Plant Leaf Disease identification.

Introduction

Every ecosystem depends on plants in one way or another. Plants provide energy to every living organism, either directly or indirectly. It's crucial to detect infections in plant components, including leaves, stems, and organic compounds. Infections, bacteria, and other factors can cause leaf diseases (1). A farmer can usually identify leaf diseases by observing the spots, shading, and general health of the leaves, but occasionally, expert assistance is needed to spot ill plants or crops. The world's most significant food crop, rice, feeds more people than any other crop. More than 3 billion people lived on rice every day in 2012, which is approximately half of the world's population (2). Additionally, it is a staple diet in Asia, which is home to almost half of the world's poorest population, and is becoming more and more popular in Africa and Latin America. More people have been fed by rice than any other crop for a longer period of time. Both in terms of how it is grown and how it is utilized by people, rice is surprisingly diverse. Rice is exceptional in that it can thrive in humid conditions where other crops cannot. In Asia, these humid conditions are typical. Thousands of different varieties of rice are currently farmed on every continent except Antarctica, making the domestication of rice one of the most significant historical occurrences (3). The rice crop encounters a number of issues due to diseases that negatively impact it and are challenging to spot with the naked eye. The plant's leaf is typically the part that is most affected, with 80 to 90 percent of plant illnesses being discovered on the leaves. Therefore, in this post, we will primarily focus on the leafy portion rather than covering the entire plant (4). Various techniques have been proposed to identify diseases in rice plants from their leaves (5). Numerous approaches, however, have fallen short of providing precise identification. Deep learning, a subset of machine learning, has numerous applications across various fields (6). The primary goal of this endeavour is to lessen field losses due to plant diseases (7). In order to detect illnesses in rice leaves, four CNN architectures namely, ResNet, Resnet152V2, VGG19, and InceptionV are proposed in this article. The concept of applying the transfer learning technique to all four models to identify leaf diseases is presented in this proposal. The remaining portions of this article are structured so that they include parts like relevant work, methodology, planned

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study and findings, and discussion. The application of convolutional neural networks in rice plant diseases identification has huge development perspectives. Rice leaf disease detection using Convolutional Neural Network by Rajani et al. achieve good results, mostly with brown spot and bacterial leaf blight, achieving an accuracy overall of 67% (8). In the comprehensive study by Burak Gülmez, rice disease detection through CNNs, worldwide works done are reviewed; a remark is made that models require fine-tuning for optimal performance (9). Hassan and Maji have proposed one more approach for the purpose of identification of diseases in plants. The main reason, according to them, is the presence of a novel convolution neural network that uses depth wise separable convolution for reducing parameters and achieving high accuracy (10). Liu H et al. used an optimal model parameter setting is used in rice plant disease identification system, realizing a recognition accuracy of 98.64%, which shows the effectiveness of deep learning in rice diseases identification (11). Islam et al. proposed a methodology to detect potato diseases by employing image segmentation and a multiclass support vector machine that can identify healthy and unhealthy potatoes (12). Lv et. al used feature enhancement and DMS-Robust Alexnet to identify maize leaf disease (13). Eggplant leaf datasets were gathered using RGB and thermal imaging cameras. They were able to attain 90.9% accuracy with SVM and 89.1% accuracy with ANN when temperature and color were considered as essential features. Venmathi et al. produced a number of implementations to compare various types of activation functions (14). Some of these include tanh, sigmoid, ReLU, and softplus for classification. ReLU achieved the highest accuracy of all of them, at 98.43%. They deduced from the findings that as the number of iterations rises, so does accuracy (15). CNN models can be developed for automatic feature extraction and categorization of plant diseases with Learning Vector Quantization (LVQ). A dataset of 500 images of diseased tomato leaves were gathered to achieve this. A supervised learning approach was applied for neural networks to increase accuracy. To classify various tomato leaf diseases, a slightly modified LeNet model was used. Deep convolutional neural network can be employed to detect illnesses in apple plant leaves. Google Net is employed for the training model. This model is capable of automatically extracting characteristics. It lists five plant diseases in their various forms. A CNN model is capable of extracting features from pictures of leaves with various yields. A neural network is used in the proposed CNN model to identify plant diseases. There are 16 layers and 32*32 filters in this model. They used a dataset of 14,810 photos to apply their model on. They were able to obtain a greater accuracy with this model, 86%. They state that the accuracy has increased by 7% when compared to MobileNet50. It was found that no Keras model was used in any of the models presented in the literature study to identify rice leaf diseases (16). Additionally, it has been discovered that the current models do not operate and give accuracy at the required level. In order to assist farmers in the early forecasting of fertilizers and medications to recover from significant losses caused by foliar diseases, it is suggested that they utilize a variety of Keras models for early detection of foliar diseases (17). It also seeks to evaluate the performance comparison of different models and confirm which model works best for a specific dataset.

Methodology

A novel notion that would increase the accuracy of illnesses detection has been applied after researching the numerous methods and approaches for disease detection in leaves. The design of the model for detecting rice leaf disease as shown in Figure 1.

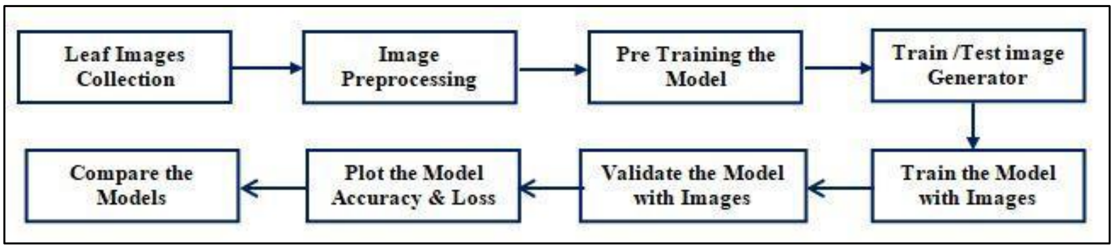

Figure 1: Block diagram of the proposed method

The specifics of detecting foliar diseases in rice are explained in Figure 1. The user hits the preview button after uploading the sheet photos to see the outcome. The API is called when the user clicks the predict button. The API transforms an image from a file into an array. The matrix is then normalized in the following step. It then makes a prediction based on the normalized value as to whether the image represents a healthy leaf or a diseased one.

ResNet50

Due to improved accuracy and lower error rates when compared to predecessors, CNN is often employed for applications linked to image processing. It is also used to extract features from the input photos. To minimize the amount of the input features from the convolutional matrix, it consists of pooling layers and convolutional layers with the ReLu function. The fact that CNN can perform both tasks—fact usage extraction and classification—is a substantial additional benefit. The main issue is that CNN architectures in deep learning are too small, leading to disappearing explosive gradient difficulties that prevent error rates from falling and overfitting models from becoming more accurate as shown in Figure 2.

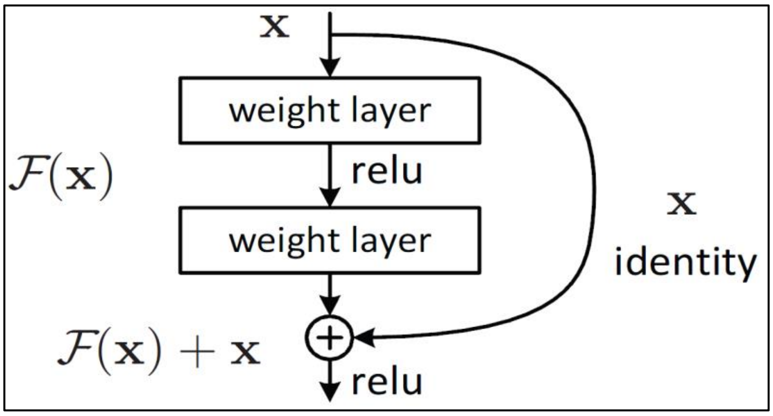

Figure 2: A Residual Block

ResNet, a residual network design that Microsoft launched in 2015 to address the aforementioned issues, is also a connection skip that omits several levels while building the model. If H(x) is the beginning notation for f(x) = H(x)-x, then H(x) = f(x) + x is the result. By excluding ineffective layers, the addition of this layer will increase accuracy and lessen the gradient outlier problems discussed in this article. Another ResNet variant utilized in the Rice Plant Disease Identification System is ResNet50. The specifics of the ResNet50 architecture are shown in Figure 3.

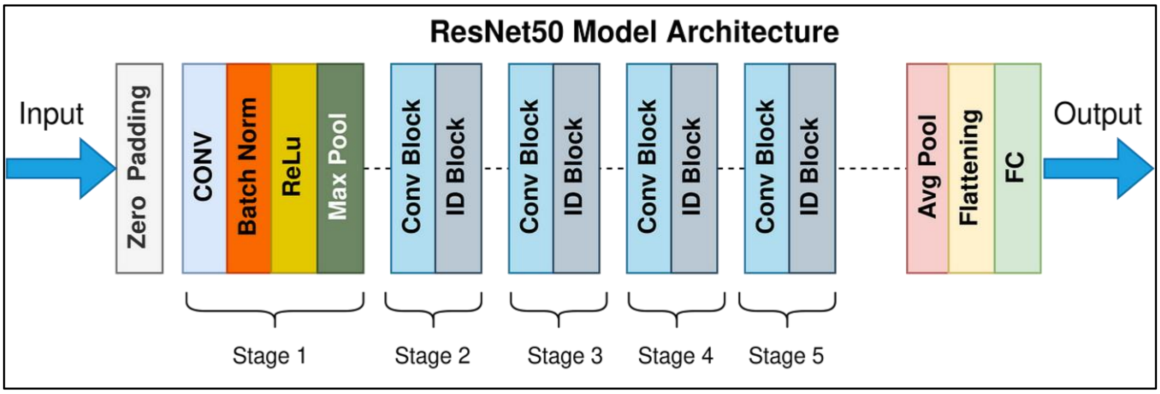

Figure 3: ResNet50 Layers Structure

VGG19

A deep convolutional neural network called VGG19, a variant of the VGG model, is utilized for image classifiers. A maximum of 5 build layers, 3 fully attached layers, 16 wrap layers, and 1 smooth layer make up this model's full layers. The Visual Geometry Group (VGG) at Oxford created VGG, which is the replacement for AlexNet. The pre-trained CNN VGG19 has 19 layers total, comprising 16 convolutional layers and 3 fully connected layers. A standard conventional neural network that was proposed at Oxford University as AlexNet's replacement is called VGG19. A pre-trained model called VGG19 was developed using an image net with more than 14,197,122 images. Additionally, it is employed in feature extraction and picture categorization. For VGG19 architectures, a 224 x 224 color input image is offered. For a number of image datasets, VGG19 has been found to be the most effective classifier. Being one of the most effective computer architectures, it is also the best model for transfer learning with pre-trained images. The first table displays the total number of layers that are available at each step. Also utilized is a 10 step size 8120 3 x 3 kernel. To safeguard the spatial properties of the image, it uses spatial padding techniques. In order to increase the non-linearity of picture features and decrease training time, this model additionally incorporates RELU. VGG19 is used here for both feature extraction and classification of the rice leaf disease identification system are tabulated as Table 1.

Table 1: VGG19 Layers

Layer Name	#Filters	# Parameters	# Activations
Input			150K
C1_1,C1_2	64	17K,36K	3.2M
Max Pooling			802K
C2_1,C2_2	128	73K,147K	1.6M
Max Pooling			401K
C3_1, C3_2, C3_3, C3_4	256	300K, 3 x 600K	802K
Max Pooling			200K
C4_1, C4_2, C4_3, C4_4	512	1.1M, 3x 2.3M	401K
Max Pooling			100K
C5_1, C5_2, C5_3, C5_4	512	2.3M	100K
Max Pooling			25K
FC6		103M	4K
FC7		17M	4K
Output		4M	1K

InceptionV3

One of Google's Deep Convolutional architectures is InceptionV3. In 2015, Google released the Inception deep convolutional neural network, also known as InceptonV1 and titled GoogleNet. The updated version was given the moniker IniceptionV2 after the introduction of the batch normalizing technique. The new version, InceptionV3, was later updated to include the factorization concept. Similarly, InceptionV3 is a model that has been pre-trained. It was pre-trained using the ImageNet dataset, which includes 1000 classes and more than 12 million high-resolution images, along with 100000 training and 50000 testing images. InceptionV3 applies the knowledge it has learned from the ImageNet dataset to new datasets for any application; this process is known as transfer learning. Transfer learning is nothing more than learning by viewing millions of photos on robust computers. The knowledge gained during this training is applied to other tiny datasets using this model. As a result, this model will produce better classification accuracy thanks to transfer learning. This trained InceptionV3 is capable of classifying photos into 1000 different categories. It has 48 layers in all. Similarly, InceptionV3 is a model that has been pre-trained. It was pre-trained using the ImageNet dataset, which includes 1000 classes and more than 12 million high-resolution images, along with 100000 training and 50000 testing images. InceptionV3 applies the knowledge it has learned from the ImageNet dataset to new datasets for any application; this process is known as transfer learning. Transfer learning is nothing more than learning by viewing millions of photos on robust computers. The knowledge gained during this training is applied to other tiny datasets using this model. As a result, this model will produce better classification accuracy thanks to transfer learning. This trained InceptionV3 is capable of classifying photos into 1000 different categories. It has 48 layers in all. The Inception V3 is a 48-layer deep convolutional neural network. Inception V3 has been pre-trained on an Image Net dataset with over 1 million images. V1 and V2 are required to run. The 5x5 wrapping of the Inception v1 model results in smaller sizes in big numbers, resulting in reduced inaccuracy. InceptionV2 reduces the package size from 5x5 to 3x3 to compress difficulties. This improves precision while decreasing computation time. Convolutional scaling improves the efficiency of InceptionV2. InceptionV3 is similar to InceptionV2, except that it employs the RHSprop optimizer. Batch normalization is also included in a fully connected layer as in Table 2.

Table 2: InceptionV3 Layers

CNN LAYER	FILTER SIZE	NO OF KERNAL	STRIDE
C1	3X3	3	2
C2	3X3	32	1
C3	3X3	32	1
P1	3X3	64	2
C4	3X3	64	1
C5	3X3	80	2
C6		192	1
3 1M		288	
5 1M		768	
2 1M		1280	
P	8X8	2048	0
LINER	1X1	2048	

This InceptionV3 is used to detect illness in rice plants because of its higher accuracy with lower mistake rates as well as its shorter calculation time.

ResNet152V2

Similar to the above model, in ResNet 152 v2 the post fix ‘152’ represents the number of layers in the model. The 152-layer ResNets are constructed using more 3-layer blocks. Even after the depth is expanded, the 152-layer ResNet has lower intricacy than VGG16 as shown in Figure 4.

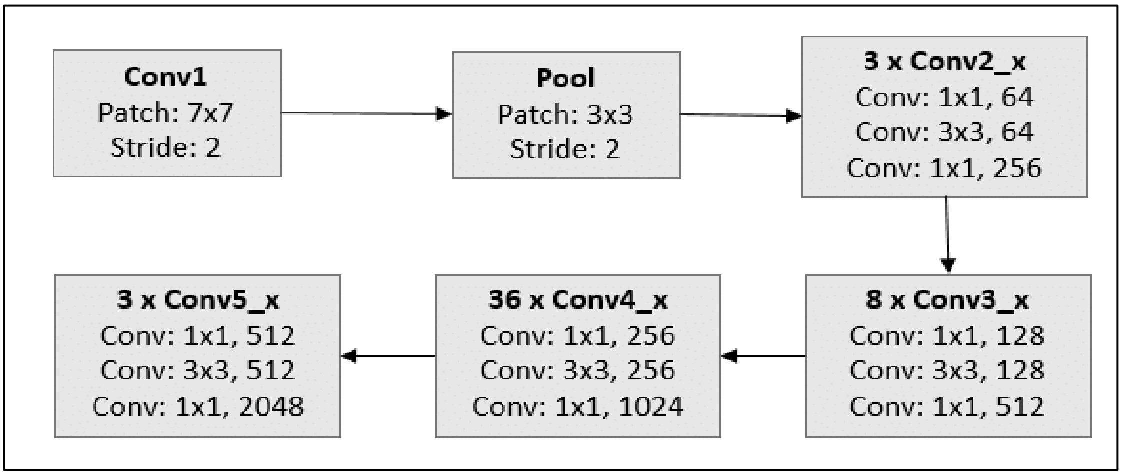

Figure 4: ResNet152V2 Layers Structure

Results

To investigate the detection performance of rice leaf diseases, top Keras models such as InceptionV3, ResNet152v2, ResNet50, and VGG19 were utilized. The model's performance was evaluated by deploying it with Jupyter Notebook with Anaconda IDE and Python 3.8 as the programming language. Visual Studio Code and Jupyter Notebook are the interface tools used to implement the project. This functionality also made advantage of the FLASK framework background feature.

Experiments were carried out by applying each model to a separate dataset, and the accuracy and loss acquired during this experiment were compared.

Transfer Learning

The ImageNet dataset, a big picture repository comprising over 1 million images, was used to pre-train the four models used here to detect rice leaf illnesses. Our model transfers and learns from ImageNet before applying it to the rice leaf dataset. It was established that transfer learning would improve identification accuracy. All four models utilized in this study have been pre-trained.

Data Collection

The rice leaf database from the Kaggle website was used in this investigation. To deliver the best classification results, the deep learning model requires a large number of images. The rice leaf database contains 2,092 images, 1,600 of which are used for deep learning model training and 492 for validation and testing. Among these rice leaf images, there were 400 brown spot images, 400 blast images, and 400 hispa images. These photographs were captured with high-resolution cameras with pixel sizes of around 2 megapixels. The images were split into a training set, a validation set, and a test set with a ratio of 7:2:1 to prepare the CNN model for deep learning. Four different CNN architectures were developed, and the dataset was applied to three disease categories.

Data Set

The dataset used to create the models is divided into two parts: testing and training. These sets are further divided into four folders. The dataset was obtained from the Kaggle website. Table 3 provides information about the folders and the number of photographs in the training and validation folders. The results of the studies show that ResNet152V2 obtains an accuracy of 98.36%, InceptionV3 achieves an accuracy of 96.46%, VGG19 achieves an accuracy of 87.64%, and ResNet50 achieves an accuracy of 75.76%. The results of the executions are shown in Figure 5 to 8.

Table 3: Dataset description

Training set	Qty	Validation Set	Qty
Brown Spot infected	400	Brown Spot infected	123
Healthy Leaves	400	Healthy Leaves	123
Hispa Infected	400	Hispa Infected	123
Leaf Blast Infected	400	Leaf Blast Infected	123

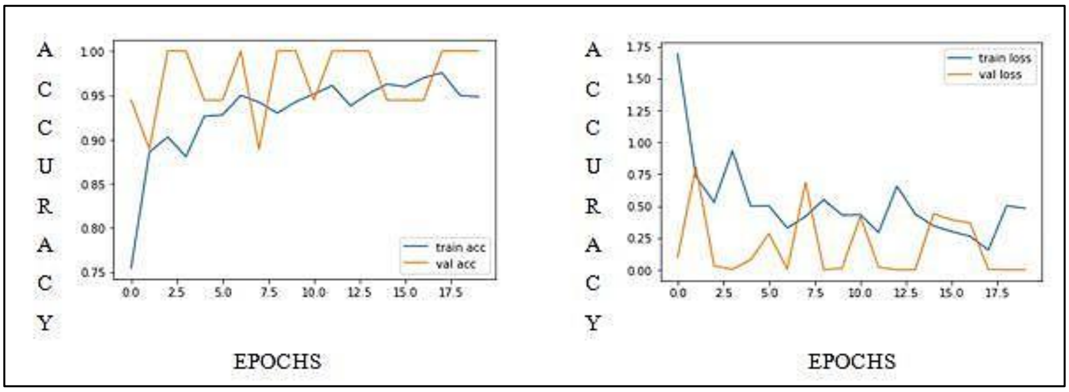

Figure 5: a) Accuracy Graph of Inception V3 b) Loss Graph of Inception V3

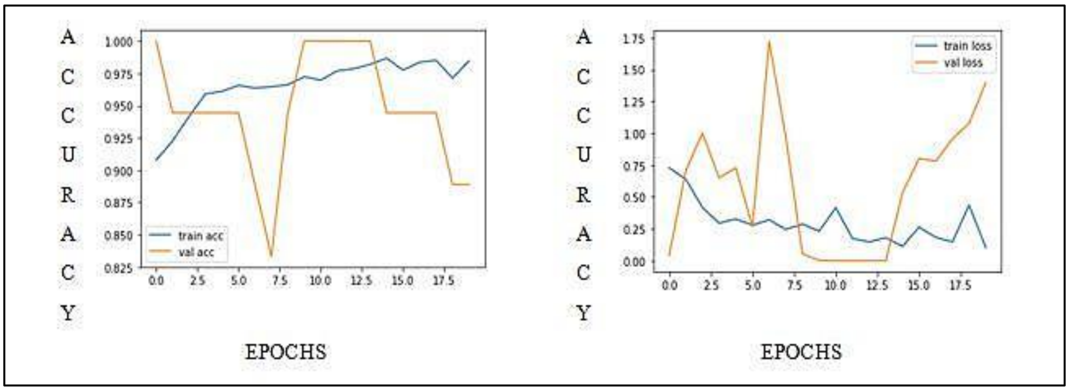

Figure 6: a) Accuracy Graph of ResNet 152V2 b) Loss Graph of ResNet 152V2

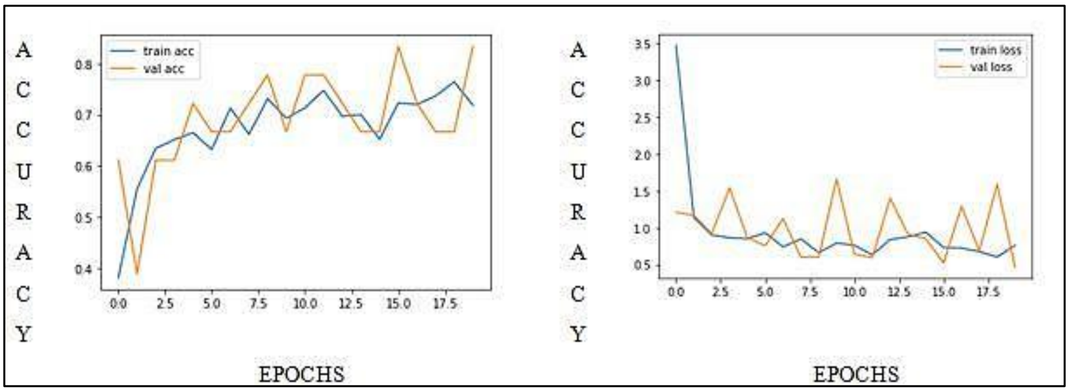

Figure 7: a) Accuracy Graph of ResNet 50 b) Loss Graph of ResNet 50

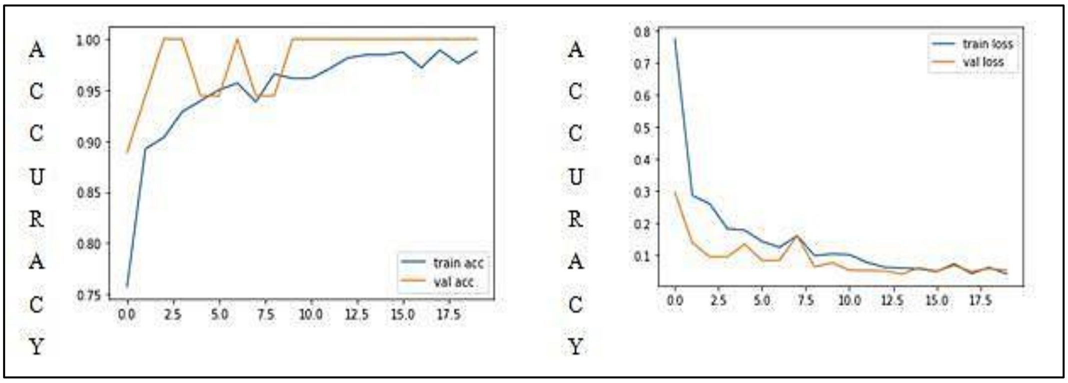

Figure 8: a) Accuracy Graph of VGG 19 b) Loss Graph of VGG 19

The rice leaf database from the Kaggle website was used in this investigation. To deliver the best classification results, the deep learning model requires a large number of images. The rice paper database contains 2092 photos, 1600 of which are for deep learning model training and 492 for validation and testing. There were 400 brown spot images, 400 batch images, and 400 Hisp images among these rice leaf databases. These photographs were captured with high-resolution cameras with pixel sizes of around 2 megapixels. The photos were split to prepare the CNN model for deep learning as Table 3.

Discussion

In this paper, we have tried to identify different diseases associated with the leaves of rice plants using some deep learning techniques. We have taken four different rice-leaf diseases for our study and considered the rice leaf database available in Kaggle's website. It has 2092 images, out of which 1600 were used for training the deep learning model and the remaining 492 for validation and test purposes. The models' effectiveness test has been carried out with the help of Jupyter Notebook using the Anaconda IDE and Python 3.8. Besides, Visual Studio Code and Jupyter Notebook were used as interface tools to support the implementation of this project. Some related functionalities have also been supported using the FLASK framework.

Table 4: comparison of CNN models

Model	No. of layers	No. of Parameters	Accuracy
ResNet50	50	2,56,36,712	75.76%
VGG19	47	14,36,67,240	87.64%
InceptionV3	48	2,38,51,784	96.46%
ResNet152V2	152	6,03,80,648	98.36%

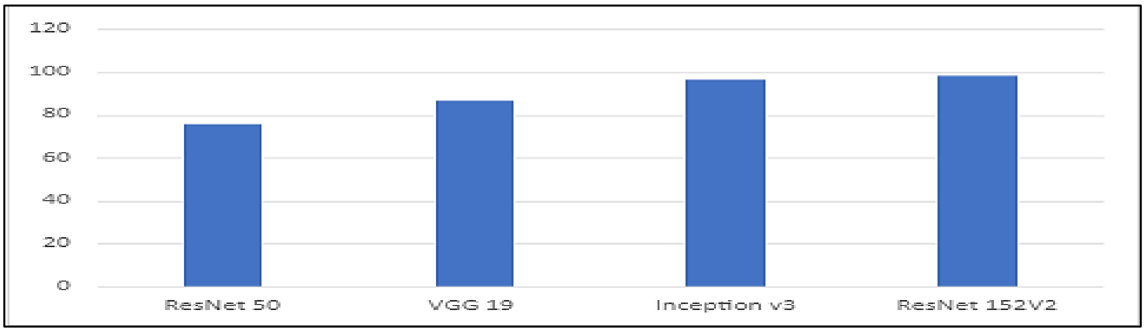

Figure 9: Comparisons of CNN Models (Represents the accuracies of ResNet50, VGG19, InceptionV3, ResNet152V2)

Table 5: Comparison with Existing Models

Model	Accuracy
Xception CNN	89 %
Pahlawanto CNN Method	93 %
Kulkarni and Shastri CNN Model	95 %
Proposed Method	98.36 %

In this research, we have processed a dataset consisting of photos of rice leaves with multiple diseases. The major components of the CNN architecture are filter size, core number, and stride. As elaborated, the complicated layers c1–c5 applied a 3x3 filter size. The training of the CNN architecture consisted of 400 images for leaf burst computation and 400 compute images. The number of cores increased linearly with increasing depth of layers to top at 2048.A pilot trial with ResNet152V2, comprising 152 layers, returned an accuracy of 98.36%. Comparative analysis of different models showed that ResNet50 had the lowest classification accuracy, while ResNet152V2 had the highest accuracy in classifying foliar diseases in rice. We have implemented four different Keras models for a proper evaluation: ResNet50, VGG19, InceptionV3, and ResNet152V2. The accuracies for these models against the same dataset were 75.76%, 87.64%, 96.46%, and 98.36%, respectively. Among these models, ResNet152V2 showed the highest accuracy with 60,380,648 parameters Table 4 and Figure 9. Our study proves that ResNet152V2 has better performance compared with other deep learning models for rice leaf diseases classification. Results indicated that while simpler models, such as ResNet50, struggled with regard to accuracy, more complex models like VGG19 and InceptionV3 made a great improvement; however, ResNet152V2 outperformed all other models, thus being confirmed as the best CNN model for this task. According to Muslikh et al., (18) the Xception CNN model reported an accuracy of 89% because it uses depthwise separable convolutions that bring about a reduction in the number of parameters and computational cost besides having very rigid performance in image classification tasks. However, the accuracy it delivers suggests there is still scope for its betterment in this particular application. In the process, Pahlawanto et al., (19) proposed a CNN method that improved the accuracy of detection to 93%. This could be due to the inclusion of more advanced techniques or a better-optimized architecture within this model. The gain in accuracy from Xception CNN to this approach underlines the potential of tailored CNN architectures for rice leaf disease classification. Kulkarni and Shastri (20) developed a tailored CNN model that achieved accuracy of 95%. Tailored models of CNN can perform finetuning and optimization according to the dataset and problem requirements. The higher the accuracy, thereby establishing the efficiency of a tailored model for disease detection in rice leaves. Our proposed model turned out to be the best with an accuracy of 98.36%, outperforming all of the above-mentioned models. This model is incorporated with ResNet152V2, which is a variant of the deep residual network. Thus, skip connections mitigate the vanishing gradient problem, ensuring very deep network training. This study essentially brings to the fore the importance of model complexity and depth in neural networks for high rice leaf disease classification accuracy. ResNet152V2, with expansive parameters and deep architectures, makes it become the most potent model in the experiment, with an accuracy of 98.36% as shown in Table 5. The research contributed many meaningful implications of deep learning applied to agricultural diseases classification tasks to the literature and set a benchmark for future works in this area of research.

Conclusion

The method for detecting foliar diseases in rice is the topic of this paper. The leaves of the plant are the primary source of rice infection. The human eye cannot distinguish the difference in color and texture between healthy and infected rice leaves. As a result, a new method for detecting plant diseases is required. Various deep learning methods were employed to select an optimal classifier for automatic classification of rice leaf diseases. In this paper, we use transformational learning models to classify rice leaf diseases. Compared to the methods mentioned in the literature, we implemented this method using four separate Keras models. The four models, ResNet50, VGG19, InceptionV3, and ResNet152V2, were applied to the same datasets, achieving accuracies of 75.76%, 87.64%, 96.46%, and 98.36%, respectively. Among the four models, ResNet152V2, with 60,380,648 parameters, provided the highest level of accuracy. It is possible to conclude that ResNet152V2 is the best CNN model for classifying rice leaf diseases. The model proposed in this paper can be utilized on different plants for disease identification in the future to improve this approach. We concentrated solely on the rice plant in this study. However, disease detection is required for all crops. As a result, this method can be further improved to classify diseases in diverse plants, which will be extremely beneficial to the agriculture sector.

Abbreviation

Nil

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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