Application of Computer Vision and Machine Learning to Recognition of Rice Leaf Diseases

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Abstract. As global population growth poses an increasing challenge to agriculture, the importance of crop pest management has increased. At present, most pest problems are solved by traditional manual methods, which are becoming increasingly inefficient in the face of increasing production capacity, so automated pest management has begun to attract people's attention. This study compared the performance of traditional models and advanced models in several fields of artificial intelligence in disease recognition tasks. The results show that Convolutional Neural Network (CNN) model has the best performance in recognition accuracy, but the execution efficiency is low. XGBoost model has an advantage in processing speed. Support vector machine (SVM) models do not perform well in identifying specific disease classes. The Random forest (RF) model also performs poorly. These experimental results show the potential and limitations of different technologies in improving the efficiency of crop disease management.

Keywords: Application, Computer Vision, Machine Learning, Automatic Recognition, Rice Leaf Diseases

1 Introduction

It is anticipated that the global population will increase by about 25% from its current level, presenting a considerable obstacle for the agricultural industry: dramatically increase crop yields to meet the growing demand for food. This challenge is compounded by widespread crop pests and diseases, which have the potential to significantly reduce yields and undermine food security. Barbetti (2012) [1] emphasizes that with the expansion of biodiversity of crop pathogens, pests and diseases will become an important challenge in crop production and management. Traditional approaches to managing these threats are largely manual and labor-intensive, often lacking the timeliness and accuracy required for effective pest management.

Amidst this backdrop, the advent of computer vision and image recognition technologies, powered by the latest advancements in artificial intelligence, has emerged as a beacon of hope. These technologies are expected to revolutionize agricultural practices by detecting digital images to efficiently identify crop pests and diseases. This innovative approach not only establishes a foundation for timely and precise

Y. Wang (ed.), *Proceedings of the 2024 2nd International Conference on Image, Algorithms and Artificial Intelligence (ICIAAI 2024)*, Advances in Computer Science Research 115,
https://doi.org/10.2991/978-94-6463-540-9_81

interventions but also conforms to the standards of sustainable agriculture by potentially minimizing the use of chemical pesticides.

Through the concerted efforts of many machine learning pioneers, particularly with the utilization of CNNs, the performance of systems tailored for image analysis has been significantly enhanced, enabling precise diagnosis of a wide range of plant pathologies. Despite these technological strides, the application of such advanced systems in agriculture encounters significant challenges. Variations in image quality, attributable to environmental factors like lighting and weather, alongside the scarcity of comprehensive labeled datasets, pose substantial hurdles to the accuracy and reliability of these detection models.

This study conducts a comprehensive analysis of the practical utility of diagnosing crop diseases and pests, thereby broadening the application scope of artificial intelligence in the agricultural domain. In contrast to previous research, this study focuses on exploring datasets associated with rice leaf. Through meticulous examination of these specific datasets, the authors aim to provide a comprehensive overview of the methods employed, achievements attained, and challenges encountered.

2 Related Work

In exploring the use of computer vision and deep learning for detecting and classifying crop diseases and pests, integrating these technologies has become key to enhancing agricultural management and food security. Recent studies show a shift from traditional machine learning to more sophisticated deep learning models, significantly advancing automatic disease detection in agriculture.

In the realm of machine learning, Singla (2023) [2] applied a variety of machine learning algorithms to automate the classification and identification of plant diseases. Their method highlights the capabilities of machine learning in streamlining complex tasks in agriculture, establishing a standard for future research. Similarly, Punam and Goyal (2022) delved into the realm of automated botanical pathogen detection through the application of advanced image processing methodologies, aiming to uncover non-disruptive and high-efficiency techniques for disease identification.

In machine learning, deep learning technology is particularly prominent in the field of crop pest identification. For example, Alqahtani (2023) [3] developed a deep learning method that can accurately locate and identify plant leaf diseases, demonstrating the ability of deep learning to bolster the precision and expedite the process of pathogen identification. In addition, Amin (2022) [4] proposed an end-to-end deep learning model for classifying maize leaf diseases, further confirming the applicability and accuracy of deep learning in the solution of specific crop diseases.

In addition to these studies on deep learning, Farhanah and Al Maki (2022) [5] utilize a feature-selection based BPSO-SVM approach to identify hop diseases. This innovative approach improves inspection accuracy while reducing computational complexity, demonstrating the benefits of customizing machine learning techniques to address specific agricultural challenges.

In the current agricultural application field of deep learning, CNN model is widely used, particularly within the realm of diagnosing and categorizing afflictions and pests that affect agricultural produce. The research by Aishwarya and Reddy (2023) [6] demonstrated The efficacy of employing an ensemble of CNNs for the categorization of peanut plant foliar diseases. By using deep learning combined with traditional image processing techniques, the method they developed not only improves the accuracy of disease recognition, but also enhances the processing speed, which is important for improving agricultural production efficiency and food safety.

While these approaches are innovative, they also have some limitations. For example, deep learning models generally require extensive data for training and have lengthy processing times. The feature selection method may be limited by the validity of the selected features, which will affect the generalization ability and practicability of the final model.

Deep learning technologies have markedly improved crop disease and pest recognition. Alqahtani (2023) [7] introduced an improved method for accurately identifying plant leaf diseases, illustrating deep learning's potential to boost detection precision and efficiency. Transitioning to a more specific application, Amin (2022) [4] created A holistic model for the categorization of maize foliar pathologies, further showcasing deep learning's effectiveness and precision. Building on the advancements in deep learning, Farhanah and Al Maki (2022) [5] shifted the focus towards a machine learning-based solution for targeted disease detection. They employed a feature selection-based BPSO-SVM approach for diagnosing hops plant diseases, aiming to enhance accuracy while simplifying the process. This method exemplifies the benefits of adapting machine learning techniques to meet distinct agricultural needs, suggesting a trend towards more tailored and efficient detection strategies.

These innovations reflect the evolving landscape of agricultural technology, highlighting a move towards precision and customization. However, the reliance on extensive and varied datasets for training, along with challenges in generalizing models across different conditions, remains a crucial consideration for future research and application in this field.

These studies collectively illustrate the rapid advancements and widespread application of deep learning and computer vision technologies in the field of agricultural disease and pest detection. By automating the classification of diseases and pests, these methods aim not only to enhance crop management and productivity but also to contribute to the sustainable development of agricultural practices.

3 Methodologies

In this research, we first optimize the image data quality through image preprocessing techniques. Then, geometric transformations and depth estimation are applied to extract richer spatial information from the images. After the feature extraction phase, a variety of models including SVM, RF, CNN and ensemble learning methods (such as XGBoost) are trained to perform precise pest and disease classification tasks. Figure 1 illustrates the workflow of our research in this paper.

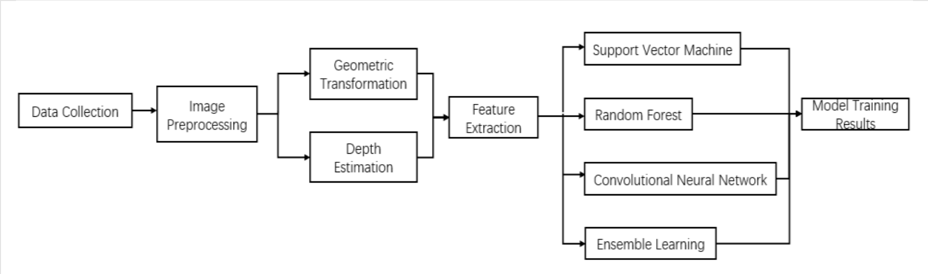

Fig. 1. Research Workflow

3.1 Image Preprocessing

Images of crop pests and diseases are collected from large public datasets. Ensure data diversity, including different crops and disease types.

Before extracting the feature values, the image needs to be preprocessed. Aiming at the problem of low definition of many crop images in the data set, in order to enhance the image details and reduce the noise, so as to improve the image processing effect, Gaussian filtering method is used to reduce the random noise of the image. Gaussian filtering achieves image smoothing by convoluting with Gaussian kernel, which improves the accuracy and robustness of the model (Chowdhury,2019) [8].

Then begin the geometric transformation of the image, adjusting the shape and size of the image, so that the different shooting angles of the image can be aligned. In this article, these operations are implemented by affine transformations, which are implemented by the following mathematical expressions:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{1}$$

Then the depth estimation is used to recover the information of the three-dimensional scene from the two-dimensional image, and the depth information is calculated by comparing the parallax of the two images.

$$Depth = \frac{f \times B}{d} \tag{2}$$

3.2 Feature Extraction

In this paper, effective features are extracted from crop pest free images by using deep learning and traditional image processing techniques. After preprocessing the image, we first extract color features using color space transformation. Specifically, we output the RGB color space as the HSB (Hue, Saturation, Brightness) color representation and the color histogram of each channel is calculated to capture the color distribution characteristics in the image. This method will be applied to the three models of SVM, RF and Ensemble learning in the following.

In addition, CNNs are utilized to autonomously derive advanced image characteristics from visual data and the details and texture information of images are captured through the multi-layer convolution structure. Combining these features extracted by deep learning and traditional image processing techniques, This paper seeks to compare the advantages and disadvantages of these techniques in the classification of crop pests and diseases.

The first is traditional image processing techniques. We convert the RGB color space into HSB color representation, work out the color histogram for each channel (H,S,V), and extract the color distribution features:

$$H_C(i) = \Sigma_{x=1}^{W}\Sigma_{y=1}^{H}1(I_C(x,y) = i) \tag{3}$$

Where Hc(i) is the number of pixels of the color channel c in the i-th histogram interval, Ic(x,y) is the value of the image at the position (x, y) of the channel c, l is the indicator function, W is the width of the image and H is the height.

CNN is subsequently employed to autonomously distill intricate patterns from the visual data. Within each stratum of convolutional operations in the CNN, a Feature Map is generated through the convolutional filter to capture specific patterns in the image. The mathematical expression is:

$$F_k = ReLU(w_k * I + b_k) \tag{4}$$

Where F_k is the KTH feature graph, w_k is the corresponding convolution kernel, I is the input image or a shallower feature graph, b_k is the bias term, * is the convolution operation, and ReLU is the activation function, which is used to increase the nonlinearity.

3.3 Model Construction

In this study, we used four model training methods: SVM, RF, CNN, and XGBoost to improve the accuracy and efficiency of crop pest classification. We exploit the respective advantages of these methods, aiming to find the best model to solve a specific detection problem.

SVM The aim of this method is to find an optimal hyperplane to maximize the spacing between positive and negative samples. For linearly separable data sets, SVM looks for hyperplanes that satisfy the following conditions:

$$minimize{:}\frac{1}{2}\|w\|^2$$

$$subject\ to{:}y_i(w \cdot x_i + b) \geq 1, \forall i \tag{5}$$

Where w represents the normal vector of the hyperplane, b is the offset term, and x_i and $y_i$are the sample points and their corresponding class labels, respectively (Figure 2).

In addressing nonlinear issues, SVM utilizes kernel methods to project the dataset into an expanded, higher-dimensional realm. Within this augmented space, SVMs aim to identify hyperplanes that serve to efficiently partition the data. Among the prevalent kernel functions are the Radial Basis Function (RBF) kernels:

$$K(x_i, x_j)=exp(-\gamma\|x_i - x_j\|^2) \quad (6)$$

In the context of kernel functions, the parameter γ is the key in modulating the dispersion of the transformed feature space, thereby influencing the model's classification performance.

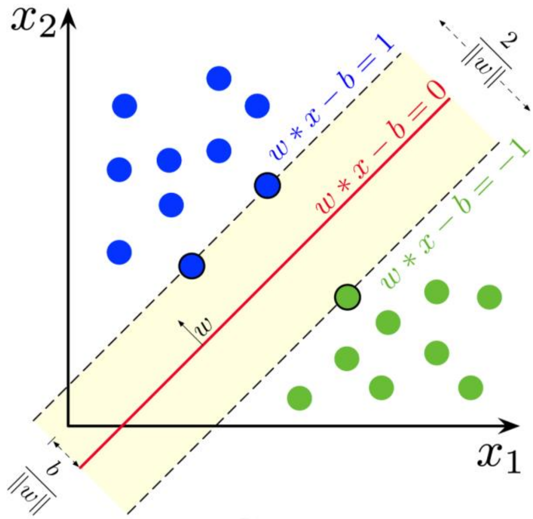

Fig. 2. SVM find the optimal hyperplane in two-dimensional space

RF The method improves prediction accuracy with its ability to construct multiple decision trees and integrate their prediction results. Its core is to randomly extract multiple subsamples from the original data set as the training data of different decision trees through self-sampling, and adopt random feature selection in the tree construction process, which not only increases the diversity of the model, but also effectively reduces the risk of overfitting (Figure 3). In the prediction phase, the random forest gets a final prediction by voting on the predicted results of all trees (for classification problems) or averaging them (for regression problems). This strategy of integrating multiple decision trees significantly improves the model's ability to generalize over a variety of data sets, making it ideal for solving complex problems such as crop pest detection. The success of RF is due in part to its ability to reduce model variance while maintaining a low level of bias, ensuring high accuracy and robustness suitable for the challenges of high-dimensional data and complex data structures. As He and Wang (2024)[9] show, this strategy of integrating multiple decision trees can significantly improve the model's ability to generalize over multiple datasets, making it ideal for solving complex problems such as crop pest detection.

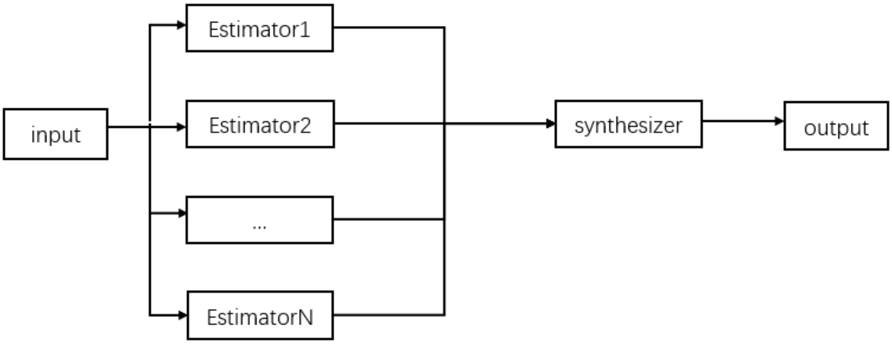

Fig. 3.Random Forest Process

CNN. The CNN model utilized in this research encompasses a series of successive convolutional stages, within each of which a ReLU activation function and a pooling operation are integrated to efficiently isolate image features and minimize the parameter count. The model starts with a preprocessing layer for resizing and normalizing the image. Following this sequence, The architecture consists of five sequential convolutional stages, with each stage succeeded by a pooling operation. Subsequently, the data undergoes a flattening process before being fed into a dense layer, complemented by an integrated Dropout mechanism to mitigate the risk of overfitting. Finally, the full connection layer of the Softmax function is used to output predictions for 38 categories.

Each convolutional layer uses a different number of 3x3 filters, and each layer is followed by a ReLU activation function and a 2x2 maximum pooling layer. The number of filters in the first layer and the second layer is 32, the third layer and the fourth layer are 64, and the fifth layer is 128.

Ensemble Learning. In the application of ensemble learning, the XGBoost algorithm operates by incrementally introducing additional tree structures, aiming to optimize the objective function. The objective function of the algorithm consists of two parts: the initial element represents a standard loss function, which measures the discrepancy between the forecasted outcomes and the true data points. The second is a regularization term, which is used to control model complexity and prevent overfitting. In contrast, the RF model builds multiple decision trees and synthesizes their results to bolster the accuracy of the robustness and prediction of the model. Kiangala and Wang (2021)[10] compare the performance of these two algorithms in dealing with nonlinear data regression problems and show that XGBoost has significant advantages in accuracy and processing speed, while random forest performs better in model stability and generalization ability. The objective function can be expressed as:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (7)$$

The l is the loss function, $\hat{y}_i$ is the predicted value of the model for the i-th sample, y_i is the actual value, K is the number of trees in the model, Ω is the regularization term, andf_k is the KTH tree.

The regularization term usually consists of the number of leaf nodes of the tree and the square of the leaf node value, as follows:

$$\Omega(f)= \gamma T+\frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2 \tag{8}$$

Where T is the number of leaf nodes in the tree, w_j is the value of the JTH leaf node, and γ and λ are regularized parameters.

4 Experimental Setup and Results

4.1 Dataset Overview

The central focus of this study lies in the application of deep learning technology to automatically identify and classify rice leaf diseases. As shown in Figure 1, our dataset contains images from ten different leaf diseases, as well as healthy plant leaves as a reference. These categories include "Normal", "Explosion", "hispa", etc. Among them, the number of "normal" samples is the highest and the number of "bacterial_leaf_streak" samples is the lowest (Figure 4).

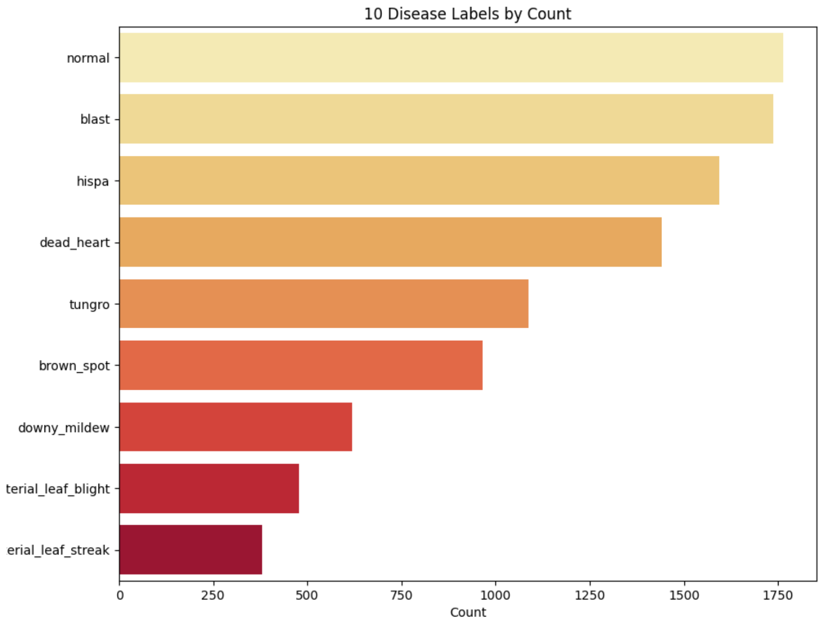

Fig.4 Dataset distribution

In this test, the critical benchmarks for gauging the efficacy of the predictive model are the precision of its outcomes and the Kappa statistic. The precision metric, an inherently straightforward measure of performance, delineates the ratio of correctly identified instances by the model relative to the entire sample pool. Within the scope of this research, accuracy is defined as the proportion of disease imagery accurately categorized by the model in relation to the entire collection of images within the examination dataset. The Kappa coefficient compares the difference between the actual observed consistency and the accidental consistency. Kappa values generally extend across a spectrum from -1 to 1, where more elevated values are suggestive of a superior classification model performance.

Before starting model training, we perform a series of pre-processing steps on the image data to optimize the input quality of the model. As shown in Figure 5, after processing, we obtained the pictures of various rice diseases with obvious characteristics.

Fig.5. Image preprocessing

4.2 Model Tests Comparation

In this paper, the performance of four models of SVM, RF, CNN and XGBoost in crop disease recognition task was carefully compared (Table 1). In the experiment, we found that the CNN model showed excellent performance with a high accuracy of 90.58% and a Kappa coefficient of 0.8956, which reflects its strong ability in processing image data. In this method, complex image features are extracted by multi-layer convolutional layers, model training is completed by 10 epoch iterations, and parameters are optimized. As shown in the figure 6, the training accuracy has increased from the initial approximately 18.73% to 88.48%, and the verification accuracy has increased from 35.22% to 90.58%. This demonstrates the model's adeptness at identifying pathologies across the spectrum of rice leaf conditions.

Table 1 The results of accuracy and kappa

Model	Accuracy	Kappa
SVM	72.81%	0.6851
Random Forest	69.77%	0.6510
CNN	90.58%	0.8956
XGBoost	88.95%	0.8731

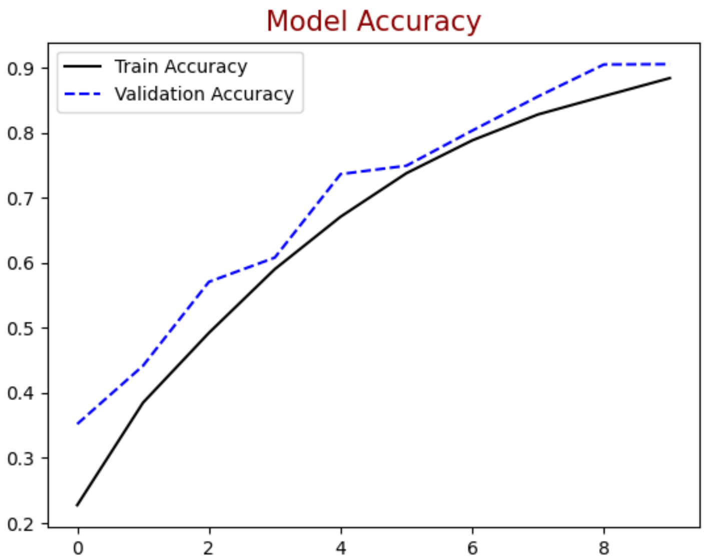

Fig. 6. SVM Model Accuracy

Compared to CNN, XGBoost's accuracy is slightly lower (88.95%), but it performs better in execution speed and takes about 70% of the time of the CNN model. This is mainly due to its gradient lifting mechanism. As shown in the table 2, XGBoost's accuracy, recall, and F1 scores across all categories show strong performance, indicating a good balance between categories.

Table 2 The result from different methods

Classification	Precision	Recall	F1-measure
normal	0.90	0.90	0.90
bacterial_leaf_blight	0.94	0.70	0.80
bacterial_leaf_streak	0.88	0.90	0.89
bacterial_panicle_blight	0.89	0.76	0.82
blast	0.88	0.92	0.90
brown_spot	0.92	0.86	0.89
dead_heart	0.95	0.91	0.91
downy_mildew	0.95	0.80	0.87
hispa	0.83	0.93	0.88
tungro	0.89	0.90	0.90

In contrast, SVM and random forest obtained similar results and were weaker in classification performance. The accuracy of SVM model was 69.77% and the Kappa coefficient was 0.6510, indicating that SVM was not accurate in distinguishing disease categories with similar visual features. This shows that even though we employ kernel techniques to accommodate the nonlinear features of this case, SVM has limitations in handling complex image datasets.

The accuracy and Kappa coefficient of random forest model in this experiment were low (72.81% and 0.6851, respectively). As shown in the figure 7, its confusion matrix shows some specific categories, such as "bacterial_leaf_streak" and "dead_heart", and the classification performance of the model is poor, which may be due to the highly similar image features between these categories. In addition, if a large number of dark squares appear in the non-diagonal part of the confusion matrix, it indicates that the model has more classification errors in this part. For example, the "dead_heart" category has deep squares in non-diagonal positions, which means that samples in this category are often misclassified as other diseases.

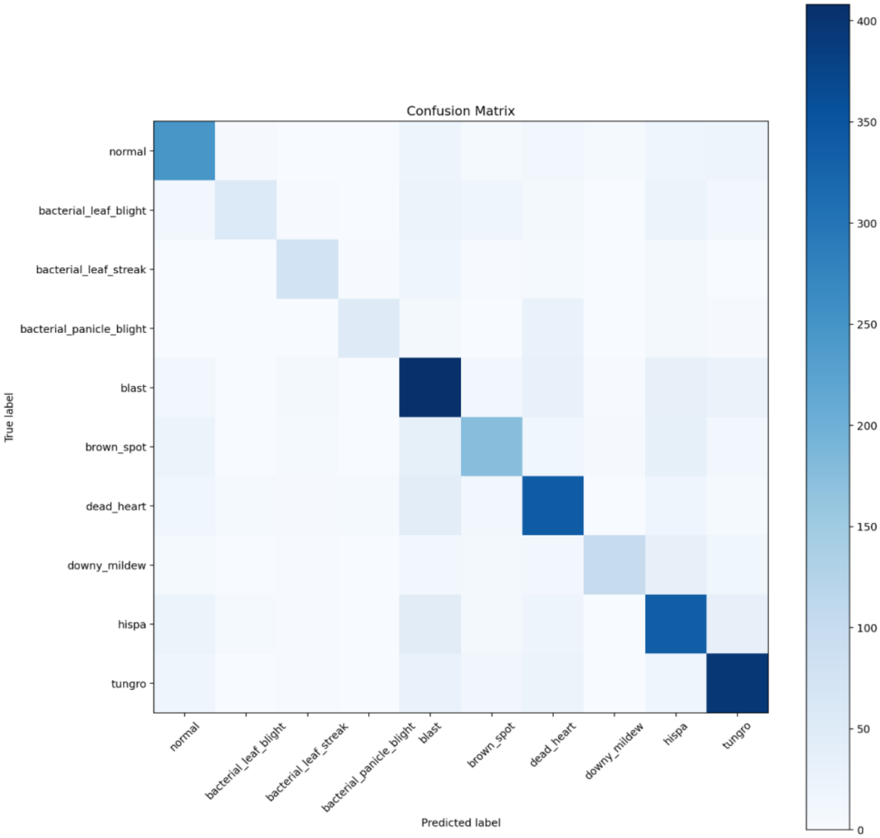

Fig. 7. Random Forest Confusion Matrix

5 Conclusion

This paper introduces a new application of computer vision in crop pest classification, aimed at addressing a major challenge in modern agriculture. Machine learning techniques are utilized to automatically identify and classify crop pests and diseases in the Rice leaf dataset. Empirical findings indicate that the CNN model's precision slightly outperforms alternative approaches, albeit with the most diminished operational efficiency. The superiority of CNN in deciphering complex patterns in agricultural images is rigorously tested and proven. When combined with other machine learning techniques, the CNN model can achieve high accuracy but requires optimization in terms of implementation efficiency. Furthermore, it is observed that image quality and the comprehensiveness of the dataset significantly impact the experiment, underscoring the need for rich and diverse data to train robust models. The convergence of computer vision and agriculture offers a promising pathway to sustainably meet the escalating demands of a growing population. Our research indicates that in the future, real-time automated detection systems could be directly deployed in the agricultural sector to provide farmers with crucial information for prompt and effective response to threats, thereby ensuring crop health and food supply.

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