An End-to-End Web-Based System for Rice Leaf Disease Classification using Deep Learning

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Abstract. The smart agriculture or intelligent farming is getting popularity day by day and for this machine learning (ML) based technologies are proven effective tools. Disease of rice plant leaf is one of the most common obstacles in the production of rice to meet the huge amount of demand all over the world. This paper represents a website framework using deep learning to classify three common rice leaf diseases: Bacterial Leaf Blight, Brown Spot, Leaf Smut and also can identify the Healthy one. Moreover, it provides an insight comparison analysis in results (accuracy, training time, model size and parameters) of different state of art methods using same dataset and we have chosen the best one among them for website development. All the used models (InceptionV3, MobileNetV2, VGG19, ResNet50, VGG16 and AlexNet) have been customized for faster operation and lower storage. In the website, for each uploading rice leaf image it can identify the disease class regarding MobileNetV2 model as it shows best result and also can show the probability of accurate identification for this model. Preprocessing comprises removing noise, missing data, and organizing images in a uniform manner in order to maximize accuracy. The models used bahribahri's dataset of 16000 images rice leaves. MobileNetv2 and Vgg16, out of all the models, had greater accuracy results (98.05% and 99.3%, respectively). However, other evaluation matrices such as speedy training, small model size, lower parameters have made MobileNetV2 perfect for this study.

Keywords: Deep Transfer Learning, Computer Vision, Rice Disease Classification, Web based Prediction System.

1 Introduction

Rice stands as a cornerstone among the essential food crops that sustain populations across numerous regions. Its significance is underscored by the fact that approximately half of the global population relies either entirely or to a significant extent on rice as a dietary staple. This reliance on rice as a dietary foundation is emblematic of its nutritional importance and adaptability to diverse cultures. The cultivation and consumption of rice have become integral components of daily life for millions, if not billions, of people around the world. This humble grain has been cultivated and cherished for centuries, forming the backbone of countless culinary traditions and livelihoods. Its adaptability to varying climates and landscapes, ranging from waterlogged paddies to dry uplands, further contributes to its widespread cultivation. With an eye on global production, the sheer scale is impressive, with roughly 480 million metric tons of rice being cultivated annually. This mammoth effort takes place across continents and countries, reflecting the agricultural dedication of countless farmers who labor to meet the world's dietary demands. This annual output not only serves as a testament to human ingenuity and agricultural innovation but also exemplifies the symbiotic relationship between people and the land they cultivate [1]. However, a significant barrier to the large production requirement is the wide range of diseases. While it's true that farmers do not always have the knowledge to recognize particular diseases harming their crops, accurate detection and categorization of diseases affecting rice leaves can be difficult. Complex backgrounds, distinct disease patterns, and a lack of knowledge provide obstacles that need for a comprehensive strategy integrating technology, cooperation, and education. While machine learning has the potential to revolutionize disease identification in agriculture, its effective application depends on a comprehensive approach that takes the local environment into account and involves both professionals and farmers. The appearance of areas affected by several diseases can occasionally be difficult to detect with human vision since it seems identical. Therefore, it is crucial to provide an automated, practical tool for classifying rice leaf disease. The development of automated disease identification and categorization is being greatly facilitated by the innovative guidance of artificial intelligence through machine learning. In bridging the gap between human abilities and machine, artificial intelligence is making amazing progress. The application of pesticides and fertilizer might be more effectively automated with the use of computer vision, even with minimal or no human participation. As a result, the advantages of intelligent agriculture will be induced. This will lead to accuracy in correct treatment against corps diseases, which can be identified from its pictures. Image processing methods have mostly been used to identify plant diseases and these methods include segmentation, masking, thresholding, clustering, edge detection, histogram analysis etc. [2, 3]. The image processing-based techniques to identify the diseases from images requires specific algorithm for specific task or groups of images, hence detection accuracy is often found poor for leaf with complex texture and diseases. Beside, conventional machine learning based classification techniques [3-8] are usually trained with smaller data hence larger dataset based deep learning techniques [9-14] exhibits proven superior performance recently. Because the background of an image of a rice leaf is typically complicated and not uniform, using conventional image processing techniques to analyze the image generally produces inaccurate results. An important machine learning (ML) technique in computer vision is the convolutional neural network (CNN). Innate filtration and automated feature extraction of deep CNN is showing promise and power in handling image classification challenges comparing with traditional machine learning-based classifiers. CNN can memorize these filter characteristics, unlike hand-engineered filters used in primitive techniques, given enough preparation.

Therefore, a well-designed CNN model with efficient image preprocessing might potentially classify the disease from a rice leaf image.

Being motivated by these facts, we have intended to categorize various rice leaf diseases using several deep learning-based state-of-the-art approaches and use the best performed model (MobileNetV2) to develop the system in website framework. This classification system is designed considering four classes: three rice leaf disease class (Bacterial Leaf Blight, Brown Spot, Leaf Smut) and one class that shows the healthy state of the leaves. Some fundamental image processing techniques have been used to prepare the data suitable for training, and models are customized for speedy operation and less storage. We have designed, trained, validated, and tested these classifiers with tuning to superior performance and also provide an insight comparison analysis in results (accuracy, training time, model size and parameters). Finally, the MobileNetV2 trained model has been integrated into the website framework for practical use after achieving good results across all segments. The website can accurately detect the disease class for each uploaded image of a rice leaf and can also provide a probability that the model will be correctly identified. The major contributions of this work are summarized as follows:

- Development of an integrated and web-based system healthy and three common rice leaf diseases classification systems.
- Use a larger dataset of 16000 images for training and testing comparing to the related works.
- Visual examination of the localization ability of the convolution layers using Grad-CAM analysis.
- A rigorous comparison analysis of the obtained results (accuracy, training time, model size and parameters) with of different state of art methods using same and different dataset.

The remaining part of this paper is organized as follows. Section 2 reviews the related literatures. The overall methodology is extensively described in the section 3. The experimental setup, results, GradCaM analysis, and comparative analysis with other studies are presented in Result and Discussions section described. Finally, some concluding remarks and futures projection are given in the Conclusions section.

2 Literature Review

In the realm of rice leaf disease classification, several notable studies have laid the foundation for the advancement of this field. These pioneering works have contributed significantly to our understanding of disease detection and classification within the context of rice agriculture. In this section, we highlight some of the remarkable contributions that have shaped the landscape of rice leaf disease classification.

The image processing-based techniques to identify the diseases from images requires specific algorithm for specific task or groups of images, so as a powerful tool CNN is being used now a days. This deep learning approach can identify the special feature of image and based on this algorithm the unique feature of the images can be detected. Sardogan et al used CNN and Learning Vector Quantization (LVQ) to classify Tomato Leaf Disease [9]. The dataset used in this research contains a total of 500 images of tomato leaves with four types of diseases. They have achieved an average of 86% accuracy from their approach [9]. Some tasks had been based on both image processing and Deep Learning algorithms Haixia et al [10] focused on automatically detecting groundnut leaf diseases using a stack ensemble technique. The research targeted the identification of four different diseases affecting groundnut leaves. The approach involved combining deep learning models with conventional machine learning methods. Among the deep layer networks utilized, ResNet50 and DenseNet121 yielded the most accurate predictions on the dataset. The highest achieved accuracy through data augmentation was 97.59%. Shreya Ghosal et al worked on Rice Leaf Diseases Classification using Transfer Learning algorithm and they gained well accuracy on the classification [11]. Rukhsar et al [12] introduced an approach that employs a pre-trained convolutional neural network (CNN) to identify images of rice leaves based on various disease types. They experimented with this method using a collection of rice leaf images and provided evidence that it can achieve high accuracy in identifying and categorizing diverse diseases. Their findings suggested that transfer learning holds substantial potential as a robust technique for identifying diseases in images of crops. Wang et al [13] developed ADSNN-BO model focusing on attention based neural network which achieved an accuracy of 94.65%. They have applied Bayesian optimization to tune the hyperparameters.

Based on the literature discussed above, it's evident that plant diseases tend to be specific to certain regions due to variations in environmental factors and geographical settings. Many researchers have put forth deep learning-based models to achieve more precise plant disease detection. Notably, deep learning models are often recommended when there's access to extensive datasets. Our present study focuses on comparing results of different customized models addressing three diseases in rice plants, with a dataset comprising 16000 images. In the subsequent section, we introduce an automated website using these deep learning models for the prediction of the diseases.

3 Methodology

The pre-processing, training, and validation of the various Convolutional Neural Network (CNN) models for the classification of rice leaf diseases are included in the proposed research's essential steps. The entire workflow is succinctly illustrated through the following flowchart, wherein each block signifies a distinct step within the process. These steps encompass Image Acquisition, Dataset, Data Preprocessing, Feature Extraction, Using Different CNN models through transfer learning and finally classification.

Figure 1 illustrates the complete methodology we propose. Image acquisition is the first phase, which entails obtaining pictures from various sources. Hardware such as cameras or sensors may be included in this. The next step is dataset collection, where a compilation of images representing the four classes we intend to predict is gathered. To improve accuracy, the models are trained using a wide variety of pictures from this dataset. Data preparation comes next in the process. This encompasses refining the collected data by performing data cleaning, rectifying inconsistencies and resizing. This procedure aims to ensure a refined dataset, contributing to improved accuracy. The subsequent feature extraction step involves isolating and retaining only pertinent and crucial features by employing several transfer learning models, which we implement to train and test the dataset accordingly.

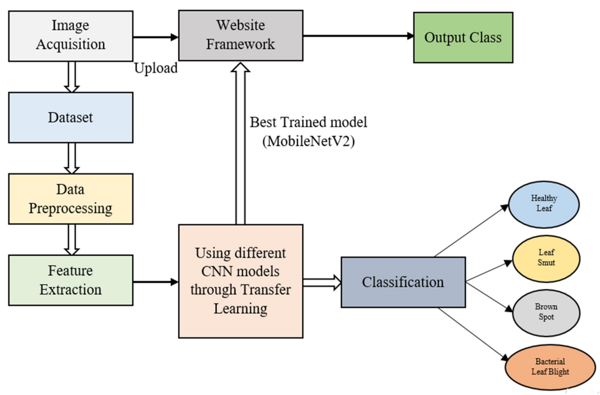


Fig. 1. : Overview of Proposed Methodology.

On the other hand, for practical application we have designed a website where trained model of MobileNetV2 is provided. When raw image is uploaded, the website can predict the disease class with probability of accurate classification simultaneously.

3.1 Dataset Description

The dataset used in this study was provided by Bahri [14] and was obtained via Kaggle. This dataset contributes to a wide range of images. The dataset contains a total of 16,000 RGB pictures, evenly distributed across four different classes, with 4,000 images each class. Each of these images is 64x64 pixels in size. The primary goal of this research is to employ deep learning techniques and a customized website to autonomously classify these four categories of rice leaf classes. Some sample dataset is shown in Figure 2.

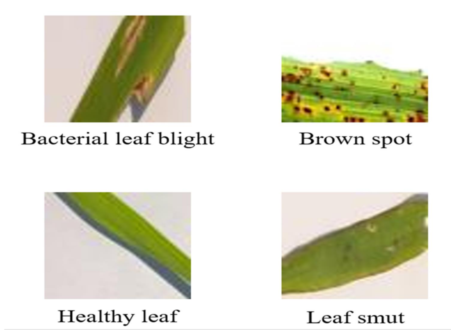


Fig. 2. : Types of Rice Leaf classes [14].

Rice Bacterial Blight is a devastating disease triggered by Xanthomonas oryzae pv. oryzae (Xoo) bacteria, affecting rice crops. Indications comprise water-soaked patches on leaves, drooping, leaf decay, bacterial discharge, and grain harm. The infection transmits through water, rain carried by wind, and contaminated seeds. Symptoms also involve yellow or white stripes at leaf edges, grayish-clear patches, plant contraction and curling, yellowing of leaves, stunted growth, plant demise, and the youngest leaf turning yellow.

Smut disease of rice, originating from the fungus Ustilaginoidea virens, is a plant ailment affecting rice crops. This condition prompts the creation of distinct black clusters of fungal spores on different parts of the rice plant, particularly the panicles or flowering structures. These spore clusters, known as "smut balls," disrupt the usual grain growth process, leading to reduced yield. The infection spreads through contaminated seeds and spores present in the soil. The pathogen invades the rice plant during its flowering stage, causing grain chalkiness. This infection targets only a limited number of grains within each spikelet. In severe instances, disease losses have been documented to reach up to 75%.

Brown spot disease is a rice plant affliction brought about by the Cochliobolus miyabeanus fungus. It displays as compact, round to oval marks on leaves, having brown centers and encircled by yellow halos. Severe infestations can curtail photosynthesis and result in diminished yield. The ailment transmits through spores, water, and contaminated implements. These circular, dark brown spots form on the leaf, sometimes repeatedly. Young plants can succumb, and affected nurseries are recognizable from afar due to their scorched, brownish look.

On the other hand, a healthy leaf has a smooth texture when touched, devoid of roughness or inconsistencies. Its color is a steady and lively green hue. The veins are distinct, giving a slightly raised aspect and contributing to the leaf's framework. No visible marks, blemishes, or oddities are apparent on the surface. The leaf lays flat without any bending, drooping, or rolling. Symmetry is upheld on both sides of the leaf's structure. A faint glossy sheen could arise from a thin cuticle covering. There is an absence of powdery substances on the leaf.

3.2 Data Preprocessing

It's common for input data to be inconsistent, to have missing values, to have outliers, and to be contaminated with noise. Data preprocessing is used to solve these difficulties by removing noise, filling in missing values, and structuring the data coherently to increase accuracy. The procedure helps to improve the quality of the data. Data cleaning, data transformation, and data reduction—also referred to as data compression—are the three main processes covered by this step. Eliminating noise from the data is known as data cleaning. To facilitate easier computations, data transformation requires transforming high-level data into a lower-level format. Data reduction aims to address high-dimensionality issues by lowering data dimensions while maintaining data quality. Working with images of a consistent size is crucial to facilitating network training. Image resizing thus becomes an essential step in this procedure. Images of varying dimensions are resized to meet the model's requirements. The RGB image is divided into three separate channels, R (red), G (green), and B (blue), each of which is represented by a 2-dimensional matrix throughout the resizing process. Subsequently, resizing is conducted individually for each channel. Following this, the resized R, G, and B channels are combined to recreate the resized RGB image. Resizing images helps networks train more effectively by compressing information into smaller data blocks. Firstly we have kept 25% images randomly for testing purpose. Then the remaining (75%) dataset is divided into two portions: 60% images were allocated for training and 15% was used for validation.

3.3 Feature Extraction using different DL models and Classification

We employed various transfer learning approaches rooted in Deep Learning (DL), which operate by taking input images and pay attention to multiple objects within the image, effectively discerning between them. A noteworthy attribute of Convolutional Neural Networks (CNNs) is their reduced dependency on extensive preprocessing, in contrast to alternative classification techniques. Unlike more straightforward methods that necessitate manual crafting of filters, CNNs have the capability to autonomously learn these filters or distinctive features through ample training [16]. The models that have been used in this study are noted below:

VGG16: VGG16 processes 224x224 pixel images. It has 13 convolutional layers using 3x3 filters, followed by ReLU activation [17]. Max pooling with 2x2 windows and stride 2 reduces feature map size. The architecture ends with 3 fully connected layers, ReLU activations (except the last), and a softmax output for class probabilities.

VGG19: VGG19 builds on VGG16's ideas, going deeper with 16 convolutional layers grouped with ReLU activations [17]. It maintains 224x224 image size, using 3x3 filters, stride 1, and padding. Like VGG16, it adds max-pooling after convolutions to shrink feature maps. VGG19 has 3 fully connected layers, mostly flattened convolutions with ReLU, and ends with a softmax layer for class probabilities.

ResNet50: ResNet50 handles 224×224 images. It begins with a 7x7 stride-2 convolution and max-pooling, followed by 3x3 convolutions [18]. It introduces residual blocks with shortcut connections to mitigate gradient issues. ResNet50 uses a "bottleneck" structure in blocks: 1x1 conv, 3x3 conv, 1x1 conv. Multiple complex blocks are used. Afterward, global average pooling and fully connected layers are employed for classification, ending with a softmax for class probabilities.

AlexNet: AlexNet has 8 layers: 5 convolutions followed by 3 fully connected [19]. It handles 227x227 RGB images. Initial layers use various filter sizes. Max-pooling with 3x3 filters and stride 2 reduces map size. Local response normalization aids feature distinction. Last layers are fully connected: 4096 neurons for the first two, 1000 for the final (matching ImageNet classes). ReLU activation is used, and a softmax generates class probabilities.

InceptionV3: InceptionV3 uses "Inception modules," convolutional blocks with multiple paths for varied feature scales [21]. These paths include 1x1, 3x3, 5x5 convolutions and max-pooling, merged by channels. It employs factorization for efficient computation and adds auxiliary classifiers during training. Batch normalization enhances training stability. To prevent overfitting, L2 regularization and dropout are used. The output passes through a softmax classifier for image .

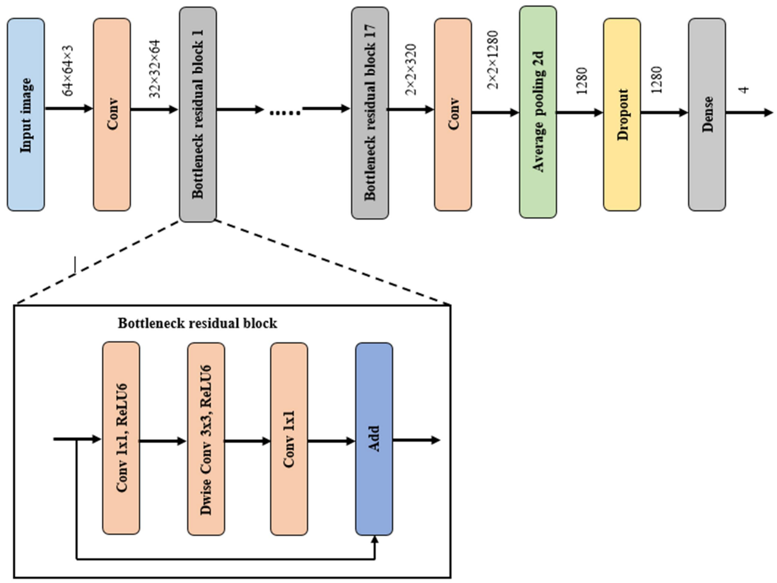


Fig. 3. Customized MobileNetV2 architecture for rice leaf disease classification.

MobileNetV2: MobileNetV2 is a convolutional neural network architecture designed to perform effectively on mobile and embedded devices [21]. It achieves this by incorporating techniques such as depthwise separable convolutions, linear bottlenecks, and inverted residuals. The Depthwise Separable Convolution, which consists of two distinct convolutional layers—Depthwise Convolution and Pointwise Convolution—is the core concept of MobileNetV2. In the depthwise convolution, each input channel is convolved with its own set of filters, considerably reducing computational load compared to traditional convolutions. A 1×1 convolution (pointwise convolution) combines the resulting feature maps, generating new features through a linear combination after the depthwise convolution. This acts as a bottleneck layer, minimizing dimensionality. Inverted residuals is a feature of MobileNetV2 that starts by expanding the channels in a bottleneck layer. This expansion is followed by a depthwise convolution, then channel reduction to the desired level. The linear bottleneck design keeps intermediate representations low-dimensional, reducing computation and memory demands. In order to reduce spatial dimensions, down-sampling and strided convolutions are utilized, which speeds up computing while preserving important data. In MobileNetV2, a modified version of the ReLU activation function, ReLU6 is frequently used for limiting activations to the range [0, 6], solving problems caused by extreme activations. In our customized MobileNetV2 model, we have used average pooling, Dropout and Fully connected Dense layer (to recognize features that are linked with output class) on the last layers. The customized MobileNetV2 architecture is shown in Figure 3. Overall, MobileNetV2 achieves a balance between accuracy and computational efficiency, making it suitable for tasks like semantic segmentation, object identification, and image classification on devices with limited resources.

3.4 Website Development for Practical Application

The development of the website includes the smooth integration of the trained model MobileNetV2, which is capable of classifying diseases affecting rice leaves. This integration enables the classification of the four rice leaf classes with its dedicated accuracy level for this model simultaneously. The Flask framework was employed to facilitate the integration of the model with the website. Flask, known for its efficiency and versatility, offers valuable tools and features, streamlining the creation of web applications in Python. The overall flow diagram of this website based rice leaf disease classification is shown in Figure 4.

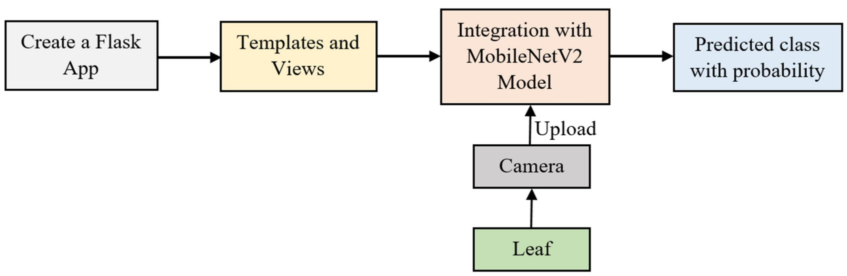


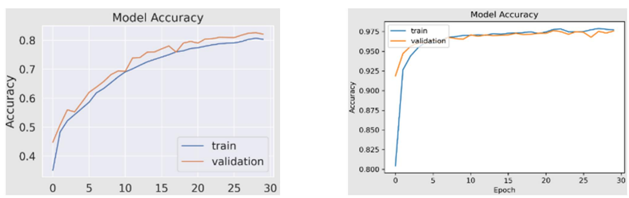
Fig. 4. : Flow diagram of website development for classification.

4 Results and Discussions

In this study, we conducted a comprehensive evaluation of various transfer learning models for the task of rice leaf disease classification. Our main objective was to evaluate how well various models performed at correctly detecting the presence of diseases in rice leaves. The findings of this study provide important information on the capabilities of these models and show how they might be used in real-world agricultural scenarios. Building this rice leaf disease classification system and training models, Python and tensorflow have been used. Google Colaboratory with 12.7 GB RAM and 12 GB NVIDIA TESLA K80 GPU and Kaggle with 16 GB RAM and 13 GB NVIDIA TESLA P100 GPU are primary platform for model training and evaluation of the system.

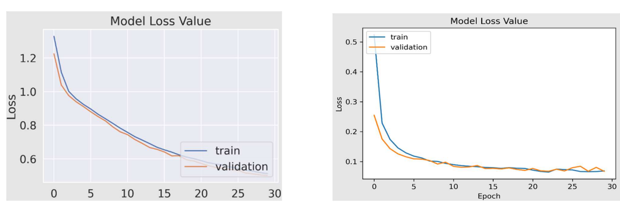
Table 1. Performance comparison with respect to evaluation metrics

Models	Accuracy (%)	Recall (%)	Specificity (%)	Precision (%)	F1 Score (%)	Cohens Kappa (%)	Parameters
VGG16	99.30	100	100	100	100	99.30	39910980
VGG19	93.77	100	99.69	99.67	99.83	93.36	45236804
ResNet50	97.98	100	100	100	100	97.93	5936580
AlexNet	95.23	100	100	100	100	94.99	12464856
MobileNetV2	98.05	100	100	100	100	98.01	**2263108**
InceptionV3	82.95	99.07	99.28	99.07	99.07	79.45	12516772



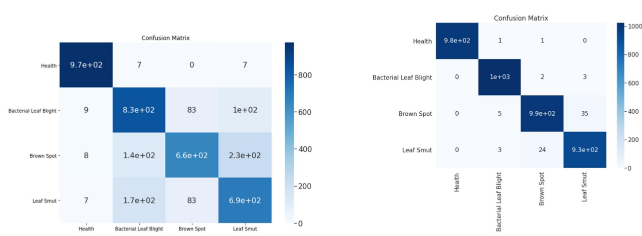
(a) InceptionV3 (Poor Result) (b) MobileNetV2 (Best Result)

Fig.5: Training and validation accuracy graph of transfer learning models.



(a) InceptionV3 (Poor Result) (b) MobileNetV2 (Best Result)

Fig.6: Training and validation loss graph of transfer learning models.



(a) InceptionV3 (Poor Result) (b) MobileNetV2 (Best Result)

Fig.6: Confusion Matrices of transfer learning models.

The efficiency of those models is determined by the results. Confusion matrix, accuracy, training time, model size, and parameters have been used as evaluation metrics in this task of classifying rice leaf diseases. Table 1 shows the accuracy, training time, model size and parameters of all models. The results of our experimentation reveal a notable variation in the performance of different transfer learning models. The VGG16 model led the field in disease classification with a remarkable accuracy of 99.30%. Not far behind, the ResNet50 and MobileNetV2 models achieved accuracies of 97.98% and 98.05%, respectively. AlexNet and VGG19 secured accuracies of 95.23% and 93.78%, respectively, while InceptionV3 attained a slightly lower accuracy of 82.95%.

Intriguingly, there appears to be a correlation between the complexity of model architectures and their performance. The impressive accuracy of VGG16, which had a massive 39,910,980 parameters, a model size of 479.1 MB, and a training time of 284.8 seconds, highlights the potential advantages of a bigger model size. Similarly, ResNet50, which has 5,936,580 parameters, a model size of 72 MB, and a training time of 240.5 seconds, also proved to be capable of accurately capturing intricate disease patterns. Figure 5 and 6 shows training and validation accuracy and loss of InceptionV3 and MobileNetV2 model respectively. Models with comparatively fewer parameters, such as InceptionV3's 12,516,772 parameters, 79.05 MB model size, and 122.5 second training time, on the other hand, showed lower accuracies. This could be attributed to the inherent trade-off between model complexity and generalization ability. While smaller models may struggle to capture intricate disease nuances, they tend to generalize better across diverse datasets. However, MobileNetV2 model provides better accuracy of 98.05% along with very small model size (only 9.4 MB), lowest training time (74.2 Seconds) and fewer parameters. Figure 7 illustrates the confusion matrix of InceptionV3 and MobileNetV2 respectively. Therefore, among all the state-of-the-art approaches in this study, MobileNetV2 exhibits the overall best result. The exceptional accuracy achieved by the VGG16 model signifies its potential as a robust tool for automated rice disease diagnosis.

Table 1 Comparative analysis of classification results with recent related studies

Study	Dataset	Method	Accuracy
Sardogan et al [9]	500	CNN + LVQ	86%
Haixia et al [10]	6029	CNN + Stack Ensemble	97.59%
Rukhsar et al [12]	240	CNN	96.09%
Wang et al [13]	2370	ADSNN-BO	94.65%
This study	**16000**	**CNN**	**99.30%**

The Grad-CAM representation has a great importance to inspect the crucial features localization capability of the last convolution layer [22]. Gradcam uses the gradients of the final convolutional layer. We have computed the Gradcam images for the VGG16 model which are shown in Fig. 7 along with the original images. It is observed that the heatmap coincides the diseases regions and hence it specifies the good sensitivity of the model.

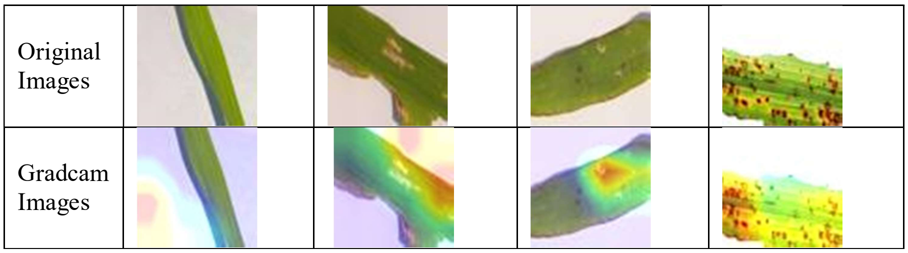


Fig. 7: Gradcam image with their original form.

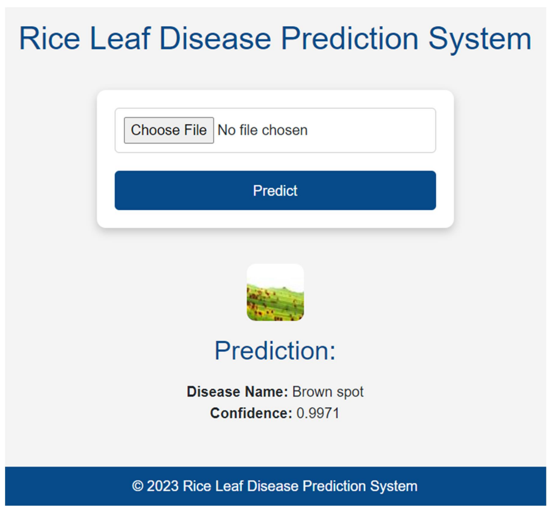


Fig.8: Website preview of the rice leaf disease prediction system.

However, it's important to note that a model's accuracy alone might not be the sole determinant of its real-world usability. It is also necessary to take into account aspects like deployment speed, resource requirements, and adaptability to dynamic agricultural conditions. Our findings suggest that a carefully tailored approach to model selection is essential. Depending on the specific requirements of an application, a balance between model accuracy and complexity can be struck. For resource-constrained environments, models like ResNet50 and MobileNetV2 could provide an optimal compromise between performance and efficiency. Table 2 shows a comparative analysis of performance of different models from respective papers. We found that due to a wide range of images in the dataset, all the transfer learning models in our study perform really well. Therefore, we did not focus in developing a new model as all the models already taken the accuracies in the saturated level. Rather, we focused in developing an end-to-end system featuring a lightweight yet high-performing model. The preview of the website is shown in Figure 8. The system's main purpose is the precise detection of rice leaf diseases through a user-friendly interface, with an emphasis on efficiency. Our solution is designed to provide an easy and intuitive experience, enabling users to identify these diseases swiftly and accurately, all within a minimal timeframe.

5 Conclusions

In this work, we focused on classifying various disease types in rice leaves using a variety of transfer learning models for four different categories of rice leaves. Our strategy includes using a dataset with a wide variety of rice leaves showing different diseases. These leaves were preprocessed and employed in conjunction with various standard DL techniques, such as VGG19, VGG16, InceptionV3, ResNet50, MobileNetV2, and AlexNet, through transfer learning. Our findings indicated that VGG16 and MobileNetV2 outperformed the other methods in accurately identifying rice leaf diseases. However, the best performance was, perhaps, displayed by MobileNetV2 across all matrices. Notably, we observed that even with models with fewer layers, accuracy can be improved by carefully adjusting training parameters including the learning rate, number of epochs, and optimizer selection. Every model underwent customization to increase efficiency and storage suitability for faster operations. The website we developed offers the capability to classify uploaded rice leaf images using trained MobileNetV2 model accurately. This innovative solution not only identifies the disease class for each image but also provides the probability score for accurate classification. This comprehensive approach simplifies disease detection, allowing farmers to properly protect their crops. Looking ahead, we have plans to expand our research by incorporating additional disease classes and algorithms. This expansion aims to make disease detection even more comprehensive, user-friendly, and expedient. Investigating ensemble methods that combine the strengths of multiple models could potentially yield even more robust results. Moreover, exploring techniques to address the challenges posed by imbalanced datasets and variations in illumination conditions will enhance the real-world applicability of these models. In alignment with our overarching objective, we remain committed to developing an end-to-end system characterized by a lightweight, high-performance model that offers a swift, intuitive, and accurate means of identifying rice leaf diseases.

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