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Research Article

A Hybrid Intelligent Framework Based on Deep Learning and Adaptive Fuzzy Diagnosis for Rice Leaf Disease Detection and Classification

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ABSTRACT

Rising incidences of leaf diseases in rice for a more stable food security has become a global challenge. Therefore, there is a need to come up with more scientific diagnostic approaches. Most of the conventional means of disease recognition depend on visual inspection and interpretation by expert predicting the disease, a process that is tedious and subject to human bias. To address these issues, new approaches such as deep learning are very effective in overcoming taken up by using the imagination of a machine. This mechanical approach and the development of new algorithms based on CNNs and all-stage datasets of healthy and infected rice leaves could accelerate the detection process and enable people to act quickly. This article discusses deep learning methods specifically designed for diagnosing diseases on rice leaves. This is achieved by reviewing the entire process, from the conception to its full implementation in agriculture. The synthetic-data study reported used 400 images from four classes, split into 300 training images and 100 test images. The CNN achieved 86.00% accuracy and a macro F1-score of 85.65% after 12 training epochs. The adaptive fuzzy part reached 92.00% accuracy on a separate task of simulated severity classification. These are only preliminary results, they don't tell how well the rice leaves will perform in the field.

Keywords: Rice Leaf, Disease, Diagnosis, Deep learning

INTRODUCTION

Integrating millions of people around the globe and promoting economic development in several agricultural societies, rice production is critical for food security. Gross Economic Value of Rice Based on, statistics from the world population are about 162 million hectares which accounts for one of the world's leading food crops that provides nearly 20 percent of calories, thus more than sufficiently meeting nutritional and subsistence needs. Nonetheless, there are increasing challenges to the significance of rice cultivation due to several plant diseases that could impair either efficiency and efficacy of such practices [1][2]. The challenge of effectively identifying rice leaf diseases is exemplified by the difficulty farmers face, as these approaches are time-consuming and need specialized knowledge. Since these restrictions can result in significant losses for farms, more farmers will look for more inventive solutions to overcome the difficulty. Cutting-edge technologies like Deep Learning are being used to address these issues, offering more accurate and effective ways to diagnose and treat rice illness. In conclusion, implementing such technologies is essential to enhancing farming methods and encouraging rice production that is sustainable [3].

These diseases can account for substantial losses in production because of several factors like insect attack, soil health and climate that promote their occurrence. Some methods to diagnose particular methods of crop

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diseases of which visual assessments are common among farmers are not only inaccurate but may also result in the inefficacious practices that worsen the level of damage sustained. In particular, deep learning technologies are already able to help with the diagnosis of diseases suffered by rice leaves. These technologies improve the precision and speed of disease identification by classifying and analyzing leaf photos using sophisticated algorithms. Enhancing the effectiveness of these diagnostic techniques is crucial in order to maximize the potential yield and achieve sustainability through the reduction of pesticide use in rice farming [4].

Traditional methods of disease diagnosis in agricultural pathology include visual inspection and sample transportation to laboratories. These methods are frequently unreliable and scalable in high-pressure settings. Due to the high labor and waiting times associated with both methods—both of which can take several hours for a single field visit and result in results that can take days or weeks to come in—late identification could cause crop losses to worsen. Conversely, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential for improving accuracy and automating diagnosis.

On the other hand, notable high results have been demonstrated in sophisticated architectures like ResNet for the diseases classification of rice leaves, which may achieve up to 91.84% Precision and 91.67% Recall[5]. Furthermore, deep learning frameworks may diagnose diseases more reliably than standard methods, which typically struggle in huge and unbalanced datasets[4].

This is because deep learning frameworks are able to operate well under these conditions. Therefore, the idea of combining deep learning with agricultural diagnostics offers many potential benefits and paints a picture that is both faster and undoubtedly more advantageous than traditional methods. It has developed into a superb diagnostic tool with recent advancements in the field brought about by deep learning, which is essential for early disease detection in agriculture. Researchers have found that deep convolutional neural networks (CNNs) outperform more conventional methods in the identification of plant diseases. By combining sophisticated algorithms like the CNN-COD model, which combines elements of convolutional neural networks and computer vision, rice leaf disease diagnosis has improved significantly thanks to the use of cutting-edge image processing features. This has resulted in a mean average precision increase of up to 3.7% over previous models that are comparable to YOLOv4 [5].

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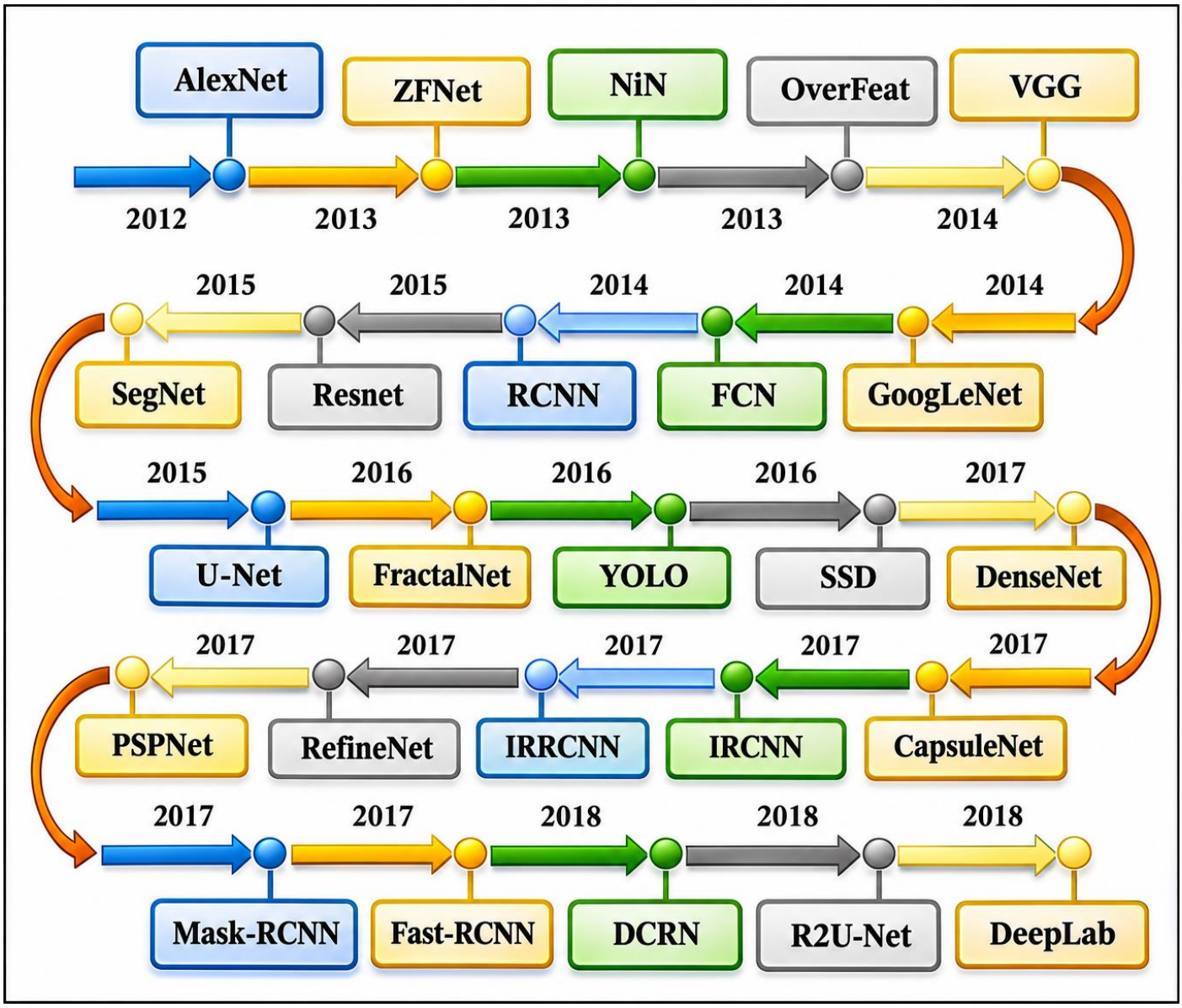


Figure 1. Summary of the evolution of various deep learning models from 2012 until now.

Additionally, the cooperation of agricultural scientists and machine learning researchers is needed to ultimately overcome the limitations including data availability and model bias for a more reliable disease classification [7]. Through this interdisciplinary collaboration, not only disease detection efficacy is increased but also the sustainable agricultural practices which in turn would lead to a better crop health and productivity. The main contribution addressed in this study is to integrate a disease-classifier based on CNN with an artificial one with a separate fuzzy adaptive stage for simulating severity grading. The proposed framework provides an extra understandable severity label, unlike a normal classifier predicting only a disease category. Available experiments consider these two results separately.

DEEP LEARNING TECHNIQUES IN PLANT DISEASE DIAGNOSIS

In this regard, deep learning has emerged as the most sophisticated technology available for identifying plant diseases in recent times, particularly with regard to large crops like rice. Now, algorithms using deep learning can easily identify diseases caused by pathogens by looking at large datasets and identifying complicated patterns in images of plant leaves. Traditional methods are often subjective and prone to inaccuracy because they rely heavily on visual cues.

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In contrast, deep learning enhances diagnostic precision through the use of mechanisms like CNNs, which outperformed conventional machine learning methods in the categorization of rice datasets by a wide margin [2].

Additionally, the creation of augmented datasets through the use of techniques such as generative adversarial networks (GANs) might enhance the generalizability and robustness of models by addressing the issue of the scarcity of data in the agricultural sector. Thus, deep learning-integrated plant disease diagnostics has enabled sustainable agriculture in addition to prompt identification [7]. Fig. 2 illustrates the main steps in a deep learning-based plant disease diagnosis pipeline, which include data preparation, data splitting, model training, model evaluation and result display. The picture is only an idea, it should not be understood as a complete detailed implementation of the hybrid adaptive fuzzy model.

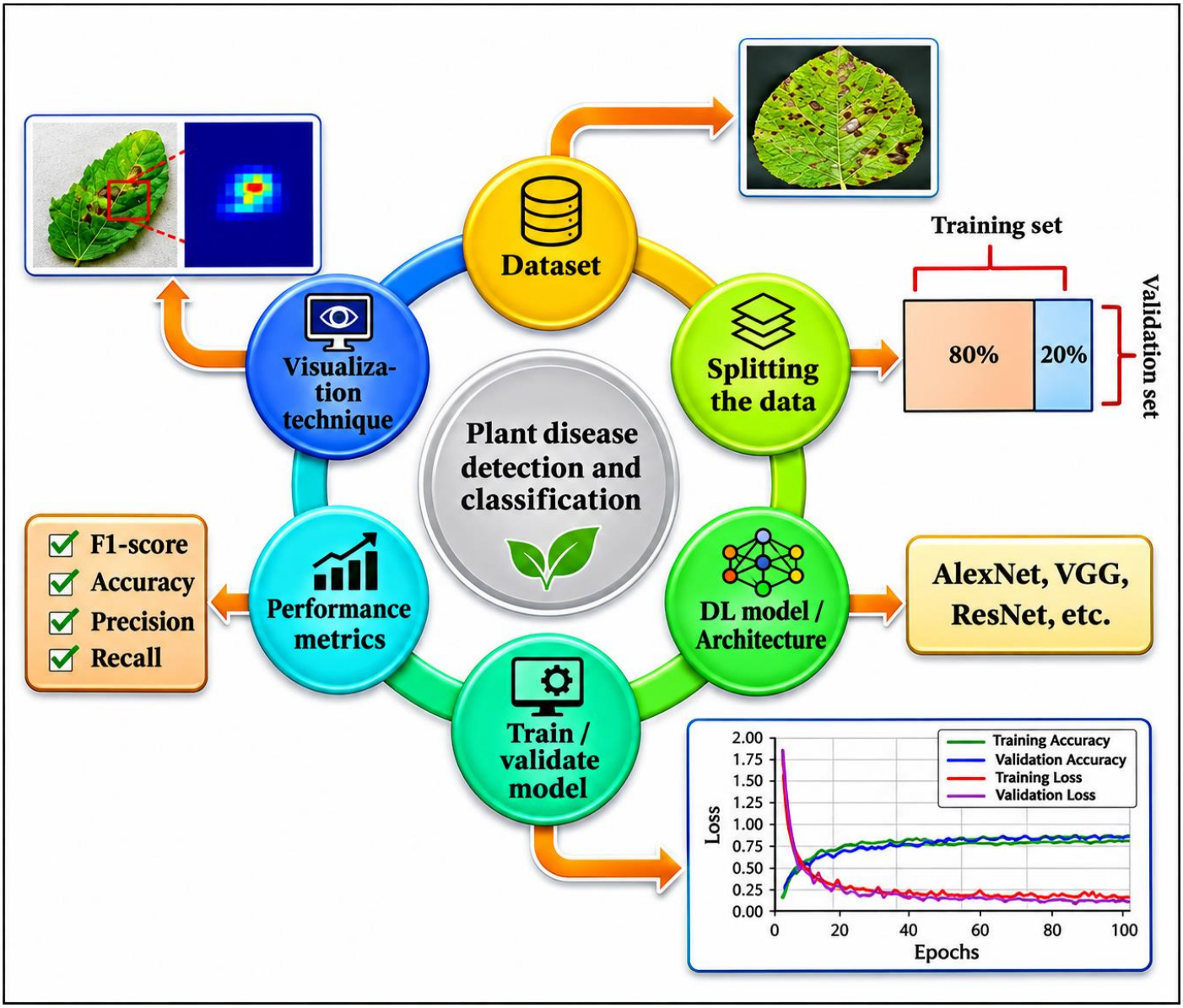


Figure 2. Flow diagram of Deep Learning implementation

STATE-OF-THE-ART METHODS

This section presents recent research that uses widely used deep learning techniques to identify and categorize rice leaf diseases. In order to attain better outcomes, various related research that introduce updated or improved versions of machine learning architectures are also reviewed.

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In [8] they suggest using a Convolutional Neural Network (CNN) framework to more precisely identify illnesses in rice leaves. Python is used in the framework to do preprocessing, segmentation, and classification of photos of rice leaves. The accuracy, precision, and recall of the suggested CNN model are assessed. The suggested framework has the potential to improve attempts to detect rice illness, as evidenced by the results, which demonstrate a notable improvement in accuracy when compared to the current models.

In [9] Using deep learning techniques, they provide an automated method for identifying three plant diseases that frequently affect rice plants: brown spot, bacterial leaf blight, and leaf smut. This study used transfer learning using a VGGNet convolutional neural network (CNN), which was pre-trained on a sizable ImageNet dataset, to successfully classify the illnesses of rice leaves. A number of cutting-edge classifiers, including Support Vector Machine (SVM), k-nearest neighbor (kNN), Convolutional Neural Network (CNN), Random Forest, and Decision Tree, are compared to the performance of the proposed framework.

In [10] they suggested using deep learning and convolution neural networks (CNNs) to identify and categorize illnesses such as false smut, sheath blight, and stem borer. The fact that the illness can attack any leaf, regardless of size, presents the biggest obstacle in diagnosing it. In order to train the KNN model, a dataset including 1045 photos was acquired. KNN first divides the leaf into those that are diseased and those that are not. CNN will be used for the Classification of the Disease in the second phase. With this method, we were able to identify healthy leaves with 95% accuracy and Sheath Blight with 90% accuracy, which is the best accuracy of any disease.

In [11] it aids in the analysis of potential diseases that affect rice plants. A deep learning algorithm was used to examine the image of the diseased leaves in an attempt to make an analysis. Custom net and Google net architecture are used. The selection process takes into account both the computational time needed to produce the model and a high degree of accuracy. The focus of disease items on rice leaves can be located with the aid of the convex hull technique. Data augmentation minimizes imbalanced datasets and promotes diversity in the amount of data. The accuracy attained by applying this technique is 80.94%, and the computation time on average is three minutes and twenty seconds. The classification error values are MAE 0.2555, RMSE 0.6501, and MSE 0.4227.

In [12] They provide the research in multiple stages, such as a review of the literature, application design and manufacture, application testing and analysis, report writing, and conclusion drawing. A Convolutional Neural Network (CNN) model was created on TensorFlow lite using deep learning technology, and it was then saved in the ML Kit service. Moreover, a detecting application developed for the Android mobile platform can incorporate the model. This will help farmers distinguish between healthy and diseased rice leaves. When the model created in this study to classify illness photos on rice leaves has an accuracy of 80%, the algorithm's development and application to an Android-based mobile application can work smoothly.

In [13] A proposed ensemble learning architecture uses the picture as input for the well-known transfer learning neural network VGG 16, which has been pretrained using the ImageNet dataset. The Light GBM then uses the features from the penultimate layer as an input. With a mobile-friendly end-to-end user interface, the Ensemble learning model is implemented on Heroku. When classifying four varieties of rice leaf disease, the suggested technique yielded an accuracy of 96.49%. It was trained on 80% of the dataset's photos and verified on the remaining 20%.

In [14] To find rice leaf disease, an automated system is employed. In order for farmers to prevent harm to their crops by taking timely precautions. A dataset of 5368 photos was gathered from Plant Village and Kaggal for the proposed work. The SqueezeNet pre-trained model was utilized for feature extraction, and a neural network classifier was employed to classify rice leaf disease. These results, which included 96.5% accuracy on 10 cross-folds and 98.3% accuracy on 20 cross-folds, are contrasted with those of various classifiers, including SVM, Random forest, KNN, Naive Bayes, and Adaboost. Of the aforementioned methods, the neural network produced the most accurate results.

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In [15] They demonstrate a machine learning-based method for detecting rice leaf disease. This study detects three of the most prevalent illnesses affecting rice plants: brown spot infections, bacterial leaf blight, and leaf smut. The input consisted of crisp pictures of the impacted rice leaves against a white background. Following the required pre-processing, a variety of machine learning methods, such as KNN (K-Nearest Neighbor), J48 (Decision Tree), Naive Bayes, and Logistic Regression, were used to train the dataset. Using a 10-fold cross-validation process, the decision tree algorithm produced an accuracy of more than 97% on the test dataset.

COMPARISON BETWEEN RICE LEAF DISEASE DIAGNOSIS USING DEEP LEARNING METHODS

The CNNs, RNNs, deep belief networks and transfer learning are some of the main methods used for rice leaf disease diagnosis, which are compared in Table 1. The comparison lists common uses, benefits, drawbacks, data needs and how they are used, but does not provide experimentally measured rankings on a common rice-leaf benchmark.

Table 1. Comparison between rice leaf disease diagnosis using deep learning methods

Aspect	Convolutional Neural Networks (CNN)	Recurrent Neural Networks (RNN)	Deep Belief Networks (DBN)	Transfer Learning
Purpose	Image classification and feature extraction from rice leaf images	Sequence prediction, could help with disease progression over time	Feature extraction and classification based on unsupervised learning	Leverages pre-trained models for faster and more accurate diagnosis
Advantages	High accuracy in visual feature extraction and classification	Works well with time-series data for disease progression	Learns hierarchical features and can work with unlabeled data	High accuracy with reduced training time and computational resources
Challenges	Requires large labeled datasets and high computational resources	Harder to train on visual data directly compared to CNNs	Training can be computationally intensive	May require careful fine-tuning and domain adaptation
Common Architectures	VGG, ResNet, DenseNet	LSTM, GRU	RBM (Restricted Boltzmann Machines)	VGG, ResNet, Inception, MobileNet
Dataset Requirements	Large, labeled, high-quality image datasets	Time-stamped sequence data	Large datasets, can be partially labeled	Large pre-trained models and smaller target datasets
Performance in Disease Diagnosis	High accuracy for identifying diseases from leaf images	Limited due to difficulty in processing visual data	Moderate performance with room for improvement	High performance, especially when using models pre-trained on similar datasets
Training Time	Long training time for complex networks	Long due to sequential data processing	Very long for deep networks and unsupervised learning	Shorter training time due to pre-trained models
Application in Rice Disease Diagnosis	Commonly used for rice leaf disease detection with high success rates	Rarely used, unless for time-based progression	Occasionally used for unsupervised feature learning	Frequently used to boost performance with fewer data and computation needs

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THE PROPOSED METHOD

The concept involves developing an intelligent system that combines deep learning and fuzzy fault diagnosis to detect rice leaf diseases, as well as to identify the specific disease type and the severity of the infection.

A deep learning model is employed to extract visual features—such as color, texture, shape, and lesions—from leaf images; these features are subsequently analyzed using an adaptive fuzzy logic system designed to handle uncertainties and the similarities between symptoms of different diseases.

The proposed scientific contribution is to automatically change the fuzzy membership functions based on the training data instead of using fixed rules. This will improve the accuracy of the diagnoses and make transparent the reason why the decisions are made in this way. We need to describe the steps used to generate and label the 400 synthetic images, the dimensions of the input images, the configuration of the CNN layers, the optimizer and learning rate, the augmentation settings, random seeds, class balance, and the validation protocol, so that independent replication can be performed. Since these settings are not referenced in the submitted manuscript, they cannot be used here as measured parameters. The original implementation is also required for the mathematical definition of severity index, membership-function optimization and fuzzy rule base.

Algorithm 1: Adaptive Deep Learning–Fuzzy Fault Diagnosis

The proposed adaptive deep learning-fuzzy fault diagnosis algorithm comprises of eight steps to identify diseases on rice leaves and estimate their severity. Initially, the images of healthy rice leaves and diseased rice leaves are collected and added to the framework for diagnosis. The noise is removed, the images are resized and the leaf regions are identified to make the images consistent and improve the quality of the images. Then, a deep learning architecture like Convolutional Neural Network (CNN) or EfficientNet is employed to detect visual features that distinguish between disease classes and estimate the probability of each. The next step is to find and measure important diagnostic indicators. These are the size of the infected area, changes in leaf color, changes in leaf texture. The deep learning model generates these indicators and disease probabilities, which are then sent to a Fuzzy Inference System (FIS) to handle uncertainty and overlapping disease symptoms. The fuzzy diagnosis mechanism is further improved by an adaptive optimization procedure, which adjusts the fuzzy rule parameters and membership functions based on training and validation data. According to the deep learning predictions and fuzzy inference outputs, the framework detects the most probable type of disease. It also classifies the infection severity into three levels, i.e., mild, moderate, and severe, and estimates the uncertainty of the situation. Finally, an interpretation step displays the important visual features and fuzzy rules that are used to perform the diagnosis, making the proposed intelligent disease diagnosis framework more transparent and easier to understand.

EXPERIMENTAL RESULTS AND DISCUSSION

Imaginary examples of the four classes are shown in Figure 3, healthy, blast, brown spot and bacterial blight. The lesion patterns presented are for illustration purposes only and are not actual field photographs validated by a third party.

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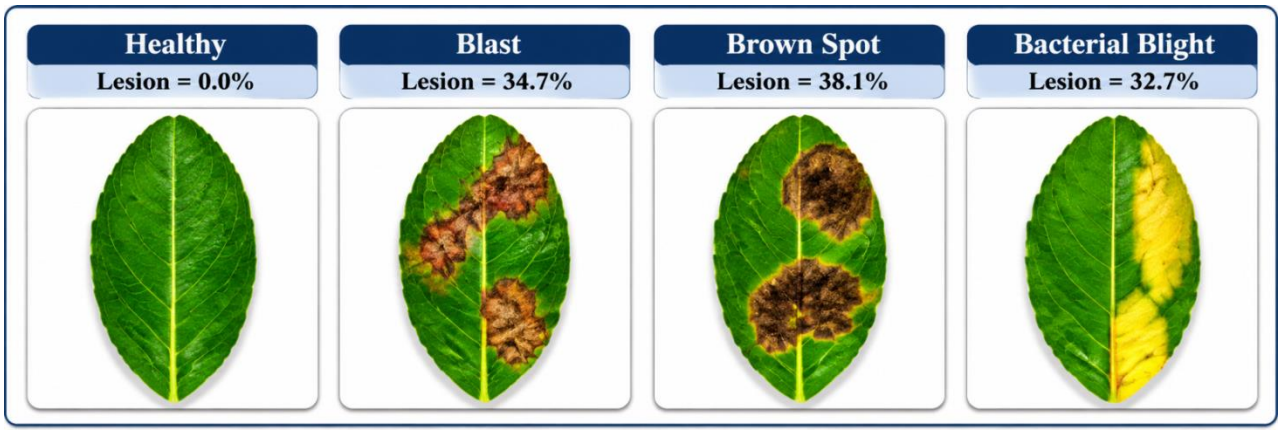


Figure 3. Synthetic rice leaf samples representing four disease classes

DISEASE CLASSIFICATION PERFORMANCE

The CNN model, when run on the fake test set, could classify with an accuracy of 86.00% and the Macro F1-score was about 85.65%. These results indicate that the network has learned some artificial visual patterns related to the spots' shape, color changes and locations. However, the presence of misclassifications suggests that the simulated pathological patterns may overlap. Figure 4 shows the confusion matrix for 100 fake test images, and the confusion matrix gets 86 of them right. All 25 healthy cases are healthy but nine brown-spot cases are put in the healthy group. This is correct. Thus, the main class-specific weakness is not being able to distinguish between fake brown spots and healthy leaves, which cannot be seen from the overall accuracy.

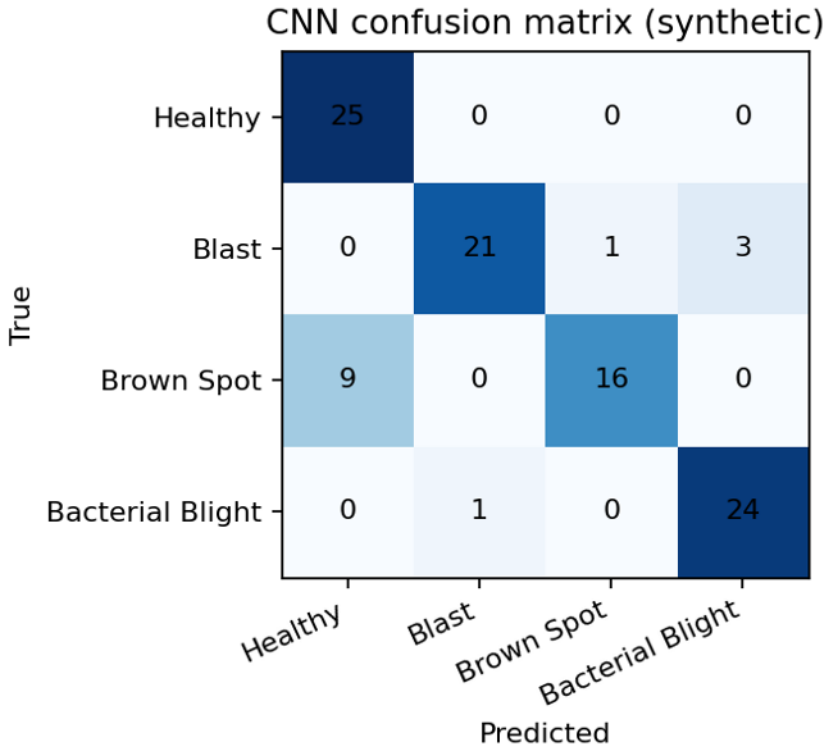


Figure 4. Confusion matrix of the cnn-based disease classification model

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ADAPTIVE FUZZY DIAGNOSIS PERFORMANCE

The adaptive fuzzy system classified 92.00% of the fake test set correctly on the levels of infection severity. This means that the membership functions, which are produced from the training data, are able to represent the level of infection by showing the percentage of infected area. However, the result should be taken with caution as both the reference severity labels and the infection index used for evaluation were provided by a human. Hence, the high accuracy alone cannot prove that the system is reliable for severity estimation from real agricultural images. The simulated change of the lesion area ratio for the mild, moderate and severe fuzzy membership functions is shown in Figure 5. Their supports overlap, so they can make gradual changes, not hard thresholds. The figure only shows membership functions used in the simulation. It does not prove by itself that adaptation is better than fixed membership functions. For consistency, the parameter-estimation procedure derived from the training should be given.

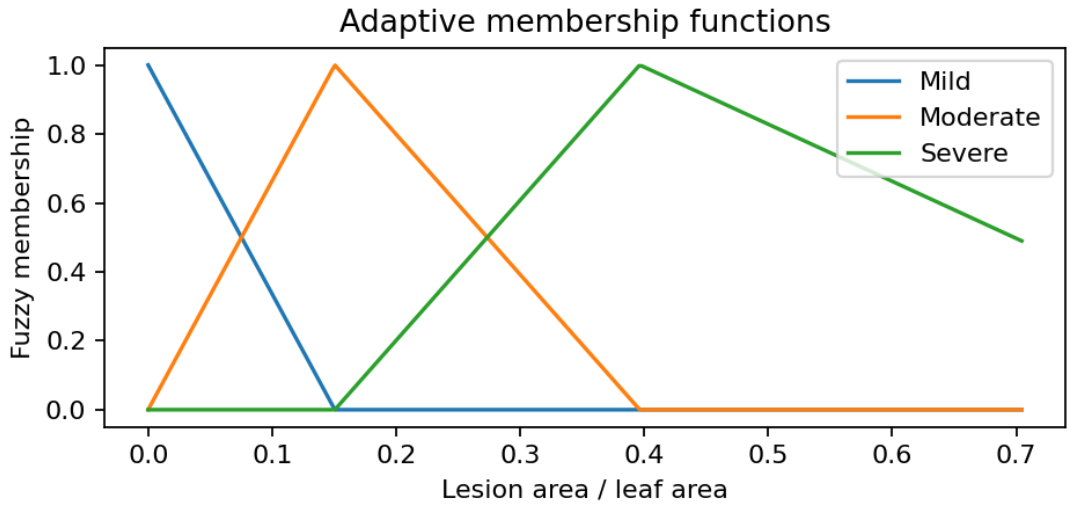


Figure 5. Adaptive fuzzy membership functions derived from training data

COMPARISON AND ANALYSIS OF RESULTS

Table 2 summarizes reported experimental settings and results: 400 fake images, 4 classes, 300 training images, 100 testing images, and 12 training epochs. The CNN classified correctly 86.00% of diseases and got 85.65% macro F1-score, and the adaptive fuzzy component classified correctly 92.00% of simulated severity categories. These numbers are for different variables, so they are not to be taken as a direct 6 point improvement in classification.

Table 2. Summary of the test settings and performance indicators of the proposed CNN–Adaptive Fuzzy framework

Parameter	Value
Total number of images	400
Number of disease classification classes	4
Number of training images	300
Number of testing images	100
Number of training epochs	12
CNN classification accuracy (%)	86.00
CNN macro F1-score (%)	85.65
Adaptive fuzzy severity classification accuracy (%)	92.00
Infection severity levels	Mild, Moderate, Severe

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The results indicate the feasibility of combining convolutional neural networks (CNNs) and adaptive fuzzy diagnosis within a single framework, where the neural network handles disease type recognition while the fuzzy system provides an interpretable estimate of severity. A key advantage of this framework is the separation of disease recognition from severity assessment, enabling the provision of more detailed information than just the disease name. However, the fuzzy system's 92% accuracy cannot be directly viewed as an improvement over the CNN's 86% accuracy, as the two metrics pertain to distinct tasks: classifying the disease type and estimating the severity of the condition. Furthermore, this implementation did not include a comparison with a static fuzzy system or an evaluation of how integrating the two systems affects disease classification accuracy—aspects that represent important areas for future experimentation.

EXPERIMENTAL CONCLUSION

The results of the simulation indicated that it is possible to use an integrated framework combining deep learning and adaptive fuzzy diagnosis to classify rice leaf diseases into groups and guess their severity. The CNN model correctly classified 86% of the fake diseases into groups and the fuzzy system correctly predicted 92% of the fake infection levels . An important contribution is that the membership functions are based on data-based centers, rather than on fixed, pre-defined centers, which allows more freedom. To prove its advantage, however, this mechanism must be compared to a regular fuzzy system. The study recommends extending the implementation to include real rice images, incorporating advanced deep learning models, testing severity estimation based on labeled infection masks, and evaluating the stability of the membership functions and the generalizability of the results.

CONCLUSION

A first version of a hybrid diagnostic framework based on convolutional neural networks and adaptive fuzzy inference was presented to classify and rate the severity of synthetic rice-leaf diseases. After 12 epochs, the CNN achieved 86.00% classification accuracy and 85.65% macro F1-score on the reported dataset of 400 fake images (300 training images and 100 test images). The adaptive fuzzy part correctly classified the simulated lesion severity into three levels: mild, moderate and severe 92.00% of the time. The confusion matrix showed that it was very difficult to detect the synthetic brown-spot cases, with nine of them being classified as healthy. The test used only simulated data and severity targets, so the results cannot be used to prove that the results apply to real photos or that adaptive fuzzy membership functions are better than fixed ones. Future work should include listing all experimental and model parameters, examining real images of rice leaves labeled by experts, comparing rigid and flexible fuzzy systems with matched severity targets, and reporting metrics for each class, variability, and external validation.

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