Learning patterns in rice leaf disease detection using deep learning architectures

ABRAR AL SAYEM, BRAC University, Bangladesh
RIFAH TASNIM MAHIN, BRAC University, Bangladesh
NAZRIN ISLAM RITU, BRAC University, Bangladesh
ABRAR MURSHED, BRAC University, Bangladesh

Rice, vital for Bangladesh's food security and livelihoods but rice diseases like Brownspot, Blast, Tungro and Bacterial blight pose threats to Bangladesh's staple crop, impacting yields and farmer livelihoods. The objective of plant disease detection is to identify the presence of infections, but certain unique leaf images present challenges to the human eye and are not easily distinguishable without assistance and sometime dataset can also fool the state of the art architectures. We have used several state of the art deep learning models; such as: Alexnet, VGG, inceptionV3, resnet and convnext, and evaluated their performance in detecting the diseases. We have observed two different dataset consisting of 5932 images on dataset A and 120 images on Dataset B, and evaluated the patterns and bias in dataset and the mentioned architectures result based on training and validation metrics. We have ultilized the popular Imagenet dataset set for our pretrained weights for our model training. And we have achieved 98% to 100% accuracy, with very less Training Loss and Validation Loss, for both Dataset-A and Dataset-B, showing over learned characteristics. Our findings and further exploration finds that Dataset-A is synthesized to increase the size of dataset and dure to that models are over learning while Dataset-B has good training trend but due its small data size models are over learning.

Additional Key Words and Phrases: CNN, Deep learning, Augmentation, Overlearning

ACM Reference Format:
Abrar Al Sayem, Rifah Tasnim Mahin, Nazrin Islam Ritu, and Abrar Murshed. 2024. Learning patterns in rice leaf disease detection using deep learning architectures. 1, 1 (May 2024), 11 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Rice plays a crucial role in the cultural heritage and economies of many Asian countries, where its farming and consumption are deeply woven into everyday life. Throughout Asia, from Japan to India and across Southeast Asia, rice has been a dietary staple for centuries, shaping culinary customs, religious ceremonies, and agricultural methods. Yet rice cultivation comes with challenges. Farmers face the pressing threat of diseases that can devastate rice crops. These include Blast, Bacterial leaf blight, and Tungro disease caused by various pathogens such as fungi, bacteria and viruses leading to significant yield reduction and quality impacts on the produced rice. Efforts are also underway to enhance farmer awareness and education about disease management practices to mitigate the impact of these diseases on rice production but it's not always easy to detect and diagnose diseases accurately and in a timely manner. Plant diseases can significantly reduce crop production and contribute to environmental pollution. For instance, diseases in rice plants can decrease yields by 10–15%, and in severe cases, losses can spike to 40–50% or even result in no income at all [1].

Authors' addresses: Abrar Al Sayem, BRAC University, Bangladesh; Rifah Tasnim Mahin, BRAC University, Bangladesh; Nazrin Islam Ritu, BRAC University, Bangladesh; Abrar Murshed, BRAC University, Bangladesh.

Manuscript submitted to ACM

This can lead to substantial economic losses for farmers who have invested a year's work into their crops. However, many farmers lack sufficient knowledge about plant diseases, including how to recognize the symptoms and effectively diagnose the diseases. This gap in knowledge often leads to incorrect or excessive use of pesticides, which not only fails to properly treat the diseases but also harms the soil and the environment. Therefore, timely and accurate disease detection and identification are crucial for effective management and treatment.

To address this issue, our project focuses on developing a deep learning-based disease detection model for rice plants, leveraging the strengths of various renowned architectures to enhance disease identification accuracy and efficiency. We have chosen several models including AlexNet, VGG, InceptionV3, ResNet, and ConvNeXt, utilizing their pretrained weights from ImageNet to recognize disease patterns effectively. AlexNet serves as our baseline, while VGG is known for its depth and robust feature extraction capabilities. InceptionV3, renowned for its complex architecture that allows for efficient image processing at multiple scales, and ResNet, celebrated for its ability to train very deep networks through the use of residual connections, are also integral to our comparative analysis. Lastly, ConvNeXt, a modern transformer-based model, is included to explore cutting-edge approaches in pattern recognition. By integrating these models, our project aims to significantly advance disease management strategies, supporting sustainable agriculture and bolstering food security in pivotal rice-growing areas.

2 LITERATURE REVIEW

Many studies have studied the use of deep learning methods for detecting rice leaf diseases and learning about patterns in the diseases, including Blast, bacterial blast, tungro, and Brownspot. Alom, M., et al. (2018) discusses the evolution of deep learning methods post-Alexnet, covering key contributions in image classification, object recognition, and natural language processing. It discusses advancements in model architecture, optimization, and training techniques, focusing on CNNs like VGG, ResNet, and GoogleNet in their work[2]. Mishra, S., et al. (2020) introduces a real-time method for recognizing corn leaf diseases using a deep convolutional neural network (CNN). By tuning hyperparameters and adjusting pooling combinations on a GPU-accelerated system, the performance of the deep neural network is enhanced. The model achieves an accuracy of 88.46%, demonstrating the method's feasibility on standalone smart devices such as Raspberry Pi, smartphones, and drones [3].

A classification task using the Alexnet deep learning model and transfer learning by fine-tuning Alexnet pretrained on ImageNet results demonstrate that larger datasets lead to higher accuracy and lower loss, with accuracies of 90.7%, 86.6%, and 81.5% for datasets of 10,000, 5,000, and 1,000 respectively [4]. Confusion matrix analysis shows strong performance in distinguishing between different types of vegetables with minimal misclassifications. Additionally, the study highlights the computational efficiency of the fine-tuned model, reducing training time and resource requirements compared to training from scratch. These findings emphasize the practical utility of deep learning models like Alexnet for accurate and efficient vegetable classification, particularly beneficial for agricultural and food processing applications.

Another study by Hossain, et al. (2020) a CNN-based model is utilized for identifying diseases in rice leaves by minimizing the network parameters. This proposed model achieves impressive training and validation accuracies of 99.78% and 97.35%, respectively. Its effectiveness is evaluated on a separate set of rice leaf disease images, achieving a high accuracy of 97.82% with an AUC of 0.99. Furthermore, binary classification experiments were conducted, with recognition rates of 97%, 96%, 96%, 93%, and 95% for Blast, Brownspot, Bacterial Leaf Blight, Sheath Blight, and Tungro, respectively. Additionally, the model's efficiency in memory storage is notable due to its reduced number of network

parameters [5]. Another deep CNN with a pre-trained ResNet-50 model and median filtering, followed by k-means clustering for segmentation is implied and achieves 97.3% accuracy across datasets[6]. Similarly, four pre-trained CNN models are developed: ResNet34, ResNet50, ResNet18 with self-attention, and ResNet34 with a self-attention layer between healthy and diseased rice leaves. Performance analysis reveals ResNet34 with Self-Attention as the top-performing model, achieving 98.54% accuracy, outperforming other models[7].
In this study, Maulana, et al. (2023) uses the InceptionV3 deep learning model to detect rice leaf diseases from images, utilizing transfer learning by fine-tuning InceptionV3 pretrained on ImageNet. Experimental results demonstrate accuracies ranging from 78.2% to 99.58% across various classification models. The study includes a detailed evaluation of the model's performance using metrics such as precision, recall and f1-score for each disease class achieving 99% precision, 93% recall, 96% f1-score for Bacterial Blight, 97% precision, 97% recall, 97% f1-score for Blast, 95% precision, 99% recall, 97% f1-score for Brownspot and 99% precision, 100% recall, 100% f1-score for Tungro. Evaluation calculation results of the InceptionV3 model using test data were - 97.47% for accuracy, 97.5% for precision and 97.46% for f1-score [8].

Another study by, Rallapalli, et al. (2021) detects rice leaf bacterias and diseases with the help of M-Net, a confined model of AlexNet, by comparing it to its previous model to prove its efficiency. The proposed model achieves 70.7% accuracy whereas the existing model achieves 65.8% accuracy overall, demonstrating better precision and reliability. The accuracy of M-Net and the existing model's experimental results for each category are 60% and 60% for Bacterial Blight, 75% and 80% for Brownspot, 29% and 28.3% for Healthy, 47.5% and 19.1% for Hispa, 15.6% and 14.9% for Leaf Blast, 20% and 90% for Leaf smut respectively. Additionally, the study contrasted the suggested model's performance with that of other CNN variants, which are AlexNet, VGG-16, VGG-19 and ResNet. Each model's validation accuracy was demonstrated by the performance, with AlexNet scoring 68.1%, VGG-16 scoring 65.67%, VGG-19 scoring 67.09%, ResNet scoring 68.5% and proposed M-Net scoring 71.98% over 320 iterations for all[9].

These studies collectively underscores the potential of deep learning methodologies in the domain of rice leaf disease detection. Through advancements in neural network architectures, transfer learning, multimodal imaging, data augmentation, and real-time monitoring systems, researchers aim to enhance the efficiency and accuracy of disease diagnosis in rice cultivation, contributing to improved crop yield and agricultural sustainability.

3 METHODOLOGY

While employing deep learning CNN architecture for rice leaf disease detection, several key steps are integral to the process. Initially, an ideal dataset comprising images of diseased rice leaves is collected, covering different conditions and environmental contexts. Following the preprocessing of the collected images, ensuring standardization in size, color, and orientation, alongside augmenting the dataset to enhance model robustness. Subsequently, a CNN architecture tailored for image classification tasks is selected or devised, optimized to automatically extract hierarchical features from raw pixel data. Through extensive training on the preprocessed dataset, the model learns to discern patterns indicative of various diseases, facilitated by substantial computational resources. Validation and fine-tuning then refine the model's performance, assessing its generalization capabilities on separate data subsets. Finally, upon achieving satisfactory accuracy, the model is deployed, potentially revolutionizing disease detection in rice fields through its scalability, automation, and potential for real-time analysis.

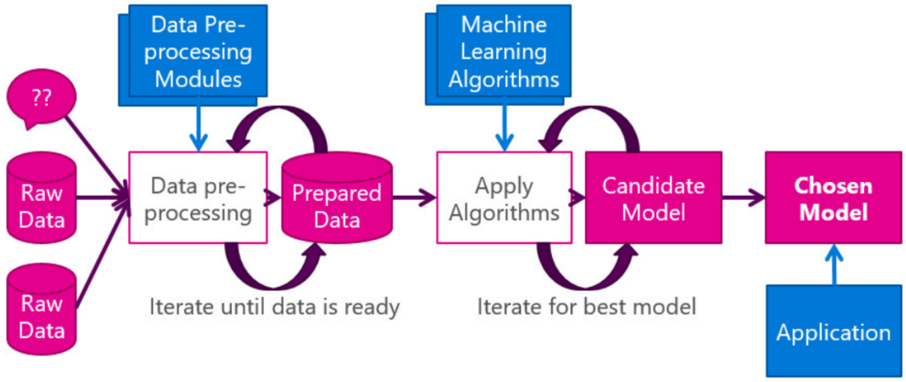


Fig. 1. Processflow

3.1 Data Acquisation

Our data comprises over 5000 images—5932 images to be precise for Dataset-A and 200 images for Dataset-B. Dataset-A was collected from Mendeley data [] and Dataset-B was collected from Kaggle open datasets. These datasets, comprising images of Blast, Brownspot, Tungro and Bacterial blight, was visualized using a bar plot, showcasing the number of images per category in the figure 2, 3. The visualization revealed potential data imbalances, with some categories having more images than others.

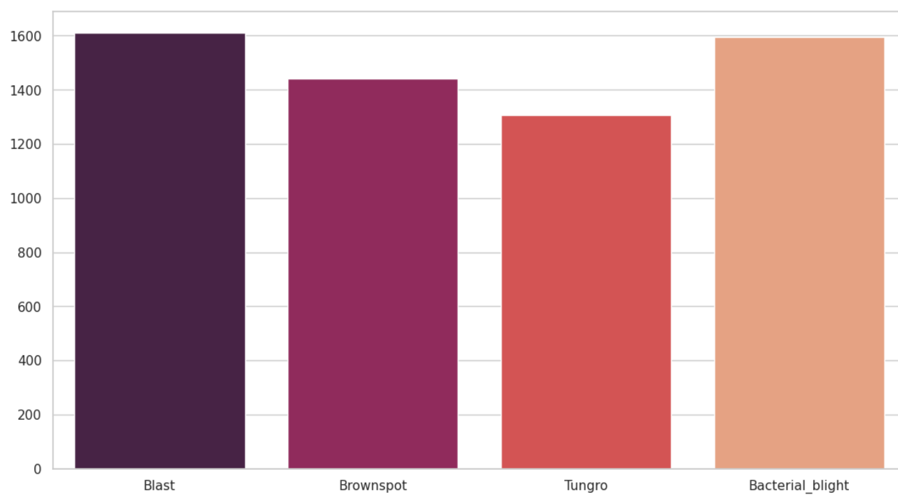


Fig. 2. Dataset-A Class Distribution

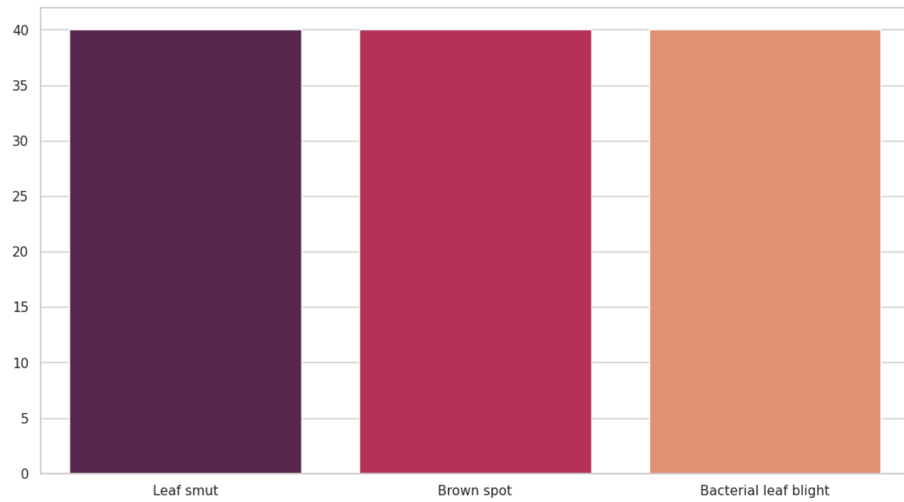


Fig. 3. Dataset-B Class Distribution

3.2 Data preprocessing

We used various techniques, such as horizontal flipping, rotation, zooming and adjustments to height and width, to augment the training dataset in the figure 4. These techniques enhance the dataset's diversity, aiding in better model generalization. To assess the impact of data augmentation, we visualized augmented sample images, enabling us to observe the transformations' effects on image appearance and quality. Several other preprocessing techniques, involving resizing images to a consistent resolution, typically 224x224 pixels, and normalizing pixel values to a standardized range. In addition, we conducted a thorough analysis of the class distribution within our dataset. This played a crucial role for our training dataset as it allowed us to understand the distribution of different classes of rice diseases and to ensure we have balance across different leaf diseases. A balanced distribution helps prevent bias during model training. Furthermore, we inspected sample images from a specific class, e.g., Brownspot were visually inspected to understand image characteristics and dataset variations.

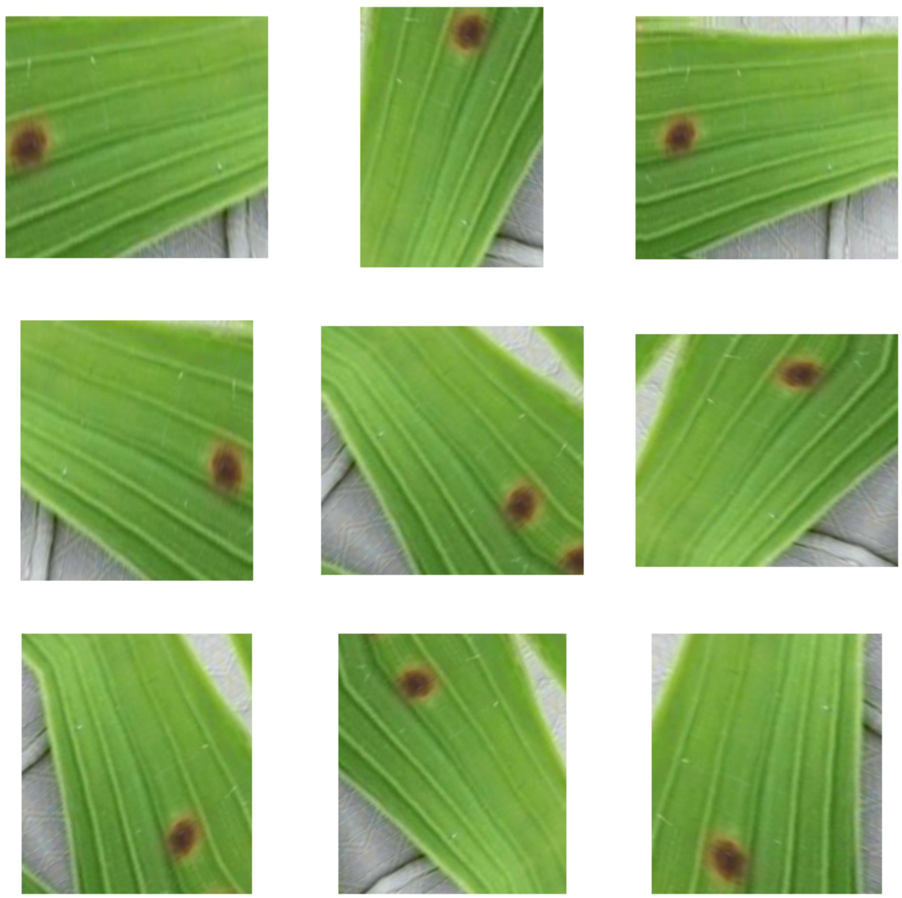


Fig. 4. Augmented Images

3.3 Model selection

Convolutional Neural Networks (CNNs) have become increasingly prominent in the detection and classification of rice diseases, leveraging their ability to analyze and interpret visual data with high accuracy. The architecture of CNNs for this purpose typically involves several layers that process images of rice plants through filters to detect patterns and anomalies indicative of diseases as shown in the figure 5. These layers include convolutional layers that extract features, pooling layers that reduce dimensionality, and fully connected layers that interpret these features to make predictions about the health of the rice plants. Advanced CNN models can differentiate between various common rice diseases, such as blast, bacterial blight, and brown spot, by learning from vast datasets of labeled rice plant images. This technology not only helps in early disease detection, improving crop management and yield, but also aids farmers in applying the correct treatments promptly, thereby minimizing damage and loss.

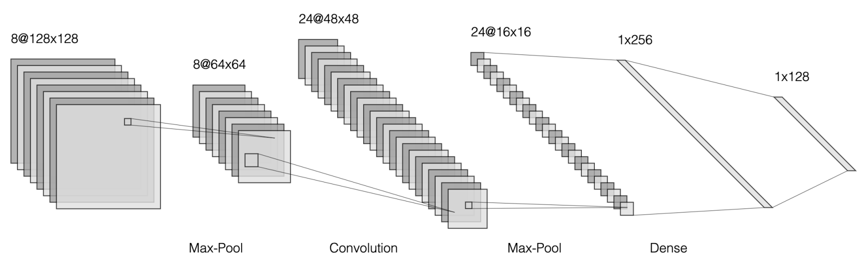


Fig. 5. Basic CNN Architecture

We started off with the InceptionV3 model for our project. This model includes convolutional and pooling layers, along with dense layers for classification. We are choosing pre-trained weights from imageNet for each of our models as leveraging our models through transfer learning allows us to fine tune the networks, saving time and computational resources required to start from scratch. We chose InceptionV3 because it can handle deep networks while keeping the number of parameters in check. Our goal was to take advantage of its strong feature extraction abilities and its capacity to detect fine details in the rice disease images. Our model has 311 layers, with activation93 as the second-to-last layer and mixed10 as the final layer. Our model has 21810980 parameters where 1943556 are trainable parameters and 19867424 are not. Since our project is based on multi-class classification, we had to use Adam, also known as, Accelerated Adaptive Moment Estimation optimizer with a sparse categorical cross-entropy loss function and accuracy metric to compile our model. The model is trained for 10 epochs using the training dataset, with validation data for evaluation. The performance of the trained model is evaluated using the validation dataset and then visualized along with their predicted and actual labels. For our second model, in our third model instance, VGG-16 was used, which is also a famous CNN algorithm for categorizing images. 13 convolution layers serve as the primary component of VGG-16's structure followed by 5 pooling layers with 3 additional fully connected ones coming at the end. We have employed the Adam optimizer in training it, whereas evaluation of its functionality was facilitated by the application of sparse cross-entropy loss technique. Just as AlexNet and InceptionV3, this model too has been learned over three epochs on several occasions with a training data set, against which test data will be compared during evaluation. To asses its performance using validation dataset, it compares how well it predicts compared with the original label. For our final model, we used Resnet50 for its advanced CNN in classification tasks. Its deep residual architecture, consisting of 50 layers wherein convolutional, pooling, activation, and fully connected layers are stacked together, allows it to effectively learn and extract features from images at various levels of abstraction. Using Adam optimizer and sparse cross-entropy loss function, we trained the Resnet50 model on our training dataset consisting of labeled images for 3 complete epochs multiple times. Using the validation dataset, the trained model's performance is assessed, and the predicted and actual labels are then displayed.

4 RESULTS

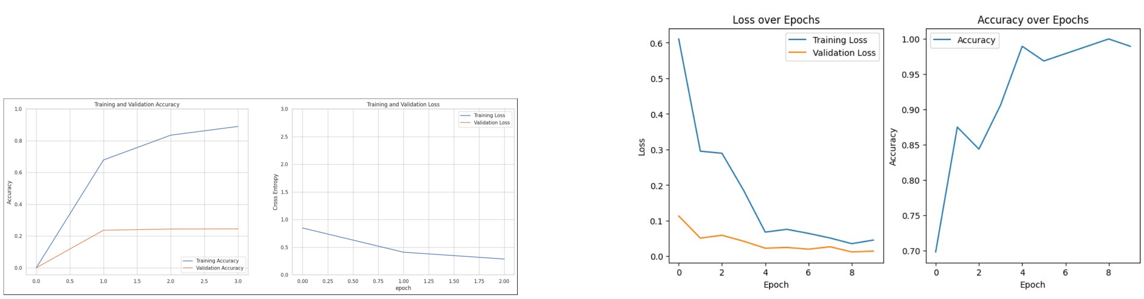
In this study, we evaluated the performance of five convolutional neural networks—AlexNet, VGG, InceptionV3, ResNet50, and ConvNext—across two distinct datasets, referred to as Dataset A and Dataset B. The models were assessed based on training loss, validation loss, and accuracy metrics, providing insights into their effectiveness and efficiency in handling diverse data characteristics. Below we detail the performance metrics for each model:

Table 1. Model Performance Comparison on datasets A and B

	Dataset A			Dataset B		
Model	Training Loss	Validation Loss	Accuracy	Training Loss	Validation Loss	Accuracy
AlexNet	X.XX	0.2052	0.2452%	0.0455	0.0145	0.9896%
VGG	0.0117	0.0034	0.9952%	0.0325	0.0038	0.9792%
InceptionV3	X.XX	0.0066	1.0000%	0.0098	0.0066	1.0000%
ResNet50	0.0006	0.0001	1.0000%	0.4258	0.1213	0.9167%
ConvNext	X.XX	X.XX	XX%	0.0537	0.0136	1.0000%

4.1 AlexNet

For Dataset A, only the validation loss and accuracy were available. AlexNet exhibited a high validation loss of 0.2052 and a notably low accuracy of 24.52%, indicating poor generalization on this dataset. Conversely, in Dataset B, AlexNet achieved a training loss of 0.0455, a validation loss of 0.0145, and a significantly higher accuracy of 98.96%, suggesting better suitability or overfitting to the characteristics of Dataset B.

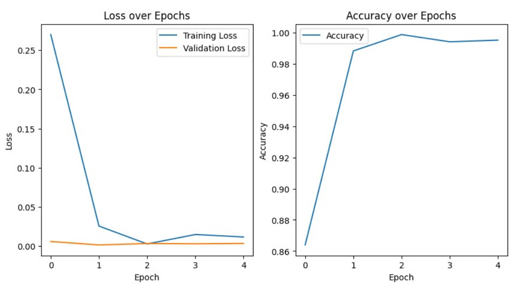


(a) Dataset A (b) Dataset B

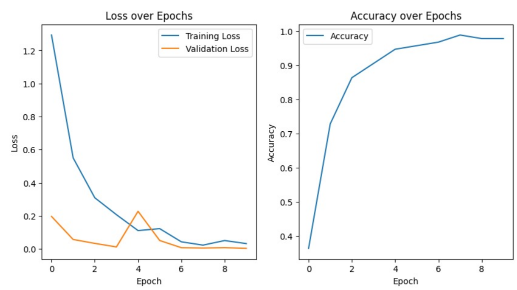
Fig. 6. Performance of AlexNet Model on datasets A and B

4.2 VGG

The VGG network demonstrated robust performance on both datasets. For Dataset A, the training loss was low at 0.0117, the validation loss was 0.0034, and the accuracy was nearly perfect at 99.52%. Similarly, for Dataset B, though the training loss increased slightly to 0.0325, the validation loss remained low at 0.0038, with an accuracy of 97.92%. These results indicate that VGG consistently learns well and generalizes effectively across different datasets.



(a) Dataset A

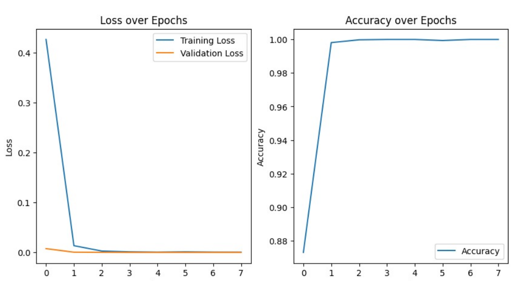


(b) Dataset B

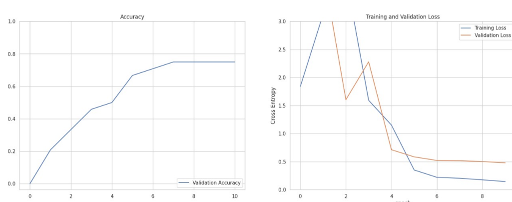
Fig. 7. Performance of VGG Model on datasets A and B

4.3 InceptionV3

InceptionV3's data for Dataset A were incomplete; thus, no conclusions can be drawn for this dataset. For Dataset B, the model showed excellent performance, with a training loss of 0.0098, a validation loss of 0.0066, and perfect accuracy of 100.00%. This suggests that InceptionV3 is highly effective at handling the data characteristics present in Dataset B.



(a) Dataset A



(b) Dataset B

Fig. 8. Performance of Inception Model on datasets A and B

4.4 ConvNext

Similar to InceptionV3, the results for ConvNext in Dataset A were not available. In Dataset B, however, ConvNext recorded a training loss of 0.0537, a validation loss of 0.0136, and an accuracy of 100.00%, matching the high performance seen with InceptionV3.

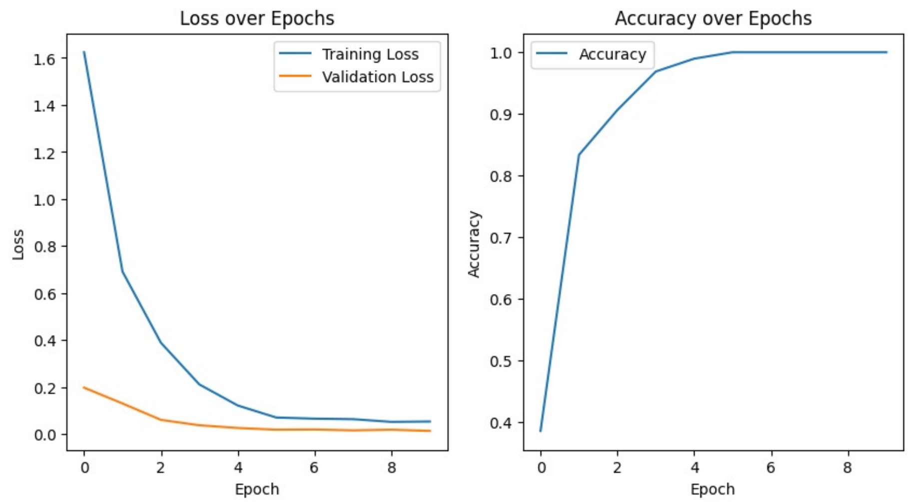
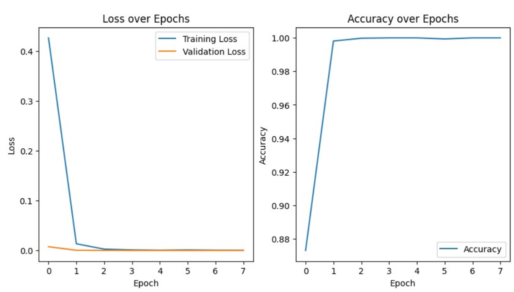


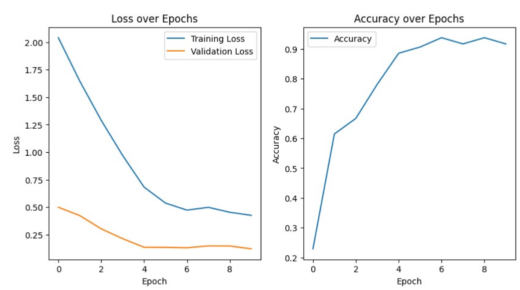
Fig. 9. Performance of ConvNext Model on datasets B

4.5 ResNet50

ResNet50 displayed a striking contrast in performance between the two datasets. For Dataset A, the model had an impressively low training loss of 0.0006 and validation loss of 0.0001, achieving perfect accuracy (100%). However, for Dataset B, there was a significant increase in both training loss (0.4258) and validation loss (0.1213), with a decreased accuracy of 91.67%. This disparity may indicate overfitting to Dataset A and less robustness to the variations in Dataset B.



(a) Accuracy of ResNet Model



(b) Loss of ResNet Model

Fig. 10. Performance of ResNet Model on datasets A and B

5 DISCUSSION

The results indicate varying degrees of success across models and datasets, highlighting the importance of model selection based on specific dataset characteristics and the intended application. Models like VGG and InceptionV3 generally performed well, suggesting a good balance between learning capability and generalization. In contrast, the performance of AlexNet and ResNet50 varied more significantly between datasets, emphasizing potential issues such as model complexity and overfitting. This study underscores the necessity for careful consideration of both model architecture and tuning to optimize performance for specific tasks and datasets.

REFERENCES

[1] Q. T. Shaobing Peng and Y. Zou, "Current status and challenges of rice production in china," *Plant Production Science*, vol. 12, no. 1, pp. 3–8, 2009.

[2] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, B. C. Van Esesn, A. A. S. Awwal, and V. K. Asari, "The history began from alexnet: A comprehensive survey on deep learning approaches," *arXiv preprint arXiv:1803.01164*, 2018.

[3] S. Mishra, R. Sachan, and D. Rajpal, "Deep convolutional neural network based detection system for real-time corn plant disease recognition," *Procedia Computer Science*, vol. 167, pp. 2003–2010, 2020, international Conference on Computational Intelligence and Data Science. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S187705092030702X

[4] L. Zhu, Z. Li, C. Li, J. Wu, and J. Yue, "High performance vegetable classification from images based on alexnet deep learning model," *International Journal of Agricultural and Biological Engineering*, vol. 11, pp. 217–223, 01 2018.

[5] S. M. M. Hossain, M. M. M. Tanjil, M. A. B. Ali, M. Z. Islam, M. S. Islam, S. Mobassirin, I. H. Sarker, and S. M. R. Islam, "Rice leaf diseases recognition using convolutional neural networks," in *Advanced Data Mining and Applications*, X. Yang, C.-D. Wang, M. S. Islam, and Z. Zhang, Eds. Cham: Springer International Publishing, 2020, pp. 299–314.

[6] P. A. S. Rani and N. Singh, "Paddy leaf symptom-based disease classification using deep cnn with resnet-50," *International Journal of Advanced Science Computing and Engineering*, vol. 4, no. 2, p. 88–94, Aug. 2022. [Online]. Available: https://ijasce.org/index.php/IJASCE/article/view/83

[7] A. Stephen, A. Punitha, and A. Chandrasekar, "Designing self attention-based resnet architecture for rice leaf disease classification," *Neural Computing and Applications*, vol. 35, no. 9, pp. 6737–6751, March 2023. [Online]. Available: https://doi.org/10.1007/s00521-022-07793-2

[8] A. Maulana, M. Asyhari, Y. Azhar, and V. Nastiti, "Disease detection on rice leaves through deep learning with inceptionv3 method," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 7, pp. 1147–1154, 10 2023.

[9] M. A. S. D. SethuMadhavi Rallapalli, "A contemporary approach for disease identification in rice leaf," *International Journal of System Assurance Engineering and Management*, 5 2021.

6 ACKNOWLEDGMENTS

We express our sincere gratitude to all contributors for their invaluable assistance as resources in this project. Because of our dedication, the project has been a real success so far.