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Hyperspectral Imaging and Machine Learning for Detection and Classification of Major Fungal Diseases in Rice

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Abstract– Rice production is severely affected by fungal diseases, making early and accurate disease identification important for timely disease management. Traditional identification mainly relies on visual symptoms and expert knowledge, which can be time-consuming, subjective, and difficult to apply at large scale. This study investigates hyperspectral imaging (HSI) combined with machine learning for pixel-level detection and classification of major fungal diseases in rice. Unlike studies that focus on a single rice disease or a limited number of disease categories, the present study comparatively evaluates Artificial Neural Network, Support Vector Machine and Random Forest using hyperspectral spectral data to distinguish three major fungal diseases brown spot, blast, and sheath blight while including healthy rice tissue as a separate control class. A total of 150 diseased leaf samples were collected, with 50 samples for each disease. Pixel-wise data extracted from the hyperspectral images comprised 1472 control pixels, 669 blast pixels, 693 brown spot pixels and 1169 sheath blight pixels. The hyperspectral data represent spectral responses of healthy and disease-affected rice tissues rather than direct spectral signatures of the pathogens. The HSI data were pre-processed to reduce noise and improve spectral reliability before classification. The experimental results showed that ANN achieved the highest classification accuracy of 98%, followed by SVM with 94% and RF with 88%. Overall, the results demonstrate that combining HSI with comparative machine learning classification can provide a rapid, non-destructive, and reliable approach for distinguishing major fungal diseases in rice and healthy tissue, with potential applications in precision agriculture. Overall, the combination of hyperspectral imaging and machine learning provides a rapid, non-destructive, cost-effective and reliable approach for detecting and classifying fungal diseases in rice. The proposed approach can support large-scale crop monitoring, facilitate early disease diagnosis, and assist farmers and agricultural experts in taking timely control measures. This technology has considerable potential for developing intelligent and automated disease management systems for precision agriculture.

Index Terms– Rice Fungal Diseases, Hyperspectral Imaging, Artificial Neural Network, Support Vector Machine, Random

Forest, Machine Learning, Disease Classification and Precision Agriculture

I. INTRODUCTION

CLIMATE change has also helped increase the number of crop pests and diseases, which is a major risk to global food security. Rice (*Oryza sativa* L.) is one of the world's most important staple crops and occupies approximately 160 million ha of agro-climatic regions [1]. By 2050, climate change will reduce the area of rice that can be grown in India by 6-7 million hectares, as other crops consume a larger portion of the land and as people move to urban and industrialized areas [2]. Rice contributes approximately 30 percent of total calorie consumption and is an essential component of India's national food security system [3]. Crop diseases reduce yield, quality, and production [4]. Annual yield loss due to diseases and pests in rice crops is 10-30 percent [5]. Blast (*Magnaporthe oryzae*) and sheath blight (*Rhizoctonia solani*) can cause substantial yield losses [6]-[8].

Previously, the Bengal famine was attributed to brown spot (*Bipolaris oryzae*) disease, which led to a loss of up to 90 percent of yield [9]. Therefore, fungal diseases must be identified and controlled effectively in rice crops. The most common technique for identifying rice diseases is based on manual observation [10], but it is time-consuming, costly over large areas, and requires skilled plant pathology expertise [11]. Hyperspectral imaging (HSI) has both high spatial and spectral resolution, and sophisticated computing methods can process large volumes of data across individual wavelengths outside the visible spectrum, making HSI valuable for precision agriculture. HSI applications in agriculture allow crop conditions to be assessed using biochemical and biophysical properties [13]. It records continuous signals with spectral resolution of less than 10 nm, allowing early disease detection and nutrient assessment in crops [14]. Crop monitoring therefore requires disease diagnostic methods that

can diagnose and categorize various rice diseases to reduce crop losses and improve production. Over recent decades, scholars have used different computer vision and machine learning (ML) methods to identify weeds, diseases, and nutrient deficiencies [15]. Based on the assumption that different diseases have different symptoms and spectral responses, selecting an appropriate machine learning algorithm is important for accurate disease detection and classification [16]. Recent research has concentrated primarily on foliar disease detection, although disease symptoms may also be exhibited on stalks, leaves, ears, grains, and fruits. Zhu et al. identified and categorized tobacco mosaic virus (TMV) disease by applying hyperspectral imaging with variable selection procedures and machine learning [17]. Song et al. utilized hyperspectral reflectance to identify powdery mildew on wheat using multiple linear regression (MLR), random forest (RF), and support vector machine (SVM) algorithms [18]. In rice smut disease, Wu et al. presented HSI to categorize the disease using principal component analysis (PCA) along with a random forest and extreme learning machine (RF-ELM) model [19]. Although these studies demonstrate the potential of HSI and ML for crop disease identification, many existing works focus on a single disease or a limited number of disease categories. The present study addresses this gap by using pixel-wise hyperspectral data to comparatively evaluate ANN, SVM, and RF for distinguishing three major fungal diseases in rice—blast, brown spot, and sheath blight—while also including healthy tissue as a separate control class. This comparative, pixel-level evaluation provides a direct assessment of the suitability of different machine learning models for multi-class rice disease classification using HSI. The particular goals are to: (1) identify and train machine learning (ANN, SVM, and RF) models to identify and classify three fungal rice diseases while distinguishing healthy control tissue, and (2) evaluate the suitability of the developed classification models.

II. EXISTING STUDY

The applications of hyperspectral imaging and machine learning have been developed recently to promote effective crop disease early detection and classification. Spectral data are recorded in hundreds of narrow wavelength bands in hyperspectral imaging and could be applied to detect minute biochemical and physiological modifications in plant prior to their detection in the visible spectrum [20]. Different researchers have been successful to apply machine learning models such as the Support Vector Machine (SVM), Random Forest (RF) and Artificial Neural Networks to identify plant disease using hyperspectral data. Indicatively, Lin et al. have demonstrated that machine learning classifiers of the hyperspectral reflectance characteristics can detect rice sheath blight accurately [21]. In the same line of thought, Wu et al. also employed near-infrared hyperspectral imaging and Random Forest and Extreme Learning machine to detect rice fake smut disease with a lot of success [22]. The hyperspectral imaging was employed in order to determine the extent of the rice leaf blast in various growth stages, and the authors found that the technique is quite discriminative at various stages of disease affected leaves [23]. Song et al. also applied

hyperspectral reflectance and machine learning methods, such as RF and SVM, to detect powdery mildew in wheat and pointed out the power of spectral-based disease detection in more recent works. In review studies, as well, it is emphasized that hyperspectral imaging machine learning and deep learning-based methods help to improve the accuracy of the disease detection system by a substantial margin and enable the application of the method in precision agriculture. Furthermore, it is noted that automated diagnosis systems of the diseases of rice relying on deep learning are highly accurate and efficient and can be scaled and applied to offer real time monitoring of the crops [24]. Even though these have been accomplished, most of the available works are reduced to limited number of disease categories or detection of a specific disease, this suggests that a strong machine learning model is required, a machine learning model that will be able to detect and classify more than two fungal diseases in rice using hyperspectral spectral signatures.

III. MATERIALS AND METHODS

The rice leaf samples exhibiting fungal diseases (blast, brown spot, and sheath blight) were collected from the locally cultivated Pusa Basmati-1121 rice variety during the booting stage at the research farm (23° 31' 33" N, 77° 40' 12" E) of ICAR-Central Institute of Agricultural Engineering during the Kharif season of 2024. A total of 150 diseased leaf samples were collected, comprising 50 samples from each disease group. Healthy rice leaves were also included as a separate control class during hyperspectral image acquisition and pixel-wise classification. Pixel-wise spectral data were extracted from the hyperspectral images and used for training and testing the machine learning models.

A) Hyperspectral Imaging

A VIS-NIR HSI system (OLES30, Specim Ltd, Oulu, Finland) were used to acquire rice leaf spectral data (Fig. 1). The HSI had 399-1003 nm wavelength range which scan 1312 pixels in one line, each pixel consisting of 97 spectral bands, with spectral resolution 2.8 nm. It comprises a spectrograph, a digital camera, a long-pass glass filter, and three tungsten halogen bulbs, each one of 50 W power output mounted at an angle of 45°. The real-time data acquisition and visualization of images was carried out by Specim/DAQ ver. 3.62 software. The black paper having low reflectivity was stick on a flat board to reduce the effect of unevenness. The samples were moved beneath the hyperspectral camera platform using an electric displacement system at a speed of 4 mm/s for hypercube data acquisition, with an exposure time of 23 ms and a frame rate of 43 frames per second.

B) Calibration of Hyperspectral Image

The hyperspectral imaging (HSI) camera was employed to capture rice leaf samples in reflectance mode. The 8-10 cm cut samples of rice leaves were placed on a blackboard during image acquisition. HSI images were acquired for both healthy and diseased leaf samples. The black and white reference images for calibration were captured simultaneously. The shutter was fully closed to acquire the black reference image

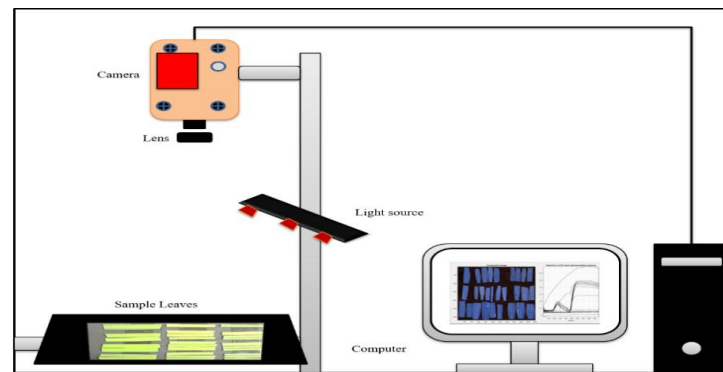


Fig. 1: A hyperspectral imaging system used to acquire spectral signature of different diseases of rice crop leaves

(D) while the reference white image (W) was acquired using a standard surface board with 99.9% reflectivity. The equation (1) was used to compute the calibrated image (R).

$$R = \frac{I-D}{W-D} \times 100 \quad (1)$$

C) HSI Image Pre-processing

The calibrated HSI was further processed and to remove unnecessary image part done by spatial crop. The background reflectance values and rice leaves was differed, so K-means clustering method were employed to remove the background from raw hyperspectral image. Erosion was applied to remove shadow effects, and unwanted pixels and regions were manually removed. To eliminate noise and light scattering effect pre-processing technique like standard normal variate (SNV) and the Savitzky-Golay filter were applied to spectral data of rice leaves. The SNV technique normalizes the data by adjusting it to a mean 0 and a standard deviation 1, making it effective for scatter correction and removing the influence of scale and offset variations. The digital Savitzky-Golay (2nd derivative with a window size of 7) filter was used in signal processing and to eliminate noisy data. The pre-processed spectra pixels were collected from healthy and disease rice leaves. The hyperspectral images spatial and spectral data were pre-processed using HYPER-Tools v.3.0 (Amigo et al., 2015), which was executed on MATLAB R2019a (MathWorks®, Natick, MA, USA)

At first, artificial intelligence was basically limited to rule-of-thumb systems, in which forecasting was done based on pre-programmed, predetermined rules created by human experts. With the growing amount of data, the need for a more data-centered approach led to machine learning. Machine learning (ML) involves training an algorithm using labelled data to make predictions, with the correct output associated with each input. In this study, three machine learning models—artificial neural network (ANN), support vector machine (SVM), and random forest (RF)—were used to classify hyperspectral pixel data into four classes: health control, blast, brown spot, and sheath blight. A hyperspectral camera (399-1003 nm) was used to acquire images of healthy and diseased rice leaves. After pre-processing, full-spectrum pixel data were extracted from the hypercube. The extracted

dataset contained 1472 healthy control pixels, 669 blast pixels, 693 brown spot pixels, and 1169 sheath blight pixels, giving a total of 4003-pixel data points. The data were divided into 70 percent for training and 30 percent for testing. The Python code was written and executed in a Jupyter notebook using Google Colab. Figure 2 depicts the process followed for developing machine learning models for the identification and classification of fungal diseases in rice using hyperspectral imaging.

At first, artificial intelligence was basically limited to rule-of-thumb systems, in which forecasting was done based on the pre-programmed, predetermined rules created by human authorities. With the growing amount of data, the necessity of a more data-centered approach was created, and machine learning was introduced. Machine learning (ML) includes the training of an algorithm to use labelled data to make some prediction, with the correct output associated with each input. It deals with multiplicity of algorithms and processes that enables machines to identify trends within the data and make choices regarding certain tasks. Through these algorithms, machine learning is able to bring out insights that are valuable in data, hence enhancing the process of making decisions. In this study, the researcher utilized three models of machine learning namely artificial neural network (ANN), support vector machine (SVM) and random forest (RF) to detect and categorize three (blast, brown spot and sheath blight) fungal infections in rice crop. Hyperspectral camera (399-1003 nm) was used to conduct the hyperspectral imaging of healthy and diseased leaves of rice. To train and test the model, in order to classify healthy and disease of rice leaves of blast, it was necessary to pick out brown spot and sheath blight pixels of pre-processed hypercube and extracted point data of the full spectrum. The data points of total healthy leaf and data of blast, brown spot and sheath blight were 1472, 669, 693 and 1169. Use and test of ML model used 30 percent data and 70 percent data respectively. The Python code was written and executed on a Jupyter notebook using Google Colab, which is a free cloud-based application. The flowchart Fig. 2 depicts the process involved in creating a machine learning models in the identification and classification of various fungal diseases (blast, brown spot and sheath blight) of the rice crop by applying hyperspectral imaging.

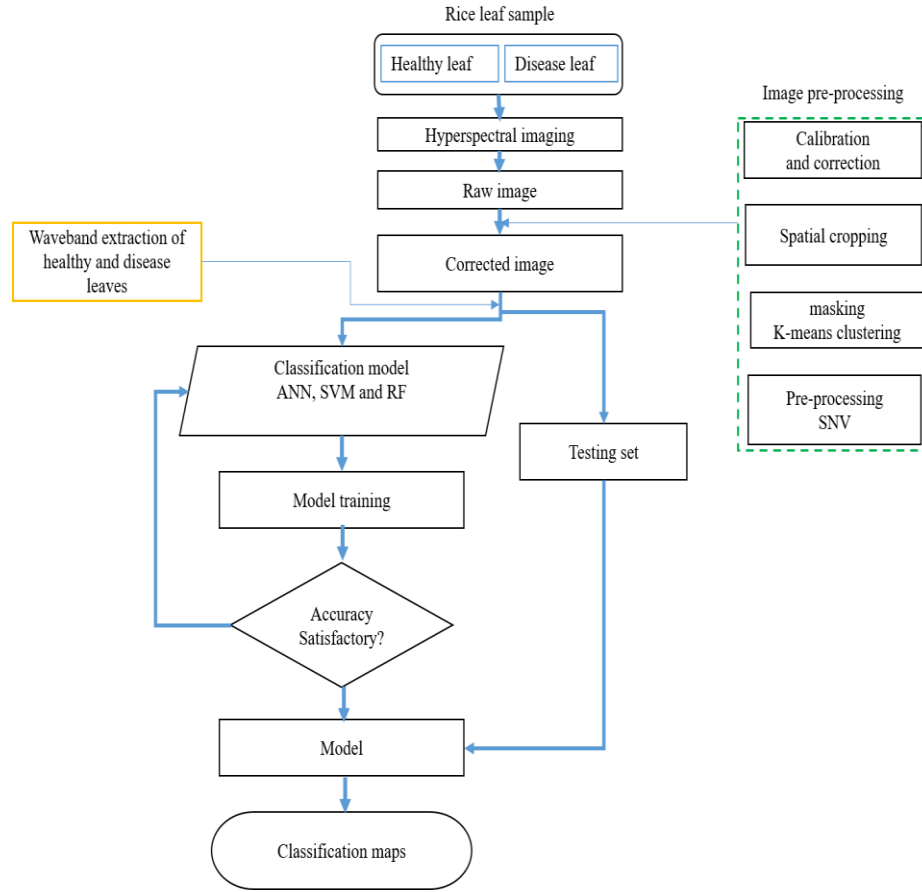


Fig. 2: A schematic diagram illustrating the procedure followed for development of classification model

Artificial Neural Network

The use of HSI is increasing in agriculture and it generate huge information and data about crops, to process these data use of ANN algorithm. This algorithm is commonly employed in classification tasks across various applications due to its high accuracy, simplicity, robustness, sensitivity, and ability to automate the learning process.

Support Vector Machine

SVM originates from statistical learning theory, aiming to maximize the margin between the hyperplane and support vectors (training sample) near the hyperplane to execute classification perfectly. SVM aims to find the optimal hyperplane that best separates data points from different classes in a feature space. The main goal is to maximize the margin, defined as the distance between the hyperplane and the nearest data points from each class, known as support vectors.

Random Forest

It is an ensemble learning technique that construct numerous decision trees from random samples of the data. It improves predictive performance and reduces overfitting by combining the output of individual trees through majority voting for classification. The model is particularly effective for dealing non-linear pattern and large-scale datasets.

D) Performance of the machine learning model

The classification model performance was accessed using the following metrics (Eqs. (2)-(5)): accuracy (the ratio of correctly classified samples to the total number of samples), precision (the ratio of correctly classified positive samples to all positive samples), and sensitivity (the ratio of correctly identified samples to the total actual positive samples), all calculated from the model's confusion matrix.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FN} + \text{TP} + \text{FP}} \times 100 \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (3)$$

$$\text{Sensitivity/Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4)$$

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Where, TP-True positive), TN-True negative, FP-False positive and FN-False negative.

IV. RESULT AND DISCUSSION

A) Spectral Curve

The difference in the average reflectance spectra of healthy and diseased leaves (blast, brown spot, and sheath blight) is illustrated in Fig. 3. The reflectance curve for diseased leaves gradually increases from 399 to 496 nm, followed by a sharp increase from 496 to 563 nm, a sharp decrease from 563 to 680 nm, a sharp increase from 675 to 750 nm, and then flat from 750 to 1003 nm. In contrast, the spectral curve for healthy (control) leaves remains steady from 399 to 508 nm and shows a steady decrease from 560 to 1003 nm.

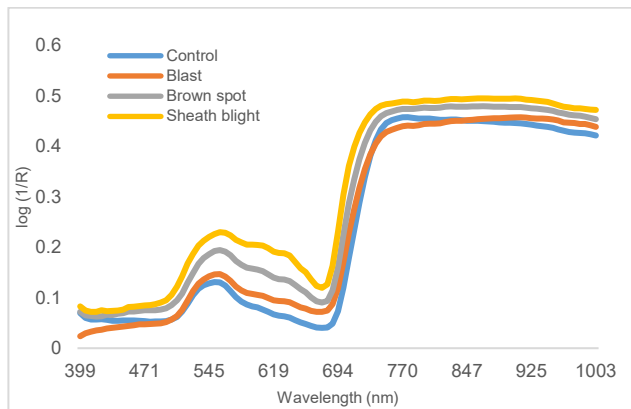


Fig. 3: Average spectral profile of healthy and disease rice leaf

B) Principal Component Analysis

The post-processed VIS-NIR hyperspectral pixel data was subjected to Principal Component Analysis (PCA) to determine the variation between rice leaves under the influence of varying fungal diseases. The number of ideal principal components (PCs) that are possible, and score plot PC1 vs PC3 plot as depicted in Fig. 4. It was found that there was a clear visible difference of control and fungal diseased leaves pixel samples, but it was difficult to distinguish between the various fungal diseases. The PC1 axis offered the best discriminative ability between the control and various diseased sample groups. The positive region of PC1 was mostly used to concentrate the healthy samples, so their distinct spectral signature was brought to the fore. Conversely, diseased samples were distributed more sparsely in both PC1 and PC3 axes which indicates a larger variability of their spectral profiles. The results of PCA score plot indicate that the model was effective in identifying the healthy leaves and the diseased ones, as the diseased samples occupy a distinct location in the negative signal of PC1 and along PC3 axis.

C) Performance of Machine Learning Models

The ML models were trained using 70 percent of the sample data and evaluated on the remaining 30 percent. ANN, SVM, and RF were trained and evaluated to distinguish healthy control and fungal-diseased rice leaf pixel data. Table 1 presents the performance of the ML models based on accuracy, precision, sensitivity/recall, and F1-score. High precision is particularly important in crop disease detection because it reduces the chance of incorrectly identifying

healthy tissue as diseased. The findings show that the ANN model achieved the highest accuracy of 98 percent, followed by SVM with 94 percent and RF with 88 percent. Based on accuracy, recall, and F1-score, ANN provided the strongest performance among the evaluated models for multi-class classification of healthy control, blast, brown spot, and sheath blight. The ANN model performance in terms of accuracy, error, and recall is presented in Fig. 5. Validation data were used to assess the generalization capability of the model and to monitor possible overfitting. During training and validation, the epochs were reduced to 100 and a batch size of 32 was used, causing the error to drop below 0.08 and accuracy to exceed 98 percent on the evaluated datasets (Fig. 5). The training and validation accuracies were high (more than 98 percent) for both control and diseased leaves.

The confusion matrices for control, blast, brown spot, and sheath blight classification using the selected machine learning models are presented in Fig. 6. The diagonal values represent the true positive samples, while the off-diagonal values indicate false-positive and false-negative samples for each class.

The ANN model achieved an accuracy of 98.2% across all classes, with very few misclassifications. The precision, recall, and F1-score for blast, brown spot, and sheath blight ranged from 0.9592 to 1.00. The SVM model showed a 93.67% accuracy, demonstrating its ability to classify the classes correctly in most instances, with precision, recall, and F1-scores ranging from 0.86 to 0.92 for blast, brown spot, and sheath blight. The RF model achieved an accuracy of 87.67%, with precision, recall, and F1-scores of 0.804 for blast, 0.8558 for brown spot, and 0.774 for sheath blight.

Table I: Classification performance of different machine learning models

Model	Class	Precision	Recall	F1-score	Support
ANN	Control	1.0	1.0	1.0	463
	Blast	0.98	0.96	0.97	196
	Brown spot	0.94	0.99	0.96	209
	Sheath blight	0.98	0.96	0.97	333
	Accuracy (%)	98			1201
SVM	Control	1.0	1.0	1.0	441
	Blast	0.85	0.87	0.86	201
	Brown spot	0.86	0.92	0.89	208
	Sheath blight	0.95	0.91	0.93	351
	Accuracy (%)	94			1201
RF	Control	1.0	1.0	1.0	441
	Blast	0.70	0.81	0.75	201
	Brown spot	0.77	0.86	0.81	208
	Sheath blight	0.91	0.77	0.84	351
	Accuracy (%)	88			1201

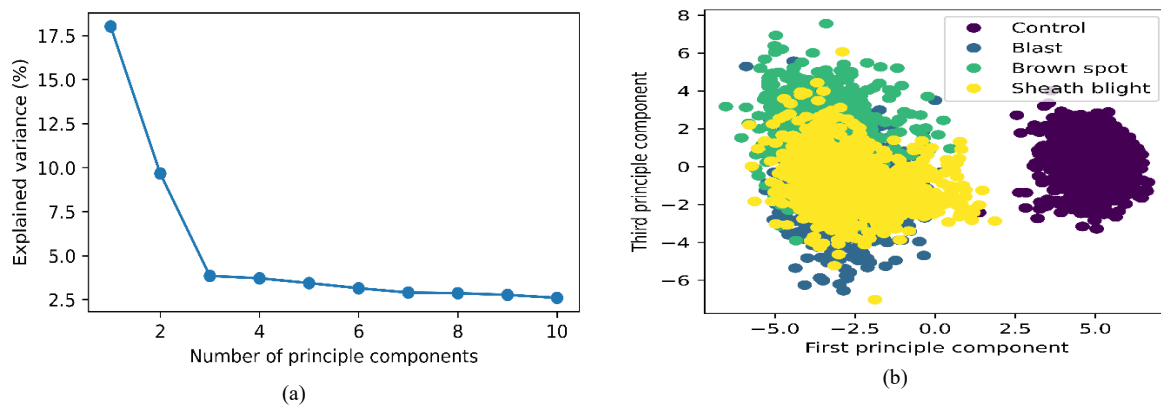


Fig. 4: PCA score plot for control and diseases of rice leaves (a) Optimal number of principal components (b) PC1 vs PC3

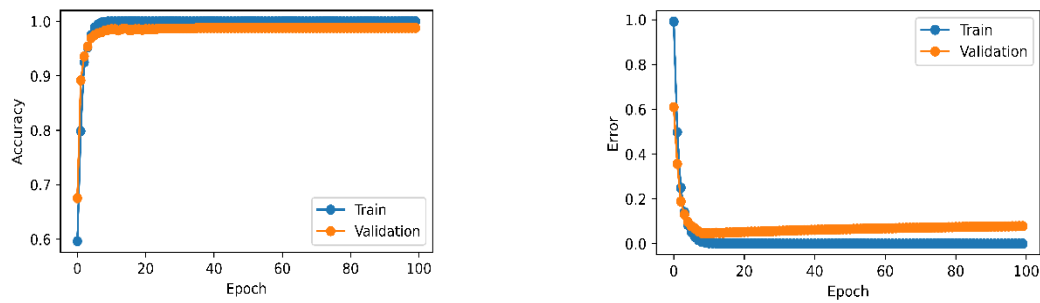


Fig. 5: ANN model training and validation accuracy and error curve

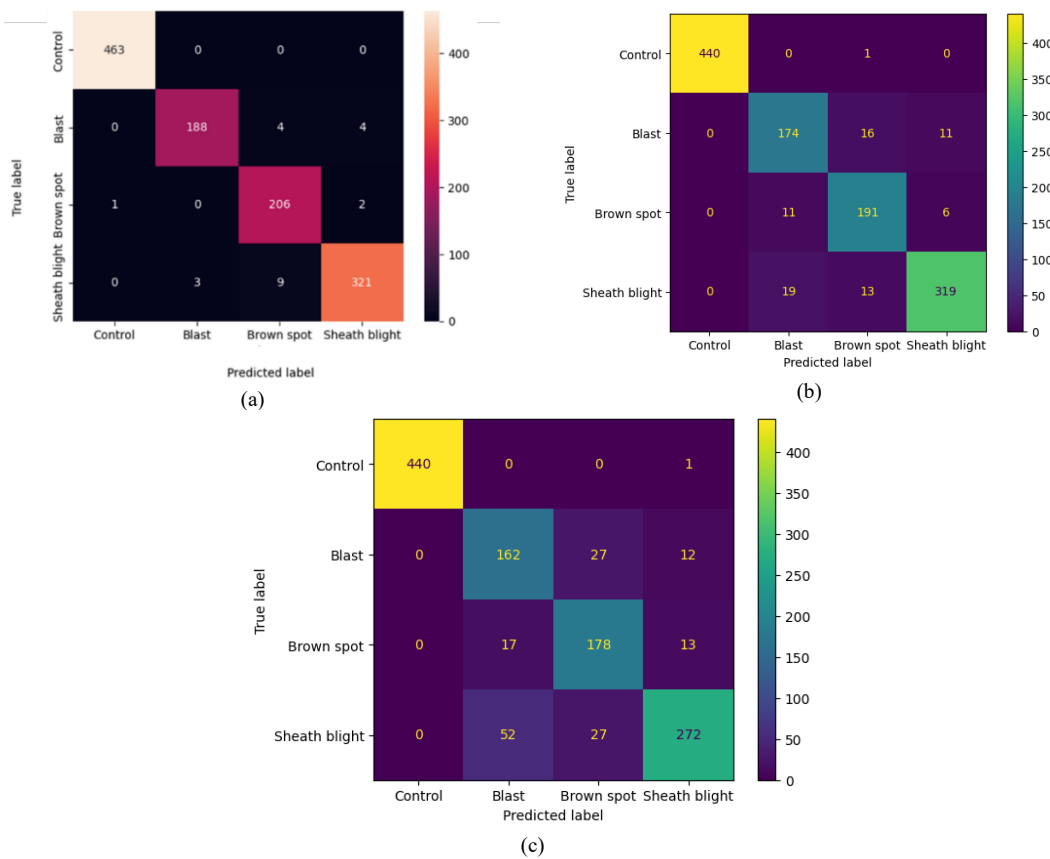


Fig. 6: Confusion matrix showing the performance of the different selected models

V. CONCLUSION

The ML models hold significant potential for disease detection and classification in crops, improving early detection and management in precision agriculture. This study demonstrated the potential of machine learning models using hyperspectral imaging for classifying fungal diseases in rice crops while distinguishing healthy control tissue. Three machine learning models (ANN, SVM, and RF) were evaluated using hyperspectral pixel data for the classification of blast, brown spot, sheath blight, and healthy control rice tissue. Among them, ANN performed best, achieving the highest accuracy, precision, and recall. The study also provides a comparative evaluation of the three models on the same hyperspectral dataset, supporting the selection of an appropriate classifier for multi-class rice disease analysis. Future work could focus on real-time detection of fungal diseases in crops, followed by the implementation of intelligent sprayers or site-specific fungicide applicators to perform targeted disease control actions based on decisions made by the ANN model.

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