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Ensemble Average and Deep Neural Networks for Detection of Rice Leaf Diseases

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معدل المجموعة والشبكات العصبية العميقة للكشف عن أمراض ورق الأرز

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ABSTRACT

Background

In this paper, the ensemble average and deep neural networks approach is proposed for detecting rice leaf diseases. The system consists of two different deep neural networks represented by GoogLeNet and MobileNetV2 where trained separately by dataset of rice leaves images.

Materials and Methods

These images represent various conditions of the leaves, including healthy leaves, and five types of diseases. The dataset is preprocessed by resizing and normalizing to standardize the inputs for the networks. Then it is split into training and testing sets to ensure robust model evaluation. After training of these two networks, the ensemble average module combines the predictions from both networks by averaging them during the testing phase.

Results

The proposed model was compared with the other two models based on the performance metrics accuracy, precision, recall, and F1-score, and the proposed model highlights the superiority of the proposed approach in detecting rice leaf diseases. The proposed model achieved the highest accuracy at 97.07%, precision at 97.1%, recall at 97.06%, and F1-score at 97.08% which outperformed the other two models across all metrics because the averaging process reduces variance and enhances the accuracy of the final decision of detection the rice leaf diseases

Conclusion

This ensemble-based approach illustrates superior performance for rice leaf diseases detection, offering a more reliable and precise tool for managing the agricultural diseases.

Keywords: Rice diseases, CNN, Deep Learning, Transfer Learning, Ensemble average.

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INTRODUCTION

Rice is one of the most important foodstuffs that people depend on all over the world. The world needs millions of tons of rice production annually to meet the needs of consumers, and this need is increasing annually with the increase in the population of the Earth. Rice is grown in many countries of the world, especially countries with hot and humid climates, because it needs large amounts of water. Rice plants, like other plants, are exposed to many problems during their life, including many diseases, including diseases that affect the leaves, which in turn affect the success of rice cultivation and the safety of the crop at the end of the agricultural season. Therefore, the process of early detection and treatment of diseases that affect plants is one of the most important things that contribute to preserving plant life, reducing losses and achieving high productivity. Modern technology has entered all fields, including agriculture, to reduce effort and cost and increase the speed of achievement. Artificial intelligence is one of the most important modern technologies that has been used to detect diseases that affect plants, including rice, as many methods of artificial intelligence and deep learning have been used for this purpose [1-5].

In Ref. [6], the authors introduced an approach for identifying rice diseases using deep convolutional neural networks (CNNs). The CNN-based model achieved enhanced classification accuracy. They employed the gradient descent algorithms for effective model training. Initially, 500 images of rice leaf and stems undergo preprocessing before serving as training data for CNNs. This model accelerates parameter convergence during training, surpassing traditional methods in recognition accuracy. The CNNs are pioneering employed for rice disease identification, accurately distinguishing 10 common diseases. Also, experimental outcomes demonstrate that CNNs not only expedite convergence but also yield superior accuracy compared to other models such as standard backpropagation, support vector machine (SVM), and particle swarm optimization (PSO).

To enhance the accuracy of maize leaf disease identification while minimizing network parameters, a study introduced a deep learning based approach to enhance GoogLeNet and Cifar10 models. These models were tailored through parameter adjustments, modifications in pooling configurations, integration of Rectified Linear Unit (ReLU) functions and dropout operations with reduction in classifier numbers. Importantly, the parameters count in these enhanced models was lower than the parameters in AlexNet and VGG. The evaluation across eight types of diseases of maize leaf, the GoogLeNet and Cifar10 achieved an average accuracy of 98.9% and 98.8%, respectively. These enhancements potentially elevate the accuracy of maize leaf disease identification and streamline convergence iterations, thereby boosting overall model training and recognition efficiency [7].

In Ref. [8], CNN models were introduced for detection and diagnosis of plants diseases using images of simple leaves from both diseased and healthy plants, employing deep learning techniques. The models were trained on a comprehensive dataset comprising 87,848 images sourced from an open database. This dataset encompasses 25 different plant species across 58 distinct classes of [plant, disease] combinations, including images of healthy plants. Multiple model architectures were trained, with the top-performing model achieving an impressive 99.53% success rate in accurately recognition of healthy plant or the corresponding plant disease status. This high accuracy considered the model as a valuable advisory tool or early warning system. Furthermore, the approach demonstrates potential for expansion into an integrated plant disease identification system suitable for real-world cultivation conditions.

A system for detecting rice leaf diseases using machine learning methods were introduced. This work focused on identifying three prevalent diseases in rice plants: leaf smut, bacterial leaf blight, and brown spot. Clear images of affected rice leaf against a white background served as input data. Following preprocessing steps, the dataset underwent training with various machine learning algorithms, including K-Nearest Neighbors (KNN), Decision Tree (J48), Naive Bayes, and Logistic Regression. Through 10-fold cross-validation, the Decision Tree algorithm achieved an impressive accuracy exceeding 97% when applied to the test dataset [9].

In Ref. [10], the authors explored the use of transfer learning with deep convolutional neural networks for identifying plant leaf diseases. They leveraged pre-trained models from large datasets and adapt them to their specific task using their own data. Specifically, they used the VGGNet pre-trained on ImageNet and incorporate the Inception module. Instead of initializing the network weights randomly, they started with weights from the pre-trained ImageNet networks. This approach significantly outperformed other state-of-the-art methods, achieving a validation accuracy of at least 91.83% on a public dataset. Even in complex background conditions, the average accuracy for classifying rice plant images reaches 92.00%. The experimental results confirm the effectiveness and efficiency of this method for plant disease detection.

In Ref. [11], a novel deep learning approach for detecting diseases in rice crop images was presented. Initially, rice plant images undergo pre-processing to eliminate noise and artifacts. Segmentation is then carried out using Segmentation Network (SegNet) to generate segments. These segments are used to extract statistical, texture, and CNN features. A deep recurrent neural network (Deep RNN) was employed for detecting of plant disease. The training of Deep RNN based on the proposed RideSpider Water Wave (RSW) algorithm, which combines the Ride Water Wave (RWW) method with Spider Monkey Optimization. The RSW-based Deep RNN demonstrates superior performance, achieving a highest accuracy of 90.5%, a maximum sensitivity of 84.9%, and a maximum specificity of 95.2%.

In Ref. [12], the authors systematically explored the issue of visual plant disease recognition for diagnosing plant diseases. To advance research of recognition of plant disease, they have created a new large-scale dataset of plant diseases comprising 271 categories of disease with a total number of 220,592

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images. Using this dataset, they addressed plant disease recognition by reweighting both visual regions and loss to emphasize the diseased parts. Their method classified five specific diseases: leaf blight, Bacterial, Tungro, Brown spot, Blast, and Leaf smut. They utilized algorithms such as VGG19, Inception and Xception, proposing an automated system to recognize the leaf diseases. They evaluated their method on this dataset and another dataset to prove the superiority of their method.

In Ref. [13] One of the convolution neural networks, the VGG-16 model, was used to reveal the sickness affecting rice plants. Images of the leaves on 4,500 rice plants were gathered in order to identify illnesses, and VGG-16 was trained using these images. Here, a novel deep learning approach was investigated to automatically identify and categorize plant diseases from images of leaves. When the VGG-16 was given images of rice plants that it had never seen, an accuracy rate of 90% was attained.

In Ref. [14], a lightweight deep CNN for detecting rice leaf diseases was presented, to outperform the other applied techniques or methods and showed good performance in comparison to Twenty-One architectures of established benchmark in that time. These include ResNet50, GoogleNet, AlexNet, MobileNet2, DenseNet121, ConvNext, and others, while utilizing significantly fewer trainable parameters. Remarkably, this method achieved of 99.81%, 0.99828, 0.99826, and 0.99827 an accuracy, a precision, a recall and an F1-score, respectively. also, they enhanced the dataset of rice leaf diseases by combining of two datasets and they added Ninety-Five images which annotated manually and collected from Internet public sources. Additionally, they developed a comprehensive crop health monitoring system for farmers and create an open API for the automatic annotation of new instances, benefiting the research community as a whole.

SYSTEM MODEL

The block diagram of the proposed system is shown in figure 1. The system block diagram for detecting rice leaf diseases using two deep neural networks (MobileNetV2 and GoogleNet) with an ensemble average approach consists of the following key components:

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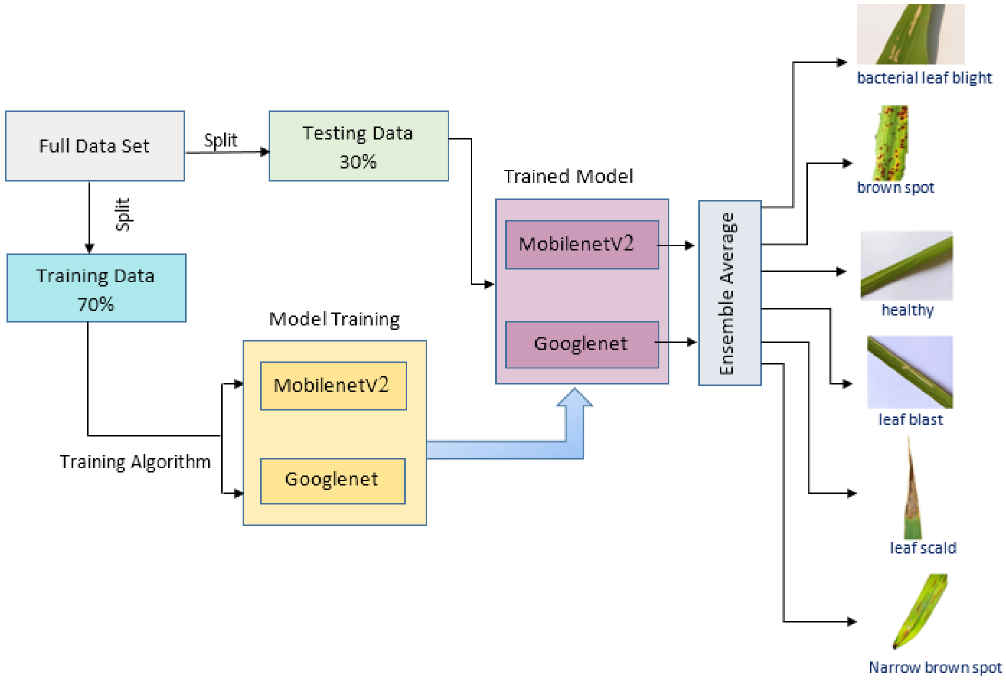

Figure (1): The block diagram of the proposed system in the current study.

1. Input Layer: The system begins with the input layer where images of rice leaves are fed into the system. These images could depict various states of the leaves, including healthy leaves or those affected by different diseases like bacterial leaf blight, brown spot, leaf blast, etc.
2. Preprocessing Module: Before passing the images to the neural networks, the preprocessing module cleans and prepares the images by resizing, normalizing. This ensures the images are standardized for the neural networks. Also, the dataset is split into training and testing group of images.
3. Neural Network 1: The first deep neural network is MobileNetV2, that used to process the preprocessed images. It extracts features and classifies the images based on the patterns learned during the training phase.
4. Neural Network 2: In parallel, the second deep neural network is GoogLeNet, processes the same set of preprocessed images. This network also extracts features and performs classification, focusing on identifying the type of disease affecting the rice leaf.
5. Ensemble Average Module: in the test mode, the ensemble average module, which takes the average of the predictions from the two networks. This averaging helps in reducing the variance and improves the robustness of the final prediction, leading to a more accurate classification of the rice leaf disease. An ensemble refers to the combination of multiple models to make predictions or decisions. To create

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an ensemble average in network selection, the decisions or predictions from each model are combined using an averaging approach as shown in Figure 2.

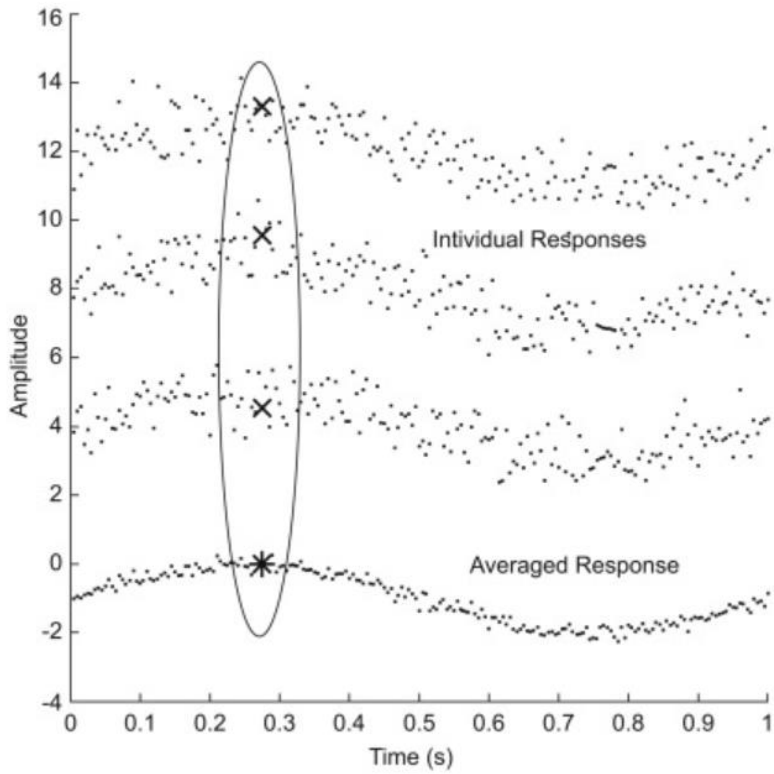

Figure (2): The Ensemble Average Example [15].

DATASETS

The dataset is used in this paper represents a rice leaf disease dataset that collected via the internet and independently. The dataset consists of 6 classes of healthy and rice leaf diseases that grouped in the train and validation folders. This dataset includes: Healthy, Leaf Scald, Brown Spot, Leaf Blast, Bacterial Leaf Blight, Narrow Brown Spot [16]. Figure 3 shows samples of this dataset

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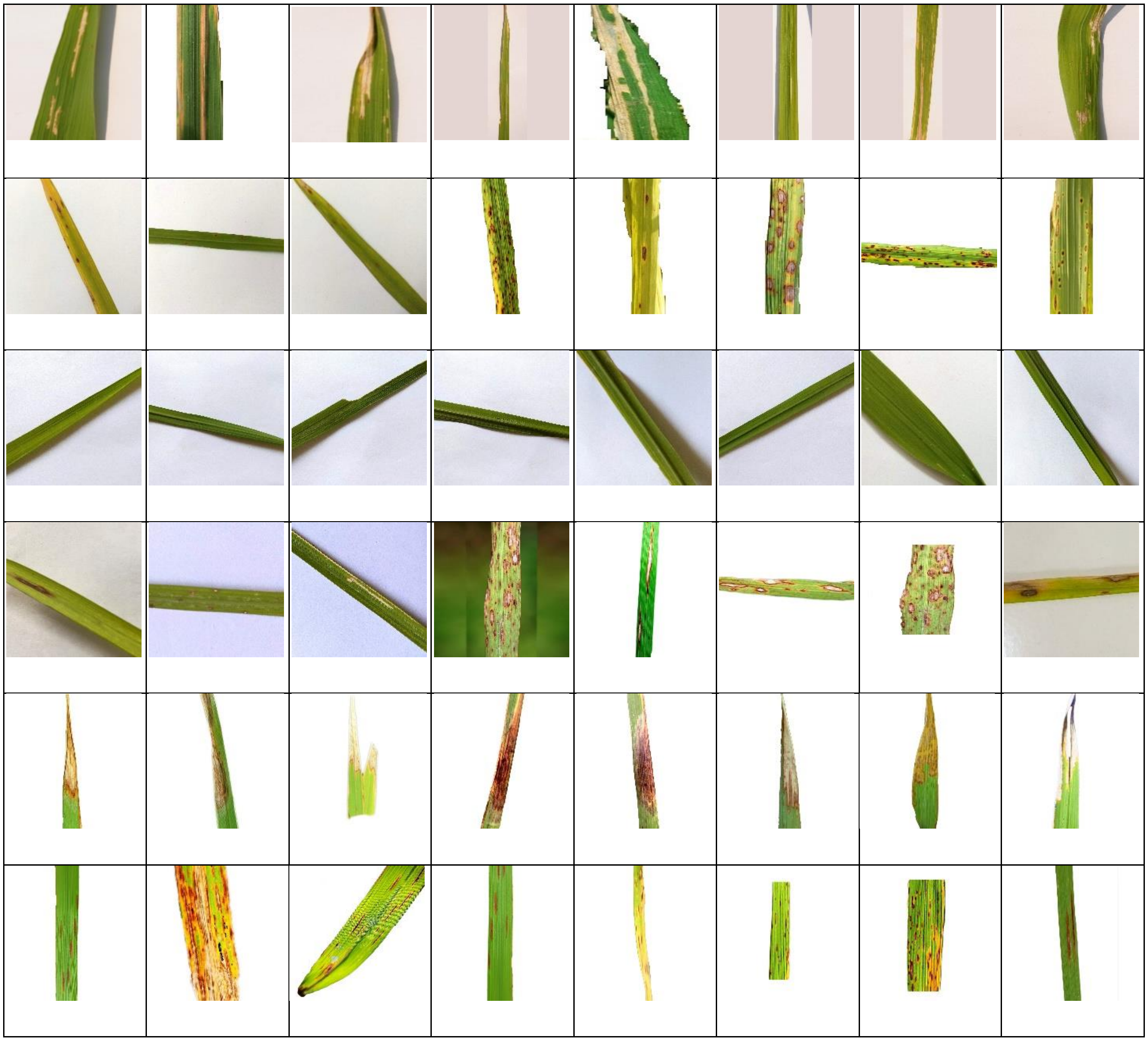

Figure (3): The samples of dataset images [16].

RESULTS AND DISCUSSION

To simulate the detection of rice leaf diseases using two different deep neural networks represented by MobileNetV2 and GoogLeNet in MATLAB. we set up an environment that leverages the capabilities of MATLAB's Deep Learning Toolbox. The setup includes the following steps, depicted in Figure 4 and Figure 5. The Figures depict the training progress of a deep learning model, showing key metrics such as accuracy and loss over 10 epochs. Here's a detailed discussion:

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The top plot (Accuracy) where the blue curve represents the training accuracy, which rapidly increases during the first epoch and continues to improve, stabilizing around 100% as the iterations progress. The black dotted line indicates the smoothed training accuracy, which smooths out the fluctuations, showing a consistent improvement trend. The orange curve represents the validation accuracy, which also shows a significant increase during the early epochs, stabilizing near the end of the training process. The final validation accuracy achieved is 94.91%, indicating that the model is performing well on the validation set, with minimal overfitting.

The bottom plot (Loss) the loss curve shows a rapid decrease during the initial epochs, which is typical as the model learns the underlying patterns in the data. The orange curve represents the training loss, which decreases steadily and stabilizes towards the end of the training process. The black dotted line indicates the smoothed training loss, which provides a clearer view of the overall trend, showing effective learning. The validation loss also decreases but with some fluctuations, suggesting that while the model is improving, it might still need further fine-tuning or regularization to minimize overfitting.

A learning rate of 0.0001 was used with a constant schedule, which seems appropriate given the smooth convergence of the accuracy and loss curves for 10 epochs and total iterations of 1840 with 184 iterations per epoch, allowing sufficient updates to the model's weights for each epoch.

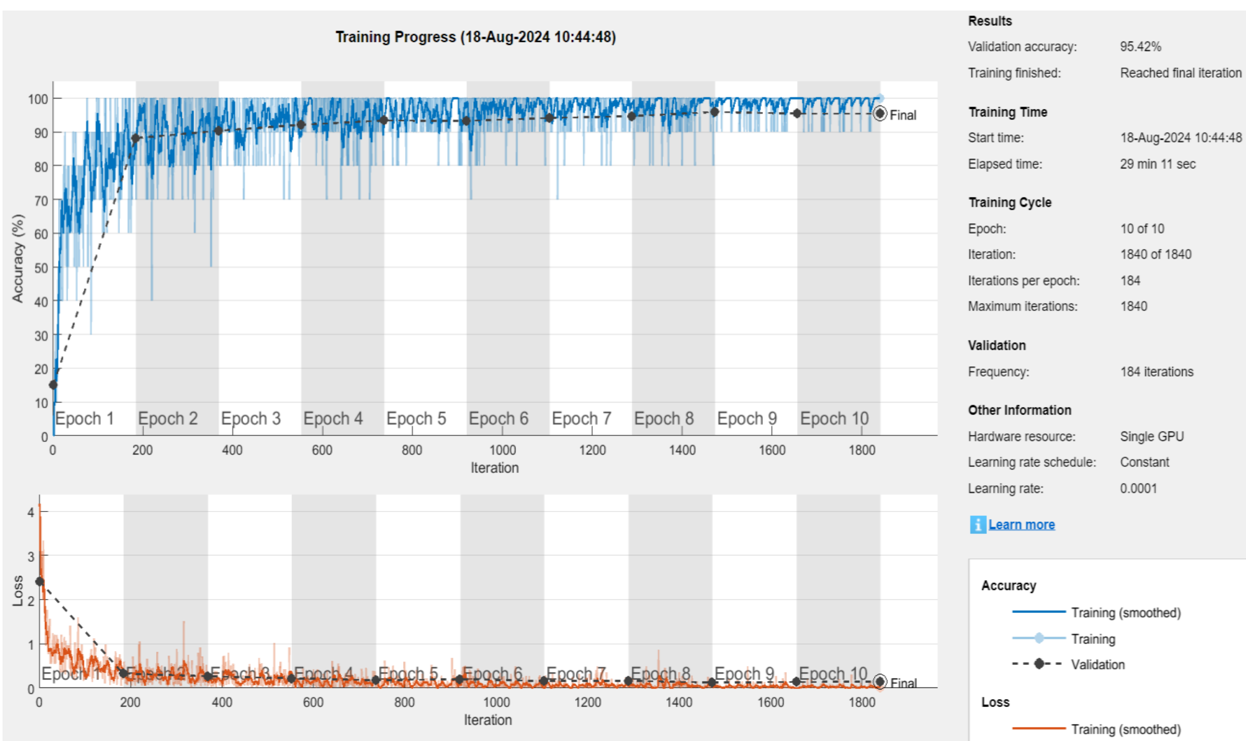

Figure (4): GoogleNet Training

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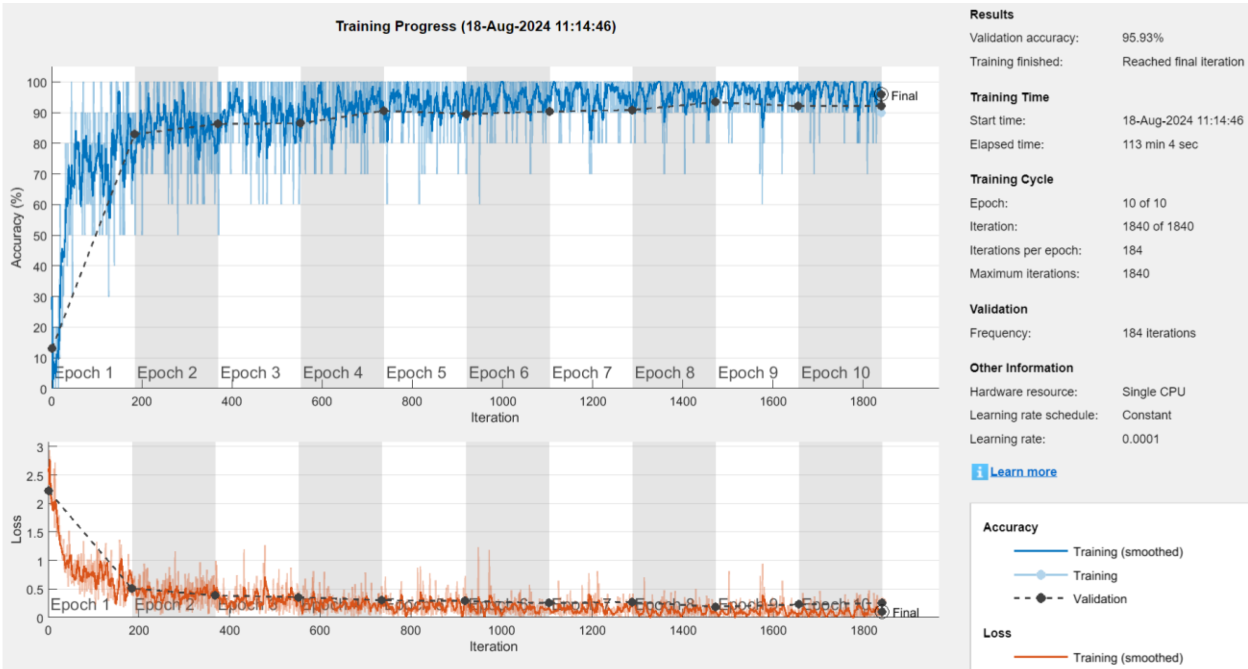

Figure (5): MobileNet2v2 training

Figure (6): The confusion matrix of the GooglNet.

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Figure (7): The confusion matrix of the MobileNet2V2.

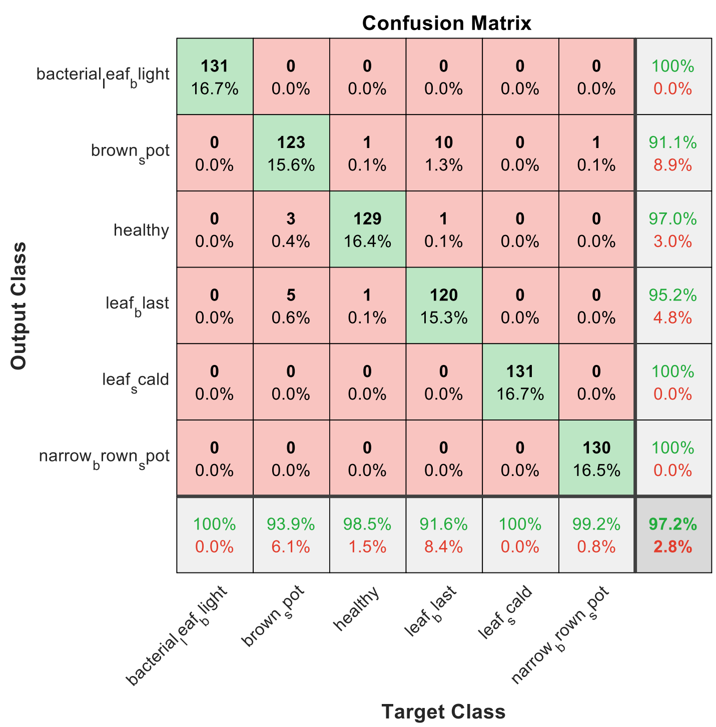

Figure (8): The confusion matrix of the proposed method.

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This ensemble approach leverages the strengths of both deep neural networks, improving overall accuracy and reliability in detecting and classifying rice leaf diseases. The table-1 presents the performance metrics of three different models GoogLeNet, MobileNetV2, and a proposed model evaluated based on accuracy, precision, recall, and F1-score. These metrics are used for evaluating the effectiveness of our model in detection the diseases of rice leaf. The discussion of the obtained results is following: The proposed model obtained the highest accuracy at 97.1%, in comparison to both GoogLeNet and MobileNetV2. Also, MobileNetV2 showed better performance than GoogLeNet, with an accuracy of 95.8%. The increasing in accuracy of the proposed model in accordance to other models showed that the proposed model has a better capability to correctly classify rice leaf images. Precision metric measures the accuracy of positive predictions. The precision of the proposed model was 96%, indicating fewer false positives in comparison to the other models. Also, MobileNetV2 showed a small improving over GoogLeNet, in which it is more precise in classifying diseased leaves. On the other hand, Recall reflects the model's ability to identify all true positives. The recall of 97% is achieved by the proposed method which indicated its ability in identifying diseased leaves. Also, MobileNetV2's recall of 94% is more than GoogLeNet's recall of 92%, but still less than the proposed model. The F1-score balances precision and recall, representing a single metric that accounts for both false positives and false negatives. The F1-scores of the proposed method, MobileNetV2 and GoogleNet are 96%, 95% and 93%, respectively. Clearly, the proposed method is the best in comparison to the other tested methods across all metrics, in which it provides superiority in detecting rice leaf diseases. The results demonstrate that the proposed method provides the most reliable and robust predictions, making it the best choice among the three methods for rice leaf diseases classification in real-world application.

Table -1: C omparison Results

Deep Neural Networks	Accuracy %	Precision %	Recall %	F1-score
GoogleNet	**95.4**	**95.47**	**95.4**	**95.43**
MobileNetV2	**95.9**	**95.93**	**95.91**	**95.91**
Proposed	**97.2**	**97.21**	**97.2**	**97.20**

CONCLUSION

In this research, the deep neural networks represented by GoogleNet and MobileNetV2 are used with the average ensemble method for detecting rice leaf diseases. The principle of average ensemble method is the averaging of the output of the two neural networks. The proposed method was implemented and tested on the dataset of rice leaf disease using MATLAB software, where the transfer learning is used to train the two networks on dataset of healthy and diseased rice leaf images. The proposed method achieved better results than the results of each network separately by comparing them based on the known performance metrics with a difference of about 2% for all the used metrics. Therefore, the proposed can be considered as suitable candidate for using in electronic detection applications for rice diseases.

Conflict of interests.

Non conflict of interest

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الخلاصة

مقدمة:

في هذا البحث، تم اقتراح معدل المجموعة والشبكات العصبية العميقة للكشف عن أمراض ورق الأرز. يتكون النظام من شبكتين عصبيتين عميقتين مختلفتين ممثلتين بـ GoogLeNet وMobileNetV2 حيث يتم تدريبهما بشكل منفصل من خلال مجموعة بيانات من صور أوراق الأرز.

طريقة العمل:

تمثل هذه الصور حالات مختلفة للأوراق، بما في ذلك الأوراق السليمة، وخمسة أنواع من الأمراض. تتم معالجة مجموعة البيانات مسبقًا عن طريق تغيير الحجم والتطبيع لتوحيد المدخلات للشبكات. ثم يتم تقسيمها إلى مجموعات تدريب واختبار لضمان تقييم النموذج بشكل قوي. بعد تدريب هاتين الشبكتين، تجمع وحدة متوسط المجموعة التنبؤات من كلتا الشبكتين عن طريق حساب متوسطها أثناء مرحلة الاختبار

النتائج:

تمت مقارنة النموذج المقترح مع النموذجين الآخرين على أساس مقاييس الأداء: الدقة، الضبط، الاستدعاء، ودرجة F1، ويسلط النموذج المقترح الضوء على تفوق النهج المقترح في الكشف عن أمراض أوراق الأرز. حقق النموذج المقترح أعلى دقة بنسبة 97.07%، ودقة بنسبة 97.1%، واستدعاء بنسبة 97.06%، ودرجة F1 بنسبة 97.08% والتي تفوقت على النموذجين الآخرين في جميع المقاييس لأن عملية حساب المتوسط تقلل من التباين وتعزز الدقة القرار النهائي للكشف عن أمراض أوراق الأرز

الاستنتاج:

نستنتج ان هذا النهج القائم على المجموعة الأداء المتفوق للكشف عن أمراض أوراق الأرز، مما يوفر أداة أكثر موثوقية ودقة لإدارة الأمراض الزراعية.

الكلمات المفتاحية: أمراض الأرز، CNN، التعلم العميق، نقل التعلم، متوسط المجموعة.

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