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MACHINE LEARNING FOR SUSTAINABLE AGRICULTURE: ENHANCING PADDY LEAF DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract:

Sustainable agriculture, crucial for long-term food security, faces challenges in maintaining rice yields amidst growing global demands, particularly in regions like Malaysia where rice is a staple. Early and accurate detection of paddy diseases is vital to minimize crop losses, but traditional manual inspection methods are time-consuming and often inaccurate. This paper addresses the need for a more efficient solution by using Convolutional Neural Network (CNN) model based on the InceptionV3 architecture to detect four common paddy leaf diseases: Bacterial Leaf Blight, Brown Spot, Leaf Smut and Hispa. The model was trained using datasets from Kaggle, employing data preprocessing and augmentation techniques to enhance accuracy. The results show high accuracy (95%), in classifying the targeted diseases, demonstrating its potential for real-world deployment in automated disease detection systems. This study presents a viable solution for modernizing paddy disease detection and management, offering a scalable tool for sustainable agriculture practices that can reduce crop losses and bolster food security amidst growing global demands.

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Keywords:

Plant Illness Identification, Paddy Fields, Convolutional Neural Network, Inceptionv3, Disease Classification

Introduction

Sustainable agriculture emphasizes practices that maintain soil health, conserve water, and reduce the use of chemical pesticides and fertilizers. One of the key elements in sustainable agriculture is food security, as to ensure long-term food availability of the present without compromising the ability of future generations to do the same (Pretty, 2008).

Rice holds a central position in Malaysia, deeply ingrained in the nation's food culture as a staple consumed by nearly everyone. As the Malaysian population grows and dietary habits evolve, rice consumption has steadily increased, transforming it into an increasingly demanding resource (Rajamoorthy et al., 2015). This heightened demand underscores the critical importance of ensuring stable and productive rice yields. The early and accurate detection of paddy diseases emerges as a vital component of this effort, enabling timely interventions to minimize crop losses and ultimately meet the escalating rice demand while bolstering food security in the face of growing consumption pressures. Thus, early disease detection in paddy crops is crucial for minimizing yield loss and environmental impact.

Deep Learning, a subset of machine learning, which uses artificial neural networks with multiple layers to analyze data, is ideal for image-based disease detection in paddy crops. Convolutional Neural Network (CNN) is one of the Deep Learning approaches that have become the leading approach for image classification tasks, demonstrating superior performance compared to traditional algorithms (Wu et al., 2019). CNN automatically extracts relevant features from images without the need for manual feature engineering, which is a significant advantage over traditional machine learning methods (Alsakar et al., 2024).

This paper will focus on the Convolutional Neural Network (CNN) model based on the InceptionV3 architecture to detect four paddy leaf diseases: Bacterial Leaf Blight, Brown Spot, Leaf Smut and Hispa. Leveraging datasets sourced from Kaggle, the model has been trained using comprehensive preprocessing and data augmentation techniques to enhance its accuracy and reliability.

Literature Review

Ensuring food security, which guarantees the ongoing availability of sustenance for current generations without jeopardizing future access, is a cornerstone of sustainable agriculture. This approach necessitates practices that protect our natural resources, keep the soil healthy, and ensure farms can produce food for the long haul. In Malaysia, this is particularly critical as the population expands and dietary preferences shift, leading to a greater demand for essential resources like rice. As Rajamoorthy et al., (2015) highlight, evolving consumption patterns are placing increased pressure on rice production, underscoring the urgency of adopting sustainable agricultural methods to meet the nation's growing needs while preserving resources for the future. This involves not only increasing yields but also minimizing environmental impact and ensuring the resilience of rice farming in the face of changing conditions.

With rising demand for rice, an increasing number of farmers are engaging in cultivating paddy. These farmers, frequently trained by the Malaysia Agricultural Research and Development Institute (MARDI), have historically used manual inspection by agricultural experts for disease detection. While effective, this traditional approach is time-consuming, labor-intensive, and struggles with accurately assessing the scope of infection in large fields (Mamat et al., 2020). The limitations of manual methods are further compounded by the complexity of distinguishing diseases with overlapping symptoms in visual analysis (Sethy et al., 2020) of symptoms like discoloration, lesions, or fungal growth on paddy leaves. These limitations highlight the need for a more efficient and accurate alternative for ensuring effective crop management and safeguarding global food security.

In ensuring effective paddy crops management, paddy leaves serve as a critical indicator for the health of paddy plants, often showing early and distinguishable symptoms of various diseases that can significantly impact crop yield and quality. These diseases, such as Blast Disease, Brown Spot, Sheath Blight, Uninfected Bacteria Leaf, Narrow Brown Spot and Infected Bacteria Leaf Disease, manifest through specific visual patterns like discoloration, lesions, or fungal growth, making the leaves a focal point for disease diagnosis (Parven et al., 2020). Early detection of these diseases is crucial, as delayed intervention can lead to the rapid spread of pathogens across fields, resulting in severe economic losses for farmers.

Digital image-based disease detection offers a transformative solution for identifying diseases in paddy crops (Sethy et al., 2020). With advancements in computer vision and machine learning, analyzing high-resolution digital images has become a reliable method for disease diagnosis. Unlike traditional techniques, this approach allows for the rapid processing of large datasets, enabling real-time monitoring and identification. The use of digital images is particularly advantageous because it captures subtle variations in color, texture, and pattern that may be imperceptible to the human eye, ensuring higher accuracy in disease classification (Rao Moparthi et al., 2021). Additionally, digital tools can be deployed in automated systems, such as drones or handheld devices, to scan extensive fields efficiently, saving time and reducing labor costs.

Moreover, integrating digital image analysis with deep learning models, such as Convolutional Neural Network (CNN), has further enhanced the precision and scalability of disease detection. These models can learn from large, annotated datasets, enabling them to recognize complex disease patterns and classify multiple types of diseases simultaneously. As such, digital image-based methods are not only a practical solution but also a forward-looking strategy for modernizing agricultural practices and safeguarding crop health in an era of growing global food demand.

Recent studies have demonstrated the versatility of CNN in agricultural applications. For instance, models like MobileNet, ResNet, and InceptionV3 have been successfully employed to detect multiple plant diseases, achieving high classification accuracies with datasets consisting of thousands of annotated images (Hu et al., 2024). Moreover, innovative architectures like 14-layer deep CNN have achieved classification accuracies exceeding 99%, showcasing their potential for real-world deployment (Pandian et al., 2022).

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In addition to accuracy, CNN offers scalability and adaptability. Through transfer learning and augmentation techniques, these models can be fine-tuned for specific crops and disease types, making them a cost-effective solution for diverse agricultural settings (Deb et al., 2023). Their integration into mobile and automated systems further facilitates on-the-spot disease diagnosis, enabling farmers to take swift remedial actions, ultimately improving crop management and productivity (Fauzi et al., 2023).

Mamat et al., 2020 had developed a paddy leaf disease recognition system using image processing techniques and a Support Vector Machine (SVM) classification model. This system is specifically designed to identify Bacterial Leaf Blight, Brown Spot, and Leaf Smut. While the system demonstrates a promising approach to disease detection, its accuracy of 88.57% suggests room for improvement. The use of SVM, although effective, might be limited compared to more advanced deep learning models like Convolutional Neural Network (CNN), which have shown superior performance in image classification tasks.

In a recent article by Zheng & Huang (2021), a mango grading system was established, utilizing a Convolutional Neural Network (CNN) model, incorporating CCD camera image acquisition, image preprocessing, model training, and evaluation. To address the need for extensive sample data in traditional deep learning, the system employs a CNN optimized for efficiency through parameter adjustments and batch size. The ultra-lightweight SqueezeNet algorithm was chosen for its small model size and fast operation speed, offering advantages over algorithms like AlexNet with comparable accuracy. The CNN model was trained and tested using 234 Jinhuang mangoes, achieving an average accuracy of 97.37%, an average error rate of 2.63%, and an average loss value of 0.44. The reported accuracy of 97.37% is quite promising, suggesting the system's effectiveness in mango grading.

Deep learning, particularly Convolutional Neural Network (CNN), holds immense potential to transform crop management and disease control by providing efficient, accurate, and scalable solutions for detecting plant diseases. Among the various CNN architectures, InceptionV3 stands out as a powerful tool for image classification tasks, making it highly suitable for agricultural applications. Developed by Google and introduced in the seminal paper "Rethinking the Inception Architecture for Computer Vision" (Szegedy et al., 2015), InceptionV3 is renowned for its ability to identify complex patterns in images. By leveraging this advanced technology, farmers can rapidly and precisely detect diseases in crops, reducing reliance on time-intensive manual inspections and enhancing agricultural productivity and sustainability. Ultimately, the effectiveness of CNN in disease detection represents a transformative leap in agricultural technology, offering unparalleled accuracy, scalability, and efficiency to address the challenges of global food security, promoting sustainable agriculture.

This study aims to create a paddy leaf disease detection model using Convolutional Neural Network (CNN). Focusing exclusively on paddy leaf diseases, the model leverages InceptionV3 architecture, has been trained and tested using secondary data sourced from Kaggle. The CNN classification model is designed to specifically detect Bacterial Leaf Blight, Brown Spot, Leaf Smut and Hispa, offering an automated, efficient, and scalable alternative to traditional, less accurate methods. By employing CNN-based digital image analysis, this study intends to modernize paddy disease detection and management, thereby assisting farmers in minimizing crop losses and bolstering food security amidst a growing global population. Ultimately, this approach contributes to enhanced crop management, reduces the need for

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manual inputs, promotes more sustainable agricultural practices, and supports food security by minimizing crop losses due to disease. This approach offers a way to modernize agricultural practices while addressing global food demand challenges.

Material and Methods

In this study, data for paddy leaf are sourced from Kaggle, which is a platform that provides public dataset to be used for machine learning. These data have been used for training and testing the model. Kaggle data have been selected for this study for several reasons, including its large and diverse dataset, which makes them the perfect choice for training machine learning models. These data are additionally well-organized, making it simple to access and utilize. Each of the paddy leaves has been categorized into four types of diseases which are Bacterial Leaf Blight, Leaf Smut, Brown Spot and Hispa.

Dataset Preparation and Preprocessing Model Design

To prepare the image data for effective model training and evaluation, a series of preprocessing steps were implemented. The primary objective of this phase was to refine the dataset by eliminating irrelevant information and artifacts that could negatively impact performance. Initially, any damaged or unreadable images were identified and removed through visual inspection. Subsequently, several techniques were applied to enhance the remaining images: first, image colors were transformed into shades of grey; next, the dataset was expanded using a variety of augmentation techniques, and image contrast was improved using Histogram Equalization. Additionally, each image was accurately labelled according to its corresponding disease class, pixel values were scaled to a standard range, and any statistical outliers or anomalous data points were removed. These meticulous preprocessing procedures ensure that the data used for model training is of high quality and free from inconsistencies, ultimately promoting the development of a robust and accurate disease detection system.

Data preprocessing is a fundamental step in machine learning, ensuring optimal model training. For image classification tasks, this involves transforming raw image data into a trainable format. A useful tool for this is the Keras Image Data Generator. This Keras function creates real-time, augmented image data in batches. This provides a flexible data preprocessing pipeline that transforms the image data as it is passed to the model. Various data augmentation techniques had been applied, including image rotations, zoom, and flips, increasing the training dataset's diversity and improving the model's robustness. Normalization of image data, achieved by scaling to a specific range (such as 0 and 1), also had been performed to improve performance. Furthermore, the Image Data Generator loads and feeds images in batches, which is particularly helpful for large datasets that cannot be loaded entirely into memory.

CNN Model Design

In this study, the InceptionV3 architecture was employed as the CNN model. The training process begins with image database pre-processing. During this stage, class labels are also stored for later reference. Following pre-processing, the next step involves feature extraction. This is where the CNN identifies and extracts relevant features from the input images, which are crucial for accurate classification. The convolutional layers within the CNN automatically handle the feature extraction process. These layers operate by convolving a set of filters (also known as kernels or weights) with the input image, effectively identifying patterns and characteristics. Once extracted, these features are compiled into a feature set. This feature set, representing the key characteristics of the image, is then fed into the fully connected layers of

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the network for classification. With the feature set and corresponding class labels stored, the trained InceptionV3 model is saved and ready for testing. The testing phase involves querying the system with a new image. This image undergoes similar pre-processing steps before its features are extracted. The system then queries the trained InceptionV3 model with these extracted features, and the model subsequently outputs the predicted class label for the input image. Lastly, the model delivers out the class label of the queried image (Saha, 2021).

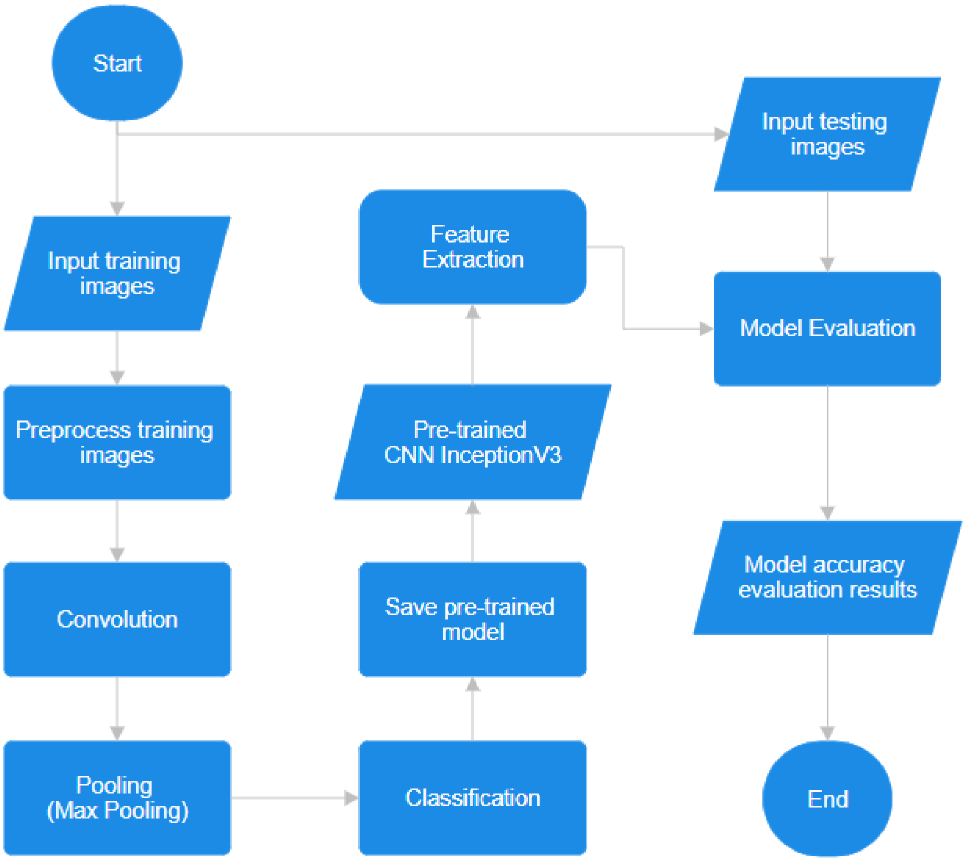

Figure 1: Flow Chart for Inceptionv3 Convolutional Neural Network Training

The Convolutional Neural Network basic architecture model (Tejaswini et al., 2022) that had been used in this study consists of several layers, each performing a specific function to process and classify the input images, as illustrated in Figure 2.

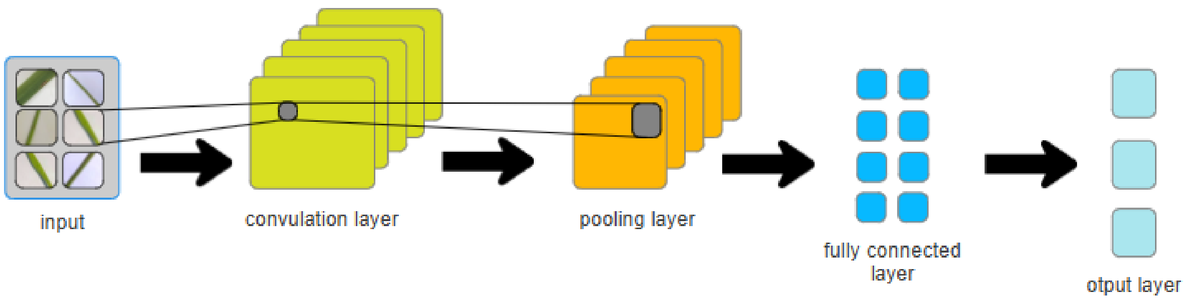

Figure 1: The Convolutional Neural Network Basic Architecture
Source: (Tejaswini et al., 2022)

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- **Input layer**: The input of CNN consists of the images that were separated as training and testing images.
- **Convolution Layer:** This layer uses filters to analyze small parts of an image, allowing it to learn and extract important features from those parts.
- **Pooling Layer:** This layer reduces the image's size, which decreases the amount of processing power needed for the following layers. In this study, max pooling is employed, where the pixel with the highest value in each section of the image is chosen and passed on to the output. This method is more commonly used than average pooling because it effectively captures the most significant features.
- **In classification layer process**, there are several layers which are:
  - **Fully Connected Layer (Dense)**: This layer, typically one of the last in CNN, identifies features closely related to the output class. The outcome is a one-dimensional vector formed by flattening the results from the pooling layer.
  - **Dropout Layer:** This technique is used to prevent model overfitting by randomly dropping a set of neurons in the layer, particularly in fully connected (FC) layers.
  - **SoftMax Layer:** This network's final layer performs classification, assigning each input image to a specific disease class according to the learned features.
  - **Output Layer:** The output layer contains the final classification result. Ensuring food security, which guarantees the ongoing availability of sustenance for current generations without jeopardizing future access, is a cornerstone of sustainable agriculture.

Results and Discussion

The CNN model was trained to distinguish between four classes of paddy leaf diseases: Bacterial Leaf Blight, Brown Spot, Leaf Smut, and Hispa. The training process involved tuning several key parameters, such as batch size, activation methods, number of dense layers, epochs, and image zoom. Preliminary experiments indicated that the number of dense layers and image zoom had minimal influence on the model's accuracy. Consequently, these parameters were fixed based on recommendations from existing literature, while other parameters were optimized to maximize performance. Table 1 summarizes the training results obtained with the optimized configuration using the RGB image dataset.

Table 1: RELU+SoftMax Activation Results on RGB Image Dataset with 4 Classes

Relu + SoftMax	Batch Size	Accuracy	Val Accuracy	Loss	Val Loss	Dense	Epochs	Zoom
	1	0.9761	0.9409	0.0717	0.1597	256	20	0.3
	2	0.9884	0.9545	0.0357	0.1111	256	20	0.3
	3	0.9893	0.9409	0.0307	0.1356	256	20	0.3
	4	0.981	0.9409	0.055	0.1408	256	20	0.3
	5	0.9851	0.95	0.0407	0.1179	256	20	0.3
	6	0.986	0.9545	0.0394	0.1171	256	20	0.3
	7	0.981	0.9636	0.0491	0.1078	256	20	0.3
	8	0.9901	0.9591	0.0292	0.0933	256	20	0.3
	9	0.9868	0.95	0.0513	0.1403	256	20	0.3
	10	0.9835	0.9273	0.0441	0.1544	256	20	0.3
	11	0.9802	0.9409	0.0618	0.1273	256	20	0.3
	12	0.9909	0.9591	0.0365	0.1029	256	20	0.3
	13	0.9835	0.9545	0.0442	0.1337	256	20	0.3

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14	0.9851	0.9409	0.0456	0.1295	256	20	0.3
15	0.9909	0.9545	0.0329	0.1002	256	20	0.3
16	0.9876	0.9409	0.0386	0.1008	256	20	0.3
17	0.9761	0.9455	0.069	0.1456	256	20	0.3
18	0.9876	0.9682	0.0357	0.104	256	20	0.3
19	0.9736	0.1257	0.0741	0.9455	256	20	0.3
20	0.9876	0.95	0.041	0.1175	256	20	0.3

Table 2: Accuracy and Loss Optimization Results

	Accuracy	Val Accuracy	Loss	Val Loss
Max Accuracy value	0.9909	0.9682		
Min Loss Value			0.0292	0.0933

The results in Table 2 indicate a maximum training accuracy of 99% and a testing accuracy of 96%. Further analysis revealed that a batch size of 8 produced the optimal model, exhibiting a 99% training accuracy, a 95% testing accuracy, and the lowest loss value compared to other batch sizes tested. The training results of the optimized parameter configuration towards the four classes' dataset of the RGB Greyscale are shown in Table 3.

Table 3: RELU+SoftMax Activation Results on Greyscale Image Dataset with 4 Classes

Relu + SoftMax	Batch Size	Accuracy	Val Accuracy	Loss	Val Loss	Dense	Epochs	Zoom
	1	0.9794	0.9182	0.0598	0.255	256	20	0.2
	2	0.9777	0.9045	0.0602	0.2307	256	20	0.2
	3	0.9901	0.9273	0.0342	0.214	256	20	0.2
	4	0.9744	0.9136	0.0812	0.2637	256	20	0.2
	5	0.9851	0.197	0.0523	0.197	256	20	0.2
	6	0.9909	0.9273	0.0319	0.1944	256	20	0.2
	7	0.9876	0.9227	0.0451	0.2439	256	20	0.2
	8	0.9851	0.9273	0.0359	0.2583	256	20	0.2
	9	0.986	0.9273	0.0546	0.2229	256	20	0.2
	10	0.9868	0.9182	0.0518	0.2452	256	20	0.2
	11	0.9884	0.9182	0.0411	0.2186	256	20	0.2
	12	0.9827	0.8909	0.0589	0.2853	256	20	0.2
	13	0.9777	0.9091	0.0551	0.2049	256	20	0.2
	14	0.9893	0.9091	0.0393	0.2254	256	20	0.2
	15	0.9802	0.9182	0.0598	0.2337	256	20	0.2
	16	0.9868	0.9318	0.0409	0.1969	256	20	0.2
	17	0.9851	0.9227	0.0447	0.2297	256	20	0.2
	18	0.9827	0.9227	0.0541	0.211	256	20	0.2
	19	0.9901	0.9182	0.0397	0.2082	256	20	0.2
	20	0.8475	0.7709	0.2814	0.4791	256	20	0.4
	20	0.9843	0.9182	0.0494	0.2162	256	20	0.2

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Table 4: Accuracy and Loss Optimization Results

	Accuracy	Val Accuracy	Loss	Val Loss
Max Accuracy value	0.9909	0.9318		
Min Loss Value			0.0319	0.1944

As illustrated in Table 4, the evaluation of the trained models demonstrated a maximum training accuracy of 99% and a testing accuracy of 93%. Further analysis indicated that a batch size of 8 produced the most effective model, characterized by a training accuracy of 98%, a testing accuracy of 92%, and the lowest loss compared to other tested batch sizes. Table 5 provides a comprehensive overview of the training results of Histogram Equalization.

Table 5: Training Performance with Histogram Equalization

Relu + SoftMax / Type	Batch Size	Accuracy	Val Accuracy	Loss	Val Loss	Dense	Epochs	Zoom
Greyscale	20	0.25	0.25	1.3863	1.3863	256	20	0.3
Greyscale	50	0.3201	0.4864	1.3435	1.335	256	20	0.3
Greyscale	100	0.3408	0.4273	1.3507	1.3409	256	20	0.3
RGB	8	0.25	0.25	1.3863	1.3863	256	20	0.3
RGB	8	0.25	0.25	1.3863	1.3863	256	20	0.3

Contrary to expectations, Histogram Equalization negatively impacted model accuracy for both RGB and greyscale images. Despite this, RGB images still achieved slightly higher accuracy than their greyscale counterparts. The optimal configuration remained the RGB model trained with a batch size of 8, even with the reduced accuracy due to Histogram Equalization.

The paddy leaf disease recognition utilizing a CNN approach, successfully demonstrates the effectiveness of machine learning, specifically the InceptionV3 model, for paddy leaf disease identification. Achieving an impressive 95% accuracy in classifying paddy leaf diseases is a significant outcome. Accurate and timely diagnosis is crucial for effective disease management in agriculture, directly impacting crop yield and reducing losses. The model effectively classified Bacterial Leaf Blight, Brown Spot, Leaf Smut, and Hispa, demonstrating its ability to detect a range of common paddy leaf diseases.

Despite its strengths, the model has some weaknesses. The model's tendency to produce incorrect classifications suggests potential limitations in the CNN architecture or insufficient diversity in the training dataset. Further, the lengthy classification process may hinder rapid and accurate field diagnoses. These limitations could be addressed by enhancing data collection to improve dataset diversity and streamlining the CNN architecture to reduce processing time.

Material and Methods

The use of CNN, particularly InceptionV3, in paddy leaf disease recognition signifies a major advancement in agricultural technology. This study successfully demonstrated InceptionV3's ability to classify four common paddy diseases with high accuracy (95%), highlighting the transformative potential of deep learning to overcome the limitations of time-consuming, labor-intensive, and error-prone manual detection. These CNN-based models enable rapid, reliable,

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and scalable disease identification, offering farmers a practical tool for improved decision-making, resource optimization, and minimized crop losses, thus enhancing rice production's productivity and sustainability. This aligns with the broader goal of machine learning in promoting sustainable agriculture through improved crop management and resource efficiency. Future improvements could further enhance the model capabilities. Incorporating a more effective classification layer, such as XGBoost, could boost accuracy. Expanding the dataset to include images captured in complex, real-world field conditions would improve the system's practical applicability. Moreover, integrating a recording feature enabling farmers to track observations and disease spread over time would facilitate better-informed crop management decisions. These enhancements would collectively contribute to a more reliable, accurate, and field-ready solution for sustainable agriculture.

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