

REVOLUTIONIZING RICE DISEASE DIAGNOSIS: AN ADVANCED CNN AND VISION TRANSFORMER METHODOLOGY

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Abstract: *In developing countries particularly, agriculture's essential role in the economy is indispensable, providing a large population segment with a considerable income source. Among the major crops cultivated across vast regions of the developing countries, rice stands out as a crucial staple food. However, rice crops are largely susceptible to multiple diseases, causing substantial economic losses in the agricultural sector. To mitigate these challenges, plant pathologists have been actively seeking precise and dependable methods for diagnosing rice plant diseases. Lately, machine learning has become popular in crop remote sensing applications, particularly for the classification of crop diseases. Moreover, deep learning has become a major research area in identifying crop diseases due to its ability to analyze large datasets and deliver accurate results.*

In this study, we present an advanced method for rice plant diseases detection via a convolutional neural network (CNN)-based approach. This research concentrates on identifying six common rice diseases: leaf scald, leaf blast, narrow brown spot, healthy rice leaves, and bacterial leaf blight. The proposed system offers a new solution for recognizing and classifying these diseases by analyzing specific features of the lesions present on the rice leaves, such as their size, shape, and color. The CNN architecture employed in this research is based on vision tokenizer (Vit), with training on a huge dataset containing 2628 healthy and diseased rice leaf images. This model aims for accurately detecting and classifying six rice diseases.

It is demonstrated by experimental results that Vit combined with support vector machine (SVM) method is fast and highly effective, with 98.2% accuracy impressively achieved on the dataset. This performance significantly surpasses the accuracy of existing methods for detecting and classifying plant disease, making it a promising solution for enhancing rice crop health management and mitigating plant disease economic impact in agriculture.

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INTRODUCTION

In ancient times, identifying plant diseases was primarily done through manual observation, where farmers or experts visually inspected plants for signs of infection. While this method provided some insight, it required an extensive workforce, manifested complexity and huge time consumption, and was susceptible to inaccuracies. Nowadays, plant diseases can be attributed to a key factor which is the excessive use of toxic chemicals. These chemicals are effective in boosting crop yield, but pose significant threats to insects, birds, and animals. Additionally, various biotic agents, commonly referred to as pathogens, including microorganisms, bacteria, and fungi, are responsible for spreading infections across crops. These pathogens can rapidly transfer from one plant to another, ultimately devastating entire fields of healthy crops [5]. Many farmers, particularly in rural areas of countries like India, China, Indonesia, Vietnam, Thailand, and even in the United States (USA) often struggle to access expert assistance due to high costs or a lack of availability. Given that agriculture is considered the backbone of developing countries' economy, ensuring healthy crop production is essential. This necessitates constant monitoring of crops to detect and address diseases before they can cause widespread damage.

Leaf smut, Hispa, Leaf Blast, Brown Spot, Alternaria, and Bacterial Leaf Blight are some of the plant diseases that are prevalent and that can significantly harm crops. Each of these diseases manifests through distinct patterns on the leaves of affected plants. By carefully analyzing these patterns, it becomes possible to identify the specific type of disease affecting the crop. This pattern recognition is a crucial aspect of disease detection. A system utilizing MATLAB software is proposed in this paper for automatically detecting plant diseases based on the visual symptoms present on the leaves. The approach employed for this task involves Image Processing techniques, employed for analyzing diseased leaves' images, identify the patterns, and classify the type of infection. By automating this process, farmers can save time and effort while improving the accuracy of disease detection. This not only helps in reducing crop losses but also promotes healthier agricultural practices.

The foundation of image processing begins with the observation and preprocessing of digitally modified images that are captured through sensors or obtained from other sources [4]. For the present study, image data was collected from a well-known dataset: the Rice Disease Image Dataset from Kaggle. From these datasets, several prominent rice plant diseases were specifically under focus, namely Leaf Smut, Bacterial Leaf Blight, Brown Spot, Hispa, and Leaf Blast. Such diseases are characterized by distinct visual patterns on the leaves, which can be detected through image analysis techniques. Image processing primarily involves analyzing and manipulating various properties of an image, such as color, texture, shape, and size, to extract meaningful information. Currently, numerous advanced techniques are used to identify plant diseases based on these properties. Among these, Support Vector Machines (SVM) and Artificial Neural Networks (ANN) received wide recognition and have been extensively applied in classification tasks related to disease detection. These methods rely heavily on feature extraction, where key aspects of the images are identified and used to distinguish between healthy and diseased plants [15]. ANN is a fundamental technique included under the broader Artificial Intelligence (AI) field, drawing inspiration from the human brain workings. Just as biological neurons work together to solve problems in the human brain, artificial neurons in ANN are structured in interconnected layers, consisting of hidden, input,

and output layers. Network data processing and learning is permitted by these layers, making it an effective tool for complex problem-solving. AI-based systems, particularly those incorporating ANN, are designed to mimic human intelligence by learning from data and improving performance over time [15]. As advancements in AI and neural networks continue, Deep Neural Networks (DNN) have emerged as a more powerful extension of the traditional ANN model. Convolutional Neural Network (CNN) is one of the most typically used algorithms within DNN, excelling in image processing tasks. CNNs are particularly effective in reducing the model's parameters and increasing their efficiency in terms of computational resources. This reduction in complexity is especially valuable for researchers and developers dealing with intricate problems in detecting plant diseases using ANN models.

A new deep learning framework is introduced in this paper, with design for enhancement of disease identification in rice leaf images. Vision transformer (Vit) [18] is a customized deep learning architecture based on transformers that has been specifically adapted for plant disease detection tasks and other different tasks. Unlike many general-purpose CNN models, such as AlexNet, GoogleNet, and ResNet, which are typically employed for various classification problems in images, the Vit model has been fine-tuned to cater to the specific requirements of plant disease identification. The remaining sections of the paper are presented as follows: Sect. 2 provides the literature review. In section 3, a description of our proposed methodology is given. The proposed methodology results are presented in Section 4. Finally, the conclusion is presented in Section 5.

LITERATURE REVIEW

Several studies have focused on diagnosing rice plant diseases. We concentrated on recently published papers that achieved the highest accuracies and classified a large number of classes. A method for detecting rice leaf diseases was proposed by Azim, et al. [2] utilizing techniques for image processing. They focused on segmenting disease-affected areas of the leaves using hue-based thresholding and extracted features such as shape, texture and color. Then, the Extreme Gradient Boosting (XGBoost) classifier is used for classifying these features. The employed dataset includes 120 images from three rice leaf disease types (Leaf Smut, Brown Spot and Bacterial Leaf Blight) from the UCI repository [17]. 86.58% accuracy is achieved by the proposed model, which is higher than earlier models, rendering it a robust method for detecting rice disease.

The InceptionResNetV2 architecture is a deep CNN intertwined with transfer learning for rice leaf disease prediction, proposed in Krishnamoorthy, et al. [10]. This model with prior training and fine tuning on 5200 images dataset from Kaggle included three disease categories: Brown Spot, Bacterial Blight, and Leaf Blast. The model, focused on improving performance through image processing and data augmentation. The proposed model achieved 95.67% high accuracy, demonstrating transfer learning effectiveness for this task. The M-Net model, a customized deep learning architecture based on AlexNet, designed specifically for plant disease identification is introduced in Rallapalli and Saleem Durai [14]. Using datasets from Kaggle and UCI repository, including Leaf Smut, Brown Spot, and Bacterial Leaf Blight diseases, the model aimed to enhance accuracy by decreasing the internal complexity seen in general-purpose CNNs like GoogleNet and ResNet. M-Net achieved a 71% accuracy, showing promising results for plant-specific disease detection applications.

Ghosal and Sarkar [7] applied transfer learning employing VGG-16 CNN model with prior training on ImageNet and fine tuning for detecting rice leaf diseases. 1649 diseased rice leaf images (Brown Spot, Leaf Blight and Leaf Blast) were included in the dataset, with data augmentation techniques employed for addressing the dataset small size. 92.46% accuracy was achieved by the model, proving that transfer learning combined with fine-tuning can be highly effective even with limited training data.

Table 1. A Literature Review on The Main Common Papers for the Diagnosis of Rice Diseases.

Author	Methodology	Dataset Used	Accuracy	Key Points
Azim, et al. [2]	Proposed an image processing technique with hue-based segmentation. Features extracted include color, shape, and texture. Classified using Extreme Gradient Boosting (XGBoost).	UCI Rice Leaf Disease Dataset (120 images of BLB, BS, LS)	86.58%	The model segments disease-affected portions of leaves and extracts features for classification. It outperforms previous models for this dataset with improved accuracy.
Krishnamoorthy, et al. [10]	InceptionResNetV2 CNN architecture combined with transfer learning for rice leaf disease classification. Pre-trained on large datasets, fine-tuned for this task.	Kaggle rice dataset (5200 images of BLB, BS, LS)	95.67%	Transfer learning with fine-tuning improved disease prediction. Preprocessing and augmentation techniques were utilized for improving the model's performance and expanding the dataset.
Rallapalli and Saleem Durai [14]	M-Net, a custom CNN architecture based on AlexNet, optimized for plant disease classification. It improves over general CNN models like GoogleNet, ResNet.	Kaggle and UCI datasets (Rice leaf diseases: BLB, LS, BS)	71%	The M-Net model customizes a general CNN architecture for plant diseases, reducing visual fluctuations during training. Outperforms general-purpose CNN models for this task.
Ghosal and Sarkar [7]	Transfer learning applied using VGG-16 architecture with prior training on ImageNet and fine-tuning for rice leaf disease classification. Data augmentation methods used.	Custom dataset (1649 images of BLB, BS, LS)	92.46%	The model leverages transfer learning on a small custom dataset and achieves high accuracy. Data augmentation was critical in expanding the training set and improving results.

METHODOLOGY

A machine learning methodology is proposed for diagnosing rice diseases. The methodology consists of three main stages. The first stage is collecting images of rice leaf leaves, and the second stage is based on employing vision tokenizer for extracting features [8]. The last stage is classifying the rice leaves using five main classifiers which are softmax, multi-layer perceptron (MLP), support vector machine (SVM), k-nearest neighbor (KNN), as well as random forest (RF).

DATA ACQUISITION

The data are obtained from Rice Leafs Disease Dataset [16] that consist of a total of 2,627 images, collected from both the internet and independent sources, and is focused on six different rice leaf diseases. Dataset organization involves creating

separate folders for validation and training purposes, providing a comprehensive resource for machine learning models development for classifying rice leaf disease. Images representing six categories are included in the dataset:

- Healthy: Rice leaf images without any obvious disease signs, used to ensure models can accurately differentiate between diseased and healthy plants.
- Bacterial Leaf Blight: Bacterium *Xanthomonas oryzae* causes this disease, leading to wilting and drying of rice leaves.
- Brown Spot: *Cochliobolus miyabeanus* causes this fungal infection which affects leaves, seedlings, and grain quality.
- Leaf Blast: A destructive fungal disease caused by *Magnaporthe oryzae*, which creates lesions on leaves that reduce crop yield.
- Leaf Scald: A bacterial disease-causing lesion that progresses to cover the leaf surface, leading to significant crop damage.
- Narrow Brown Spot: Another fungal disease that causes elongated brown spots on rice leaves, typically affecting older plants.



Figure 1: Rice Leaf Diseases of Different Types: the First Row Represents Brown Spot, Bacterial Leaf Blight, And Healthy, The Second Row Shows the Narrow Brown Spot, Leaf Scald and Leaf Blast.

Feature Extraction using Vision Transformer (ViT)

One of the deep learning model types is Vision Transformers (ViTs) [8], where the transformer architecture, designed initially for natural language processing (NLP), is applied to image classification and other computer vision tasks [19]. CNNs use convolutions to process image data, while ViTs handle images by treating them as sequences of patches, similar to how transformers in NLP treat sentences as sequences of words. ViT divides the input image into smaller patches (i.e., 16x16 pixels), with flattening of every patch into a vector. These patches are then treated like tokens in a sentence for processing. Each patch has a positional encoding added to it for providing information about each patch's position within the original image, considering that the patches' order is not inherently known to transformers (unlike convolutions, which process spatial information directly). This ensures that spatial relationships are preserved in the model [3].

The multi-head self-attention mechanism is leveraged from the transformer

architecture for learning relationships between different image patches. Each patch's importance relative to others is weighed by the model through self-attention. This allows for transformer's focus on the image's most important parts for classifying purposes. After transformer layers process the sequence of patches, a classification token is appended to the sequence. Passing through a multi-layer perceptron (MLP), the final output moves to classification. Figure 2 represents the entire Vit model.

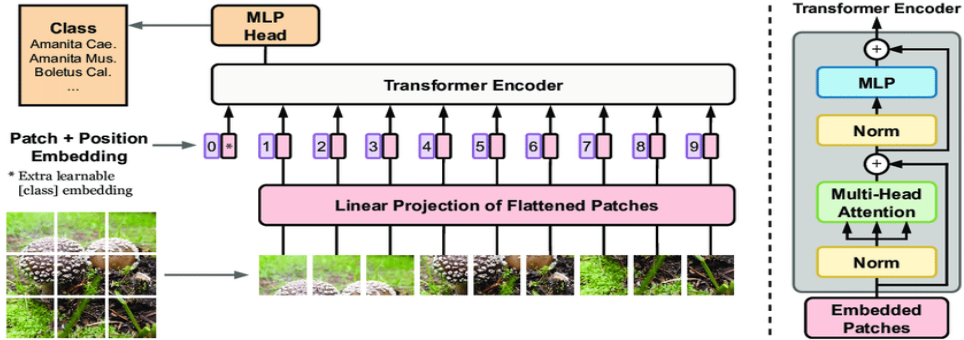


Figure 2: Layers in Vision Transformer (ViT) Model.

The main operation in transformers is self-attention, and its mathematical formulation can be adapted to ViTs. The self-attention mechanism works by creating three matrices from the input sequence: Values (V), Queries (Q), and Keys (K). Each pair of input patches attention score is calculated as the Key and Query matrices dot product, scaled by the keys dimension square root, then passed via a softmax function for computing attention weights. Then, the values weighted sum is computed by the resultant attention weights.

The self-attention equation is:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)v \quad (1)$$

Where:

- Q(Queries), K (Keys), and V (Values) are linear projections of the input patch embeddings. Images are split into small patches with fixed size (for instance, 16x16 pixels). Flattening each patch into a 1D vector is made, treating it as token, akin to a word in natural language processing. These tokens are then embedded into a continuous vector space to make them compatible with transformer inputs. A linear layer or a convolutional layer is usually applied to each flattened patch to generate an initial patch embedding, which is the "embedding" for that specific part of the image.
- d_k represents the keys dimension, employed for scaling the dot products for numerical stability.
- The softmax function normalizes the attention scores.

This equation is computed for each patch in relation to all other patches in the image, allowing for the model's capture of global dependencies between the image's different parts. In multi-head self-attention, multiple sets of (Q, K, V) matrices are used in parallel, and their outputs are concatenated and projected, where simultaneous focus on the input data different aspects is allowed for the model.

Classification

Classification is the methodology's last phase in which feature extraction models' performance is tested. 4 different classifiers are applied in this phase, such as SVM, MLP, RF, and Softmax. This mainly aims to determine the most robust model and the classifier with the highest performance in extracting features. The following subsections illustrate each classifier.

Softmax

As mentioned before, Softmax is the logistic regression extended version concentrating on solving multi-class problems. If the training samples are defined by x and its corresponding class is known by $\bar{x}$. Then, sample x , defined as $P(y = j|x)$, is forecasted to be the probability of class j [11]. The n -dimensional vector is the final Softmax layer output corresponding to a probability distribution.

K-Nearest Neighbor (KNN)

As an instance-based, non-parametric learning method, the K-Nearest Neighbors (KNN) algorithm is employed for regression and classification tasks. Its work leans on assuming that similar data tasks have tendency of belonging to the same class or having the same output values [9]. In the context of classification, a class label is assigned by KNN to a new data point, depending on the majority class among its k nearest neighbors. The distance metric is one of the KNN algorithm key components, employed for measuring similarity between data points. In KNN, the Euclidean distance is the most typically employed distance metric, although distance metrics such as Cosine similarity, Minkowski, or Manhattan are also employed. In the KNN algorithm with Euclidean distance, when classifying a new data point, computing distances between the new data point and all other data points within the training set is conducted. Then, depending on the smallest Euclidean distances, the new data point k nearest neighbors are identified. Finally, assigning the majority class among the k nearest neighbors as the new data point predicted label is performed [12].

Multi-Layer Perceptron (MLP)

A machine learning classifier, MLP's applications span several different problems and applications. MLP can be used for prediction, estimation, classification, and regression. In this study, MLP is used to classify the features into the corresponding classes [1]. The learning methodology is based on multi-layer perception. MLP is mainly advantageous due to adding hidden layers for solving the linear classification problem. Three main layers make up the MLP: Output, input and hidden. Layers are connected using a set of weights and biases. The backpropagation algorithm is utilized by MLP for error transmission back to hidden layers, as well as weights and bias update leaning on this error. The type of backpropagation applied in this study is momentum optimization backpropagation (MOBP).

Support Vector Machine (SVM)

Proposed by Vapnik, SVM has been employed for regression, classification as well as other numerous applications. SVM mainly functions by employing a nonlinear

for input features' mapping into a high dimensional feature field [13]. SVM training process is a quadric optimization problem. The following equation defines the hyperplane construction:

$$W^T x + b = 0 \quad (1)$$

Where input features are indicated by x , b is the bias factor, W represents the hyperplane coefficients. The purpose is margin maximization between the hyperplane and the nearest point. This leads to a quadratic optimization problem. This optimization problem is solved using sequential minimal optimization (SMO), and this requires correctly choosing the kernel function. The polynomial kernel function is the kernel function applied in this study.

Random Forest (RF)

Three classifiers combination form this classifier, where each classifier development leans on a random vector independently sampled from the input data. For input verification, a vote is produced by each tree for the most popular class. A set of randomly chosen features at each node make up the random forest classifier in this study for tree development [6]. Applying a bagging technique, a training set is generated using N examples random replacement, where the original training data size is known as N . Moreover, the tree design decision is based on the selection of the attributes and type of the pruning method. In this study, the Gini index was used for attributes selection. It calculates specific attributes' impurity associated with the classes. As an example, if Tr defines the training set, a feature sample is selected, and this sample feature is said to belong to a specific class Cs_i . The Gini index will be calculated as follows:

$$\sum \Sigma (f(Cs_i, Tr)/|Tr|)(f(Cs_i, Tr)/|T|) \quad (2)$$

Where the probability of a sample feature belonging to a particular class is defined by $f(Cs_i, Tr)/|Tr|$.

Experimental Setup and Discussion

The model was implemented using MATLAB, which supplied all the requisite libraries, on a laptop that has these specs: Intel Core i7-8565U 8 MB cache, 2.81 GHz central processing unit, 12 GB RAM and a graphics card NVIDIA GeForce MX 310 M 4 GB.

Experiments conducted by different classifiers (KNN, MLP, and SVM) are presented in Table 2, where rice leaf images are classified into three categories: Bacterial Leaf blight (BLB), Leaf blast (LB), Leaf scald (LS), Brown spot (BS), as well as narrow brown spot (NBS). Each row in the table represents a specific experiment comparing two classes or all three classes.

Here's a breakdown of the metrics and what they signify:

- A: indicates comparing classes of every experiment (e.g. Brown spot (BS), Healthy (H), Bacterial Leaf blight (BLB), narrow brown spot (NBS), Leaf scald (LS) and Leaf blast (LB)).
- TP: means True Positives, which is the correctly classified instances number for the specified class or classes.
- FP: represents False Positives, which is the number of instances incorrectly classified as positive.
- K: manifests the number of classes that the experiment involves.

- TPR: indicates the True Positive Rate (Sensitivity), which is the proportion of actual positive instances that the model correctly identifies.
- FPR: means the False Positive Rate, which is the proportion of actual negative instances that are classified incorrectly as positive.
- P: means Precision, which is the proportion of positive instances correctly predicted out of all instances predicted as positive.
- R: indicates Recall (Sensitivity), which is the proportion of actual positive instances that the model correctly identifies.
- F1: means F1 Score, indicating recall and precision harmonic mean, offering balanced measure between these two.
- MCC: means Matthews Correlation Coefficient, representing a measure of binary classifications quality, taking into account false and true negatives and positives.
- ROC: exhibits the Receiver Operating Characteristic, which indicates a graphical plot illustrating the binary classifier system diagnostic ability.
- PRC: stands for Precision-Recall Curve, which is a graph indicating the trade-off between recall and precision for various thresholds.



Figure 3: The Five Presented Classifiers' Confusion Matrices for the Diagnosis of Rice Diseases Based on Vit.

Table 2: Classifiers Results for Rice Leaf Diagnosis Depending on Vision Transformer.

Classifiers	Performance Measurements											
	A	TP	FP	K	TPR	FPR	P	R	F1	MCC	ROC	PRC
Softmax	97.9087	515	11	0.9749	0.979	0.004	0.979	0.979	0.979	0.975	0.987	0.963
KNN	97.9087	515	11	0.9749	0.979	0.004	0.979	0.979	0.979	0.975	0.987	0.963
MLP	98.0989	516	10	0.9772	0.981	0.004	0.981	0.981	0.981	0.977	0.996	0.984
SVM	98.2890	517	9	0.9795	0.983	0.003	0.983	0.983	0.983	0.980	0.993	0.973
Random Forest	98.0989	516	10	0.9772	0.981	0.004	0.981	0.981	0.981	0.977	0.995	0.984

The **SVM** classifier is the best performer, scoring the highest accuracy (98.29%), the highest true positive rate (0.983), as well as the lowest false positive rate (0.003). It also has a high F1-score, MCC, and ROC AUC. The **MLP** and **Random Forest** classifiers perform comparably well, with similar accuracy (98.10%) and precision-recall characteristics, while **Softmax** and **KNN** have slightly lower performance metrics as shown in Table 2.

The confusion matrices in Figure 3 illustrate the classification performance of five distinct classifiers for diagnosing rice diseases using Vision Transformer (ViT)-based methods. Each matrix shows how well each classifier correctly identifies instances across different disease categories, with true positives (correctly classified instances) presented along the diagonal. High values on the diagonal indicate strong classifier performance, as these values represent accurate predictions for each disease class. In contrast, off-diagonal elements represent misclassifications, where one disease was incorrectly predicted as another. These misclassifications reveal the challenges some classifiers face in distinguishing between certain disease types, likely due to similarities in visual characteristics or overlapping features among classes.

A detailed analysis of these confusion matrices allows for the calculation of important performance metrics, such as F1 score, recall, and precision, for every class. Such metrics provide a clearer understanding of each classifier's strengths and weaknesses, especially in handling class-specific imbalances. By comparing the matrices across classifiers, we can observe which model consistently achieves higher accuracy and where certain models may underperform. This comparison offers insights into which classifier may be best suited for real-world deployment in rice disease diagnosis, where credible and meticulous classification is essential for disease management and early intervention.

CONCLUSION

This paper offers a robust and innovative approach for detecting and classifying rice plant diseases employing a convolutional neural network integrated with a vision transformer and support vector machine methodology. By focusing on six prevalent rice diseases, the proposed system effectively analyzes critical features of lesions on rice leaves, leading to highly accurate results. The model's impressive accuracy of 98.2% demonstrates its superiority over existing plant disease detection methods, highlighting its potential for real-world application in agricultural practices. This advancement not only provides a reliable tool for plant pathologists and farmers but also contributes significantly to enhancing rice crop health management. By facilitating timely and accurate disease identification, this method can help mitigate economic losses in the agricultural sector, ultimately supporting food security and the livelihoods of millions of people who rely on rice cultivation in Egypt. The promising results from this research allow for additional development and exploration of deep learning and machine learning techniques in agriculture, reinforcing their importance in addressing the challenges posed by crop diseases.

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