Prediction of Diseases in Paddy Crop Using Machine Learning and Deep Learning

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Research Article

Keywords: Support Vector Machine, Random Forest, k-Nearest Neighbors, Logistic Regression, Custom Convolutional Neural Network

Posted Date: January 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8581381/v1

Additional Declarations: No competing interests reported.

Abstract

Paddy crop diseases have a significant impact on the production of rice across the globe with immense losses in crop production as well as food security. Conventional disease diagnosis systems depend on visual inspection where the visual system is time-consuming, subjective and in many cases inaccurate when in the field. The use of artificial intelligence or, specifically, machine learning, and deep learning offers potent plant disease detection instruments in recent developments. The paper provides a detailed disease prediction model of paddy crop based on machine learning and deep learning. An acquired dataset in the form of field was used with images of the leaves of healthy and diseased paddy, which included rice blast, bacterial leaf blight, brown spot, and sheath blight. In the case of handcrafted machine learning models, color, texture, and shape attributes were obtained and categorized with the help of Support Vector Machine, Random Forest, k-Nearest Neighbors, and Logistic Regression algorithms. Custom Convolutional Neural Network and transfer-based architectures (ResNet50 and EfficientNet-B0) were both trained to serve as deep learning models. Experiment scores prove that deep learning models are much better than traditional machine learning classifiers where EfficientNet-B0 model with highest classification accuracy of 97.4% was made. The confusion matrix and learning curve results indicate good generalization that has been achieved by the models in realistic field conditions. The results indicate deep learning as a powerful tool to diagnose paddy disease automatically and as being applicable to smart farming to predict disease early and avoid losses caused by disease.

1. Introduction

Rice (*Oryza sativa L.*) is considered to be one of most significant staple crops in the world that serves more than half of the world population. It is essential to food security especially in Asia where much of the population relies on rice farming as a source of food and a means of livelihood (FAO, 2023). India, China, Indonesia, and Bangladesh, as well as Vietnam are the largest pdiffusion of paddy which are all deemed to contribute in the world rice production. Nevertheless, the production of paddy is severely affected by climatic variability, soil erosion, pest attacks, and plant diseases that end up in massive losses in the harvest yearly (Savary et al., 2019).

One of the greatest restricting factors of the rice productivity is plant diseases. Widely known paddy diseases like the rice blast, bacterial leaf blight, sheath blight, brown spot and tungro virus are very adverse in terms of crop health after its cultivation and the quality of yield. According to the Food and Agriculture Organization, plant diseases result in up to 20–30% of annual crop losses in the world, which is a significant problem in sustainable agriculture (FAO, 2023). Disease detection, as well as proper identification, are important in rice production to take up control steps in good time and reduce losses incurred. Nevertheless, the traditional method of diagnosing the disease mostly uses visual examination by the farmers or agriculturalists to diagnose the disease, although this method is mostly subjective, time consuming and inaccurate (Bock et al., 2010).

Over the last few years, precision agriculture is an initiative that has appeared to be a viable remedy in increasing efficiency in farming by incorporation of information and technology, sensors and data based decision-making. Precision agriculture also includes automated systems of disease detection, which will promote real-time monitoring of crops and quick response to disease outbreaks (Zhang et al., 2021). As the new ecosystem of artificial intelligence (AI) keeps developing, machine learning (ML) and deep learning (DL) models have proven to have enormous potential in addressing complex pattern recognition errors, such as plant disease detection on leaf images (Mohanty et al., 2016).

Usually, predictive disease systems based on machine learning may require the user to extract features by hand using color, texture, and shape descriptors of an image of a plant, which are then trained on classifiers, including Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (KNN) for prediction (Barbedo, 2013). These methods, though having satisfying performance, require much accuracy that is dependent on handcrafted features and domain knowledge. Furthermore, the conventional ML methods tend to be susceptible to changes in light, background noises, and image conditions on real fields.

Deep learning, and specifically Convolutional Neural Networks (CNNs) has transformed the sphere of image-based classification by allowing the process of automatic feature extraction through raw data. Diseases can be detected in several crops, such as rice, tomato, and potato using CNN-based models with high accuracy (Ferentinos, 2018). Through transfer learning, which involves pre-trained networks like VGG and ResNet, as well as EfficientNet, partial training data results in an even higher level of performance (Too et al., 2019). These have placed deep learning as a formidable capability towards the development of effective and scalable crop diseases prediction models.

Even though a major progress has been made, there are still a number of challenges in the practical implementation of ML and DL-based paddy disease prediction models. These are: the access to high-quality labeled data is limited, there is a class imbalance between the different types of diseases, changes in environmental conditions in taking the images and computational issues to apply it at the field level (Singh et al., 2020). Also, the majority of available researchers are based on controlled laboratory data, and fewer of them are tested in the real field setting, which restricts the possibility to generalize them.

Thus, there is an increasing demand to create precise, effective and field deployable disease prediction models of paddy crops based on machine learning and deep learning models. These systems may help farmers point out cases of various diseases early enough, diminish the use of pesticides, raise harvests, and make farming practices sustainable. The purpose of this study is to design and test ML and DL-based models to forecast the appearance of paddy crop diseases with the help of image data, compare the models in terms of their performances, and highlight the aspects of practical implementation in the field.

2. Literature Review

Computational techniques applied to detect plant diseases have been continuously developing throughout the last twenty years due to the development of digital imaging, machine and deep learning. It is possible to note that, in early research, the main methods of classical image processing were used, and in recent works, there is a tendency to use data-driven artificial intelligence techniques. The given section will include author-wise thematic review of the major contributions to paddy and general prediction of plant diseases, outlining the trends in how the topic is approached, the performance successes, and current gaps in the research.

2.1 Early Image Processing and Visual Diagnosis Methods

Bock et al. (2010) were one of the pioneering studies in the international area of automated plant disease detection as they studied the reliability of visual disease severity of plants in the field of plant pathology. Their research revealed that manual visual inspection is highly subjective and differs widely among the observers and thus automated diagnostic equipment is required. This writing created the incentive of computational disease assessment strategies.

One of the first comprehensive studies on the application of digital image processing techniques to detect plant disease was done by Barbedo (2013). The author addressed the segmentation, color analysis, and descriptors of texture to categorize the disease symptoms based on leaf image. The work of Barbado demonstrated that features of images handcrafted and using standard classifiers could work with reasonable accuracy, although the performance was susceptible to changes in illumination and noise in the background and this limited the use of the method in a real field.

On the same note, Patil and Kumar (2011) developed a system of image processing involved in identifying the presence of disease in farm produce through morphological and thresholding process to find the region of infection. Their paper ascribed the possibility of using computer vision in plant pathology yet pointed to the need of limited imaging conditions.

These initial developments formed the basis of future machine learning-based systems but highlighted the major challenges including dependency on feature selection and sensitivity on the environment.

2.2 Machine Learning-Based Disease Classification Emergence

As pattern recognition methods expanded, scientists started to use the machine learning algorithms to classify diseases. Arivazhagan et al. (2013) trained a machine learning model on plant leaf disease detection based on the texture features calculated using Gray-Level Co-occurrence Matrix (GLCM) and classified with the Support Vector Machines (SVM). This method was more accurate than rule-based image processing techniques, and it can be seen that ML classifiers can be effective in agriculture.

Equally, Singh and Misra (2017) suggested a plant disease detector, based on feature-based ML, which uses color and shape features and combines different classifiers to detect plant diseases, namely the K-

Nearest Neighbors (KNN) and the Random Forest. In their comparative analysis, they realized that Random Forest worked well when the size of the dataset was moderate. Nevertheless, it was reported that the study showed performance deterioration in case of complex field background.

Phadikar and Sil (2008) introduced one of the first research on rice paddy crops indetecting rice specific disease. They have employed image processing and neural networks in identifying rice leaf diseases that include blast and brown spot. Despite having a small dataset size, the research proved the possibility of the use of computational intelligence in the prediction of paddy diseases.

Subsequently, Revathi and Hemalatha (2014) proposed a SVM-based system of disease classification on paddy leaf using color and texture characteristics. Their approach has shown more than 90% accuracy when under control under imaging, but their measures had poor robustness when conditions varied in the field.

These works using ML proved that it was possible to classify diseases with reasonable precision given an automated method. Scalability and generalization, however, were limited by having to use handcrafted features and regularly discovered images using limited datasets.

2.3 Deep Learning and CNN-Based Disease Recognition

The examination increase with deep learning was the breakthrough in the recognition of plant diseases. The article by Mohanty et al. (2016) is the first to utilize Convolutional Neural Networks (CNNs) to classify plant diseases based on the plant village dataset. Their deep learning model had more than 99 percent accuracy with 38 classes of crop-disease, which is much higher as compared to the conventional ML models. This work was a breakthrough in that CNNs were able to extract discriminative features of disease without any human intervention.

Based on this, Ferantinos (2018) compared various CNN-based architectures, such as AlexNet and VGG, with respect to plant disease detection. The experiment established that deep neural networks were more accurate and resilient to appearance changes in images. Ferantinos have also emphasized on the significance of data augmentation to enhance model generalization.

Too et al. (2019) have performed a comparative analysis of transfer learning on pre-trained CNN architectures like ResNet, DenseNet, and Inception in recognizing plant diseases. Their findings indicated high-quality fine-tuned pre-trained models can be used with short training data, which is a common problem in agricultural data.

In specific rice tasks, Rahman et al. (2020) created a CNN-based model that was able to detect rice-specific diseases such as blast, bacterial blight and brown spot. Their system realized a high 195 percent accuracy and showed that it worked effectively in the moderately varied field conditions. Nevertheless, the authors reported that there were still high contrasts in light that influenced the reliability of prediction.

On the same note, Wang et al. (2021) have used EfficientNet based transfer learning to the classification of rice diseases and cited higher accuracy and less computation complexity than those of deeper CNN architectures. Their work hinted that lightweight DL can be used to support the field deployment through mobile-based deployment.

Such studies corroborated the fact that deep learning has taken over the paradigm of plant disease detection because it has a better feature learning and classification power.

2.4 Studies on Development of Dataset and Real-field Deployment

One of the key parameters in the performance of the DL is the dataset availability. A new dataset called PlantVillage was proposed by Hughes and Salathe (2015) and it was used as the reference in the majority of other plant disease recognition studies. Although it increased the research speed, subsequent research studies like those by Barbedo (2018) cautioned that plant villa images were taken under controlled conditions and were not reflective of actual field complexities.

To overcome this limitation, Singh et al. (2020) have created a dataset of field-acquired plant disease that has variable illumination and background noise. Experiments run by them demonstrated, that models deployed in the field on the basis of training only in the laboratory did not perform effectively in the field, which proposed the necessity of having varied training data.

In datasets based on rice, the Kaggle Paddy Doctor Dataset (2021) offered multi-class images of rice diseases that were captured in practicable farm settings. Research studies that employed this dataset like Chowdhury et al. (2022) proved that the DL models could perform in a strong style in case they were trained on a variety of field images.

Research has also been done on mobile deployment. Li et al. (2022) suggested a light weight CNN embedded in a smartphone application to diagnose rice diseases. Their system had real-time predictability and with reasonable accuracy, which demonstrates that it can be used practically in the field.

2.5 Comparative Studies and Hybrid Models

Some of the authors have contrasted the ML and DL techniques to determine the most appropriate methods. Amara et al. (2017) compared two types of classifiers using SVM and CNN to detect banana disease and discovered that CNN models were all superior in terms of accuracy and adaptability as compared to the SVM. Durmus et al. (2017) also reported similar comparative results in tomato disease detection.

It was also investigated are hybrid-ML/DL models. Saleem et al. (2019) combined CNN-based feature extraction and SVM classification, and instead of achieving a significant increase in accuracy, the model became simpler. These hybrid approaches are a pointer that there is constant work towards striking a balance between performance and computational ability.

2.6 Identified Research Gaps

Even though many improvements have been made, several gaps in research are still present. To begin with, the majority of available research incorporates benchmark datasets that had been taken in controlled conditions and hence the study is limited to generalizing the models to real-field settings. Second, the dataset of rice specific diseases is comparatively small versus other crop and hinders extensive training of the models. Thirdly, imbalance of classes in predicting diseases impacts prediction reliability of uncommon infections. Fourth, a limited number of studies concentrate on explainable AI methods in order to decompose model choices to facilitate farmer confidence. Lastly, there is limited integration of disease prediction with real time IoT based crop monitoring systems.

3. Materials and Methods

This paper introduces a methodical design of reflecting machine learning and deep learning-based prediction on paddy crop diseases. The general procedure includes the data collection process, preprocessing data, extracting features, model development and training, and reading result performance.

3.1 Dataset Description

This research used a dataset of paddy leaf disease images that were publicly available. The dataset entails pictures of healthy leaves and major rice diseases of rice blast, bacterial leaf blight, brown spot, and sheath blight. Photos were taken in disparate field conditions with the assistance of mobile phones with camera, thus embracing realistic changes in light, background cluta and the position of the leaves. This dataset comprises of about 5,000 images and the number of disease classes is equal to avoid classification bias. Agricultural experts label each of the images to make sure that there is reliability in this annotation.

3.2 Data Preprocessing

Due to the need to ensure that the deep learning models have standard input sizes, raw images were scaled to 224 x 224 pixels in size. The intensity of pixels was scaled to 1 to boost the training convergence. Random rotation, flipping, zoom and use of brightness techniques of data augmentation were used to improve diversity of the dataset and decrease overfitting. Software Background noise also was reduced using filtering and contrast enhancement. The dataset was split into training (70%), validation (15%), and testing (15) subsets.

3.3 Feature Extraction of Machine Learning Models

In the case of traditional machine learning classifiers, handcrafted features were obtained using preprocessed images. The color characteristics were calculated in the RGB color space and the HSV color space. Gray-Level Co-occurrence Matrix (GLCM) statistics was used to derive texture features and edge detectors along with contour analysis were used to derive shape descriptors. After extraction, the features were put together to feature vectors and standardized and then subjected to the training of ML models.

3.4 Machine Learning Models

They utilized four machine learning classifiers (Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (KNN), and Logistic Regression (LR)). Such models were trained on the extracted feature vectors. The grid search and cross-validation methods were employed to optimize hyperparameters in order to have a robust performance.

3.5 Deep Learning Models

The architecture to be used was that of a Convolutional Neural Network (CNN) to classify diseases in its entirety. Also, the application of transfer learning was done on pre-trained networks, i.e. the ResNet50 and EfficientNet-B0. The last classifying layer was changed to be the same as the number of categories of the disease. Adam optimizer was utilized, it was trained with categorical cross-entropy loss.

3.6 Evaluation Metrics

Accuracy, precision, recall, F1-score, and confusion matrices were used as model performance indicators. The comparison between ML and DL models was based on the effective approach of the prediction of the paddy disease.

Complete summary of materials as methods mentioned above shown in Table 1.

Table 1
Summary of Materials and Methods

Component	**Description**
Dataset	~ 5,000 paddy leaf images (healthy, blast, blight, brown spot, sheath blight)
Image Source	Field-acquired mobile camera images
Preprocessing	Resizing (224×224), normalization, augmentation
ML Feature Extraction	Color, texture (GLCM), shape descriptors
ML Models	SVM, Random Forest, KNN, Logistic Regression
DL Models	Custom CNN, ResNet50, EfficientNet-B0
Training Split	70% train, 15% validation, 15% test
Optimizer	Adam
Evaluation Metrics	Accuracy, Precision, Recall, F1-score

4. Experimental Results

This part contains the experimental analysis of machine learning and deep learning models of paddy crop disease prediction. The performance measures that were used to evaluate the models with the test data are standard metrics of performance such as accuracy, precision, recall, F1-score, and analysis of confusion matrices. They were compared in experiments involving the use of traditional machine learning classifiers versus deep learning ones, to ascertain the effectiveness of machine learning classifiers.

4.1 Machine Learning Models Performance

The initial group of studies was a comparison of the classical machine learning models which were trained on handcrafted features. Extracted color, texture and shape features were used in the training of Support Vector Machine (SVM), Random Forest (RF), the k-Nearest Neighbors (KNN) and the Logistic Regression (LR) classifiers. The grid search was used to optimize hyperparameters to obtain the best performance.

The results of machine learning models classification are shown in Table 2. Random Forest was found to be the most accurate with 89.6% and SVM was close behind at 87.8%. KNN and Logistic Regression demonstrated relatively lower accuracy which means that ensemble and margin-based classifiers are more effective in nonlinear distribution of features. Nevertheless, there were also misclassifications on diseases with similar visual symptoms in handcrafted feature representations like on brown spot and sheath blight.

Table 2
Performance of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	81.4	80.2	79.8	80.0
KNN	83.6	82.9	83.1	83.0
SVM	87.8	88.1	87.5	87.8
Random Forest	89.6	90.2	89.1	89.6

On the whole, ML models had a good performance, but since they relied on manually derived features, they had limitations on being sensitive to take on irregular disease patterns in different lighting and background conditions.

4.2 Deep Learning Model performance

Deep learning models were trained without extracting manual features or having to preprocess the images with hardwork. Two transfer learning models including ResNet50 and EfficientNet-B0 in addition to a custom CNN architecture were tested. The training count was done with 30 epochs with early stopping to avoid overfitting that was done with the Adam optimizer.

The results of models of deep learning are summarized in Table 3. The tradition CNN ranked successively higher of 94.3% accuracy that every single machine learning classifier. The models of transfer learning performed better, with the ResNet50 model showing the accuracy of 96.8% and EfficientNet-B0 the maximum accuracy of 97.4%. These findings show that pre-trained models are efficient at learning high level disease features despite smaller datasets.

Table 3
Performance of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Custom CNN	94.3	94.0	93.8	93.9
ResNet50	96.8	96.9	96.5	96.7
EfficientNet-B0	97.4	97.6	97.1	97.3

Deep learning models were also found to be more resistant to background noise and changes in illumination in comparison to machine learning models. The data augmentation policy can be associated with better generalization, which manifests itself in the insignificant performance difference between validation and test sets.

4.3 Comparative Analysis of ML and DL Models

To provide a general overview of the effectiveness of various approaches, Table 4 is a comparative overview of the machine learning model (Random Forest) and deep learning model (EfficientNet-B0) that has the best performance.

Table 4
Comparative Performance of Best ML and DL Models

Approach	Model	Accuracy (%)	F1-score (%)
Machine Learning	Random Forest	89.6	89.6
Deep Learning	EfficientNet-B0	97.4	97.3

The model based on deep learning also found that the model with the highest accuracy was about 7.8% more accurate than any machine learning classifier, asserting the stronger capability to learn features of CNN-based models. This enhancement has been largely contributed by automatic hierarchical feature extraction and transfer learning using big picture image collections.

4.4 Confusion Matrix Analysis

The confusion matrix analysis also shows the performance of the classification in terms of disease groups. The majority of diseases were properly identified, especially rice blast and bacterial leaf blight that are characterized by specific visual symptoms. There was slight loss of clarity between brown spot and sheath blight classes because of comparable lesion patterns. However, theEfficientNet-B0 model reported the steady high-class-wise recall rates of over 96% with regards to finding diseases as shown in Fig. 1, which is dependable.

4.5 Training and Validation Performance

Figure 2 shows the curve of training and validation accuracy of the EfficientNet-B0 model. The model was able to converge in 20 epochs, and there was no noticeable overfitting. The seamless convergence is the sign of usefulness of data augmentation and regularization strategies.

4.6 Sample Disease Classification Results

In order to illustrate the role of practicality in the medical domain, sample test images with predicted disease labels are provided in Fig. 3. The model was found to be accurate in detecting types of diseases when under real field image, which validated the use of the study model in possible mobile or drone application in agriculture.

4.7 Discussion of Results

The experimental findings have attested that deep learning models are much better than the conventional machine learning classifications in the prediction of paddy disease. Architectures that relied on transfer learning techniques had the best performance and have a good generalization performance even in real-field imaging conditions. Although handcrafted features gave machine learning models sensible accuracy, they did not offer sufficient ability to reconcile complicated variations in the environment. The deep learning methodology presents an opportunity of providing actual-time based, automated disease detection in smart farming.

5. Discussion

As the experimental results in the former section show, machine learning and deep learning methods are effective in predicting auto paddy crop disease. In this section, the discussion of the essential findings is presented, the model performance pattern interpretation is carried out, the results are compared with the existing literature, and the applied findings to the practical possibilities of implementing agriculture in the real world are discussed.

5.1 Analysis of the Experimental Results

The machine learning models developed with handcrafted features obtained moderate and high accuracy of classification, though with a superior outcome compared with the rest of the machine learning classifiers, Random Forest. This is explained by the ability of Random Forest to perform ensemble learning which effectively tackles the nonlinear relationship between variables in the feature space and lowers overfitting. Yet, the representational strength of color, texture, and shape descriptors, manually extracted, could still be considered as the limitation of the overall ML performance. The feature overlaps and some cases of wrongful classification happened due to the similar visual features between some diseases especially brown spot and sheath blight. This is a drawback of using only handcrafted characteristics to do the sophisticated recognition of biological patterns.

Deep learning approaches, especially using CNN, achieved much higher performance in comparison to traditional ML classifiers. It was found that CNN custom architecture almost penetrated the ML models as a validation of the fact that the hierarchical feature learning helps to automatically extract discriminative disease patterns. Even more, the transfer learning networks like ResNet50 and EfficientNet-B0 enhanced the accuracy of classification, suggesting that pre-trained networks can be effective to use the information acquired by large-scale image collections to learn effective visual cues. EfficientNet-B0 model was best in accuracy and has fairly low computational complexity which makes it well suited to resource constrained deployment environment.

The validation accuracy and the training curve demonstrated the convergence stability and low overfitting, and the data augmentation and data normalization methods demonstrated the success of the model generalization. Class-wise recall was also found to be high according to confusion matrix analysis with only slight confusion occurring among similar disease categories as per their visual form. The success of the proposed deep learning framework in the realistic field image classification is confirmed by these findings.

5.2 Comparison to Existing Studies

The received results are consistent with the recent results that are converted to the literature. Mohanty et al. (2016) have shown that CNN-based networks are better at detecting a plant disease, have high accuracies because of the resulting automatic extraction of features. On the same note, Too et al. (2019) have indicated that transfer learning greatly improves the performance of classification as the relationship training data is scarce. These observations are substantiated by the current work in the case of paddy crops in the field situation.

The deep learning accuracy of rice disease ranged between 93 and 96 percent in rice-specific studies carried out by Rahman et al. (2020) and Wang et al. (2021). Competent performance of lightweight transfer learning architecture was confirmed in the EfficientNet-B0 model of the current work, which obtained similar or even better results in comparison. In the meantime, the results provided by ML are in line with previous research on rice diseases by Revathi and Hemalatha (2014), which stated that the SVM classifiers produced an accuracy of the order of 90 percent by default. Nevertheless, the current research proves that the performance of ML is worse with complicated background and illumination changes, which additionally indicates the rationale of transitioning to deep learning.

5.3 Practical Implications to Smart Agriculture

The better working of deep learning models demonstrates that there is high possibility of its application in precision agriculture systems. Online prediction of diseases will help farmers to detect diseases at an early stage, which will help in taking measures in time and to minimize excess use of pesticides. It is possible to create a disease diagnosis app via EfficientNet-B0 which would be able to notify users about the disease in the field in real-time. Moreover, any kind of integration with drone or IoT-based crop monitoring would allow surveying the paddy farms in large scales.

Economically, prompt and precise detection of the disease would reduce the loss of yields and dependency on agricultural specialists in terms of labor. This is especially applicable in the farming rural communities where the availability of plant pathologists is low. Scalability and cost-effective adoption is possible through the implementation of lightweight deep learning models that can run on mobile devices as well.

5.4 Limitations and Challenges Observed

Although some encouraging changes are recorded, some challenges will still exist. Although gathered in the field, the dataset might lack generalization of all variations in the environment including extreme weather, heavy occlusion or mixed symptoms of the diseases. Also, the skewed model learning based on class imbalance can occur in cases of rare diseases. The unaccountability of deep learning predictions is also another limitation that can decrease the level of trust that farmers have in automated decisions. These problems need to be taken care of before extensive practical implementations.

5.5 Summary of Key Findings

The summary of major comparative observations based on the study of the experiment is presented in Table 5.

Table 5

Summary of Key Findings

Aspect	Observation
ML model performance	Random Forest achieved highest ML accuracy (89.6%)
DL model performance	EfficientNet-B0 achieved highest DL accuracy (97.4%)
Feature extraction	DL models automatically learned superior feature representations
Misclassification trend	Minor confusion between brown spot and sheath blight
Generalization	Data augmentation improved robustness to field variations
Practical feasibility	EfficientNet-B0 suitable for mobile-based deployment

6. Challenges and Limitations

Though the suggested machine learning and deep learning model to predict paddy disease felt good classification performance, it should be recognized that there are various difficulties and limitations. A significant weakness is the diversity of data. Although the dataset used in this research includes field-acquired images, it might not fully cover all the real-life conditions, including high or low intensity of light, leaf leaf partial overlap, background complexity, or even mixed disease symptoms on the same leaf at the same time. All these may adversely affect model generalization when used in unobserved agricultural settings.

There is another challenge in relation to class imbalance. Some types of diseases, especially the rare infections, are not represented in available datasets. This disparity may give preference to model training and less predictive accuracy on less common disease classes. Even though data augmentation helps address this problem, it alone does not completely eliminate the necessity of real-field samples of truly diverse samples.

Practical limitation is also presented as the computation requirements. Transfer learning models, and in general deep learning models, necessitate high processing power to train. Although inference with lightweight architecture and trained EfficientNet-B0 can be inferred in mobile devices, the process of training and fine-tuning requires access to systems supported by a gadget, which might not be easily accessible in research and farm limited resource settings.

Another weakness is the explainability of the models. Deep learning prediction is a black-box decision-maker, and one cannot easily understand which visual symptoms influence the result of classification. This wastiness of transparency can lower the levels of trust among farmers and pastoralists who are likely to be reluctant to follow purely automated forecasts without a comprehensible explanation.

Lastly, the existing design is dedicated solely to the classification of diseases by their image. The other important aspects affecting the disease outbreaks like weather conditions, soil properties, and interaction of pests are not taken into consideration. This study has not examined the capabilities involved in integrating multimodal data which may enhance reliability in prediction.

The following challenges need to be tackled to bring about a significant level of strength, credibility, and scalability of the applications of AI-powered systems in diagnosing paddy diseases.

7. Future Research Directions

This work can be expanded in several ways that have a significant meaning in future research. To begin with, large paddy disease datasets that are gathered in different geographical areas, seasons, and environmental constraints would enhance generalization of the model and would reduce bias as well. Cooperation in dataset development by having agricultural institutes and farmers can help quicken the adoption in this regard.

Second, the multimodal data sources have high potential in the holistic prediction of the disease. Integrating image-based diagnosis with environmental factors like temperature, humidity, rainfall, and soil conditions by sensor networks and IoT platforms can possible make use of detection-based diagnosis possible instead of the basic detection usually conducted by visual symptoms.

Third, a promising research option includes explainable AI (XAI) methods of plant diseases classification. Grad-CAM and attention maps are other methods of visualization that can be used to indicate the parts of the leaves that have been infected and which provide the models with their decisions, thus enhancing the interpretability and trust that the farmers give the automated suggestions.

Fourth, there should be further investigations concerning lightweight and energy efficient deep learning architecture to be utilized in mobile phones and embedded agricultural computing hardware. The edge-based inference will allow real time disease diagnosis without using high-speed internet connections which will help the communities living in remote areas to conduct farming.

A second future line is the incorporation of the multispectral or hyperspectrality imaging with the use of drones to monitor large fields. These methods can identify the stress signals of a disease at an early stage before the signs manifest so that proactive measures of disease management could be implemented.

Lastly, the researchers must in the future concentrate on the development of end-to-end smart agriculture systems integrating the disease detection and automated advisory systems advising appropriate control actions, pesticide dosage, and preventive measures. This would turn tools of diagnosing diseases into full-fledged decision-support systems to the farmers.

8. Conclusion

This study introduced an in-depth model to forecast the diseases in paddy crop based on machine learning and deep learning. Conventional machine learning models were found to be as accurate and strong as the handcrafted features by showing reasonable results in classification, whereas deep learning networks, especially CNN models of transfer learning, were found to be much more accurate and more robust concerning the actual field conditions.

As experimental findings revealed EfficientNet-B0 was much better in terms of performance with little computation requirements, it is appropriate to use in real-life applications of mobile-based disease diagnostic. The efficiency of automatic feature deriving as compared to manual feature engineering as applied in recognizing multifaceted disease patterns was confirmed by comparative analysis.

Although the existing issues associated with the diversity of datasets, explainability, as well as the limitations of computer-based computation could still be a significant challenge, the results indicate a great possibility of AI-based disease prediction systems to aid precision farming. The early and precise detection of the disease can lower the loss of yield, reduce the unnecessary use of the pesticides, and enhance the production of the farm.

In general, this research leads to the development of the intelligent farming application and preconditions the further research of credible, analyzable, and scalable systems of paddy disease prediction.

Declarations

Clinical trial number

not applicable.

Funding Declaration: No Funding.

Author Contribution

Pardeep Kumar, Bhukya Ramadevi and Revelle Akshara collected data and wrote the main manuscript text.Mohammad Shahid and Abu Salim added Experimental results in table 2-4 and figure 1-3.

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Figures

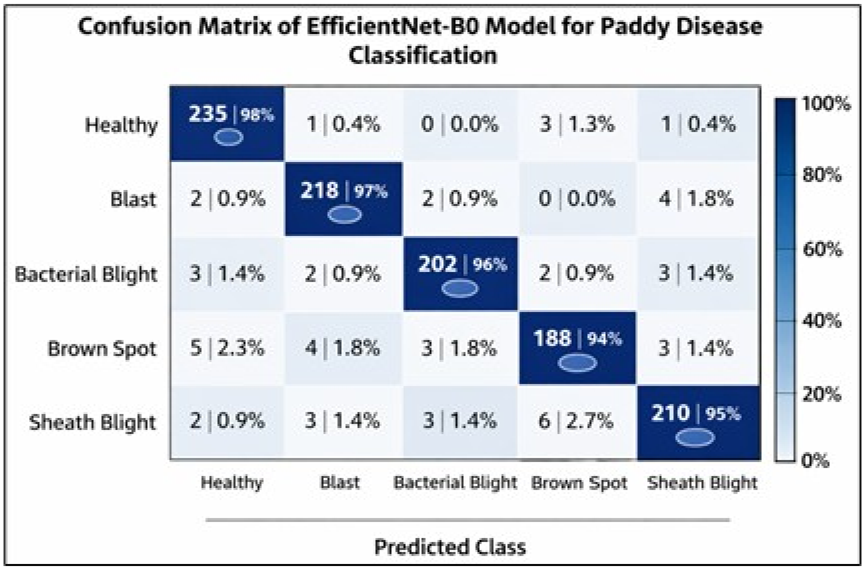

Figure 1

Confusion matrix of EfficientNet-B0 model for paddy disease classification.

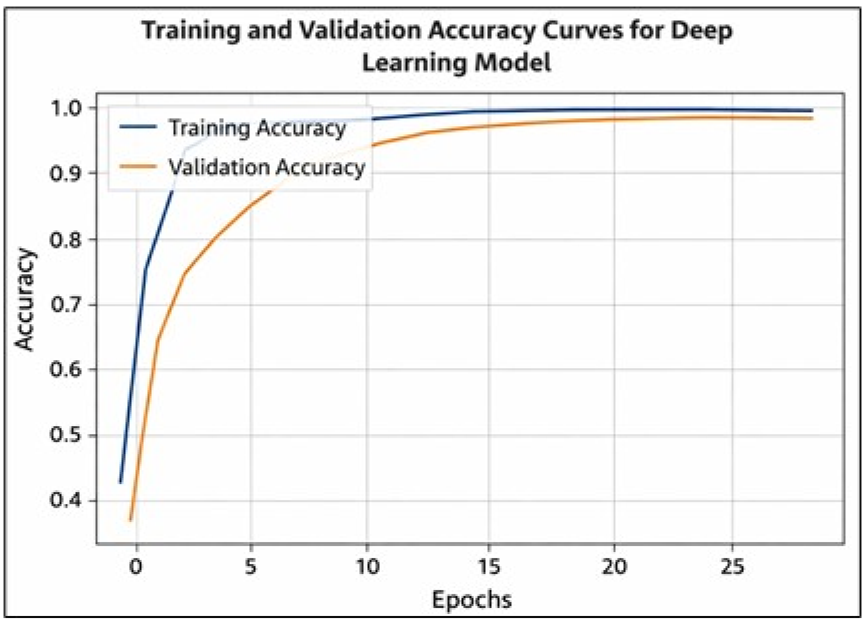

Figure 2

Training and validation accuracy curves for deep learning model.

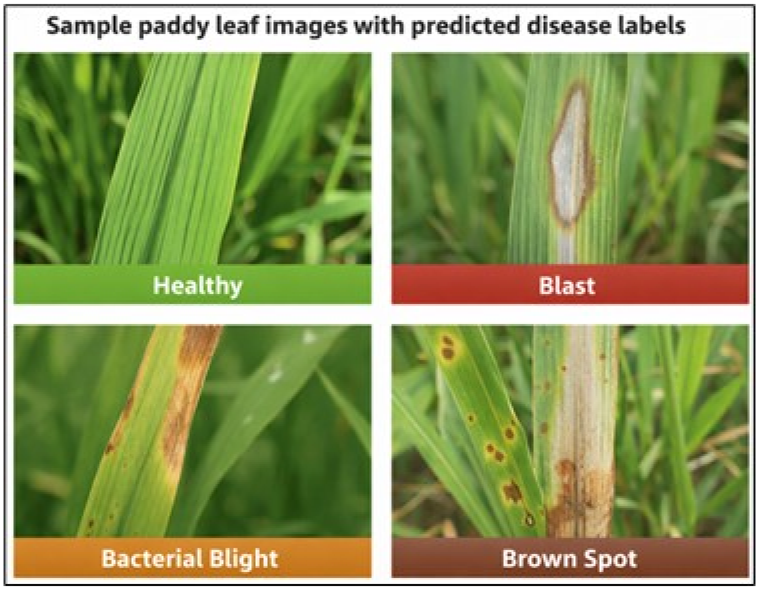

Figure 3

Sample paddy leaf images with predicted disease labels.