Enhancing Rice Disease Binary Classification. An Analysis of Deep Neural Network Models

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ABSTRACT

The study examines deep neural network models for the binary classification of rice plants, with a specific emphasis on distinguishing between healthy and ill states. The utilization of convolutional neural network designs such as VGG16, Inception V3, ResNet18, and MobileNet is commonly observed. The study gathered a sample of 500 photographs depicting both good and unhealthy conditions in Kathmandu and Sindhupalchowk. The objective was to evaluate the efficacy of the models in generalizing the health states of rice. The results indicated that model Resnet exhibited superior performance with a high level of accuracy, whereas model VGG and Inception had lower accuracy. The model exhibits promising potential in influencing the diagnosis and early detection of rice diseases.

Keywords: Rice Disease Classification, Deep Neural Network, Image-based Disease Detection

1. INTRODUCTION

A) Background

Rice is the predominant agricultural product in South Asia, including Nepal, making a substantial contribution to both economic expansion and the alleviation of poverty. Rice constitutes 25% of Nepal's Gross Domestic Product (GDP) and serves as the predominant staple food, contributing about 40% of the population's dietary caloric consumption [1]. Nevertheless, the growth and quality of rice are greatly affected by diseases such as blight caused by bacteria and burst. Among the several abiotic agents influencing rice, rice blast is the most destructive, resulting in 70-80% yield loss. This disease developed in China approximately 7000 years ago. In Nepal, it was first documented in Thimi, Bhaktapur in 1966[2]. Identifying rice diseases accurately and timely is crucial for successful agricultural practices. Manual biological identification consumes resources and has low detection rates. Computer vision algorithms can help detect diseases automatically and efficiently, increasing rice yields and lowering costs [3]. Advancements in machine learning and artificial intelligence offer a promising opportunity to improve rice disease classification using deep neural networks, enhancing accuracy and efficiency.

B) STATEMENT OF PROBLEM

Traditional methods of diagnosing plant diseases have relied on laborious and error-prone manual examinations. Modern approaches necessitate knowledge of plant pathology, physiology, reagents, and sample processing. Misdiagnosis may result from this. There has been a decline in output due to farmers' reluctance to use modern diagnostic tools for rice diseases in Nepal. A reliable, automated system for disease classification in rice is required to resolve these concerns. Models trained using Deep Neural Networks (DNNs) have performed exceptionally well in this area.

C) SCOPE OF STUDY

This research paper aims to develop and evaluate deep neural network models for binary classification of rice disease, focusing on early detection and improving rice quality and quantity. The study will use a dataset from Kathmandu Valley, implementing preprocessing techniques to improve the quality. Different deep neural network architectures will be evaluated for effective classification, with metrics like accuracy, precision, recall, F1 score, and confusion matrix comparison.

D) OBJECTIVES

- To assess the effectiveness of various Deep Neural Network (DNN) models, such as VGG, ResNet, Inception, and MobileNet, in the classification of rice diseases.

- Optimization is necessary to improve the classification process and achieve higher levels of accuracy and efficiency in the identification of rice diseases.

2. LITERATURE REVIEW

Deep learning techniques, particularly Deep Neural Network models, have revolutionized plant disease classification, enabling automatic and accurate detection of plant diseases, with numerous studies focusing on these algorithms. The 2010 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was a competition for computer systems to accurately identify and categorize objects and scenarios. It sparked research into machine learning and deep neural networks, leading to their application in plant disease classification, resulting in significant advancements in automated plant disease diagnosis. Tejaswini et al. classified rice leaf diseases using deep learning techniques, including a 5-layer convolutional network. They found the 5-layer CNN model had the best accuracy at 78.2%, 6% higher than other models. Adjusting training parameters like learning rate, epochs, and optimizer methods improved accuracy with a handmade model with fewer layers. This suggests that adjusting these parameters can enhance the accuracy of a handcrafted model [4]. Liu et al. developed a new attention-enhanced DenseNet Network model that combines a DenseNet classification model with a lesion feature extractor using a region of interest (ROI) extraction algorithm, resulting in a 96% accuracy rate for rice leaf disease identification [5]. Moiz M, Akmal M et al. present a deep learning-based method for identifying plant diseases like bacterial leaf blight, brown spots, and leaf smut using VGGNet convolutional neural network. Compared to other classifiers, the CNN-transfer architecture outperforms them, with a mean accuracy of 97.22%.[6]. Meena et al. utilized deep learning algorithms to identify rice diseases using 33,026 images. They used ResNet-50, ResNeXt-50, DenseNet-121, ResNet-50, and SE-ResNet-50 submodels, with DenseNet-121, ResNet-50, and ResNet-50 being the most effective [7]. Pherry F, Gregorius et al. used four models, VGG16, VGG19, ResNet50, and InceptionV3, to improve their functionality through regularization and data augmentation, with VGG19 offering the best loss model accuracy [8]. Bhujel & Shakya's study uses Convolutional Neural Network (CNN) architectures EfficicentNet-B0 and EfficicentNet-B3 to classify rice leaf diseases into four classes: Brown Spot, Healthy, Hispa, and Leaf Blast. The results show discriminative fine-tuning is more effective than cyclical learning rate fine-tuning [9]. Reddy S et al. developed a modified PDICNet model for detecting and categorizing plant leaf diseases, using ResNet-50 for feature extraction and MRDOA for optimal feature selection. The model achieved 99.73% accuracy and F1 score [10]. Ahad M et al. compared six CNN-based deep learning architectures for rice disease classification in Bangladesh. They used an ensemble model and transfer learning approach, improving accuracy by 17%. The deep CNN model is promising for real-time agricultural system detection, particularly in identifying and classifying rice leaves [11]. Liangquan Jia et al. developed a model using MobileNetV3 for feature extraction, reducing parameterization and improving accuracy, with 92.3% accuracy on a rice pests and diseases dataset [12]. Nayak A. et al. used 2259 smartphone photos to classify rice plant components. They compared various image classification models and found DenseNet201, Xception, MobileNetV2, and ResNet50 as the top four with high validation accuracies of 0.9803, 0.9778, 0.9756, and 0.9718, respectively [13]. Yang H et al. automated rice leaf disease identification using transfer learning on 15 CNN models, with InceptionV3 outperforming with 99.64% accuracy, while AlexNet performed poorly with 97.35%.[14]. Shah et al. developed a rice blast disease diagnostic method using deep learning, image processing, and transfer learning. The method, based on 2000 photos, achieved the best accuracy of 99.75% with a 0.33 loss rate, With an F1-score of 99.70 and an AUC of 99.83%, outperforming other modes [15]. Singh et al. developed Inception_v3, a pre-trained model for rice illness categorization, utilizing publicly available images from three leaf diseases, achieving 100% training and 75% validation accuracy [16]. Archana U, Khan A, et al. developed a method for diagnosing rice plant diseases based on color features using deep convolutional neural networks. The study used a pre-trained deep CNN and residual network for tomato leaf disease classification, achieving an accuracy of 96.35% [17]. Al-Gaashani et al. developed a self-attention network (SANET) for precise AI-assisted rice illness categorization. The model uses attention modules to extract contextual dependencies from images, focusing on key disease characteristics. Cross-validated experiments showed SANET's accuracy of 98.71%, outperforming state-of-the-art techniques [18].

3. RESEARCH METHODOLOGY

The research methodology explains the overall study process of this research paper. It starts with the collection of data, pre-processing, data split to train, validation, and test dataset. After that build a model, compile, train, and evaluate the model.

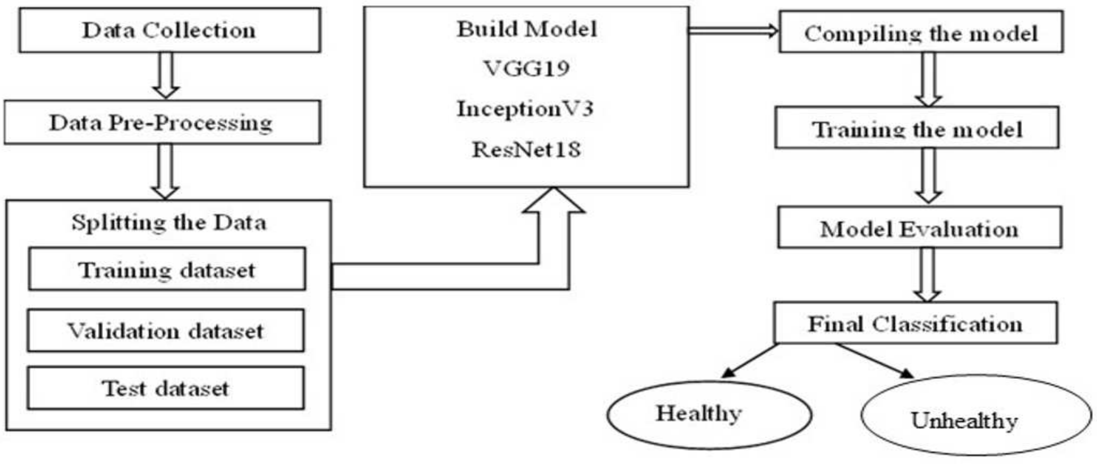

Fig. 1. Research Process

Data Collection

This research collected high-quality images of rice plants from Kathmandu and Sindhupalchowk, capturing 500 healthy and 500 diseased leaves using a OnePlus mobile device. The goal was to create a reliable, accurate dataset, preventing class imbalance, and establishing a solid foundation for training and testing the proposed model for rice plant disease classification.

Fig 2. Healthy and Diseased Rice Leaf

Data Pre-Processing

Preprocessing is a crucial step in image analysis for inference and model training. It enhances image quality, removes distortions, and prepares data for input into models. This process is essential for convolutional neural networks and can accelerate inference and reduce training time. Preprocessing includes geometric transformations and aims to improve image data by reducing distortions or enhancing essential characteristics for further processing.

Splitting the Data

Data splitting involves breaking data into subgroups, such as two-part splits. This method ensures the development of data models and their procedures. Training and training are done using a standard two-part split, with 80% used as the training dataset, 10% as the validation dataset, and 10% as the test dataset.

Build Model

This is a very crucial step in our deep learning model-building process which defines how our model will look. These is steps where build a desired model that is imported by pre-trained models. The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), which uses 14 million photos to categorize one among a thousand distinct labels, has been used to fit many accessible CNNs. Four CNN models were constructed: VGG19, IncepetionV3, MobileNet, and ResNet18.No version of Resnet18 is available for import so a custom ResNet18 model was used.

Compiling the Model

Compilation is the final step in creating a model, where an optimizer, loss function, and metrics are implemented. Keras offers a large number of loss functions, such as mean_squared_error, and categorical_crossentropy. Optimizers like SGD, RMSprop, and Adam are used to compare the loss function with predictions. Performance metrics like accuracy, binary_accuracy, and sparse_categorical_accuracy is also available.

Training the Model

Deep neural network models use specific epoch and batch sizes to automate iteration through training data and evaluate on a validation set. These parameters significantly influence model learning from the training dataset. The appropriate number of epochs depends on the convergence of training and validation loss, while batch size depends on computational resources and model complexity. Larger batch sizes allow faster training but limit model complexity, while smaller batch sizes allow larger models and datasets.

Model Evaluation

The evaluation process is where the model is evaluated and it provides insights into how well the model generalizes and performs on unseen data. Test data where 10% of the total collected data is used for the performance evaluation of the model. For the classification, the evaluation matrices that can be used are Accuracy, precision, recall, F1 score, confusion matrix, etc.

4. RESULT

VGG Model

Table 1. Classification Report for VGG Model

Classification Report				
	Precision	**Recall**	**F1-score**	**Accuracy**
Healthy	0.90	0.94	0.92	92%
Unhealthy	0.94	0.90	0.92	

Overall classification reports show 92% accuracy for the VGG model with an f1 score of 92% for both healthy and Unhealthy classes.

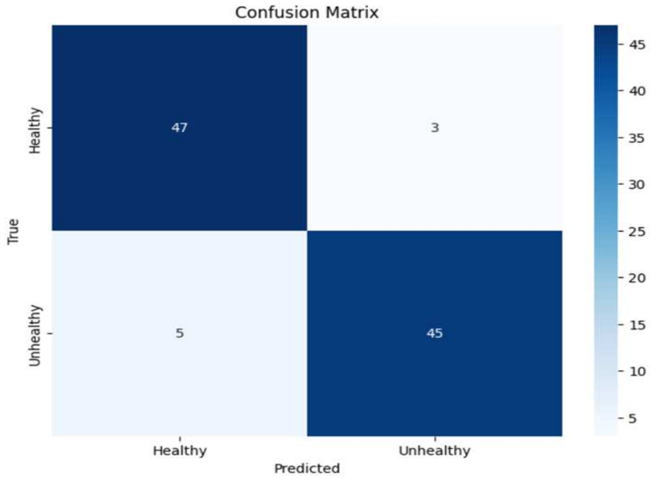

Fig 3. Confusion Matrix for VGG Model

The Confusion matrix for the VGG model shows that-

- 45 instances correctly classified as "Unhealthy" (True Negative).
- 47 instances correctly classified as "Healthy" (True Positive).
- 3 instances incorrectly classified as "Unhealthy" (False Positive).
- 5 instances incorrectly classified as "Healthy" (False Negative).

Inception Model

Table 2. Classification Report for Inception Model

Classification Report				
	Precision	**Recall**	**F1-score**	**Accuracy**
Healthy	0.92	0.92	0.92	92%
Unhealthy	0.92	0.92	0.92	

Overall classification reports show 92% accuracy for the Inception model with an f1 score of 92% for both healthy and Unhealthy classes.

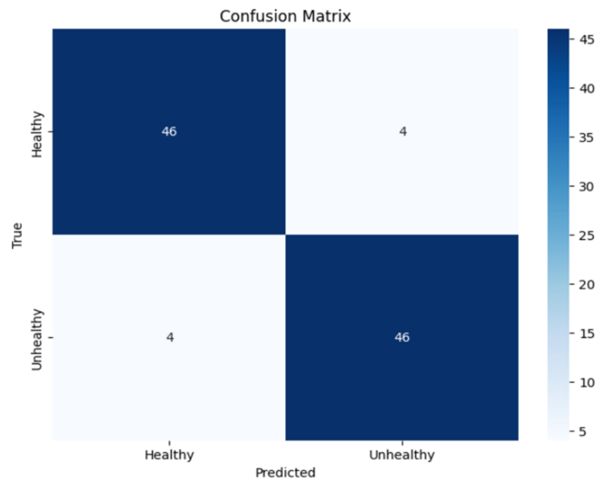

Fig 4. Confusion Matrix for Inception Model

The confusion matrix for the Inception model shows that-

- 46 instances correctly classified as "Unhealthy" (True Negative).
- 46 instances correctly classified as "Healthy" (True Positive).
- 4 instances incorrectly classified as "Unhealthy" (False Positive).
- 4 instances incorrectly classified as "Healthy" (False Negative).

Resnet Model

Table 3. Classification Report for Resnet Model

Classification Report				
	Precision	**Recall**	**F1-score**	**Accuracy**
Healthy	1	0.96	0.98	98%
Unhealthy	0.96	1	0.98	

Overall classification reports show 98% accuracy for the Resnet model with an f1 score of 98% for both healthy and Unhealthy classes.

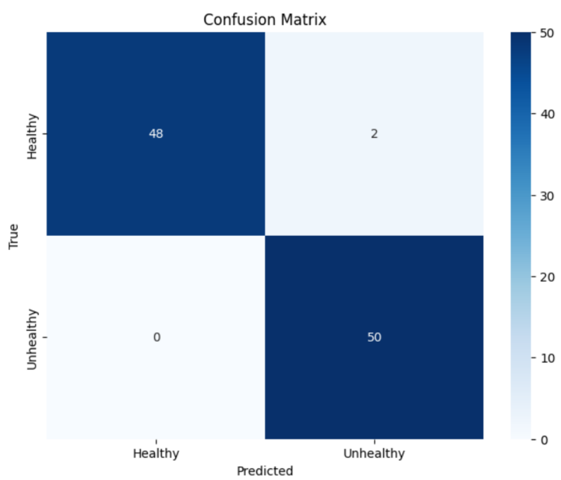

Fig 5. Confusion Matrix for Resnet Model

The confusion matrix for the Resnet model shows that-

- 50 instances correctly classified as "Unhealthy" (True Negative).
- 48 instances correctly classified as "Healthy" (True Positive).
- 2 instances incorrectly classified as "Unhealthy" (False Positive).
- 0 instances incorrectly classified as "Healthy" (False Negative).

MobileNet Model

Table 4. Classification Report for MobileNet Model

Classification Report				
	Precision	**Recall**	**F1-score**	**Accuracy**
Healthy	1	0.94	0.97	97%
Unhealthy	0.94	1	0.97	

Overall classification reports show 97% accuracy for the MobileNet model with an f1 score of 97% for both healthy and Unhealthy classes.

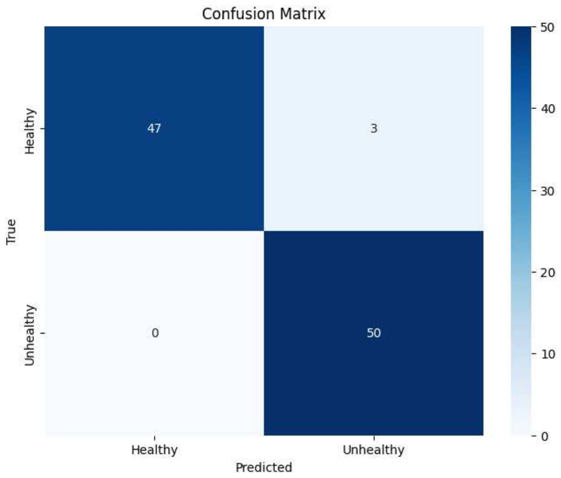

Fig 6. Confusion Matrix for MobileNet Model

The confusion matrix for the MobileNet model shows that-

- 50 instances correctly classified as "Unhealthy" (True Negative).
- 47 instances correctly classified as "Healthy" (True Positive).
- 3 instances incorrectly classified as "Unhealthy" (False Positive).
- 0 instances incorrectly classified as "Healthy" (False Negative).

5. DISCUSSIONS AND ANALYSIS

This section analyzes the performance of four deep neural network models for the binary classification of rice disease. The hyperparameters, epoch, and batch size, were changed to 10 and 20 epochs and 8 and 16 batch sizes. The accuracy metric was used to evaluate the models' impact on improving rice disease classification.

Table 4. Comparative Analysis of Each Model

Model	Epoch	Batch	Class	Precision	Recall	F1-score	Accuracy
VGG	20	16	Healthy	90%	95%	92%	92%
			Unhealthy	94%	90%	92%	
Inception	20	16	Healthy	92%	92%	92%	92%
			Unhealthy	92%	92%	92%	
Resnet	20	16	Healthy	100%	96%	98%	98%
			Unhealthy	96%	100%	98%	
MobileNet	10	8	Healthy	100%	94%	97%	97%
			Unhealthy	94%	100%	97%	

A) VGG Model

The overall accuracy has improved over Epoch 10 to Epoch 20 which indicates that the model is learning better over time. For Healthy classes, Precision and Recall are relatively high but there is a noticeable drop in precision on Epoch 20 batch 16 where values go from 100% to 90%. For Unhealthy classes, Precision, Recall, and F1-score are generally good across all the epochs and Batches. The highest accuracy is observed in Epoch 20 and Batch 16 with a value of 92% and the lowest accuracy is observed in Epoch 10 and Batch 8 with 83%.

B) Inception Model

Overall accuracy is consistent and high across all the epochs and Batches. Both unhealthy and healthy classes show high precision, recall, and F1 scores which indicates a well-balanced performance. The highest accuracy is observed in both Epoch 20 with the value of 92% and the lowest accuracy is observed in Epoch 10 and Batch 16 with 88%.

C) Resnet Model

In the initial epoch 10, the model performs very well with high precision, recall, and F1-scores for both healthy and unhealthy classes but there is a decrease in performance in Epoch 20 Batch 8, especially for unhealthy classes with lower precision and recall. But in Epoch 20 Batch size 16 the performance stabilizes and improves with perfect precision, recall, and F1 scores for both the classes. The highest accuracy is observed in Epoch 20 Batch size 16 with 98% and the lowest accuracy is observed in Epoch 20 Batch size 8 with 88%.

D) MobileNet Model

For both Healthy and Unhealthy classes the model maintains a balanced performance in terms of precision and recall. On Epoch 10 and Batch 8, the model achieves very high precision, recall, and F1 scores and it performs very well for both classes. However, there is a slight decrease in the performance with lower precision, recall, and F1 scores for both classes on Epoch 20. The highest accuracy is observed in Epoch 10 batch size 8 with 97% and the lowest accuracy is observed in Epoch 20 batch size 8 with 88%.

6. CONCLUSION

This study mainly contributes to agricultural technology and plant disease detection, particularly for rice crops. The main goal of this study is improving rice disease classification mainly healthy and diseased by in-depth study of various deep neural network models.

This study can help us create a robust system that can analyze the images of the rice plant and determine whether the plant is well or not. This can help farmers in the early detection of rice disease and apply correction measures on the rice plant that can contribute to the quality as well as quantity of the rice yield which helps farmers for the overall productivity of the farm. This study also contributes to sustainable agriculture practices by providing a computer application for the farmers to manage disease efficiently which supports a more environment-friendly approach for promoting early detection and targeted treatment.

REFERENCES

[1] N. Sapkota, P. K. Yadav, and S. Sapkota, "AN ECONOMIC ANALYSIS OF RICE PRODUCTION IN RAUTAHAT DISTRICT OF NEPAL," *Food and Agri Economics Review*, vol. 1, no. 1, pp. 01–09, May 2021, doi: 10.26480/FAER.01.2021.01.09.
[2] K. Simkhada and R. Thapa, "Rice Blast, A Major Threat to the Rice Production and its Various Management Techniques," *Turkish Journal of Agriculture - Food Science and Technology*, vol. 10, no. 2, pp. 147–157, Mar. 2022, doi: 10.24925/turjaf.v10i2.147-157.4548.
[3] H. Yang *et al.*, "Disease Detection and Identification of Rice Leaf Based on Improved Detection Transformer," *Agriculture 2023, Vol. 13, Page 1361*, vol. 13, no. 7, p. 1361, Jul. 2023, doi: 10.3390/AGRICULTURE13071361.
[4] P. Tejaswini, P. Singh, M. Ramchandani, Y. K. Rathore, and R. R. Janghel, "Rice Leaf Disease Classification Using Cnn," *IOP Conf Ser Earth Environ Sci*, vol. 1032, no. 1, p. 012017, Jun. 2022, doi: 10.1088/1755-1315/1032/1/012017.
[5] W. Liu, L. Yu, and J. Luo, "A hybrid attention-enhanced DenseNet neural network model based on improved U-Net for rice leaf disease identification," *Front Plant Sci*, vol. 13, p. 922809, Oct. 2022, doi: 10.3389/FPLS.2022.922809/BIBTEX.
[6] M. Moiz, M. Akmal, M. S. Ishtiaq, and U. Javed, "Classification of Rice Leaves Diseases by Deep CNN-Transfer Learning Approach for Improved Rice Agriculture," *2022 International Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering, ETECTE 2022 - Proceedings*, 2022, doi: 10.1109/ETECTE55893.2022.10007235.
[7] R. Meena, S. Joshi, and S. Raghuwanshi, "Detection of Varieties of Diseases in Rice Plants using Deep Learning Techniques," *4th International Conference on Inventive Research in Computing Applications, ICIRCA 2022 - Proceedings*, pp. 664–674, 2022, doi: 10.1109/ICIRCA54612.2022.9985745.
[8] F. Pherry, Gregorius, J. Kristanto, and F. I. Kurniadi, "Rice Plants Disease Classification Using Transfer Learning," in *2022 4th International Conference on Cybernetics and Intelligent System (ICORIS)*, IEEE, Oct. 2022, pp. 1–4. doi: 10.1109/ICORIS56080.2022.10031449.
[9] S. Bhujel and S. Shakya, "Rice Leaf Diseases Classification Using Discriminative Fine Tuning and CLR on EfficientNet," *Journal of Soft Computing Paradigm*, vol. 4, no. 3, pp. 172–187, Sep. 2022, doi: 10.36548/JSCP.2022.3.006.
[10] S. R. G. Reddy, G. P. S. Varma, and R. L. Davuluri, "Resnet-based modified red deer optimization with DLCNN classifier for plant disease identification and classification," *Computers and Electrical Engineering*, vol. 105, p. 108492, Jan. 2023, doi: 10.1016/J.COMPELECENG.2022.108492.
[11] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification," *Artificial Intelligence in Agriculture*, vol. 9, pp. 22–35, Sep. 2023, doi: 10.1016/J.AIIA.2023.07.001.
[12] L. Jia *et al.*, "MobileNet-CA-YOLO: An Improved YOLOv7 Based on the MobileNetV3 and Attention Mechanism for Rice Pests and Diseases Detection," *Agriculture 2023, Vol. 13, Page 1285*, vol. 13, no. 7, p. 1285, Jun. 2023, doi: 10.3390/AGRICULTURE13071285.
[13] A. Nayak, S. Chakraborty, and D. K. Swain, "Application of smartphone-image processing and transfer learning for rice disease and nutrient deficiency detection," *Smart Agricultural Technology*, vol. 4, p. 100195, Aug. 2023, doi: 10.1016/J.ATECH.2023.100195.
[14] H. Yang *et al.*, "Automatic Recognition of Rice Leaf Diseases Using Transfer Learning," *Agronomy 2023, Vol. 13, Page 961*, vol. 13, no. 4, p. 961, Mar. 2023, doi: 10.3390/AGRONOMY13040961.
[15] S. R. Shah, S. Qadri, H. Bibi, S. M. W. Shah, M. I. Sharif, and F. Marinello, "Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A Case Study on Early Detection of a Rice Disease," *Agronomy 2023, Vol. 13, Page 1633*, vol. 13, no. 6, p. 1633, Jun. 2023, doi: 10.3390/AGRONOMY13061633.
[16] S. Singh, N. Kaur, and N. Neeru, "Multiclass's Classification of Rice Diseases Using Pre-Trained Deep Neural Networks," *Eur. Chem. Bull*, vol. 2023, pp. 15750–15762.
[17] U. Archana, A. Khan, A. Sudarshanam, C. Sathya, A. K. Koshariya, and R. Krishnamoorthy, "Plant Disease Detection using ResNet," *6th International Conference on Inventive Computation Technologies, ICICT 2023 - Proceedings*, pp. 614–618, 2023, doi: 10.1109/ICICT57646.2023.10133938.
[18] M. S. A. M. Al-Gaashani, N. A. Samee, R. Alnashwan, M. Khayyat, and M. S. A. Muthanna, "Using a Resnet50 with a Kernel Attention Mechanism for Rice Disease Diagnosis," *Life 2023, Vol. 13, Page 1277*, vol. 13, no. 6, p. 1277, May 2023, doi: 10.3390/LIFE13061277.