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Supervised Machine Learning Algorithms Used In The Detection Of Rice Blast Disease

Biswajit Saha[1], Gour Sundar Mitra Thakur[2]
[1]Department of CSE(AIML), Dr. B. C. Roy Engineering. College, Durgapur, West Bengal,India, sahabiswaji@gmail.com
[2]Department of CSE(AIML), Dr. B. C. Roy Engineering College, Durgapur, West Bengal, India cse.gsmt@gmail.com

Abstract
Agriculture serves as a vital component of the global economy, particularly in developing nations like India. It stands as the primary livelihood source for a majority of the rural population in India and makes a significant contribution to the country's Gross Domestic Product (GDP).As per the World Bank, agriculture constitutes approximately 17% of India's GDP and engages over 50% of the nation's workforce. However, the agriculture sector faces setbacks, notably from insect infestations that can considerably impact crop production. The absence of a systematic scientific approach to manage these infestations often results in substantial crop losses for farmers, complicating the task of safeguarding crops from insect attacks. The application of Artificial Intelligence (AI) holds immense promise in effectively addressing the challenges of insect management and enhancing crop production. Machine Learning (ML) techniques, in par- ticular, can empower farmers in safeguarding their crops from insect-related threats. Rice blast disease, caused by Pyricularia oryzae, a fungus, is one of the most significant and widespread diseases affecting rice plants. This disease can infect rice plants at various growth stages and affect different aerial parts, including leaves, neck, and nodes. This paper aims to present a comprehensive overview of the applicability of supervised machine learning algorithms in the detection of rice blast disease.
Keywords— *Agriculture, Rice Blast Disease, Artificial Intelligence, Machine Learning, Deep Learning*

1 INTRODUCTION

Agriculture serves as the predominant origin of employment to nearly 58% of India's population. In the fiscal year 2019, the combined contribution of agriculture, forestry, and fishery amounted to almost Rs 18.55 lakh crore (nearly US $ 265.51 billion) in terms of Production Equivalent (PE). With trade constituting 70% of total sales, India stands as the sixth-largest food and grocery market globally. The Indian food distribution industry, a major sector, constitutes 32% of the overall food market of the nation. Considering export, consumption, and anticipated growth, the rank is fifth. It accounts for roughly 8.80% and 8.39% of the Gross Value Added (GVA) in the industrial and agricultural sectors, respectively. Furthermore, it contributes 13% to India's exports and makes up 6% of the total manufacturing-related investments [1].

Rice, a vital crop for ensuring security of food, takes precedence as the most significant crop in India. Millions of small-scale, economically disadvantaged farmers prefer cultivating rice for both income and household food security. Despite a fourfold increase in production over the past four decades, the rice industry has witnessed a declining trend in production curves and a slowdown in productivity since the latter half of the 1990s, marking the onset of an agrarian impasse, especially in states like Punjab, the central region of the green revolution, as well as Tamil Nadu, Andhra Pradesh, Kerala, and others [2].

The rice crop faces a multitude of challenges, with more than 100 insect species posing a threat globally, and 20 of them having the potential for significant economic damage. Stem borers, leafhop- pers, planthoppers (which directly harm crops and spread viruses), gall midges, a group of defoliating species (primarily lepidopterans), and a complex of grain-sucking bugs that feed on growing grains are among the insect pests capable of significantly reducing yields. In Asia, which produces over 90% of the world's rice, the average yield loss due to various insect pests is approximately 20%. Any mitigation of insect damage translates to an increased requirement for rice production. Throughout the rice crop's lifecycle, from nursery bed preparation to harvest, it is susceptible to insect attacks. The species complex of insects varies in abundance and distribution from place to place and year

to year. These insects may infest all parts of the plant at different growth stages [3].
Magnaporthe grisea, is a pathogen responsible for rice blast disease, poses a significant danger to rice cultivation worldwide. Since 60% of the world's population depends on rice as a staple food source, the impact of the disease could be catastrophic. In addition, the pathogen has become a leading model system for studying host-pathogen interactions. The severity following the outbreak of the disease is influenced by weather and climatic factors in different regions, with variations in prevalence and symptoms from one nation to another. Rice yield losses in susceptible cultivars are substantial, primarily attributed to pathogenic variability that undermines resistance to rice blast disease [4].
The use of automated techniques for the detection of plant diseases offers significant benefits by reducing the need for extensive monitoring in large agricultural fields and facilitating the early detection of disease symptoms [5]. Artificial Intelligence (AI) plays an important role in mitigating rice blast disease, contributing to improved agricultural production yields. Modern machine learning (ML) techniques outperform their older counterparts in terms of time and efficiency consumption. The combination of technologies such as the Internet of Things (IoT), AI, and unmanned aerial vehicles (UAVs) supports plant leaf illnesses detection in agricultural areas, enhancing accuracy and timely reporting [6].
Effectively managing climatic and agricultural changes is closely linked to the challenge of safe-guarding plants from diseases. Computer vision technology, which uses techniques such as color detection and thresholding, helps farmers in safeguarding agricultural yields. Convolutional Neural Network (CNNs) stand out as widely used approaches of deep learning for the detection of plant diseases, utilizing advances in computer vision, pharmaceuticals, and bioinformatics [7].The fast growing field of deep learning has achieved significant success in academia and industry, driven by the massive daily data generation and the capability of deep models to leverage compute parallelism through Graphics Processing Units (GPUs). [8].
A detailed review of the detection of deadly rice blast disease using machine learning and deep learning is important, given the pressing need for innovative agricultural solutions. Rice blast is a severe fungal disease that threatens global rice production, endangering food security and liveli-hoods. Conventional detection methods often fail in speed and accuracy, delaying intervention and resulting in significant crop losses. The adoption of deep learning and machine learning techniques has emerged as a promising approach to enhance diagnostic efficiency.
A review paper on this subject is crucial to consolidate the diverse research efforts in the field.It will provide a systematic overview of existing methodologies, algorithms, and technologies, allow- ing practitioners and researchers to evaluate the strengths and limitations of various approaches. Ultimately, this paper supports the global effort to enhance food security and promote sustainable agriculture amid ongoing challenges. The paper comprises three sections: an introduction, a review of relevant research in Section 2 which concludes with a brief discussion on the future direction of research and its significance. Finally, Section 3 is the conclusion which emphasizes the usefulness of supervised machine learning techniques for detecting rice blast disease.

2 Machine Learning in Rice Blast Disease Detection

The following sub-section discusses various researches carried out on supervised machine learning techniques.

2.1 Supervised Learning

A novel approach involving a hybrid CNN (Inception-ResNet) and SVM model has been created by Chaudhuri et al. [9] to identify and address damaged rice leaves. In this devised model, pictures of rice leaves are obtained by capturing images in agricultural fields using a camera. These images are then improved to enhance their visibility and quality, making them more suitable for accurate assessment. The refined images are further processed using the Grab-Cut algorithm to eliminate any unwanted portions. Subsequently, features from the segmented images are extracted and subjected to classification using the hybrid CNN (Inception-ResNet V2) and SVM algorithm. The outcomes of the study of the model developed are thoroughly examined and compared with recent techniques. The suggested model achieved commendable values for accuracy, precision, recall, and error, measuring at 0.97, 0.93, 0.03 respectively. In summary, the suggested model surpasses previous methodologies with respect to performance.

The main objective of the research by Rajathi et al. [10] is to develop a system called Rice Leaf Disease Detection (RLDD), designed to recognize various types of rice leaf diseases like brown spot, hispa, and leaf blast. This system utilizes rice plant images acquired from the Kaggle API and employs deep learning models for training. Data fusion is employed to combine information from multiple sources, aiming to enhance overall efficiency. The core idea behind the suggested system is to utilize a technique called late fusion, which involves merging information at a later stage, to effectively categorize different rice leaf diseases. The motivation driving this system is to implement the late fusion approach for disease classification. Through experimentation, the suggested model demonstrates an impressive accuracy rate of 98.85%, outperforming other existing models in this domain.

For the categorization of leaf types, the study by Bajpai et al. [11] encompassed four distinct classes. To discern the actual disease in affected plants, the power of deep learning methods was har- nessed. Specifically, they employed three architectures: VGGNet16, ResNet101, and AlexNet. Among these alternatives, it was found that AlexNet exhibited the most noteworthy performance. Within our dataset, the AlexNet model demonstrated remarkable outcomes, achieving training and test- ing accuracies of 92.35% and 85.27% respectively. This underscores the efficacy of our approach in accurately identifying and classifying the diseases present in the plant leaves.

In their research, Ou et al. [12] developed a new deep learning model, BlastGRU-TW, to predict rice explosion outbreaks. The study utilized a dataset of approximately 1,000 rice blast surveys from 50 fields across Taiwan (2014–2021) alongside meteorological data from Taiwan's weather observation network. Common weather variables such as temperature, humidity, wind and precipitation were transformed into a total of 20 daily meteorological characteristics. These features were analyzed over time intervals spanning 1 to 30 days before each survey to train the model.

The results identified seven key meteorological features—daily maximum, minimum, and mean temperature; daily mean water vapor; daily mean humidity; and daily mean wind velocity—within a 4- to 24-day window before a survey as critical for predicting disease outbreaks. This indicates that BlastGRU-TW can accurately forecast rice blast risk using meteorological data from 4 to 24 days before symptom onset. An accuracy of 87.3% was achieved by the model.

Additionally, integrating 3-day prediction data from the Weather Research and Forecasting (WRF) model extended the prediction horizon to 7 days before current symptoms surfaced. The study also validated the applicability of the Japanese-developed BLASTAM model in Taiwan to assess its effectiveness across different regions. As a result, a practical early warning system for rice blast has been established, featuring an interactive web-based map for real-time risk prediction in Taiwanese paddy fields.

Dubey and Choubey [13] introduced an automated leaf detection method employing machine learning. The approach comprises three major stages: pre-processing, feature extraction, and classification. In the initial step, the image taken as an input is converted into red, green, and blue channels, followed by the removal of noise from the green channel using a median filter. Subsequently, significant characteristics from the green channel are extracted. These features are then utilized by an OSVM classifier to categorize the image as either normal or exhibiting pathology. In order to enhance the performance of the SVM, the algorithm optimizes SVM parameters using the Adaptive Sunflower Optimization (ASFO) technique. Further, a level-set segmentation algorithm is employed to isolate the infected region. The effectiveness of the suggested method is evaluated using parameters such as accuracy, sensitivity, and specificity. Remarkably, the approach achieves a peak accuracy of 97.54% for predicting plant diseases, underscoring its efficiency and potential impact in this domain.

Kamrul et al. [14] focused on six prevalent diseases generally found in paddy fields in Bangladesh, meticulously gathering an authentic dataset. They harnessed the power of three well-known pre-trained CNN models: Inception-v3, MobileNet-v1, and ResNet50. Before conducting the research, great care was taken in augmenting and scaling the dataset appropriately. The results obtained were highly encouraging, demonstrating the potential of machine learning in agriculture. This success demonstrates the impactful synergy between machine learning and the agricultural sector. Researchers believe that this research can serve as a stepping stone for machine learning techniques to make significant contributions to the agricultural domain in our country. Additionally, it holds the promise of benefiting future generations of young people entering the field of agriculture.

Kaundal et al. [15] presented a novel method for predicting plant diseases using SVMs and weather data. The research showcases the superiority of SVMs over current machine learning methods and traditional regression (REG) approaches in anticipating plant diseases. A specific case study illustrates the effectiveness of SVMs in disease forecasting. Additionally, the researchers have created a groundbreaking web server that utilizes SVMs for predicting rice blast disease, a pioneering initiative on a global scale. This innovation holds the potential to greatly assist plant scientists and farmers in making informed decisions regarding disease management.

Efficiently identifying pests and diseases affecting rice plants is essential to prevent crop dam- age.In response to the constraints of traditional manual detection methods and existing approaches based on machine learning, a novel model for recognizing rice pests and diseases has been de- veloped by Jia et al. [16].This model is built upon an enhanced YOLOv7 algorithm, integrating MobileNetV3, a lightweight network, for efficient feature extraction. The inclusion of the coordinate attention mechanism (CA) and the SIoU loss function further enhances accuracy. The performance of this model was evaluated using a dataset containing 3773 images of rice pests and diseases, resulting in an impressive accuracy of 92.3% and an mAP@.5 of 93.7%.The suggested MobileNet-CA-YOLO model represents a lightweight yet high-performance solution for detecting rice pests and diseases. It offers precise and timely results that can greatly benefit farmers and researchers alike.

Tran et al. [17] introduce an approach to detect diseases in rice leaves through the use of three transfer learning models: EfficientNetB3, VGG-16, and MobileNetv2. The suggested technique attains accuracy rates of 90%, 93%, and 94% for the detection of nine distinct disease types as well as normal leaves. These outcomes hold potential for predicting diseases on rice leaves through image analysis, thereby recommending suitable prevention and treatment strategies to aid farmers in enhancing rice productivity.

Mohapatra and Das [18] introduces an AlexNet model to automatically detect and diagnosis tasks using transfer learning. The research focuses on three prevalent rice plant diseases—bacterial leaf blight, leaf smut, and brown spot which are difficult to differentiate with the bare eye. The dataset used to investigate is sourced from the 'Kaggle' platform. The suggested AlexNet model de- livers notably strong performance to detect and classify these diseases within the 'Kaggle' dataset. Its precision,accuracy, recall, F1 score, and kappa coefficient metrics outshine those of other machine learning and approaches based on transfer learning detailed in existing literature. These comparisons hold across similar or distinct datasets with the same task objectives.

Singh et al. [19] proposed an automated framework to accurately distinguish blast-affected leaves from healthy ones in paddy plants. This framework combines machine learning and image processing techniques, employing color slicing and gray-level co-occurrence matrices (GLCM) to extract texture-related features from leaf images.

These extracted features are fed into various machine learning classifiers, including decision tree, kNN, random forest, XGBoost, AdaBoost, and a histogram-based gradient boosting algorithm. A comprehensive evaluation of these classifiers across multiple performance metrics revealed that the random forest classifier achieved the highest accuracy (99.10%), sensitivity (99.05%), and specificity (99.05%) in detecting leaf blast disease in paddy crops.

Thus, the combination of color slicing, GLCM features, and the random forest classification method proves to be a promising approach for future IoT-enabled automated systems, ensuring precise detection of blast-affected leaves within paddy crops.

Das et al. [20] employ data fusion techniques to evaluate leaf blast occurrence by integrating multiple data sources, including land surface temperature data from spectral indices such as Normal- ized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Moisture Index (NDMI) and the Moderate Resolution Imaging Spectroradiometer (MODIS), and Soil Adjusted Vegetation Index (SAVI), along with moisture stress data from Sentinel-2.

A deep learning-driven model is prepared to evaluate rice blast disease on a field-wide scale, achieving a training accuracy of 90.02% and a validation accuracy of 85.33%. By leveraging deep learning with remote sensing imagery, this model facilitates real-time monitoring and assessment of leaf blast occurrences, enhancing early detection and disease management strategies.

Aggarwal et al.[21] introduced a robust and suitable technique to categorize different types of rice leaf disease employing deep learning methodologies. At the beginning of the study, classifi- cation was achieved using machine learning and ensemble learning classifiers. These results were then contrasted with those obtained from CNN transfer learning models CNN. Among them, InceptionResNetV2 demonstrated the highest validation accuracy, reaching 88 percent.The comparison revealed that transfer learning models outperformed machine learning classifiers in terms of classi- fication performance.

In the research by Akyol [22] introduces a three-stage approach for detecting rice leaf diseases, involving keypoint detection, extraction of hypercolumn deep features from classification and multiple CNN layers. A hypercolumn represents a vector that aggregates activations from all CNN layers for a specific pixel, while keypoints highlight significant image features.

In the first stage, keypoints within the image are identified, followed by the extraction of hyper- column features from these points. Next, machine learning classifiers are applied to the extracted features for disease detection. The evaluation results demonstrate the effectiveness of this approach, with the Random Forest classifier showing outstanding performance, achieving 89.58% sensitivity, 94.79% specificity, 93.06% accuracy, and 89.58% precision.

This method proves to be a promising addition to computer-assisted systems for diagnosing rice leaf diseases, offering valuable support to agricultural experts in disease management.

The study by Rajpoot et al. [23] explores the detection of three major rice plant diseases—bacterial leaf blight, leaf smut, and brown spot—out of six potential ailments affecting rice crops. The pro- posed approach integrates VGG-16 transfer learning with the Faster R-CNN deep architecture for feature extraction.

Following the transfer learning stage, extracted features are classified using the random forest technique, which segments rice field imagery into three distinct disease categories. The dataset used for this study comprises rice plant leaf images sourced from the UCI Machine Learning Repository. The proposed method achieves an impressive average prediction accuracy of 97.3% in classifying rice disease images. Extensive experimental results confirm the effectiveness and reliability of this approach in accurately detecting diseases of rice plants, highlighting its potential for practical agricultural applications.

Pan et al. [24] introduced an innovative approach called RiceNet to effectively detect and classify four main diseases of the rice plant: rice panicle neck blast, rice false smut, rice leaf blast, and rice stem blast. The methodology follows a two-stage process.

In the first stage, the YoloX detection model was used to identify affected regions of rice plants. Based on these detection results, the original disease images were cropped to create a refined dataset of rice disease patches. In the second stage, a Siamese Network was used to accurately classify the disease patches.

During the detection phase, YoloX demonstrated outstanding performance, achieving a mean Average Precision (mAP) of 95.58% on rice disease images. This approach highlights the effec tiveness of combining object detection and deep learning techniques for precise and automated rice disease diagnosis. Comparative experiments indicated that YoloX outperformed other models in terms of detection capabilities. Shifting to the recognition stage, the Siamese Network yielded exceptional results, achieving a recognition accuracy of 99.03%.This accuracy level surpassed that of alternative models. The empirical findings underscore the superiority of the suggested RiceNet model in comparison to prevailing methodologies. Notably, RiceNet managed to achieve both high detection speed and a compact model size, making it an efficient choice for identifying rice diseases. Sahith and Reddy [25] presents a technique that employs machine learning for the detection of diseases in rice leaves. The study focuses on four prevalent diseases affecting rice plants: Bacterial Leaf Blight, Blast, Tungro, and Brown Spot. The input comprises well-defined images of diseased rice leaves, which undergo suitable preprocessing. Various machine learning algorithms such as Random Forest, J48, and REP Tree were trained on the provided dataset. Following a 10-fold cross-validation process, the decision tree approach exhibited promising outcomes, achieving an accuracy exceeding 94% on the test dataset.

Rajesh and Girish [26] introduces a successful method for diagnosing blast disease across fifteen distinct paddy crop varieties. The study employs three transfer learning multi-layer CNN models: CapsNet, EfficientNet-B7, and ResNet-50.These models are utilized to capture and classify field images of blast disease based on levels of severity categorized as low, medium, high, and se- vere.

Among these models, the CapsNet approach demonstrates remarkable outcomes, utilizing a dataset containing 20,000 labeled images. It achieves a testing accuracy of 90.79% and a validation accuracy of 93.29%.The ResNet-50 and EfficientNet-B7 models exhibit average testing accuracies of 85.10% and 88.72%, respectively. When assessed on a separate dataset of blast disease-affected paddy field images, the CapsNet model surpasses both the EfficientNet-B7 and ResNet-50 CNN models, excelling in both computational efficiency and classification accuracy.
Corrales et al.[27] gave an idea of supervised learning algorithms which are commonly used in agriculture for the dual purpose of detection of pests and diseases in crops such as corn, rice, coffee, mango, peanut and tomato. Their aim was to select the best performing supervised learning algorithm for the purpose of detection of pests and diseases in crops mentioned above. They concluded that Decision Trees (DT) are highly regarded as the most widely utilized and effective algorithms for generating classifiers that are easily understandable. They are followed by SVM and Artificial Neural Networks (ANN), which are considered accurate algorithms for disease and pest prediction and classification. However, K-Nearest Neighbors (K-NN) and Bayesian Networks (BN) are rarely employed in the agricultural domain. Despite this, K-NN and BN excel in terms of their fast learning speed during training.
In another research, an automatic lesion segmentation process which is based on super pixel segmentation and random forest classifier was suggested by Xiaochun and Max.[28].The process was tested by using 2 data sets which were collected at different time. Results of their experiment achieved good segmentation performance. The suggested process successfully segments lesion from rice images which are affected by leaf blast disease.
An algorithm was suggested by Ghyar and Birajdar [29] for the diagnosis of diseases caused by pests in the rice plants. They used SVM and artificial neural networks (ANN) for classification. A total of three types of feature extraction was carried out in their experiment. The relevant features were selected and redundant features were discarded using Genetic algorithm based feature selection approach. A 14-D feature vector was generated to reduce the complexity. The accuracy obtained was 92.5% using SVM and while using ANN it was 87.5%.
A novel rice diseases identification method which is based on deep CNNs techniques was sug- gested by Lu et al.[30].The data set that was used consisted of 500 natural images of diseased and healthy rice leaves and stems. These images were captured from experimental field of paddy. A total of 10 common rice diseases were identified by training CNNs. An accuracy of 95.48% was obtained by the suggested CNN-based model which is higher as compared to conventional machine learning model. The researchers claimed that the experimental results prove the effectiveness and feasibility of their suggested methodology.
Table 1: Comparison of different Supervised models

Sl. No.	Algorithm Used	Key Improvement/Features	Performance	Reference
1	A hybrid CNN(Inception-ResNet),SVM	Pictures of rice leaves are obtained by capturing images in agricultural fields and subsequently after further processing subjected to classification	The suggested model achieved commendable values for accuracy precision, recall, and error, measuring at 0.97, 0.93, 0.03 respectively.	[9]
2	Random Forest	The core idea behind the suggested system is to utilize a technique called late fusion which involves	The suggested model demonstrates an impressive accuracy rate of 98.85%	[10]

		merging information at a later stage, to effectively categorize different rice leaf diseases.		
3	VGGNet16, ResNet101, and AlexNet	Three architectures were employed: VGGNet16, ResNet101, and AlexNet.	The model achieved raining and testing accuracies of 92.35% and 85.27% respectively.	[11]
4	RNN	By incorporating 3-day forecast weather data from the Weather Research and Forecasting (WRF) model into the BlastGRU-TW model, the forecasting horizon extended to 7 days before new symptoms became visible.Furthermore, the applicability of the BLASTAM model, initially developed in Japan, was tested and validated in the Taiwanese context to assess its effectiveness across different geographical regions.	The suggested model achieved an impressive accuracy rate of 87.3%.	[12]
5	OSVM	The algorithm optimizes SVM parameters using the Adaptive Sunflower Optimization (ASFO) technique.Further, a level-set segmentation algorithm is employed to isolate the infected region.	The approach achieves a peak accuracy of 97.54%	[13]
6	Three well-known pre trained CNN models Inception-v3, MobileNet-v1, and ResNet50.	Great care in augmenting and scaling the dataset appropriately was taken. The results obtained were highly promising, showcasing the	The Accuracy rate of training reached to 98%, 99% and 96% respectively for model Inception-V3, MobileNet-V1 and ResNet-50.	[14]

		potential of machine learning in agriculture.		
7	SVM	The research showcases the superiority of SVMs over current machine learning methods and traditional regression (REG) approaches in anticipating plant diseases.	The SVM-based method outperformed all the three approaches used by further increasing r to 0.74 with improvement in %MAE to 44.12.	[15]
8	This model is built upon an enhanced YOLOv7 algorithm, integrating MobileNetV3, a lightweight network for efficient feature extraction.	The suggested MobileNet-CA-YOLO model represents a lightweight yet high-performance solution for detecting rice pests and diseases.	The performance of this model was evaluated using a dataset containing 3773 images of rice pests and diseases, resulting in an impressive accuracy of 92.3% and an mAP@.5 of 93.7%.	[16]
9	EfficientNetB3, VGG-16, and MobileNetv2.	Utilization of three transfer learning models: EfficientNetB3, VGG-16, and MobileNetv2.	The suggested technique attains accuracy rates of 90%, 93%, and 94% for the detection of nine distinct disease types as well as normal leaves.	[17]
10	CNN	An AlexNet model for automatic detection and diagnosis tasks using transfer learning.	Accuracy, precision, recall, F1 score, and kappa coefficient metrics outshine those of other machine learning and transfer learning-based approaches.	[18]
11	Random forest, decision tree, K-NN, XGBoost, AdaBoost, and a histogram-based gradient boosting algorithm.	This framework combines image processing and machine learning techniques. To process and extract texture-related features from leaf images of paddy plants, the approach employs color slicing and grey level	Random forest classifier demonstrates the highest accuracy of 99.10%, sensitivity of 99.05%, and specificity of 99.05% for accurately identifying leaf blast disease in paddy crops.	[19]

		co-occurrence matrices (GLCM) methods.		
12	Deep learning-driven model	Analyzing data from various sources, including land surface temperature data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and several spectral indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Moisture Index (NDMI), Soil Adjusted Vegetation Index (SAVI), along with moisture stress data from Sentinel-2.	This model achieves a training accuracy of 90.02% and a validation accuracy of 85.33%.	[20]
13	CNN	Classification was achieved through the utilization of machine learning and ensemble learning classifiers. These results were then contrasted with those obtained from CNN and transfer learning models.	InceptionResNetV2 demonstrated the highest validation accuracy, reaching 88 %.	[21]
14	Random Forest classifier	Three main stages: keypoint detection within images, extraction of hypercolumn deep features from various CNN layers, and subsequent classification.	Random Forest classifier's performance when applied to hypercolumn deep features is 93.06% accuracy, 89.58% sensitivity, 94.79% specificity, and 89.58% precision	[22]
15	The suggested methodology employs a combination of	Three distinct types of ailments of rice plant diseases	The suggested approach achieves a notable average	[23]

	VGG-16 transfer learning and the Faster R-CNN deep architecture to extract relevant features.	bacterial leaf blight brown spot, and leaf smut, which are among the six potential diseases affecting rice plants are considered.	prediction accuracy of 97.3% in predicting the classes of rice disease images.	
16	YoloX, a detection model and a Siamese Network	Effectively address four significant rice diseases: rice panicle neck blast, rice false smut, rice leaf blast, and rice stem blast.	YoloX exhibited impressive performance, achieving a mean Average Precision (mAP) of 95.58% when dealing with rice disease images while the Siamese Network yielded exceptional results, achieving a recognition accuracy of 99.03%.	[24]
17	Random Forest, J48, and REP Tree	The study focuses on four prevalent diseases affecting rice plants: Blast, Bacterial Leaf Blight, Tungro, and Brown Spot.The input comprises well-defined images of diseased rice leaves which undergo suitable preprocessing	The decision tree approach exhibited promising outcomes, achieving an accuracy exceeding 94% on the test dataset.	[25]
18	The study employs three transfer learning multi-layer CNN models: CapsNet, EfficientNet-B7, and ResNet-50.	A successful method for diagnosing blast disease across fifteen distinct paddy crop varieties.	Testing accuracy of 90.79% and a validation accuracy of 93.29%.The ResNet-50 and EfficientNet-B7 models exhibit average testing accuracies of 85.10% and 88.72% respectively.	[26]
19	Decision Trees	An overview of supervised learning algorithms which are commonly used in agriculture for the dual purpose of detection of pests and diseases in crops like	Decision Trees (DT) are highly regarded as the most extensively utilized and effective algorithms for generating classifiers that are easily understandable.They are followed by SVM and Artificial Neural Networks (ANN).	[27]

		corn, rice, coffee mango, peanut, and tomato are discussed.	which are considered accurate algorithms for disease and pest prediction and classification.However, K-Nearest Neighbors (K-NN) and Bayesian Networks (BN) are rarely employed in the agricultural domain. Despite this, K-NN and BN excel in terms of their fast learning speed during training	
20	Super Pixel Segmentation and Random Forest Classifier	The process was tested by using 2 data sets which were collected at different time.	Results of their experiment achieved good segmentation performance.The suggested process successfully segments lesion from rice images which are affected by leaf blast disease.	[28].
21	SVM and Artificial Neural Networks (ANN) for classification.	A total of three types of feature extraction was carried out in their experiment. The relevant features were selected and redundant features were discarded using Genetic algorithm based feature selection approach. A 14-D feature vector was generated to reduce the complexity.	The accuracy obtained was 92.5% using SVM and while using ANN it was 87.5%.	[29]
22	Deep CNNs	The data set that was used consisted of 500 natural images of diseased and healthy rice leaves and stems. These images were captured from experimental field of paddy. A total of 10 common rice diseases	An accuracy of 95.48% was obtained by the suggested CNN-based model which is higher as compared to conventional machine learning model.	[30]

		were identified by training CNNs.		

Table 1 is depicting the comparison between different supervised machine learning models based on the following parameters supervised algorithm used in the model, key improvement/features and performance of the model. It can be concluded from the table that various supervised learning algorithms are widely used to detect rice blast disease.

While exploring the complexity of real-world problems, several researchers have opted to employ multiple supervised algorithms in their analyses. By using more than one supervised algorithm, researchers can gain a more comprehensive understanding of the data and its underlying patterns. This approach helps to make a robust comparison of different methodologies, leading to more informed decisions regarding the most effective modeling techniques for a given problem.

2.1.1 Future Scope

The future scope of supervised learning algorithms in predicting and detecting rice blast disease in the Indian subcontinent is promising and holds significant potential for advancements in agricultural practices. Here are some key aspects of the future scope:

- Enhanced Accuracy and Precision: Continued research and development in supervised learn- ing algorithms are likely to lead to more accurate and precise prediction models. Improved accuracy is crucial for early detection and timely intervention to prevent the spread of the disease.
- Integration with Advanced Technologies: Supervised learning algorithms can be integrated with other advanced technologies such as remote sensing, satellite imagery, and IoT devices. This integration can provide a comprehensive and real-time understanding of environmental conditions, contributing to more robust disease prediction models.
- Customization for Regional Variations: The Indian subcontinent exhibits diverse agro-climatic conditions. Future research can focus on tailoring supervised learning models to specific regional variations, considering factors such as temperature, humidity, and soil types that influence the prevalence of rice blast disease.
- Deployment of Mobile and Web Applications: The development of user-friendly mobile and web applications powered by supervised learning algorithms can empower farmers with ac- cessible tools for disease prediction. These applications can provide real-time information, actionable insights, and recommendations for disease management.
- Integration with Agricultural Extension Services: Collaboration with agricultural extension services can facilitate the adoption of supervised learning models at the grassroots level. Extension workers can use these models to provide timely advice to farmers, enabling them to take preventive measures and optimize their crop management practices.
- Data Sharing and Collaboration: Collaborative efforts among researchers, agricultural insti- tutions, and technology developers can contribute to a more extensive and diverse dataset. Shared data can enhance the training of supervised learning algorithms, making them more robust and adaptable to varying conditions.
- Continuous Model Improvement: Continuous monitoring and feedback loops can be estab- lished to improve the performance of supervised learning algorithms over time. As more data becomes available and the understanding of rice blast disease dynamics evolves, the models can be refined for increased effectiveness.
- Capacity Building for Farmers: Training programs and capacity-building initiatives can be designed to educate farmers about the use and interpretation of predictions generated by supervised learning algorithms. This knowledge transfer is essential for widespread adoption and effective utilization of these technological tools.
- Early Warning Systems: The ultimate goal is to develop early warning systems that can pro- vide farmers with actionable insights well in advance of disease outbreaks. Supervised learning algorithms can contribute to the creation of reliable and efficient early warning mechanisms for rice blast disease.
- Policy Support and Adoption: Government policies and initiatives that support the integration of advanced technologies, including supervised learning, into agriculture can accelerate the adoption of

these tools. Policy frameworks that encourage research, development, and the practical application of predictive models can drive positive change in the agricultural sector.
In conclusion, the future scope of supervised learning algorithms in predicting and detecting rice blast disease in the Indian subcontinent is promising, with opportunities for innovation, collaboration, and positive impact on agricultural productivity and food security.

3 CONCLUSION

One of the most significant inventions in human civilization is agriculture. Most of the world's population is thought to work in it as their primary occupation. The production in the agriculture sector is expected to fall over the next few decades. At the same time, the global population is increasing at an alarming rate.The majority of the techniques and supplies utilised in rural agriculture today have been around for a while. However, they are inadequate to help the farmers.In order to maintain a balanced food chain the automatic detection and diagnosis of diseases of rice plant is necessary as rice is considered to be the dominant food of the majority people.
In summary, leveraging supervised machine learning techniques for detecting rice blast disease marks a significant advancement in tackling agricultural challenges. The fusion of cutting-edge technology with plant pathology has accelerated disease identification while improving diagnostic accuracy and efficiency. The reviewed studies highlight the strong potential of these algorithms in effectively differentiating between healthy and diseased rice plants, paving the way for early and precise detection. Additionally, the flexibility of machine learning models to adapt to varied envi- ronmental conditions and process large datasets enables the detection of subtle infection patterns.
As agriculture and technology converge, these innovative methods hold the potential to transform disease management, minimize crop losses, and enhance global food security. Moving forward, collaboration among researchers, agronomists, and technologists will be essential in refining and scaling these models, fostering a more sustainable and resilient future for rice cultivation. Continued research in this field will play a pivotal role in mitigating food loss caused by plant diseases, contributing to long-term food security.

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