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A MOBCEPTION MODEL FOR RICE DISEASE DETECTION WITH RECOMMENDATIONS USING IMAGES IN ASIAN COUNTRIES.

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Abstract

Rice is a principal staple food crop of the world that ensures food security and economic stability, particularly in Sri Lanka. However, plant diseases are a major problem in rice farming, as they reduce both the yield and the profit. Traditional disease diagnosis methods rely on human inspection and domain expertise, which are not accurate and reliable. Visually similar diseases are routinely misdiagnosed by farmers, leading to incorrect treatment and further crop loss. Young farmers in particular have limited field experiences. Although AI and deep learning-based solutions in agriculture have gained global popularity and a comprehensive, automated rice disease diagnosis and management system is yet to be implemented in Sri Lanka. This study aims to bridge this gap by developing a hybrid deep learning model that classifies rice plant diseases accurately and provides actionable pesticide recommendations. This work collects a diverse range of rice plant disease images from Asian countries and preprocessed for the models to train. Feature extraction and disease classification are performed using a hybrid deep learning architecture of MobileNetV2 and InceptionV3. The model is trained and evaluated on the prepared dataset with a very high classification accuracy of 94%. The additional use of a recommendation system further enhances the real-world usability of the model through the generation of personalized pesticide solutions to farmers depending on disease prediction. This system guides farmers to proper disease management practices, fulfilling the critical need for accurate and timely decision-making in agriculture. The study not only introduces a novel AI-based approach to rice disease diagnosis but also contributes to the broader goal of digitizing agriculture in Sri Lanka.

Keywords*:* CNN architectures, Inceptionv3, Machine Learning, Mobile Net, Remedies

Background

Rice is one of the world's principal food crops, serving as a staple food for over half of the global population. Rice is not only a food security key but also economic sustainability for Sri Lanka. Rice cultivation is, however, severely threatened by plant diseases with a devastating impact on yield and profitability. (Fan et al., 2021)

Having grown up in a village where paddy cultivation is the backbone of our rural economy, I have personally observed how hard it is for farmers to protect their crops from diseases. Rice farming has been the principal source of livelihood for generations of many families. But year after year, I have witnessed their toil being threatened by the sudden onset of plant diseases. There is one case which is still fresh in my mind. There was a farmer in my village who noticed unusual brown spots on his rice plant. Assuming it to be a common fungal infection, he applied a pesticide recommended by another farmer. Unfortunately, the

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disease was bacterial leaf blight, and the inappropriate treatment worsened the condition further leading to a heavy loss of his crop. This is not an isolated case. There are many farmers who struggle to diagnose and treat diseases in plants because they look so alike.

Farmers, particularly the young ones, lack adequate farming experience to effectively diagnose and treat plant diseases. Traditional disease identification methods are typically time-consuming, not available, or susceptible to errors, leading to misapplications of treatment that can worsen crop decline. The traditional method of disease identification through consulting old-time farmers or through agricultural officers' result in delays or misdiagnosis. Although younger farmers are significantly adept at using digital tools, they lack access to reliable technological aids to assist them in making informed decisions.

Although deep learning and AI for agricultural purposes have increased over the years, Sri Lanka has no comprehensive solution based on deep learning to diagnose and manage the diseases of the rice plant. The lack represents a window for developing a revolutionary and low-cost system based on deep learning with the capability of accurately identifying diseases and recommending an appropriate pesticide.

Problem statement

Disease diagnosis today relies on human inspection and domain knowledge, which is neither scalable nor reliable. Diseases with similar appearances, such as bacterial leaf blight and brown spot strains, tend to be misidentified with each other by farmers due to due to their similar visual appearances, such as discoloration, spots, and lesions.

Figure 01: Brown Spot

Source: Kaggle

Figure 02: Bacterial Leaf Blight

Source: Kaggle

Misdiagnosis could lead to improper treatment being administered, and the problem could end up being worsened rather than cured. Hence, there is an urgent need for an intelligent, accurate, and user-friendly system to support rice farmers in disease identification and appropriate treatment recommendation, using deep learning techniques.

Research Objectives

- Collecting diverse rice plant disease data and preprocessing it through augmentation and normalization to ensure quality and balance for model training.

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- Extracting features from rice plant disease data using CNN and training a deep learning model for accurate classification of diseases from smartphone-captured images
- Provide clear and actionable pesticide recommendations tailored to the detected diseases.

Methodology

Dataset Acquisition and Preprocessing

A total of 12,707 rice leaf images were initially collected from publicly available platforms such as Kaggle, TensorFlow, and Mendeley. These images encompassed ten categories: nine disease classes and one healthy class. The dataset primarily features rice plant images from Asian countries where rice is a staple crop, including regions like Sri Lanka, India, Bangladesh, and the Philippines ensuring the relevance of the model to real-world agricultural conditions in these areas. To address class imbalance, data augmentation techniques including flipping, zooming, and brightness adjustments were applied, expanding the dataset to 22,000 images. However, the augmented dataset introduced noise, adversely affecting model performance. Consequently, acurated dataset comprising 5,996 high-quality images was manually assembled, ensuring balanced representation across classes and improved image quality.

Pesticide Recommendation Dataset

With the enhanced dataset at hand, I turned my focus to disease treatment suggestions. expert consultations were conducted with Mr. V.A.K. Chandrasiri, Coordinator of the Women Farmers Organization at the Department of Agrarian Development, and gathered pesticide information from manuals in pesticide shops. Combining these results, I created a systematic Excel sheet linking each disease to its corresponding remedies and pesticides. This database was used as the foundation for the automated recommendation system, bridging the gap between disease detection and effective treatment.

Model Architecture and Training

A detailed comparison of various Convolutional Neural Network (CNN) architectures was performed, including InceptionV3, Dense Net, Mobile Net, Efficient Net, ResNet50, ResNet101, Xception, and VGG19.

Model	Accuracy	F1-Score
Dense Net	0.51	0.46
Efficient Net B0	0.28	0.23
ResNet50	0.34	0.27
ResNet101	0.44	0.41
Xception	0.83	0.83
Mobile Net	0.81	0.80
Inception V3	0.80	0.78
VGG19	0.65	0.64

Source: Author’s estimation

In order to measure the performance of the proposed model in a systematic and authentic way, we employed a range of evaluation metrics very well known within the field of machine learning and image classification. They are Accuracy, Precision, Recall, and the F1 Score. All of them present a different perspective through which the model's predictability can be seen.

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Accuracy

Accuracy is one of the most fundamental evaluation metrics, measuring the proportion of correctly classified images out of the total number of images.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

- TP (True Positives): The number of correctly classified disease images.
- TN (True Negatives): The number of correctly classified non-diseas e (healthy) images.
- FP (False Positives): The number of healthy images misclassified as a disease.
- FN (False Negatives): The number of diseased images misclassified as healthy

Accuracy provides a rough sense of how good my model is performing. Accuracy is best utilized when the classes are well balanced,

Ex: There are approximately the same number of images for each disease and healthy plants. However, if the data is imbalanced, some diseases have fewer images than others, accuracy alone can be misleading as it may not reflect the model's performance across all classes accurately.

Precision

Precision measures the percentage of images that were correctly classified as a specific disease out of all images that were predicted as that disease.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Precision is crucial if false positives are costly (e.g., if a healthy plant is wrongly diagnosed as diseased, unnecessary pesticides might be used).

High precision means the model is predicting fewer incorrect diseases.

Recall (Sensitivity)

Recall measures the percentage of actual diseased plants that were correctly classified by the model.

$$\text{Recall} = \frac{TP}{TP+FN}$$

Recall matters when false negatives are costly (e.g., missing a diseased plant could lead to infection across an entire field). High recall means the model correctly identifies most diseased plants.

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balance between them. It is particularly useful when dealing with imbalanced datasets

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$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

It balances precision and recall, ensuring that both false positives and false negatives are minimized. A good F1-score indicates that the model is neither over-predicting nor under-predicting diseases.

Through the inclusion of these metrics, the model evaluation exceeds basic accuracy and provides a multi-dimensional view of its robustness and possible weaknesses. This is especially crucial in crop disease prediction systems, where erroneous projections could lead to excessive dependence or misappropriation of chemical applications. A thorough metric analysis thus becomes a cornerstone of this study's validity and usefulness.

Deep learning models like Dense Networks like an experienced eye traversing every pixel of an image. It begins with the convolutional layers, which are the model's visual cortex detecting edges, textures, patterns, and color transitions. The layers gradually learn low-level to high-level features, such as spots on leaves, color transitions, or strange patterns vital indicators of some rice plant diseases. The further back the picture travels in the network, the more discerning the model becomes and keeps learning idiosyncratic characteristics, which define each disease and how it differs from all others. These are directed on to a specialty fully connected layer, utilized for decrypting that learned input. Think of it as the model's chamber where decisioning is done based on input from all filtered features obtained.

The following is the SoftMax activation layer, which accepts the output of the fully connected layer and converts it into probabilities. This allows the model to run all the possible disease classes through it and provide a probability for each. For example, it might conclude there's a 90% chance the disease is 'Leaf Blast' and 10% for the remainder.

Finally, the model predicts selecting the most likely disease class. Through this intelligent mapping of image features to disease classes, the model simulates the diagnostic power of an expert.

To improve accuracy, use fine-tuning as well, where we adapt certain layers of a pre-trained Dense Net architecture to become even more attuned to the distinguishing features of our dataset. We do this to ensure that not only does the model generalize extremely well but it also specializes in identifying rice crop diseases, including in difficult or subtle instances.

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This is how models select the features and identify the diseases.

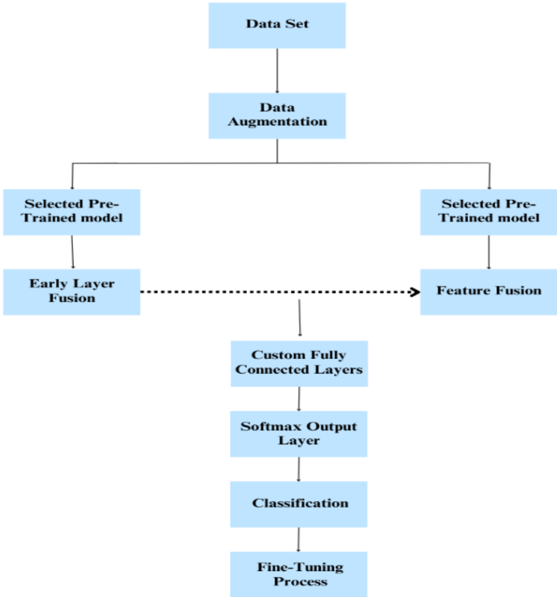

Figure 03: Layer-wise Structure of the Proposed Hybrid Model
Source: Author's estimation

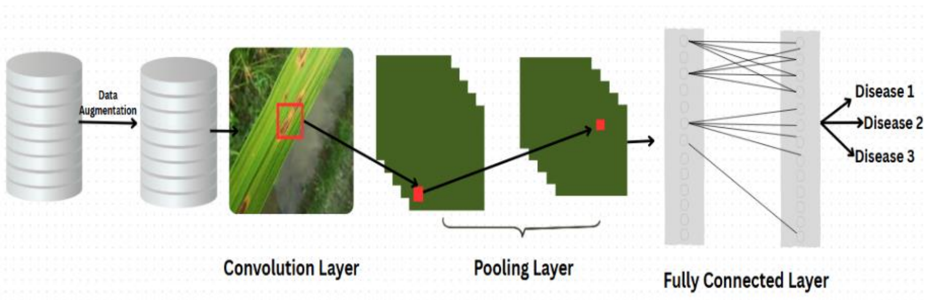

Figure 04: Architecture of the Model
Source: Author's estimation

To ensure the efficacy of the proposed hybrid deep model, an ablation study was conducted. The objective was to check what impact the different components of the model had on classification accuracy and find the optimal configuration. A series of experiments were conducted by modifying parts of or deleting parts of the model systematically and evaluating their impact on performance.

To maximize the hybrid model's quality, an ablation study was undertaken, and different CNN models were experimented with. Experiments were conducted with VGG19, InceptionV3, EfficientNetB0, ResNet101, and Xception, Mobile Net to check their performance. After the best-performing models were identified, different combinations of hybrid models were created to enhance feature extraction as well as classification. Different combinations were experimented with, including VGG19-InceptionV3, Dense Net-Mobile Net, Efficient Net-Res Net, Xception- Dense Net, and Mobile Net-Inception. As Efficient Net and Res Net individually had good performance, these two models were investigated further using ensemble learning as well as layer modification techniques. The final hybrid model selection was made based on the combination

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that had the highest classification accuracy and robustness, such that it would achieve a trade-off between feature extraction and computational cost.

By comparison, my research uses Mobile Net and InceptionV3 to overcome limitations of current research. Although some models like DCNFM, Dense Net, and DBN have high accuracy, they take considerable computational powers, which reduces their applicability in real-time, particularly where there are resources limitations. Mobile Net, having a light weight architecture, makes it possible to do inference more quickly without compromising the performance in classification, hence being a deployable option for use in actual agricultural environments. InceptionV3, with its high-speed feature extraction, also adds to the model's ability to classify diseases correctly. Through these architectures combined, my approach is a balance between efficiency and precision, allowing for effective classification of disease on machines with limited processing power.

For recommending pesticides, a rule-based system was utilized, which executes once the hybrid model identifies the disease from the preprocessed image. Once the disease has been identified, the rule-based system cross-references the identified disease with a predefined mapping of remedies and pesticides stored in the dataset. This enables the system to provide the most appropriate treatment recommendations for each identified disease, enhancing farmers' decision-making. To demonstrate the performance of the model in a readily accessible format, I built a temporary user interface using Gradio. The interactive interface offered real-time testing of the hybrid model, with the ability of users to upload images, receive disease predictions, and corresponding pesticide recommendations efficiently.

Figure 05: User interface of the System
Source: Author's estimation

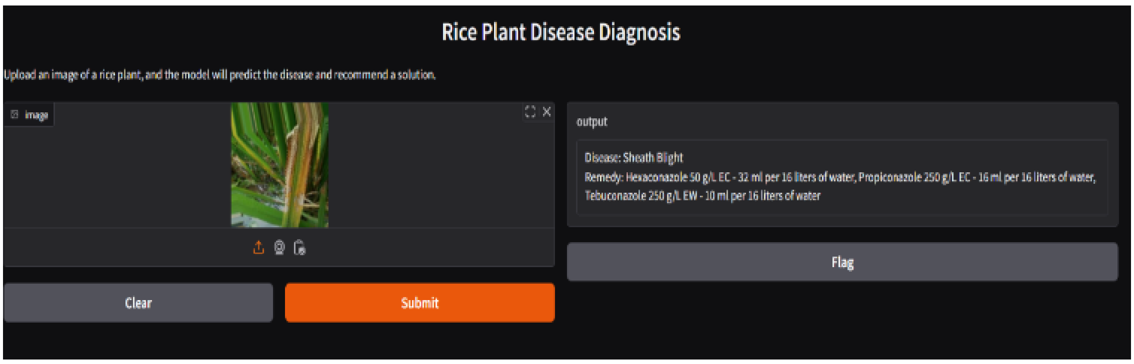

Figure 06: User interface of the System
Source: Author's creation

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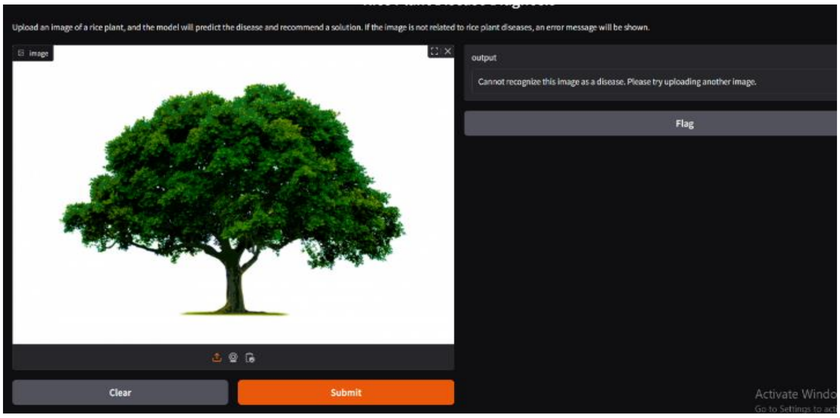

Figure 07: User interface of the System
Source: Author's creation

Literature review

Applications of deep learning in agriculture have grown dramatically in recent years, revolutionizing plant disease diagnosis with automatic image-based diagnosis. Convolutional Neural Networks (CNNs) have particularly emerged as powerful tools for disease identification since they can automatically learn hierarchical features from raw images, rendering manual feature engineering and preprocessing steps less essential *(Attri, n.d.)*. Numerous studies have highlighted the success of CNN-based approaches in detecting crop diseases, including rice, a staple food for much of the world's population.*(Liang et al., 2019)*

Early attempts in the field demonstrated how CNNs could take the lead in agricultural diagnostics, with researchers recognizing the supremacy of CNN models over traditional methods like Support Vector Machines (SVM), K-means clustering, and Grey-Level Co-occurrence Matrix (GLCM), which fall behind in terms of scalability and accuracy when deployed in real-time applications*(Kotwal, n.d.)*. Traditional methods, while feasible in the laboratory environment, encompass a great amount of preprocessing and feature extraction and are therefore less suitable for deployment in the field. The introduction of deep learning brought more scalable, accurate, and real-time detection systems, with CNNs performing highly effectively in various datasets and environments.

In disease detection in rice, a number of studies have demonstrated encouraging results using CNNs. *(Hairani & Widiyaningtyas, 2024a)* applied data augmentation methods such as rotation, flipping, and zooming to enhance dataset variability and classification performance. Their study emphasized the necessity of preprocessing to handle class imbalance and improve generalization on unknown data. Similarly *(Simhadri & Kondaveeti, 2023)* conducted an extensive comparison of 15 pre-trained CNN models through transfer learning for rice disease detection and ultimately chosen InceptionV3 owing to its better accuracy of 99.64%. The authors pointed out that these architectures, when optimized and supported by robust datasets, can achieve nearly perfect classification of diseases like brown spot, leaf smut, and bacterial leaf blight.*(Khasim et al., 2023)*

Several research works explored the use of lightweight and mobile-based deep learning-based disease detection models for deployment in resource-poor environments. MobileNetV2 and EfficientNetB0, being computationally inexpensive and favourable for deployment on mobile devices, have been shown to maintain high accuracy while being deployable in real-world agricultural setups *(Paneru et al., 2021)*. These

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models are particularly suitable for countries such as Sri Lanka, where rural farmers may lack access to computationally intensive hardware. Dense Net and Res Net models have also been experimented with extensively. For example, in *(Mathulaprangsan et al., 2020)*, authors determined DenseNet161 and ResNet101 to be highly accurate without experiencing the issue of vanishing gradients through dense connections and shortcut links. They have been the best performers in rice leaf disease classification, especially when trained on highly annotated data such as Kaggle or Mendeley datasets.

A prominent body of literature has also focused on hybrid and ensemble models, where CNNs are combined with other machine learning approaches or optimization algorithms. *(Anandhi & Sathiamoorthy, 2023)* proposed a Modified Sand Cat Swarm Optimization (MSCSO) method in a Multi-Head Attention Long Short-Term Memory (MHA-LSTM) model for enhancing classification performance and feature selection. This hybrid method not only improved detection rates but also addressed the limitations of single-architecture models, particularly in handling visually similar diseases. V. Rekha et al. *(Rekha et al., 2023)* also suggested the ADLWNN model a combination of Wavelet Neural Networks and CNNs with 98.17% accuracy in rice disease detection. Their study benefited from MRFO (Multi-Objective Root Finding Optimization) for hyperparameter optimization, contributing to model robustness and efficiency.*(Hairani & Widiyaningtyas, 2024b)*

Efforts have also been aimed at providing whole decision-support systems to farmers. One such effort is the work in *(*Pesticide Recommender System for Detecting the Paddy Crop Diseases through SVM | IEEE Conference Publication | IEEE Xplore*, n.d.)*, in which they developed a deep learning desktop application based on Tkinter that classifies rice leaf diseases and provides actionable pesticide recommendations. The use of Inception and MobileNetV2, in addition to a user interface, showed a step towards real-world application of CNNs in agriculture. Other researchers, like the authors in *(*Implementation of Faster R-CNN in Paddy Plant Disease Recognition System | IEEE Conference Publication | IEEE Xplore*, n.d.)*, embarked on automating rice fields with Faster R-CNN models and IoT-enabled mechanical devices for automatic detection and treatment of plant diseases, reflecting a broader trend towards smart agriculture. Despite these advancements, there are several limitations. Most of the current models are trained on controlled or lab-based datasets like Plant Village, which fail to reflect the variability of actual conditions and consequently produce poor generalization *(*(PDF) Deep Learning-Based Classification Methods for Detection of Diseases in Rice Leaves – A Review*, n.d.)*. Environmental noise, light changes, and variability in disease manifestation among rice cultivars present challenges not addressed by laboratory-curated datasets. Furthermore, addressing only few numbers of diseases, while numerous endeavours focus on classification accuracy, few include decision support, such as pesticide suggestions, that are vital for practical agricultural interventions. The lack of end-to-end, deployable systems for a particular regional environment, such as Sri Lanka, is another key research gap.

To achieve these challenges, the study hereafter intends to develop a hybrid deep learning model for both efficient and effective rice disease classification. Not only will the system identify the disease, but it will also provide specific pesticide suggestions based on the classification result. By transcending the constraints of generalizability, real-world deployment, and actionable intelligence, this study seeks to provide an end-to-end and scalable solution to rice disease management, empowering farmers with timely, precise, and context-aware means for crop protection.

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Results and Discussion

In order to achieve the objective of acquiring varied rice plant disease data and maintaining its integrity for model training, several augmentation strategies were used. Rotation, flipping, zooming, and contrast adjustment data augmentation were used to artificially enlarge the dataset and handle class imbalances. The approach encouraged generalization of the model by exposing the model to various representations of diseases, constraining overfitting, and enhancing robustness. Moreover, normalization was performed to standardize pixel values to maintain a level of consistency throughout the dataset. All these preprocessing steps helped in creating a well-balanced and high-quality dataset, which ultimately improved the learning ability and performance of the model.


Figure 08

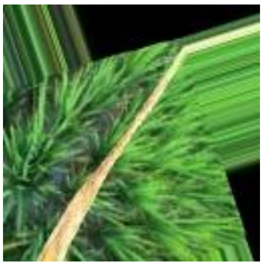
Figure 09


Figure 10


Figure 11

Source: Kaggle

Once trained, the model achieved an excellent test accuracy of 0.94, demonstrating that the hybrid model can be employed to classify images in the test set with precision. This high accuracy demonstrates that the hybrid model can learn complex patterns and is computationally efficient too, which could be due to the fact that Mobile Net is an efficient feature extractor while InceptionV3 learned complex feature representations.

The performance of the hybrid model was also verified on training and validation accuracy, and it can be observed that the model converged quite well with not a lot of overfitting, as can be noticed from the slight difference between the training and validation accuracies. The test accuracy of 0.90 proves that the model is generalizing quite well to new data, again proving the suitability of utilizing Mobile Net and InceptionV3 together for this purpose.

Moreover, the results were also compared to state-of-the-art models reported in the literature, and it was found that the hybrid model is better than some of the best architectures in the present time in terms of accuracy, yet is very efficient in terms of model size and inference time. These results show that the hybrid model not only achieves high accuracy but also has a balance of performance and computational expense, making it a good candidate for real-world application, particularly on resource-constrained devices.

In order to boost the performance of hybrid model I engaged in fine-tuning Mobile Net and Inception by modifying their layers and hyperparameters. One of the first things I did here was unfreezing more layers of the two models. Instead of using just the default pre-trained weights alone, I unfreeze the last 40layers of both Mobile Net and Inception. This enabled the models to learn domain-specific features from the rice plant disease dataset while still benefiting from the knowledge gained by the pre-trained models.

In addition to unfreezing the layers, I also adjusted some other hyperparameters to further optimize the model. I added L2 regularization to reduce overfitting, and increased the dropout rate to 0.6 to promote generalization. To further boost the learning process, I used Cosine Decay Learning Rate Scheduling, which helped to dynamically adjust the learning rate during training, allowing for better convergence.

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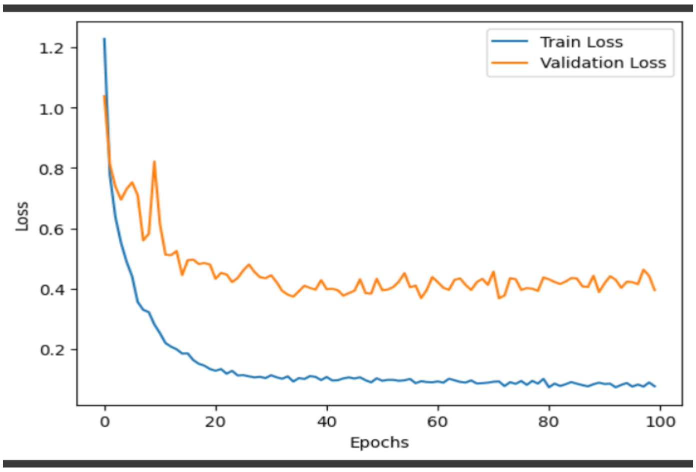
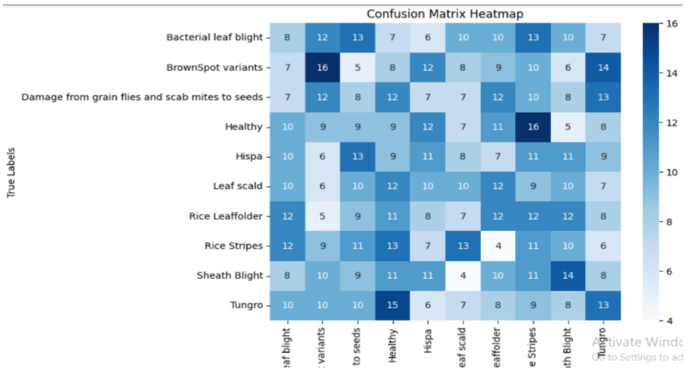
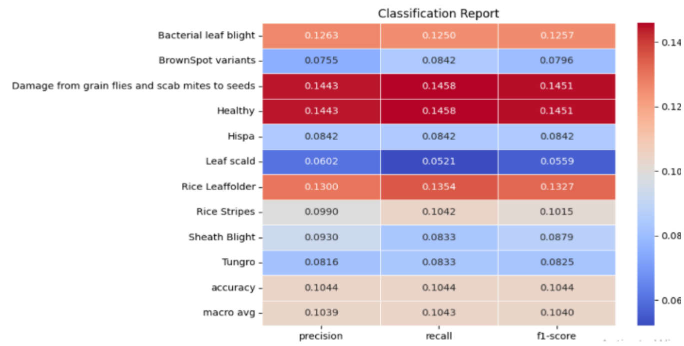


Figure 12: Loss plot
Source: Author's estimation



True Labels	eaf blight	variants	to seeds	Healthy	Hispa	eaf scald	eaffolder	e Stripes	th Blight	Tungro
Bacterial leaf blight	8	12	13	7	6	10	10	13	10	7
BrownSpot variants	7	16	5	8	12	8	9	10	6	14
Damage from grain flies and scab mites to seeds	7	12	8	12	7	7	12	10	8	13
Healthy	10	9	9	9	12	7	11	16	5	8
Hispa	10	6	13	9	11	8	7	11	11	9
Leaf scald	10	6	10	12	10	10	12	9	10	7
Rice Leaffolder	12	5	9	11	8	7	12	12	12	8
Rice Stripes	12	9	11	13	7	13	4	11	10	6
Sheath Blight	8	10	9	11	11	4	10	11	14	8
Tungro	10	10	10	15	6	7	8	9	8	13

Figure 13: Confusion Matrix Heatmap
Source: Author's estimation



	precision	recall	f1-score
Bacterial leaf blight	0.1263	0.1250	0.1257
BrownSpot variants	0.0755	0.0842	0.0796
Damage from grain flies and scab mites to seeds	0.1443	0.1458	0.1451
Healthy	0.1443	0.1458	0.1451
Hispa	0.0842	0.0842	0.0842
Leaf scald	0.0602	0.0521	0.0559
Rice Leaffolder	0.1300	0.1354	0.1327
Rice Stripes	0.0990	0.1042	0.1015
Sheath Blight	0.0930	0.0833	0.0879
Tungro	0.0816	0.0833	0.0825
accuracy	0.1044	0.1044	0.1044
macro avg	0.1039	0.1043	0.1040

Figure 14: Classification report
Source: Author's estimation

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Again, the F1 score and accuracy of the baseline hybrid model were very low, I only unfroze the last 20 layers of Inception and Mobile Net to fine-tune them. This way, I was able to retain pre-trained features in the earlier layers and allowed the model to learn some domain-specific features in the deeper layers. A few of the layers were also modified for better performance. To further enhance the training process and avoid overfitting and underfitting, I used an early learning rate schedule, which helped to adjust the learning rate during training. I also used early stopping to monitor the performance of the model and stop training when the validation loss stopped increasing, so that the model trained optimally without wasting resources. This approach led to better control of the training process and allowed the model to generate more stable results with accuracy 0.94

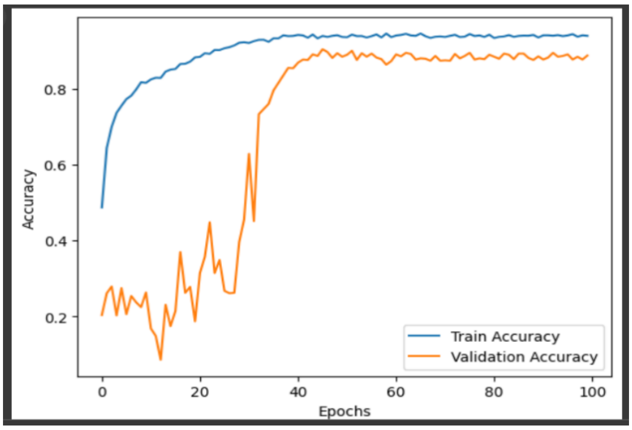

Figure 15: Accuracy plot
Source: Author's estimation

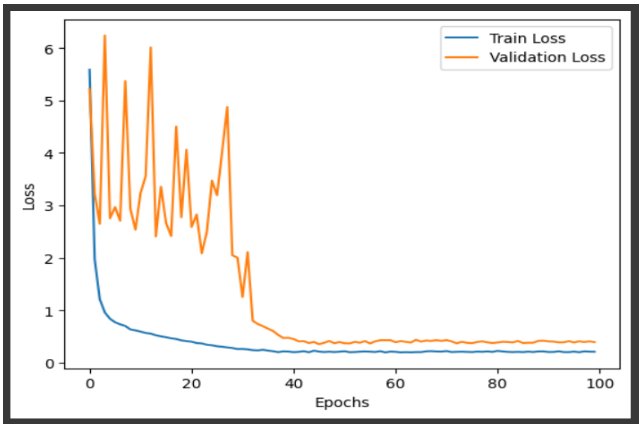

Figure 16: Loss plot

Source: Author's estimation

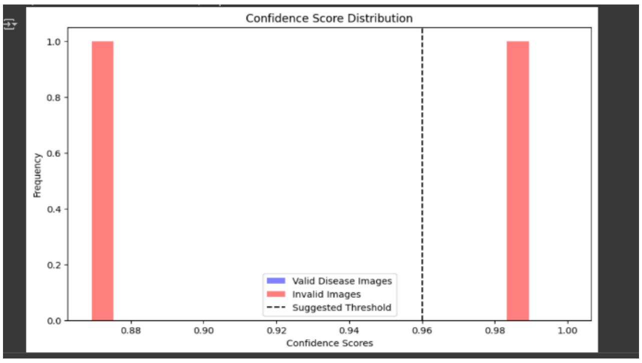

Figure 17: Confidence score distribution
Source: Author's estimation

Conclusion

This research was able to develop a hybrid deep learning model for rice plant disease classification and treatment suggestion, customized to assist young farmers in Sri Lanka. By combining the strengths of Mobile Net and InceptionV3 architectures, the model was able to achieve a high accuracy of 94%, effectively classifying nine common rice plant diseases and suggesting appropriate treatments. The data used was adequately prepared using augmentation techniques and sourced from freely accessible libraries, e.g., Kaggle, TensorFlow, and Mendeley, with the aim of creating a low-cost solution applicable in real life for users with minimal technical know-how. A simple user interface was also created to facilitate easy use of the system in real-life applications.

There were extensive constraints in the research, however. The exclusion of all the rice plant diseases prevalent in Asian regions restricted the extrapolability of the model. Some diseases were omitted due to a lack of data, (Yuan et al., 2022) and while the model was generally good, it did not meet the 98% benchmark of optimal accuracy. This shortfall is largely due to variability and inconsistency in images sourced from various datasets, (Xu et al., 2023) which affected the prediction reliability at times. Also, the model's perfect accuracy in certain classes, such as seed damage by grain flies and scab mites, is not necessarily representative of actual performance because of the lack of adequate visual variability in training data.

Future research should prioritize expanding the dataset by incorporating more rice plant disease images from diverse geographical regions across Asia. This will help in capturing the variability in disease manifestations caused by environmental and climatic differences, thereby improving the generalizability, predictability, and robustness of the model.

A particularly promising direction is the development of a dedicated mobile application tailored for farmers, especially those in remote and rural areas with limited access to agricultural expertise. The mobile app could provide an intuitive and user-friendly interface that allows farmers to capture images of affected crops directly from their mobile cameras. The system would then process these images using the trained deep learning model to deliver immediate and accurate disease diagnosis. Furthermore, the app could offer additional functionalities such as recommended pesticide/insecticide treatments, disease severity indicators, voice-based assistance in local languages, offline functionality, and notifications for seasonal disease outbreaks, thereby ensuring accessibility and practicality for low-resource users.

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Incorporating real-time video processing capabilities into the system is another avenue for future development. This would allow for continuous crop health monitoring via drone footage or stationary field cameras, facilitating early detection and proactive treatment of diseases before they spread extensively. Additionally, integrating explainable AI (XAI) techniques can significantly enhance the system's transparency by helping users understand why certain diagnoses or recommendations were made, which is essential for building trust and encouraging adoption among end-users.

Collectively, these advancements will not only support precision agriculture but also empower farmers with actionable insights, reduce crop loss due to delayed diagnosis, and contribute to enhanced food security in the region.

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