Model for Effective Rice Disease Recognition Based on Deep Learning Techniques

Firas Muneam Bachay[1], *Mohammed jawad* AL_dujaili[2] and *Ahmed* Al-Fatlawi[3*]

[1]Department of Scientific Affair, University of Kufa, Najaf, Iraq
[2]Department of Electronic and Communication, Faculty of Engineering, University of Kufa, Najaf, Iraq
[3]Computer Technical Engineering Dept., Technical Engineering College, University of Alkafeel, Najaf, Iraq

Abstract. Iraq's primary crop, crucial for both domestic consumption and exports, is rice. The prevalence of rice infections poses a significant challenge to farmers, impacting crop yield and resulting in substantial losses. Human identification of diseases relies on expertise, making early diagnosis crucial for sustaining rice plant health. To address the limited number of rice leaf images in the database, our approach incorporates augmentation and dilation rate. Integrating drone technology and machine learning algorithms offers a promising solution to efficiently diagnose rice leaf diseases. However, existing methods face challenges such as picture backgrounds, insufficient field image data, and symptom variations. This work introduces a robust methodology, leveraging a specialized Convolutional Neural Network (CNN) model for rice leaf photos, effectively enhancing disease classification accuracy. The proposed approach successfully identifies and diagnoses three distinct classes: leaf smut, brown spot, and bacterial leaf blight.

1 Introduction

Ranked second only to wheat in both planted areas and production, rice stands as one of the world's most crucial crops. Nourishing approximately half of the global population, it serves as a primary resource for millions in Asia. In 2014, rice cultivation covered around 163 million hectares, constituting 11% of all arable land. Notably, 114 out of 193 countries engage in rice farming, with 90% of global rice production and consumption concentrated in Asia. Within the Arab world, rice production gains significance for ensuring food security, especially in Iraq, where it ranks third in farmed and productive areas after wheat and barley [1,2].

To enhance rice yield, an effective disease management program is imperative. Early field diagnosis is the initial step in controlling the discovery and spread of rice illnesses. Yet, identifying these diseases is challenging, relying on the expertise of plant pathologists or farmers [3]. Timely identification is crucial for sustaining rice production, enabling the use of pesticide control methods [4,5].

Predicting and forecasting diseases affecting rice leaves is vital for maintaining both quantity and quality. Early detection facilitates timely intervention, preventing disease progression and promoting healthy plant growth, ultimately boosting rice production. Common rice diseases include sheath blight, bacterial blight, rice blast, bacterial leaf blight, brown spot, and leaf smut [6].

Diagnosis traditionally relied on visual analysis, a costly, labor-intensive, and time-consuming method [7]. Recent advancements, employing deep learning and artificial intelligence, offer efficient and cost-effective alternatives for early disease diagnosis in various agricultural fields. This article presents a comprehensive methodology to enhance the classification accuracy of rice leaf disease [8,9].

Utilizing a Convolutional Neural Network (CNN) model tailored for rice leaf images, our approach reliably identifies bacterial leaf blight, brown spot, and leaf smut. Overcoming the challenge of a limited dataset, we applied diverse picture augmentation techniques and adjusted kernel dimensions in the CNN model's convolutional layer without altering parameters.

2 Related Work

The surge in deep learning applications has prompted researchers to explore its potential in addressing the challenges of rice disease recognition. Notably, [10] employed the VGG-16 model on a dataset with six disease classes, achieving an impressive 96.08% accuracy. However, their reliance on a commercially available CNN model poses a significant limitation. Similarly, [11] utilized various models on a dataset of nine common rice diseases, achieving 98% accuracy, yet their dependence on available CNN models raises concerns. [12] opted for convolutional neural networks (CNNs) to

* Corresponding author: ahmed.fatlawi@alkafeel.edu.iq

extract features from rice leaf images, using SVM for classification and achieving 96.8% accuracy. However, their complex methodology involves feature extraction with a CNN model before classification. Likewise, [13] proposed a deep learning approach for identifying 10 common rice diseases, achieving 95.48% accuracy with CNNs. Meanwhile, [14] achieved 98% accuracy using ResNets and DenseNets on the K5RD database but faced criticism for relying on off-the-shelf CNN models.

These studies, while contributing to the field, expose limitations, such as dependence on pre-existing CNN models. These constraints emphasize the necessity for ongoing research and advancements in deep learning techniques to establish robust systems for rice disease identification.

3 The Proposed Approach

This section will provide a detailed analysis of the methodology underlying the recommended approach for identifying rice illnesses. The main phases of this procedure are depicted in (Figure1).

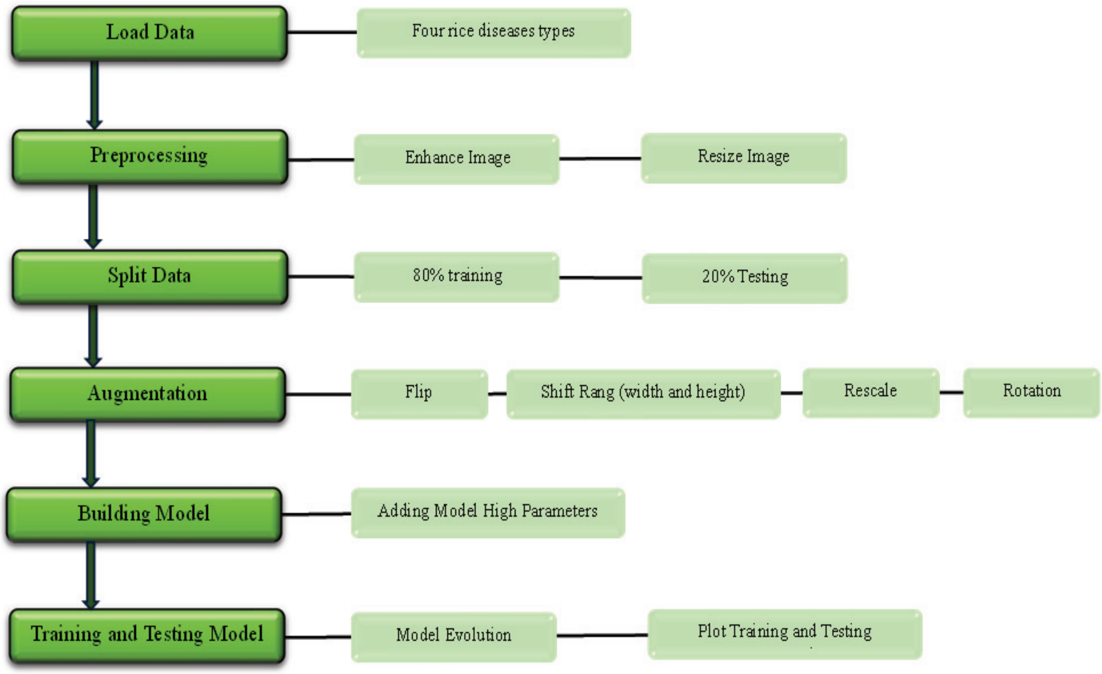

Fig. 1. The general framework of the proposed work

Preprocessing is the first step in the proposed methodology, which aims to get the input images ready for the next steps and make sure they work with the suggested technique. This includes operations like resizing the input image and improving it. After that, a detailed explanation of all the layers in the specially designed CNN-based model created just for rice disease images is given. The input, convolution, activation function unit, pooling, fully connected (FC), dropout, and output layers are among the various layers that make up the model. Setting up the input layer to accept 224x224 pixel images of rice diseases is the first stage. Next, the application of convolutional layers occurs. Two convolution layers in total are suggested in this context, and they both aid in the feature analysis of the image of rice diseases. Each of these convolution layers has an activation function called a rectifier linear unit (LeakyReLU). Each individual convolution layer is followed by a pooling layer in the convolution process. This layer efficiently minimizes the size of the data by utilizing windowing and maximum operations. The architecture is continued with the introduction of a flatten layer. This particular layer converts two-dimensional data into a representation that is only one dimension. After that, the classifier is used. A deep learning method called the SoftMax classifier is adjusted to accommodate the quantity of categories. This method is frequently applied to problems involving numerous classifications. Empirical evaluation is used to determine the ideal dimensions of the suggested CNN design. This entails increasing the convolutional and max-pooling elements gradually, then methodically adjusting the filter amounts. The network with the best performance is the one that will ultimately be chosen. Table 1 provides an outline of the suggested CNN structure.

Table 1. Summary of the proposed CNN architecture

Layer Type	Filter size	Activation Function	No. of filter	Input Shape	Output Shape	No. of parameter
Convolution1	3×3	Leaky_ReLU	20	224,224,3	220,220,20	560
Max pooling 2D	4×4	-	-	220,220,20	55,55,20	0
Convolution2	3×3	Leaky_ReLU	10	55,55,20	51,51,10	1810
Max pooling 2D	2×2	-	-	51,51,10	12,12,10	0
Flatten	-	-	-	-	1440	0
Fully Connected	-	Leaky_ReLU	256	1440	256	368896
Dropout	0.5	-	-	256	256	-
Output layer	-	Softmax	-	256	3	771
Total params: 372037 Trainable params: 372037						

Moreover, (Figure 2) shows the underlying architecture of the proposed CNN model.

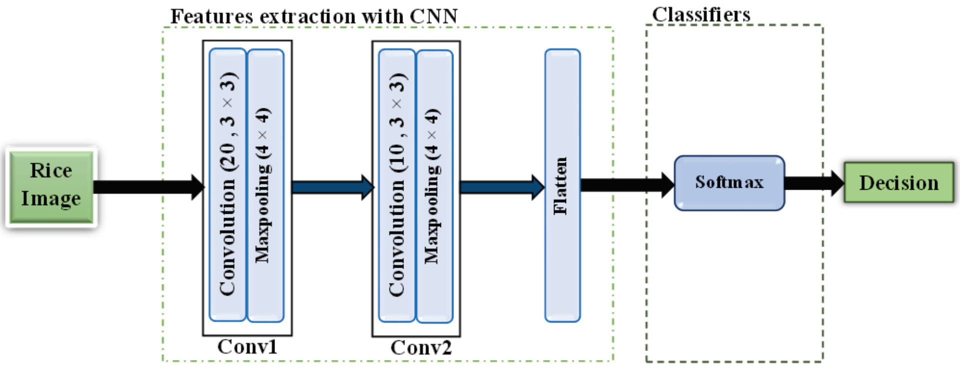

Fig. 2. The architecture of the proposed approach

4 Experimental Result

Using Google Colab's free Python3 environment, the recommended approach for verifying rice illnesses is run on an Nvidia Tesla K80 GPU with 12GB of RAM and 13GB of memory. The rice illnesses database from [15] on Kaggle is used to assess the effectiveness of the suggested method. A measure of the overall efficacy of the proposed recognition technique is the F1_score metrics and accuracy.

4.1 Dataset

There are 120 jpeg images of disease-infected rice leaves (leaf smut, brown spot, and bacterial leaf blight) in the rice diseases database that is used. Depending on the type of ailment, images are divided into three classes. Every class contains forty images. Figure 3 uses sample photographs to show some of the difficulties in the database that was used.

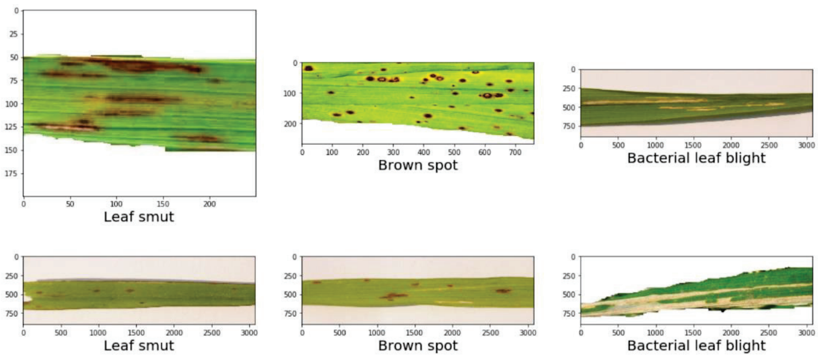

Fig. 3. Samples of face mask images in the database

4.2 Evaluating the Proposed Technique's Performance through Accuracy and F1-Score

The database is pre-processed to improve image resolution, and the dataset is split into two parts: 20% is used for testing and 80% is used for training. The restricted number of images, which presents a significant problem in training the CNN model, is addressed by applying augmentation techniques prior to incorporating photos into the training model. The Softmax function is used as the classification method during the training phase on the Keras deep learning platform. We do 100 training epochs and use the Leaky_ReLU function to initialize the weights of each convolution layer. To determine the ideal model parameters, a large number of experiments are designed and examined. After a number of training iterations, 92.63% accuracy rates are the most favourable ones. These outcomes occur when 20 kernels are used in the first convolution layer and 10 kernels are used in the second convolution layer. The kernel dimensions for the first and second convolutions are 3x3, with using 4x4 Maxpooling. The dilation_rate technique was also used to help overcome overfitting, as more than one dimension was tested and the results were compared to reach the highest accuracy. The outcomes of evaluating diverse network parameters are outlined in (Table 2). This table systematically assesses the convolution and pooling layer parameters, varying dilation_rate while keeping others constant. The evaluation metrics for the proposed technique encompass accuracy and F1-score.

Table 2. The performance results of assessing the proposed technique

No. of filters in Conv1	Maxp1	dilation _rate	No. of filters in Conv2	Maxp2	dilation _rate	Accuracy	F1_score
20 (3x3)	4x4	2,2	10 (3x3)	4x4	2,2	92.33	91.29
20 (3x3)	4x4	2,2	10 (3x3)	4x4	4,4	90.11	90
20 (3x3)	4x4	4,4	10 (3x3)	4x4	4,4	91.7	90.5
20 (3x3)	4x4	2,2	10 (3x3)	4x4	6,6	88.23	88.23
20 (3x3)	4x4	4,4	10 (3x3)	4x4	6,6	89.62	88.24
20 (3x3)	4x4	6,6	10 (3x3)	4x4	6,6	87.15	86.41

The relationship between the number of iterations used during the training process and the accuracy of the recommended network is also depicted in (Figure 4).

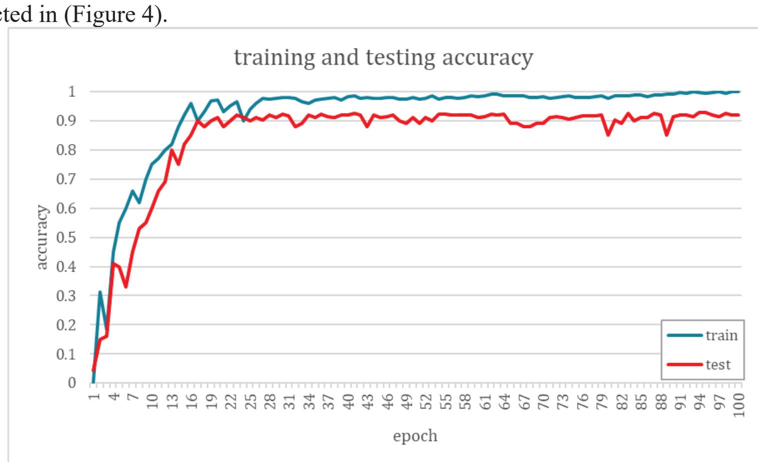

Fig. 4. Accuracy of the proposed model

The graph that is shown shows a noticeable initial increase in accuracy. After this, a steady increase is seen about epoch 20. The accuracy then shows oscillations between 20 and 88 epochs before stabilizing at approximately epoch 88.

4.3 Visualizing Convolutional Layers through Feature Map Technique

In this section, we evaluate and learn from the model's predictions using the feature map technique. This method makes it easier to comprehend how the model learns different filters and how input moves through the different levels. It is assumed that feature maps that are closer to the input pick up on little or fine details, whereas feature maps that are closer to the model's output pick up on larger features. The visual feature maps of the first convolutional layer, which consists of 20 filters, are shown in (Figure 5). The graphic that follows illustrates the variety of characteristics that are generated when the filters in the first convolutional layer are applied.

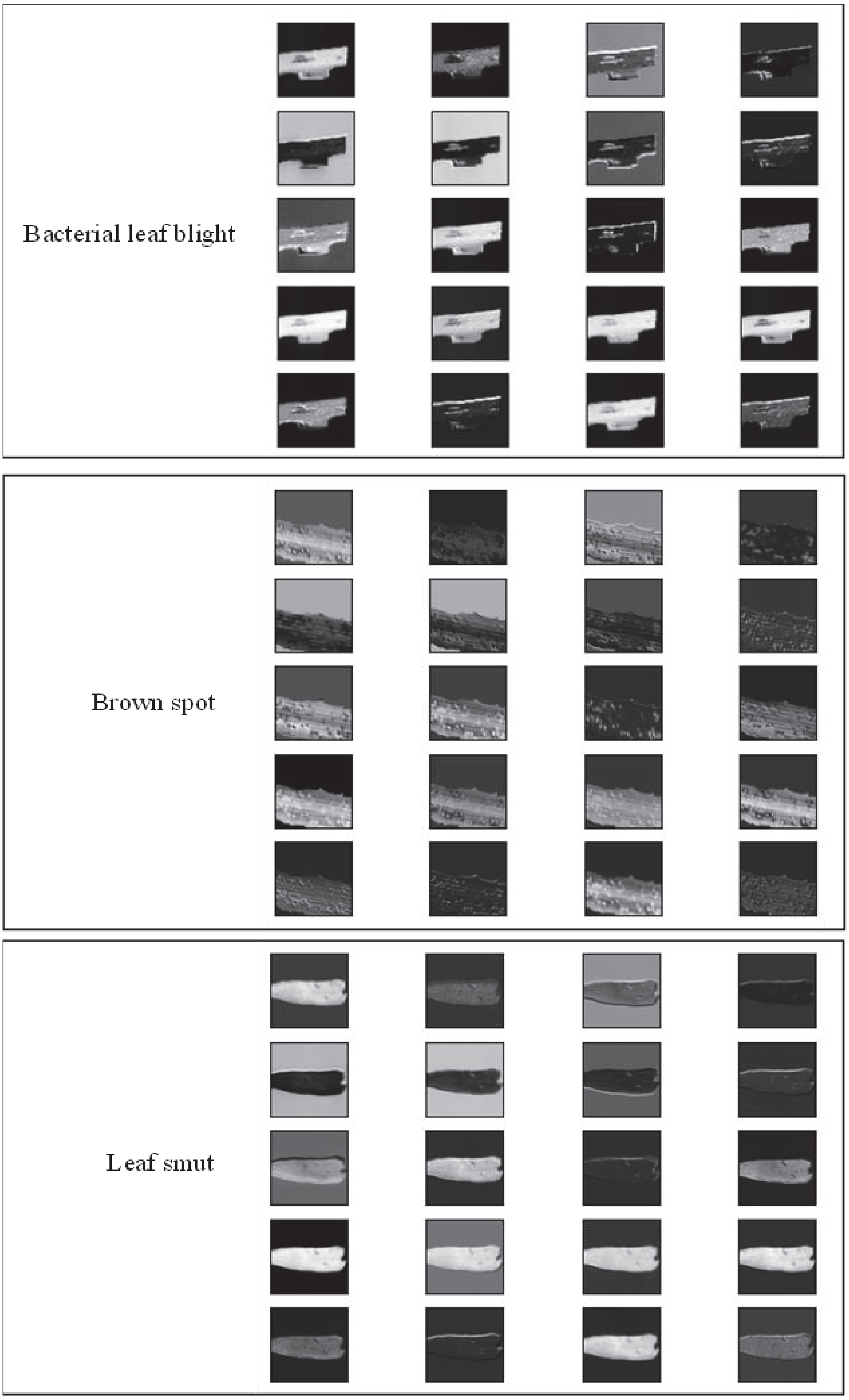

Fig. 5. Visualization of Feature Maps in the Initial Convolution Layer with 20 Interpretability Filters

5 Conclusions

This investigation delves into the application of Convolutional Neural Networks (CNN) for identifying rice diseases, emphasizing the challenge posed by a limited image dataset. The experiment utilized a 120-image dataset representing three types of rice diseases. The CNN's efficacy in feature extraction, learning intricate patterns, and making generalizations from a representative dataset resulted in a commendable 92% success rate in rice disease recognition. Additionally, the study examines the impact of dilation_rate technology on the suggested model's outcomes. Overall, the findings provide optimistic insights into addressing challenges associated with identifying rice diseases from a small photo pool. Integration with drone technology in agriculture may further enhance the detection of rice diseases.

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