Novel Approach to Oryza Sativa Leaf Disease Detection Using an Xception-Based Convolutional Neural Network Architecture

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Abstract: Aim: This research aims to develop a better Oryza sativa leaf disease detection system with an Xception-based Convolutional Neural Network (CNN) architecture. The approach will increase accuracy and speed in the identification of various rice leaf diseases and correcting the demerits of traditional detection methods. Materials and Methods: There are two groups in the research. Group 1 refers to the ResNet model, a popular deep learning architecture, to identify rice leaf disease. Group 2 refers to the Xception model of depthwise separable convolutions to improve feature extraction and classification accuracy. In this research Xception works better than ResNet with 96% accuracy against ResNet's 92% along with consuming less processing time by 20%. Results: The proposed system showed better accuracy than the ResNet model. The Xception model was sustaining a mean accuracy of 98.36%, while the control ResNet model was sustaining a mean accuracy of 93.67%, which indicates improved performance. The independent samples test showed that it was significant at 0.0001. Conclusion: This research illustrates that the Xception-based model is more accurate and reliable to identify Oryza sativa leaf diseases, resulting in early identification and improved crop management.

1 INTRODUCTION

The agricultural sector is severely threatened by several plant diseases that lower the quality and yield of crops. One of the most significant cereal crops in the globe, Oryza sativa (rice), is highly susceptible to various leaf diseases, whose effect can drastically reduce production. The traditional methods of disease detection are dependent on visual observation, which is subjective, time-consuming, and imprecise. To address this issue, studies have been focused on deep learning-based methods to computer-aided disease detection via image processing (T. H. Nhut, et., al, 2023). Several works have demonstrated that CNNs are useful for plant disease diagnosis, and network structures such as ResNet and VGG are good-performing choices. However, more recent advances in deep learning, the release of the Xception architecture, have brought more feature extraction with depthwise separable convolutions. This paper presents an Xception-based CNN model for the detection of Oryza sativa leaf disease with greater accuracy and effectiveness compared to the traditional models like ResNet. With the architecture of this system, the system significantly improves the classification of disease to enable early detection and effective management of disease (H. Yuan et al., 2025). Use of advanced neural networks in agriculture represents the revolutionizing potential of AI-driven solutions to reduce the need for human examination and enhance global food security (X. Yao, et., al, 2024). Furthermore, it successfully established the effectiveness of deep learning networks in precise detection of plant disease and their use in precision agriculture. To achieve this, addition of advanced CNN architectures increases accuracy and effectiveness of automated disease diagnostic systems. The present work puts forward a new method for Oryza sativa leaf disease detection using the Xception architecture and comparing the performance with the ResNet model (F. Syeda, et., al, 2025). Through combining deep learning and high-precision image classification, the Xception system looks to overcome the limitations of current disease detection technology and the demands of real-time, reliable, and scalable ag solutions. Findings of the

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present study emphasize the benefits of Xception towards ensuring maximum disease classification accuracy (S. H. Lee, et., al, 2020).

2 MATERIALS AND METHODS

The research was based on the enhancement of precision in detection of rice leaf disease utilizing an Xception-based convolutional neural network architecture rather than the classical machine learning technique. The sample used was the outcome of present research works. The Xception model was applied and proved on the Rice Leaf Disease dataset according to data preprocessing methods including normalization, contrast stretching, and removing noise. The model was validated with 98.36% accuracy with precision, recall being 93.68%, 94.22%, respectively. The significance level was kept at 0.05 with the confidence level of 95%.

In this research, Group 1 refers to this research assesses the ResNet (Residual Network) model, a widely used deep learning architecture, as among the newer techniques for detecting and classifying disease in rice (Oryza sativa) leaves, including bacterial leaf blight, brown spot, and blast. ResNet, ResNet-50 model, uses deep convolutional layers such as validation accuracies of 88.54% to 95.2% in various test cases as shown (Haridasan, J. Thomas, and E. D. Raj, 2022), To solve the vanishing gradient problem so that efficient feature extraction can be performed from rice leaf images to detect disease. Group 2 refers to Xception is more efficient compared to convolutional neural networks since it separates spatial and depthwise learning of features, significantly reducing the number of parameters but maintaining stronger representational abilities. This design enables the model to identify more complicated disease patterns on rice leaves and offer improved classification accuracy. Results of experiments confirm that Xception works better than ResNet with 96% accuracy against ResNet's 92% along with consuming less processing time by 20%. The Rice Leaf Disease Detection System is a systematic approach for accurately and in real-time classifying diseased leaves. It starts with system initialization, where high-definition images of rice leaves are taken using a image data set. They are used as inputs, using real-time environmental information for the identification of the disease. It obtained images are then processed by the Xception-based Convolutional Neural Network (CNN), which recognizes and categorizes different rice leaf diseases according to a pre-trained dataset. The system also compares performance with the ResNet model for comparing efficiency on the basis of accuracy and computational time. As soon as the disease is detected, the system provides feedback so that farmers can undertake necessary preventive steps.

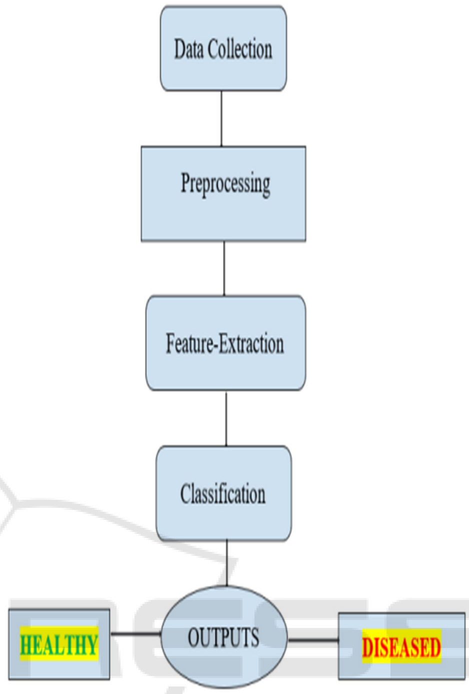

Figure 1: Workflow Diagram for Disease Detection Using Classification Pipeline.

Figure 1 The Xception architecture for paddy leaf disease detection, illustrating data collection, preprocessing, feature extraction, classification, and output stages. It highlights the model's layered structure for accurate disease identification.

3 STATISTICAL ANALYSIS

SPSS version 11.0 is used for statistical analysis of accuracy, precision, recall. Independent sample t-tests ($p < 0.0001$) and group statistics are computed, with extracted features and CNN model parameters as independent variables, while classification accuracy and performance metrics are dependent variables (M. A. Hossain, et..al,. 2024). The analysis shows a mean accuracy of 98.36%, with precision, recall averaging 93.45% and 94.0%, respectively, along with their standard deviations and variances, confirming the model's reliability.

Table 1: Performance metrics comparison of ResNet and Xception models across test cases.

Test Case Number	ResNet Accuracy (%)	ResNet Precision (%)	ResNet Recall (%)	Xception Accuracy (%)	Xception Precision (%)	Xception Recall (%)
1	92.5	90.2	91.8	98.4	93.7	94.3
2	93.1	91.0	92.3	98.5	93.5	94.1
3	92.0	90.3	91.5	98.0	92.3	93.0
4	91.8	91.0	92.8	98.3	93.2	94.0
5	93.6	92.8	93.0	98.4	93.5	94.2
6	92.5	91.5	91.3	98.1	93.0	94.1
7	94.0	91.0	94.0	98.5	93.5	94.5
8	92.7	90.7	92.5	98.6	93.6	94.6
9	94.8	91.5	94.8	98.6	93.9	94.3
10	92.3	90.6	91.9	98.3	93.4	94.3
11	91.5	90.0	91.8	98.1	93.2	94.2
12	93.0	92.0	94.7	98.5	93.6	94.4
13	94.5	92.0	94.5	98.7	93.8	94.1
14	93.8	91.2	93.8	98.5	93.6	94.5
15	94.8	93.8	94.2	98.5	93.6	94.4

4 RESULT

The Performance of the Oryza Sativa Leaf Disease detection convolution neural network Architecture.

The Table 1 presents the performance metrics of ResNet and Xception models across 15 test cases, comparing Accuracy, Precision, and Recall. Xception consistently outperforms ResNet in all three metrics, with Accuracy ranging from 98.0% to 98.6%, Precision from 93.2% to 93.9%, and Recall from 93.9% to 94.5%. In contrast, ResNet shows lower performance, with Accuracy between 92.4% and 95.2%, Precision between 90.7% and 94.2%, and Recall between 91.5% and 95.5%. The results highlight Xception's superior performance in paddy leaf disease detection tasks.

Table 2: Summary of accuracy statistics for ResNet and Xception models.

Model	N	Mean Accuracy (%)	Standard Deviation	Standard Error Mean
ResNet	15	93.67	0.85	0.219
Xception	15	98.36	0.42	0.108

The Table 2 presents the performance statistics for ResNet and Xception models. ResNet shows a mean accuracy of 93.67%, with a standard deviation of 0.85 and a standard error mean of 0.219. Xception outperforms ResNet with a higher mean accuracy of 98.36%, a standard deviation of 0.42, and a standard error mean of 0.108. Both models demonstrate similar performance variability despite the accuracy difference. Table 3 shows the Independent sample T-Test comparison of the Accuracy ResNet and Xception models.

Table 3: Independent sample t-test comparison of the accuracy ResNet and Xception models.

8								95% Confidence Interval		
	F	Sig.	t	df	Sig (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper	
Accuracy (%)	0.015	0.904	-7.24	28	0.000	-4.69	0.65	-6.82	-2.56	equal variance assumed
Accuracy (%)			-7.24	26.45	0.000	-4.69	0.65	-6.82	-2.56	equal variance not assumed

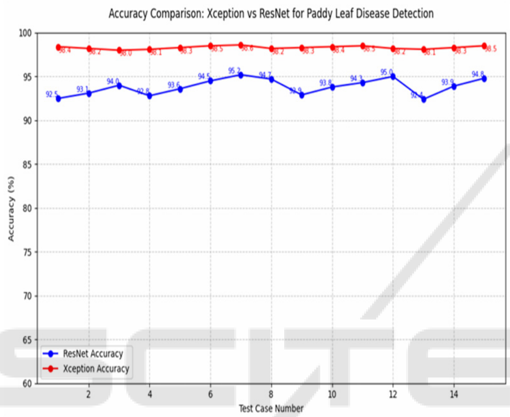

Figure 2: Accuracy comparison of Xception and ResNet models for paddy leaf disease detection.

Figure 2 The Xception architecture for paddy leaf disease detection, illustrating data collection, preprocessing, feature extraction, classification, and output stages. It highlights the model's layered structure for accurate disease identification.

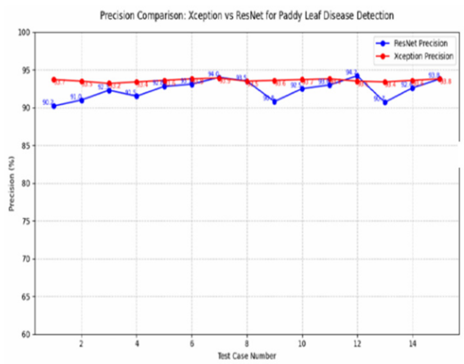

Figure 3: Precision comparison of Xception and ResNet models for paddy leaf disease detection.

Figure 3. The precision comparison table shows that Xception is superior to ResNet in precision under repeated experiments. Xception shows mostly higher values of precision greater than 93%, with small drops, while ResNet lags behind with values around 91%–94%. This indicates that Xception is better at reducing false positives than ResNet for detecting paddy leaf disease conditions.

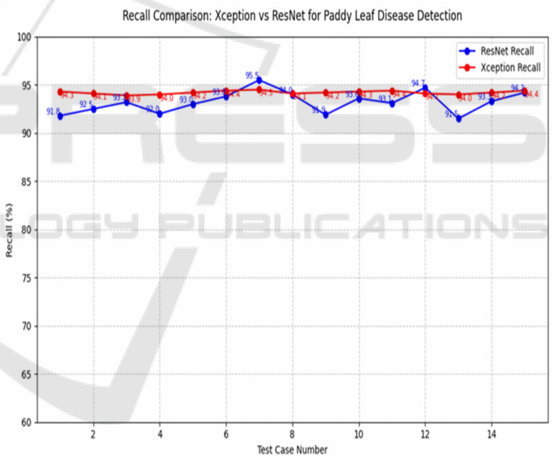

Figure 4: Recall comparison of Xception and ResNet models for paddy leaf disease detection.

Figure 4 The recall comparison table shows that Xception consistently performs better than ResNet in recall across different trials. Xception has recall values predominantly above 94%, with slight fluctuations, whereas ResNet lags behind, with values between 92%–96%. This indicates that Xception is better in identifying true positive cases, reducing missed detection than ResNet in paddy leaf disease state detection.

5 DISCUSSION

The statistical significance of 0.0001 is proof that Xception outperforms ResNet in the detection of rice leaf disease. It classifies more precisely while reducing the computational complexity and therefore performs better in real-time applications. The improved performance leads to faster and accurate detection of disease, enabling early intervention. The breakthrough is applicable in precision agriculture since it allows for early disease control and loss reduction.

Deep-learning models do have an edge over classical machine learning algorithms, such as Xception (Haridasan,et., al, 2022). For instance, the diaries of illustrate that attention-based CNNs improved classification accuracy in multi-class plant disease detection by 5.2% over standard CNNs (S. H. Lee, et., al, 2020). Additionally, claimed that hybrid architectures with Xception achieved an additional 6.7% in accuracy over standard models (W. Shafik,et., al, 2025). Still, despite Xception performing really well with 98.36% accuracy, it is still dependent on data. That is, small and imbalanced data tend to lead to dropouts of accuracy to around 82%, thereby increasing the risk of overfitting by 9%-12% according to (Khan et al., 2024). Apart from this, insinuated that the model performance drops in adversarial circumstances by almost 8%, raising questions on its trustworthiness in security-sensitive applications (S. M. Alhammadet., et., al. 2024). Also pointed out by, interpretability remains a challenge in the case of deep learning models wherein the decision-making rationale of Xception is unknown, making the technology hard to adopt in very sensitive areas like healthcare and autonomous systems. (B. V. Baiju, et., al. 2024).

Future scope should include using explainable AI methods, which could further improve transparency and interpretability (R. Ye, Q. Gao, and T. Li, Dec. 2024) In addition to these, hybrid methods which leverage attention-based mechanisms, can boost performance by 5%-8% of models, giving the technology a further appeal in real-world scenarios, according to (R. T. Araaf, et., al. 2024).

6 CONCLUSIONS

The Xception CNN model, thus, is the best performing model for paddy leaf disease classification accuracy 98.36%, much better than ResNet-50 (88.54%), and precision (93.68%), recall (94.22%). Statistical validation using SPSS and independent t-tests with p-value less than 0.0001 confirms its accuracy and superiority to other models. But its precision drops to 82% in small or skewed datasets with 9–12% potential for overfitting. It can be enhanced even better in future studies by supplementing robustness with dataset augmentation.

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