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A Comparative Analysis of Destructive Methods and Non-Destructive Methods with Machine Learning and Deep Learning Approaches for Rice Leaf Disease Identification

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Abstract. *Rice vital fundamental crop, serving as a staple food in numerous regions across the world. Various diseases can impact rice cultivation, arising from diverse pathogens like bacteria, viruses, and fungi. It's important to detect and manage these diseases early to minimize their impact on rice yield and quality. This paper studies a comprehensive survey of the destructive and non-destructive techniques utilized for identifying rice leaf diseases. It also examines the use of Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) to precisely identify these diseases using non-destructive imaging techniques. Visual inspection for detecting rice leaf diseases can be subjective, time- consuming, destructive, and limited in its detection ability. The review highlights the importance of early detection of rice leaf diseases and the need for developing accurate, reliable, and non-destructive methods for disease diagnosis in order to improve rice yield and production. The accuracy of the CNN model was 97.72%, compared to the SVM model's accuracy of 84.27%. This comparison highlights the superior performance of the CNN model in accurately identifying rice leaf diseases.*
Keywords: Rice leaf Diseases, Machine Learning, Deep Learning, Convolutional Neural Networks, Support Vector Machines.

1. **Introduction.** Rice, being a cereal grain, holds significant importance as a basic food worldwide. Its significance is evident as a significant portion of the world's population, mainly in Asian countries, relies on it as the most widely consumed staple food [1]. According to researchers, both droughts and severe rains that could flood the fields are a constraint on India's ability to produce rice.

The top countries according to the output of milled rice in 2021–2022 are listed in the United States Department of Agriculture (USDA) report that was published in October 2021. The top countries according to refined rice cultivation in 2021–2022 as shown in Figure 1, are China followed by India, Bangladesh, etc.

In 2021, there were 515.05 million tonnes of rice produced. In 2022, it is anticipated that there will 503.2 million tonnes of rice produced worldwide, a decrease of 11.78 million tonnes or 2.29. The diseases that damage a plant's ability to grow normally can harm any component of the rice crop, including the root, stem, leaf, seedling, and flower [2]. The detection of rice crop infection by the human eye requires time, needs constant observation, and is generally less reliable. Automated disease detection saves time and effort while producing accurate results. Due to their inadequate knowledge of plant diseases, farmers

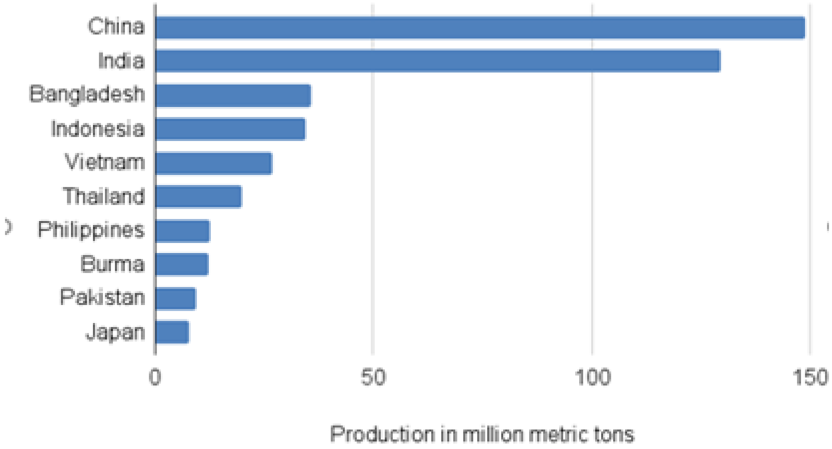

FIGURE 1. Top countries according to refined rice cultivation in 2021–2022

would highly help from an automated plant disease detection system. The leaves of the rice plant play a vital role as an integral component, of the crop's growth, development, and productivity. Climate change, pests and diseases [3], water scarcity, and soil degradation all have an effect on the challenges caused by leaf diseases. According to the International Rice Research Institute[IRRI], common rice leaf diseases Bacterial blight, Bacterial leaf streak, Blast (affecting leaves and collars), Brown spot, Tungro, Leaf Scald, Narrow brown spot, and Red stripe. Identifying rice leaf diseases can be a challenging task, as many of the symptoms may look similar or can be caused by multiple diseases. There are some common signs and symptoms that can help identify the presence of a disease in rice leaves are lesions, leaf spots, wilting and yellowing, Leaf curling, and sheath rotting. Figure 2 represents the common diseases of rice leaves. water scarcity, and soil degradation all have an effect on the challenges caused by leaf diseases.

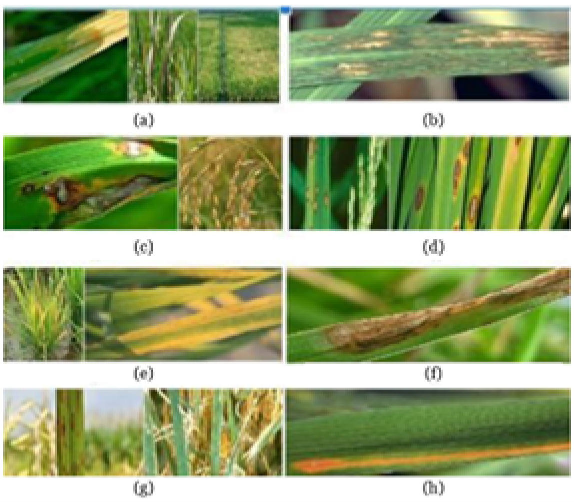

FIGURE 2. Common rice leaf diseases (a) bacterial blight (b) bacterial leaf streak (c) blast (d) brown spot (e) tungro (f) leaf scald (g) narrow brown spot (h) red stripe.

According to the International Rice Research Insti tute[IRRI], common rice leaf diseases are Bacterial blight, Bacterial leaf streak, Blast (leaf and collar), Brown spot, Tungro, Leaf Scald, Narrow brown spot, and Red stripe. Identifying rice leaf diseases can be a challenging task, as many of the symptoms may look similar or can be caused by multiple diseases. There are some common signs and symptoms that can help identify the presence of a disease in rice leaves are lesions, leaf spots, wilting and yellowing, Leaf curling, and sheath rotting. Figure 2 represents the common diseases of rice leaves.

A non-destructive method such as Artificial Intelligence (AI) can be an effective tool for the automatic detection of leaf diseases. It can easily detect the disease in crops such as rice, providing early and accurate detection, efficient processing, and valuable data for disease research and management. The reliability and efficiency of automatic detection systems will increase with Visual inspection, Smartphone apps, Image analysis software, and Crowdsourcing methods.

This study aims to examine various approaches for the diagnosis of diseases in rice leaf, encompassing both destructive and non-destructive methods. We also discuss several techniques used in destructive methods along with their pros and cons. The study of non-destructive methods with a comparison of different classifiers used in machine learning and deep learning techniques is also discussed in this paper.

The organization of this paper is outlined as follows: Section 2 covers destructive techniques for detecting rice leaf diseases, including various methods and their respective benefits and drawbacks. Moving on to Section 3, non-destructive methods for identifying these diseases are discussed, including both machine learning and deep learning approaches. In section 4, Comparative analysis of Machine learning algorithms. In Section 5,a discussion is presented on the papers related to leaf diseases and models used in non-destructive methods. Finally, Section 6 concludes with a summary and future directions for classifying rice leaf diseases. The destructive and non-destructive methods for detecting rice leaf diseases can be hierarchically represented as follows in Figure 3.

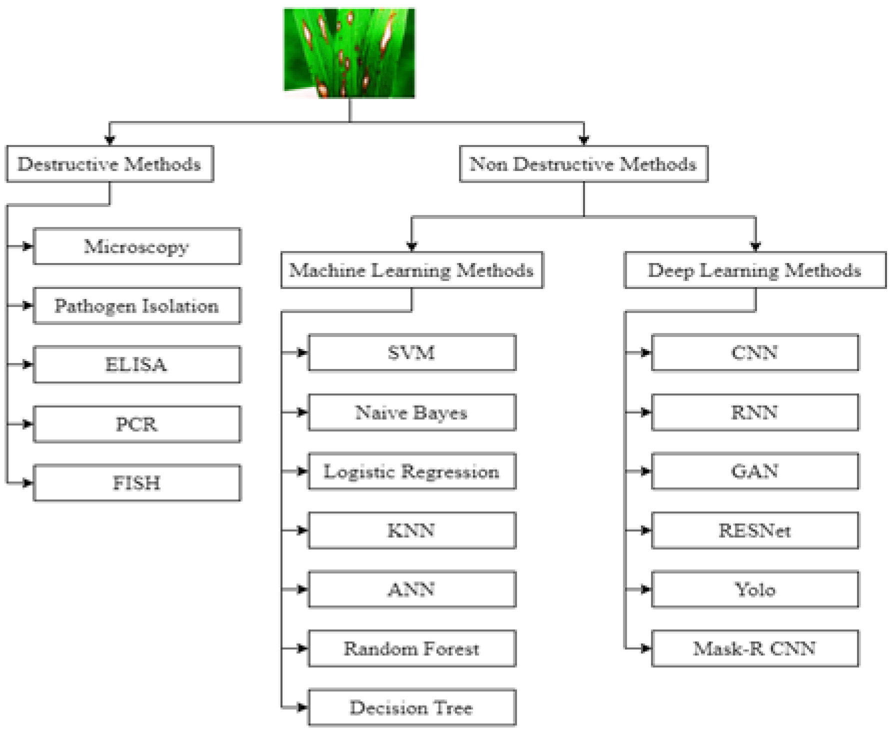

FIGURE 3. Detecting rice leaf diseases using destructive and nondestructive methods

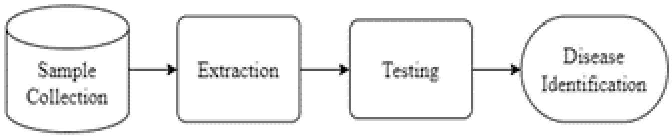

Figure 4. Block diagram for destructive method

2. **Destructive Methods to Identify Rice Leaf Diseases.** Plant disease diagnostic laboratories use a range of laboratory methods to identify the presence of rice leaf diseases. The Block diagram for destructive methods identification is represented in Figure 4. Some of the common methods used are listed below. Some of the common methods used:

Microscopic examination: This process entails microscopic examination of plant tissues or spores to detect the presence of pathogenic agents like fungi, bacteria, or viruses. DNA-based methods: These methods involve using polymerase chain reaction (PCR) or other DNA-based techniques to amplify and analyze the genetic material of the pathogenic agent to identify the disease.

Serological methods: These methods use antibodies to detect the presence of specific pathogenic agents in the plant sample. Common serological methods include western blotting and enzyme-linked immunosorbent assays (ELISA)

Molecular techniques: These methods use techniques such as real-time PCR, DNA sequencing, and microarrays to identify the pathogen and its genetic makeup.

Table 1 summarizes the different laboratory-based techniques used to detect diseases in rice leaves. Table 2 represents the advantages and disadvantages of various methods employed in the destructive identification of rice leaf diseases. Disease detection in rice leaves in the laboratory can be challenging, as many diseases share similar symptoms, and the accuracy of the diagnosis depends on the quality of the samples, the expertise of the technicians, and the sensitivity of the testing methods. Laboratory methods play a crucial role in detecting and diagnosing rice leaf diseases. Identifying rice leaf diseases in the laboratory can be challenging, as many diseases share similar symptoms, and the accuracy of the diagnosis depends on the quality of the samples, the expertise of the technicians, and the sensitivity of the testing methods. Conventionally, laboratory methods play a crucial role in detecting and diagnosing rice leaf diseases.

Table 1. Summary of destructive methods using laboratory methods.

Methods	Leaf diseases	Techniques used	Reference
Molecular	Rice sheath blight	PCR	[4]
	Bacterial blight	PCR	[5]
	Bacterial blight	PCR	[6]
	Bacterial Blight	Pathogen isolation	[7]
DNA-based	Rice blast disease	PCR	[8]
	Sheath rot disease	Pathogen Isolation	[9]
	Rice Blast	PCR	[10]
Microscopic	Rice Blast	Electron microscopy	[11]
	Rice blast	Fluorescence microscopy	[12]
Serological	Rice Tungro	Indirect ELISA and Dot-Blot Assay	[13]
	Rice black-streaked dwarf virus (RBSDV)	ID-ELISA	[14]

3. **Non-Destructive Methods to Identify Rice Leaf Diseases.** Identifying different kinds of leaves of rice diseases based on their external appearance can be extremely difficult even for specialists in the field. Consequently, there is an increasing demand for an automated system capable of accurately recognizing and categorizing these diseases

Table 2. Summary of laboratory methods and their advantages and disadvantages.

Methods	Technique	Advantages	Disadvantages
Molecular	Polymerase Chain Reaction (PCR)	Highly specific, Sensitive, Speedy, and Versatile	High cost, Limited detection range, False-positive results, False-negative results
DNA Based	Polymerase Chain Reaction (PCR)	High sensitivity and specificity, Rapid results, High throughput	False-positive and false-negative results, Expensive, Limited detection range
	Pathogen Isolation	High specificity, Identification of multiple pathogens, Useful for unknown pathogens	Time-consuming, Destructive, Limited sensitivity, Limited detection range
Microscopic	Electron microscopy	High-resolution, Non-specific, Opportunity for further analysis	Expensive, Limited sample size, Limited detection range, Specialized equipment, and training

through visual inspection. Machine learning algorithms can be trained on large datasets of images to accurately identify the diseases, causing the symptoms on the rice leaves. Several approaches can be utilized for rice leaf disease detection, including object detection, image classification, transfer learning, and edge computing.

3.1. **Machine Learning Methods for Identifying Rice Leaf Diseases.** It is possible to achieve very high accuracy in detecting rice leaf diseases based on images, utilizing machine learning techniques. The basic steps for identification of the leaf diseases are shown in Figure 5.

Image Preprocessing

It refers to a set of techniques and operations that are applied to digital images to improve their quality, enhance their features, and facilitate further analysis or processing.

Image Segmentation

It is the procedure of partitioning an image into different sections or segments according to particular characteristics or features. The aim is to simplify the image data and make it more meaningful for analysis or further processing.

Feature Extraction

It is to simplify the image data and extract only the most relevant information, making it easier to analyze and process. Some common features that can be extracted from an image include color, texture, shape, and histograms.

Color Feature

Color features are characteristics that are related to the color information displayed in an image. The distribution, design, or relationships of the colors in an image are identified and represented using those characteristics.

Shape Feature

Shape features are descriptive features that accurately represent the geometric or spatial characteristics of objects or regions in an image. These features enable the study and identification of various shapes contained in an image by providing information about the shape, structure, and contour of objects.

Texture Feature

Texture features are the descriptive features or characteristics that capture the visual patterns, deviations, or structural arrangement of pixels or local neighborhoods in an image. These characteristics reveal details about the texture, smoothness, or repeating patterns in various areas of an image.

Classification

Classification of an image refers to the process of assigning one or more labels or categories to an image based on its visual content or features. K-nearest neighbor (KNN), support vector machines (SVM), logistic regression (LR), random forests (RF), decision trees (DT), naïve Bayes (NB), and artificial neural networks (ANN) are some of the common classification methods. Non-destructive methods for the classification of rice leaf diseases using Machine Learning Techniques are shown in Table 3. Most of the machine learning models used for identifying a greater number of rice leaf diseases exhibit a high level of accuracy. But still, machine learning models face several challenges that researchers and practitioners strive to overcome. selecting and engineering relevant features from raw data can be time-consuming and require domain expertise. Extracting informative and discriminative features is crucial for model performance. Machine learning models heavily rely on large and diverse data sets for training.

Table 3. Summary table for image classification of rice leaf diseases using machine learning techniques.

Classification, leaf disease Models	Preprocessing	Segmentation	Feature extraction	Accuracy	Reference
SVM Brown spot, Leaf blast, and Bacterial blight	Resizing, Filtering, Contrast enhancement	K means Clustering	Color and Texture	92.06	[15]
Bacterial leaf blight, Brown spot, and Leaf smut.	RGB to HSV color	K-means clustering	Color, texture, and shape	93.33	[16]
KNN Blast	RGB color space to Lab, Otsu method	K-means clustering	Color and shape	94	[17]
Blast and Brown Spot	NA	Otsu segmentation	Color features	76.59	[18]
ANN Rice blast	RGB to HSV	K means clustering	Mean Value, Standard Deviation, and GLCM	90	[19]
Brown spot and Leaf Smut	RGB to Lab color space	Thresholding	Shape and Color	76	[20]
SVM leaf blast, brown spot	RGB to Lab color space	K means clustering	Area, Grey level co-occurrence matrix (GLCM), Color moment	SVM-92.5 ANN-87.5	[21]
SVM and KNN bacterial blight of rice, rice blast, tungro, and false smut	Resize	Thresholding	Color features	SVM-91.23 KNN-89.54	[22]
Optimized DNN (Deep Neural Network) normal, blast, brown spot, bacterial blight, and sheath rot	RGB to HSV	K-Means Clustering	Color and Texture	93	[23]
Twin SVM Rice Blast and Bacterial Blight	Contrast stretching, Noise removal, Filtering	K-Means Clustering	GLCM	95	[24]
Multilevel SVM Bacterial Blight, Blast, and Brown spot	Lab color space	Fuzzy C-Means (FCM)	Shape, Texture, and Color	86.51	[25]
Random Forest Bacterial Blight, Blast, and Brownspot	RGB to grayscale	NA	Color features	91.47	[26]
DNN bacterial blight	Wiener filtering	K-Means Clustering, Hue based	Color	97	[27]

3.2. **Deep Learning methods for Identifying Rice Leaf Diseases.** Deep learning has significantly advanced the fields of image analysis and computer vision in the development of highly accurate and efficient image recognition and classification models. One common deep learning models in images are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Residual Networks (ResNets), YOLO (You Only Look Once), Mask R-CNN.

- Convolutional Neural Networks (CNNs): CNNs are a specific deep learning neural network created with image processing techniques.
- Recurrent Neural Networks (RNNs): RNN, a class of neural networks is capable of processing sequential data, including video frames or image sequences.
- Generative Adversarial Networks (GANs): A deep learning model known as a GAN can produce new images that are comparable to the training set.
- Residual Networks (ResNets): ResNets, which are a variant of convolutional neural networks (CNNs), employ residual connections in their architecture to allow for deeper networks without suffering from the vanishing gradient problem.
- YOLO (You Only Look Once): The real-time object detection system YOLO utilizes a solitary neural network to make predictions on bounding boxes and class probabilities for multiple objects present in an image.
- Mask R-CNN: An advanced object recognition and segmentation model called Mask R-CNN can precisely identify and separate objects in an image.

Non-destructive methods for the classification of rice leaf diseases using Deep Learning Models are shown in Table 4. Deep learning models can automatically learn and abstract higher level features from raw data. The models often require demands significant volumes of labeled data to achieve optimal performance. Machine learning models can be effective with smaller datasets and can handle a wider range of data types. Both machine learning and deep learning have their strengths and limitations, and the choice between them depends on the specific problem, available data, resources, and interpretability requirements.

4. **Comparative Analysis of Machine Learning and Deep Learning Algorithms.** A dataset comprising 7,463 rice leaf images from five different classes, including Bacterial Blight, Blast, Brown Spot, Healthy, and Tungro, was utilized. The dataset used in the experiments originates from Mendeley dataset [41]. The pre-processing steps, such as image normalization and resizing, are detailed to ensure compatibility with the machine learning models. The architecture of the CNN model, comprising 16 convolutional layers and a dense net structure, is presented. The training process, hyperparameter tuning [42] incorporating learning rate, batch size, number of convolutional layers, filter sizes, and optimization techniques, and Adam optimizer [43] is used. SVM utilizes mathematical equations and hyperparameter selection to effectively classify data, including in the context of rice leaf disease identification. It aims to find an optimal hyperplane that separates the different classes in the data. The choice of kernel function determines the decision boundary's flexibility and the model's ability to capture nonlinear relationships in the data. The results of the comparative analysis of the accuracy of the CNN model (97.72%) is compared to the accuracy of the SVM model (84.27%). Confusion Matrix for CNN and SVM Models given in Figure 6 and Figure 7.

TABLE 4. Summary table for image classification of rice leaf diseases using deep learning techniques.

Classification Models	Leaf Diseases	No of images	Size of the image	Result	Reference
CNN	rice blast, rice false smut, rice brown spot, rice bakanae disease, rice sheath blight, rice sheath rot, rice bacterial leaf blight, rice bacterial sheath rot, rice seedling blight, and rice bacterial wilt	500	224×224 pixels	95	[28]
	Bacterial Blight, Blast, Brown mark	2000	500×500 pixels	78.44	[29]
	Blast, Brown Spot, Bacterial Leaf Blight, Sheath Blight, and Tungro	323	512×512 pixels	99.78	[30]
	Healthy leaf and diseased image	3500	500×500 pixels	70	[31]
Deep CNN	rice blast disease	5808	128×128 pixels	95.82	[32]
5-Layer CNN	Brown spot, Leaf Blast, Hispa	1600	1449×1449 pixels	78.2	[33]
CNN With Transfer Learning	Brown spot, Leaf blight and leaf blast	500	512×512 pixels	92.46	[34]
ResNeSt-50	leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot	33,026	224 × 224 pixels	98	[35]
DenseNet161	blast, bacterial blight, brown spot, narrow brown spot, and bacterial leaf streak	12223	224×224 pixels	95.74	[36]
AlexNet	bacterial blight, brown spot and leaf smut	120	227×227 pixels	99	[37]
GAN	Bacterial Blight, Brown spot, Blast, and Tungro	5932	256×256 pixels	91.83	[38]
InceptionResNetV2	Bacterial blight, rice blast, and brown spot	5000	300×300 pixels	98.9	[39]
InceptionV3 model	Bacterial leaf blight, brown spot, Hispa, leaf blast, leaf scald, leaf streak, narrow brown spot, sheath blight, Tungro, and a healthy state	10,080	128 × 128 pixels	99.64	[40]

5. **Discussion.** Based on the survey, we discussed various techniques for identifying rice leaf diseases using destructive methods such as PCR, pathogen isolation, microscopic methods, and ELISA methods. Among the survey, PCR is the most commonly used testing method. In terms of machine learning and deep learning methods.It was found that deep learning models provide higher accuracy. Among the survey from Summary of Machine Learning and deep learning models, Figure 8 indicates that SVM is commonly used

as the machine learning model, while CNN is commonly used as the deep learning model in most research papers. The most frequently identified disease in the research papers is rice blast from Figure 9. The Comparative analysis of machine learning algorithms report clearly demonstrates the superior performance of the CNN model in accurately identifying rice leaf diseases compared to the SVM model. The CNN model achieved an impressive accuracy of 97.72%, indicating its ability to correctly classify the majority of rice leaf samples. On the other hand, the SVM model achieved an accuracy of 84.27%, showing a relatively lower performance in comparison.

Predicted Values

Actual Values	Bacterial Blight	Blast	Brown Spot	Tungro	Healthy
Bacterial Blight	141	9	0	0	1
Blast	6	136	0	0	0
Brown Spot	1	32	141	0	1
Tungro	6	4	0	120	1
Healthy	0	1	0	0	146

FIGURE 5. Confusion matrix of CNN

Predicted Values

Actual Values	Bacterial Blight	Blast	Brown Spot	Tungro	Healthy
Bacterial Blight	108	17	0	15	16
Blast	14	135	0	16	4
Brown Spot	0	0	145	0	0
Tungro	17	19	0	119	8
Healthy	0	1	0	2	120

FIGURE 6. Confusion matrix of SVM

6. **Conclusion.** This survey examined various techniques for identifying rice leaf diseases, including both destructive methods and machine learning/deep learning approaches. The results indicate that PCR is the most commonly used destructive method for disease testing in rice crops. In terms of machine learning and deep learning models specifically, CNN has demonstrated higher accuracy than conventional machine learning models like SVM. Furthermore, the survey revealed that rice blast is the most frequently identified disease in the research papers examined. This highlights the significance of developing

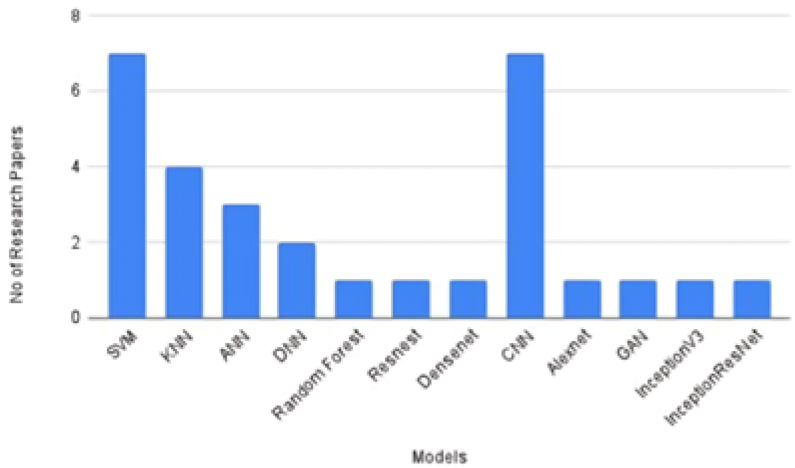

FIGURE 7. Number of research papers based on machine learning and deep learning models.

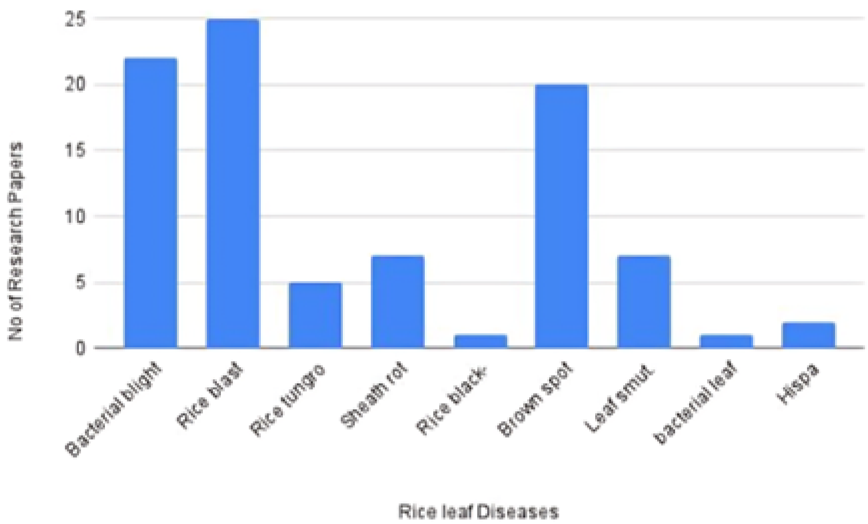

FIGURE 8. Number of research papers based on rice leaf diseases.

effective detection methods for this particular disease. Based on comparative analysis, emphasize the potential of deep learning techniques, particularly CNN, in enhancing the precision and efficiency of rice leaf disease identification. Implementing such advanced methods can contribute to early disease diagnosis, enabling timely management strategies and ultimately leading to enhanced rice yield and production. To gain an improved understanding of the disease, both types of methods may be combined because they each have benefits and drawbacks. Continued research and development in this field will contribute to improving disease management practices in rice cultivation and ultimately benefit farmers and global food security.

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