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A Hybrid Approach: SVM-Ensemble Transfer Learning For Comprehensive Rice Plant Disease Detection

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Abstract : Accurate and timely identification of diseases and pests impacting rice cultivation is critical for farmers to swiftly intervene and minimize economic losses. While recent advancements in convolutional neural networks (CNNs) have boosted image classification accuracy, their resource-intensive nature necessitates leveraging pre-trained models. Additionally, this paper introduces an ensemble approach combining deep learning with traditional machine learning methods, enhancing disease and pest detection effectiveness in agriculture. Leveraging the ResNet-50 architecture, the study proposes a model integrating ResNet-50 with SVM for rice disease and pest detection. Experimental results on authentic datasets demonstrate the model's effectiveness. Furthermore, considering the limitations of large-scale architectures for mobile or embedded devices, the proposed model is introduced and evaluated, achieving a superior accuracy of 90.6%. This highlights its potential for practical implementation in real-world scenarios.

Keywords: Deep learning, Ensemble methods, Rice plant disease detection, Pretrained models, Support vector machines

1. INTRODUCTION

Automated detection systems for plant diseases have become indispensable in modern precision agriculture. Various diseases caused by fungi, bacteria, and insects pose significant threats to crop yield and overall productivity. The classification of diseases affecting plant leaves presents a substantial challenge due to the similarities between different disease classes and the complex variations in patterns. Additionally, changes in climate conditions can exacerbate the spread of plant infections. Early detection of diseases affecting plant leaves is crucial for maintaining optimal agricultural productivity. Given that diseases contribute to more than half of the reduction in plant productivity, timely identification allows for swift intervention, thus minimizing crop losses.

In agriculture, rice cultivation encounters significant hurdles posed by diseases that compromise both the quality and quantity of the crop. This underscores the urgent need for automated identification and detection of plant diseases to enhance yield. Rice holds crucial significance as a staple cereal crop, with its cultivation playing a central role in our agricultural economy. Across the growth stages of rice, diseases affecting the plants emerge as a major worry for farmers, resulting in considerable losses alongside challenges posed by pests and environmental factors. Despite the array of methods available for disease detection in crops, including image processing and remote sensing, these systems frequently demonstrate subpar accuracy.

The rapid expansion of India's population underscores the pressing need for significant advancements in agricultural practices and cultivation methods. Rice, a staple crop, holds paramount importance as the nation's primary food source [1]. However, rice is particularly susceptible to plant diseases, posing significant challenges to cultivation and overall profitability. To overcome these hurdles and enhance crop yields, it is crucial to detect and prevent plant diseases at their early stages [2]. Relying solely on visual observation for disease prediction is often slow, occasionally inaccurate, and can lead to increased costs. Additionally, accurately identifying disease types presents difficulties and is prone to errors [3]. These challenges stem from a limited understanding of the plant's complexities. Consequently, the failure to anticipate or identify diseases in rice plants at an early stage has detrimental effects on rice production, as observed over recent decades [4].

The image processing technique for disease detection typically involves several steps, including image acquisition, preprocessing, segmentation, feature extraction, and classification [5]. However, handcrafted feature extraction for rice plant disease detection comes with inherent limitations [6]. Firstly, crafting effective features manually demands specialized domain knowledge and consumes significant time, posing challenges in capturing all pertinent information comprehensively. Moreover, handcrafted features may lack robustness in generalizing across various types of rice plant diseases and diverse environmental conditions. Furthermore, this approach exhibits limited adaptability, necessitating manual intervention for feature modifications to address evolving disease patterns or incorporate new data.

The limitations associated with the utilization of Convolutional Neural Networks (CNNs) for detecting diseases in rice plants include the requirement for extensive labeled data, susceptibility to overfitting, and computational complexity, presenting challenges in resource-limited settings [6].

The research paper presents a novel approach that combines a Convolutional Neural Network (CNN), specifically utilizing a ResNet-50 architecture, with traditional machine learning methods such as Support Vector Machine (SVM). The study leverages a substantial dataset containing images of both healthy and unhealthy rice plants gathered from real-world scenarios. By utilizing a pretrained ResNet model for feature extraction, the paper aims to minimize training time overhead. The proposed model involves feeding the output features of ResNet-50 directly into an SVM classifier. To evaluate the effectiveness of the proposed models, benchmark datasets are employed. Performance metrics including accuracy, precision, recall, and F1 score are utilized to assess this approach.

2. RELATED WORK

In the realm of agricultural image recognition and classification, two primary technological categories dominate: deep learning and traditional machine learning [7]. Deep learning has particularly demonstrated rapid advancements and notable achievements in this field. For instance, Mohanty et al. successfully developed a deep learning model capable of identifying 14 different crop species and detecting 26 various crop diseases [8]. However, previous research efforts in the area of rice plant infection recognition and classification have been limited. Lu et al. introduced a novel method utilizing Deep Convolutional Neural Network (DCNN) for predicting rice plant diseases. Their research utilized a dataset containing numerous images depicting both healthy and diseased paddy stems and leaves, resulting in enhanced accuracy compared to conventional machine learning methods. Furthermore, Dhingra et al. developed a segmentation model based on neutrosophic logic, derived from fuzzy set theory, to estimate Regions of Interest (ROI). This model utilized three Membership Functions (MFs) for segmentation, utilizing feature subsets for predicting the presence of plant leaf infections based on segregated sites. Additionally, Islam et al. introduced an innovative method for predicting and classifying rice plant diseases. Their approach employs image processing (IP) techniques to detect diseases by analyzing the proportion of RGB values in the affected area. In the context of paddy leaf disease prediction, automated disease detection is facilitated through the utilization of image processing (IP) techniques. In this investigation, a hybridized methodology integrating grayscale co-occurrence matrix, Discrete Wavelet Transform (DWT), and Scale Invariant Feature Transform (SIFT) was adopted for feature extraction. These extracted features were subsequently employed in conjunction with various machine learning classifiers to distinguish between healthy and diseased crops.

Kaya et al. [9] conducted an analysis on the outcomes of implementing four distinct Transfer Learning (TL) strategies for plant classification using Deep Neural Networks (DNNs) on four standard datasets. Their findings highlighted the significant advantages of TL in automated plant prediction, consequently enhancing the performance of plant disease classifiers. In a previous study [10], a Convolutional Neural Network (CNN) model was employed to forecast weeds in soybean crop images, distinguishing between grass and broadleaf weeds. The image dataset comprised various soil, soybean, broadleaf, and grass weed images. CNN, utilized for Deep Learning (DL), demonstrated optimal results in image recognition tasks.

3.THE PROPOSED RICE PLANT DISEASE DETECTION MODEL

3.1 Framework Overview

Our research endeavors in rice plant disease identification employ a dual approach, integrating transfer learning and traditional machine learning algorithms, delineated in Fig. 1, where Fig. 1 corresponds to the proposed Model. Initially, rice plant images are categorized based on predefined classes as detailed in Table 1, then processed through a pretrained ResNet-50 model via transfer learning. This model, initially trained on the ImageNet dataset featuring 1000 classes, adeptly extracts multi-level features. Leveraging transfer learning enables us to conserve computational resources by retaining the pretrained network parameters.

In the proposed Model, the pretrained ResNet-50 model automatically extracts features, yielding embeddings utilized for classification via an SVM machine learning classifier. Further elucidation on these methodologies is provided in subsequent sections.

3.2 Overview of the proposed Model

Figure 1 presents a detailed block diagram illustrating our proposed model for rice plant disease detection. The depicted flowchart outlines the sequential steps, beginning with the input of rice plant images into the model. Our model integrates a pre-trained ResNet-50 model, renowned for its proficiency in feature extraction from input images. These extracted features are then input into an SVM classifier to accurately classify the images into their respective disease categories.

One noteworthy advantage of our methodology is the incorporation of a pretrained ResNet-50 model [11], which notably decreases training time while benefiting from the model's proficiency in image feature extraction. Furthermore, by employing a Support Vector Machine (SVM) [12] classifier instead of Artificial Neural Networks (ANN) [13], we ensure seamless operation of our model even on systems with limited resources, such as mobile devices or embedded systems. This strategic decision guarantees the accessibility and applicability of our model across various platforms, including those with low-end resources.

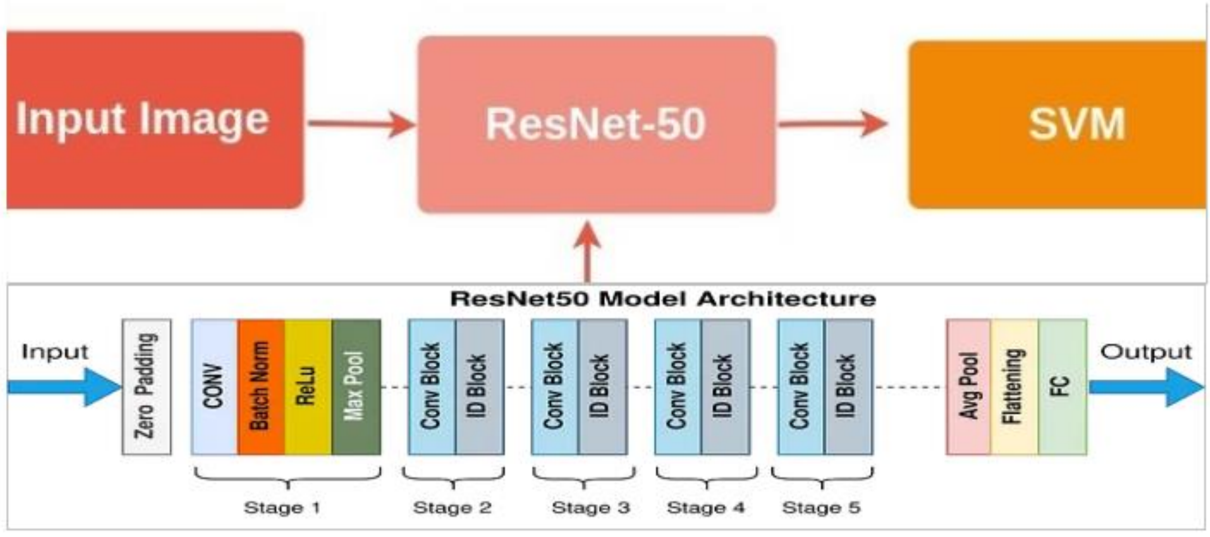

Figure 1: Integrated Framework for Disease Detection in Rice Plants.

A clear advantage of our approach is the integration of a pretrained ResNet-50 model, significantly reducing training time while leveraging its expertise in feature extraction from images. Additionally, harnessing the effectiveness of a Support Vector Machine (SVM) [14] classifier over Artificial Neural Networks (ANN) [15] enhances the adaptability of our model, enabling seamless operation even on resource-constrained platforms such as mobile or embedded systems. This strategic decision ensures the accessibility and applicability of our model across diverse platforms, including those with limited resources.

3.3 ResNet-50

ResNet-50 [16] is a distinguished convolutional neural network architecture renowned for its depth and effectiveness in image-related tasks. With 50 layers, it excels in extracting features from input images typically sized at 224x224 pixels in RGB format. Its output dimensions vary depending on the task, often resulting in 1000 classes for ImageNet classification. ResNet-50 introduces innovative skip connections, directly linking layers to address the issue of vanishing gradients and promote smoother gradient flow during training. Additionally, ResNet-50 incorporates bottleneck blocks, where 1x1 convolutions reduce computational complexity while maintaining representation power. Lastly, it adopts global average pooling as its final layer, summarizing feature maps into a concise representation instead of traditional fully connected layers, contributing to its widespread adoption and success in computer vision applications.

3.4 SVM

Support Vector Machines (SVMs) [17] are utilized for classifying a rice image dataset comprising 9 classes, including 5 diseases, 3 pests, and 1 healthy class. SVMs function by identifying the hyperplane that optimally separates these classes in the feature space, with the objective of maximizing the margin between classes. By employing kernel functions, SVMs can accommodate both linear and non-linear classification, facilitating the classification of rice images affected by various diseases and pests. Their resistance to overfitting makes SVMs well-suited for this task, enhancing their effectiveness in identifying and distinguishing between different rice health conditions [18].

4. RESULTS AND DISCUSSION

In this section, a series of tests were conducted on a laptop T490, equipped with a Core i7 CPU and 16 GB of memory. The experimental setup utilized Jupyter Notebook operating with Python 3.7. Initially, tests were performed on the dataset using the proposed Model, followed by experiments with the proposed Model. Subsequently, a comprehensive comparison and evaluation were conducted, examining performance across various evaluation metrics including accuracy, precision, recall, F1 score, and feature count [19].

4.1 Dataset

Rice plants are susceptible to numerous diseases and pests that can affect various parts of the plant. This study encompasses nine classes, comprising five diseases, three pests, and one healthy plant class. The classification details are outlined in Table 1, with certain diseases grouped together due to similar treatment methods and occurrence patterns. Symptoms are evident in different parts of the rice plant, with diseases like Bacterial Leaf Blight and pests like Brown Plant Hopper primarily impacting the leaves. Other diseases such as Sheath Blight and pests like Stemborer target the stem, while Neck Blast and False Smut affect the grains. To avoid confusion between diseased and dead plant parts, images of both have been included in the dataset. Additionally, some classes display multiple symptom variations, as detailed in Table 1, to encompass all observed variations found in BRRI's paddy fields. Sample images for each class are illustrated in Figure 3.

Table 1: Collection of images representing various classes.

Class Name	Type	Number of collected Images	In tra-class variations in symptoms	Images count
Flase smut	Disease	93	Brown symptoms	66
			Black symptoms	27
Brown Plant	Pest	71	Early detection of BPH infestation	50

Hopper (BPH)			Advanced stage of BPH infestation.	21
Bacterial Leaf Blight (BLB)	Disease	138	No noticeable symptoms variation.	138
Neck Blast	Disease	286	No noticeable symptoms variation.	286
Stemborer	Pest	201	Symptoms of stem borer pest infestation on grains.	180
			Symptoms of stem borer pest infestation on stems.	21
Hispa	Pest	73	black pests and also white spots visible on plant leaves	53
			Pronounced spots on leaves with no visible pests suggest a potential issue or infection.	20
Sheath Blight & Sheath Rot	Disease	219	Black stems indicate a potential problem or disease affecting the plant.	70
			White spots on the plant indicate potential issues	77
			Mixed black and white symptoms	72
Brown Spot	Disease	111	No noticeable symptoms variation.	111
Healthy	Healthy	234	Healthy green leaves and stems indicate optimal plant health.	96
			Yellow grains indicate that the plant has reached maturity and is healthy.	71
			Dead leaves and stems	67

The dataset utilized in this research, consisting of 1426 images illustrating different rice diseases and pests, was collected from real-life scenarios in Bangladesh Rice Research Institute's [BRRI] paddy fields. This dataset has been made publicly available by Chowdhury R. Rahman et al. [15]. It comprises nine classes, including eight classes representing various rice diseases and pests, as well as one class denoting healthy rice plants. Access to the dataset can be obtained through the provided link

(https://drive.google.com/open?id=1ewBesJcguriVTX8sRJseCDbXAF_T4akK)[15]. Additional details about the dataset can be found in the referenced publication [15].

Figure 2 : A sample image of each detected class.

4.2 Experimental findings

In this study, we conducted experiments to assess the performance of the proposed model for a specific task, utilizing the Rice dataset. The proposed model incorporates an ensemble approach, comprising a pretrained ResNet-50 and Support Vector Machine (SVM). The dataset was split into training and testing sets in an 8:2 ratio.

The proposed model employs a pretrained ResNet-50 for feature extraction, generating a total of 100,352 features from the input data. These features are then input into a Support Vector Machine (SVM) classifier for classification. The accuracy achieved by the proposed model was measured at 90.6%, with an F1 score of 74.32. Furthermore, the recall and precision rates were found to be 73.02% and 80.38%, respectively.

4.3 Performance of the Proposed Model

To assess the performance and generalizability of our proposed model, we conducted experiments using a dataset comprising 1426 images of paddy. This dataset consists of 9 classes, comprising 8 diseased classes and 1 healthy class. All images are standardized to a size of 256x256 pixels with 3 channels. The dataset is partitioned into training and testing sets at a ratio of 8:2. Evaluation metrics include precision, recall, F1-score, and the number of parameters.

$$\text{Accuracy} = (T_n+T_p) / (T_n+F_p+T_p+F_n)$$

$$\text{Precision} = T_p / (T_p+F_p)$$

$$\text{Recall} = T_p / (T_p+F_n)$$

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

In binary classification, the terms Tp (True Positive), Tn (True Negative), Fp (False Positive), and Fn (False Negative) are technical terms used to evaluate classifier performance. Specifically, Tp refers to positive samples correctly classified, Tn denotes negative samples correctly classified, Fp indicates positive samples misclassified, and Fn represents negative samples misclassified [20].

The experimental comparison results are presented in Table 2. These experiments were conducted in a designated experimental environment, ensuring consistency and reproducibility in the obtained results. The results offer valuable insights into the efficacy of the proposed models for the given task. Here, we provide a comparative analysis of their performance.

Table 2 : The metrics from the comparison experiments.

Dataset	Indicator	Results
Rice	**Accuracy**	**0.9055**
	Precision	**0.8038**
	Recall	**0.7302**
	F1-score	**0.7432**

The proposed model showcases superior performance across all metrics evaluated on the rice image dataset. With higher accuracy (0.9055), precision (0.8038), recall (0.7302), and F1-score (0.7432), it demonstrates a notable proficiency in accurately identifying rice instances within the image dataset. The elevated precision signifies its enhanced capability to correctly identify true positives, while the heightened recall indicates its ability to capture a larger proportion of actual rice instances. Consequently, this results in a better balance between minimizing false positives and false negatives, emphasizing the effectiveness of the proposed model in rice image classification.

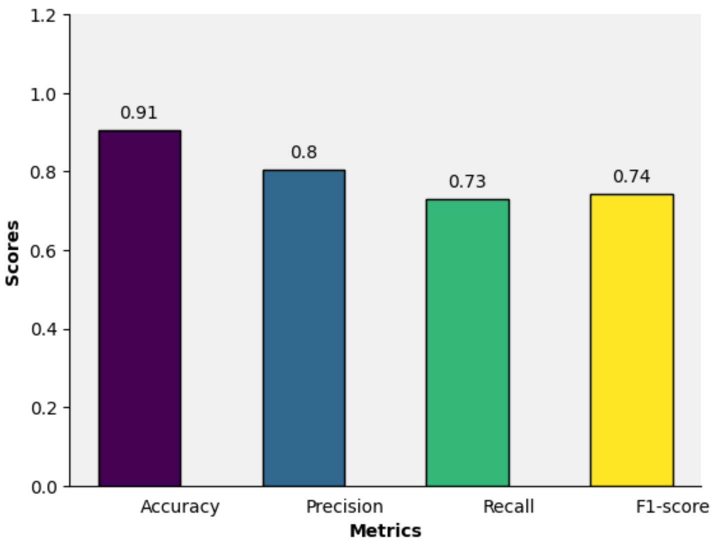

Figure 3. Performance of the proposed model

The proposed model emerges as the preferred choice for the rice image dataset due to its consistently higher performance across all evaluated metrics. Its effectiveness in achieving high accuracy, precision, recall, and F1-score despite a significantly smaller number of features underscores its efficiency in rice image classification tasks. This highlights the importance of model architecture and feature selection in optimizing performance.

Below is the confusion matrix generated on test samples using the proposed Model. The confusion matrix illustrates how well the model performs in classifying various rice diseases and health states. Strong identification of healthy rice (H) and diseases like Hispa (His) and Blast (Blb) is evident, with notable misclassifications in distinguishing between Blast and Blast affected high (Bphs), and in classifying False Smut (Fs) and Shudra Rot (Sbr). These findings highlight both the model's strengths and areas for refinement in rice disease classification.

However, challenges arise in distinguishing between similar diseases, such as misclassifications between Brown plant hopper early symptoms (Bphe) and Brown plant hopper severe symptoms (Bphs), as well as between Hispa (His) and Bacterial leaf blight (Blb). Additionally, some instances of healthy rice are misclassified as Hispa (His), indicating a need for refinement in distinguishing between healthy and diseased rice. Despite these challenges, the

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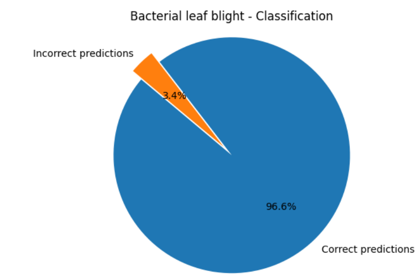
model's overall performance suggests promising prospects for rice disease classification, with opportunities for further optimization to enhance accuracy and robustness.

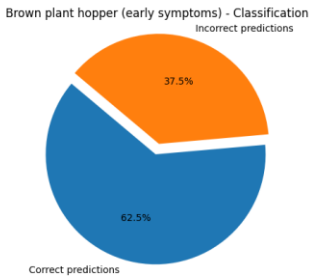
Table 3 : Confusion matrix generated using Model-1.

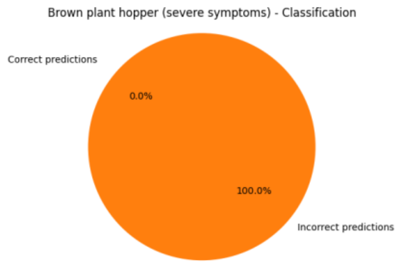
True Label	**B_{lb}**	28	0	0	0	0	0	0	0	1	0
	B_{phe}	0	5	0	0	0	0	1	0	2	0
	B_{phs}	0	1	0	0	0	1	1	0	1	0
	B_s	1	0	0	1	0	1	0	0	1	0
	F_s	0	0	0	0	25	1	0	2	0	0
	H	0	0	0	0	0	46	0	0	3	0
	H_{is}	0	2	0	0	0	1	10	0	0	0
	N_b	0	0	0	0	0	0	0	42	0	0
	S_{br}	1	0	0	0	0	2	0	0	63	0
	S_{tm}	0	0	0	0	0	0	0	4	0	39
		B_{lb}	**B_{phe}**	**B_{phs}**	**B_s**	**F_s**	**H**	**H_{is}**	**N_b**	**S_{br}**	**S_{tm}**
		Predicted Label									

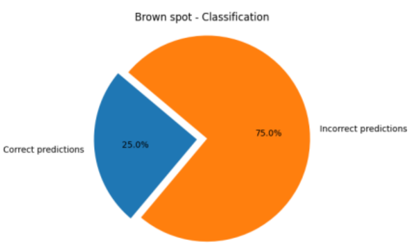
B_{lb} :Bacterial leaf blight, B_{phe} :Brown plant hopper early symptoms,B_{phs} : Brown plant hopper severe symptoms, B_s :Brown spot, F_s :Flase smut, H: Healthy, H_{is} : Hispa, N_b : Neck Blast, S_{br} : Sheath blight and/or sheath rot, S_{tm} : Stemborer.

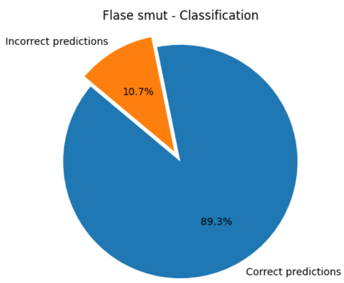
Through a systematic examination of the confusion matrix, we construct a series of pie charts, each chart dedicated to visualizing the model's performance for a specific class. Here, we dissect the model's predictions, illuminating its ability to correctly identify or misclassify different disease symptoms and healthy plants.

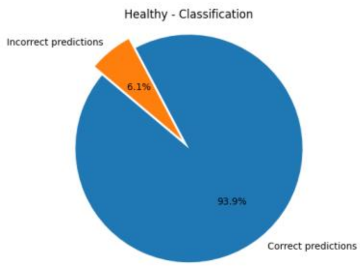


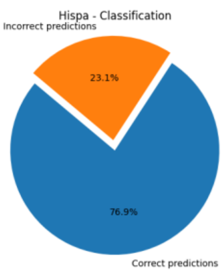


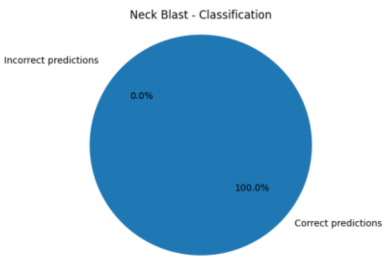


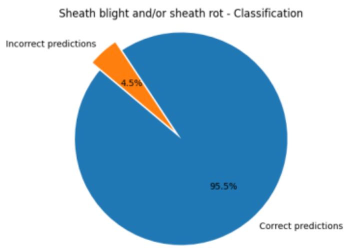












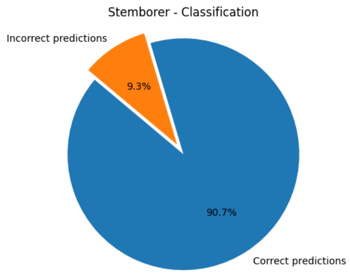


Figure 4 : Class wise distribution of predictions of the proposed Model.

The pie chart [Figure 5] illustrates the accuracy of rice disease detection, showcasing correct predictions at 90.6% and incorrect predictions at 9.4%. This high rate of correct predictions signifies the effectiveness of the model in identifying various diseases affecting rice plants. Despite a small fraction of incorrect predictions, the overall accuracy underscores the potential of advanced machine learning techniques in bolstering agricultural disease detection efforts. The chart serves as a visual representation of the model's performance, emphasizing the importance of precision in crop health monitoring. Such advancements contribute significantly to optimizing agricultural productivity and sustainability. Continued research and innovation in this field are crucial for addressing ongoing challenges and ensuring global food security.

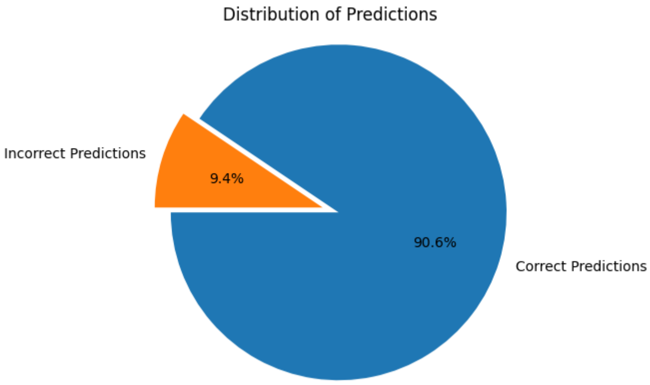


Figure 5 : Distribution of predictions of the proposed Model

5. CONCLUSION

The study underscores the crucial role of accurate and efficient disease and pest identification in rice cultivation for effective agricultural management. By harnessing advancements in convolutional neural networks (CNNs) and ensemble learning approaches, as exemplified by the proposed Model, promising avenues for improving classification accuracy in agricultural settings are unveiled. The integration of state-of-the-art architecture such as ResNet-50 with machine learning techniques demonstrates the potential for enhanced disease and pest detection. These findings not only advance agricultural technology but also address practical challenges such as model scalability and compatibility with resource-constrained environments. By offering insights into optimizing model efficiency and performance, this research contributes to the development of accessible and effective tools for disease and pest management in rice cultivation, thereby promoting agricultural sustainability and economic resilience.

In forthcoming advancements, integrating location, weather, and soil data with images of diseased plant parts holds potential for formulating a comprehensive and automated plant disease detection system. Further investigation into segmentation or object detection algorithms has the potential to improve the accuracy of classifying rice diseases and pests, including assessing disease severity. This could assist farmers in minimizing losses, especially in environments with diverse backgrounds, by enabling early detection and timely intervention.

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