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Identification and Categorization of Paddy Leaf Diseases using Deep Learning for Efficient Agricultural Practices

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***Abstract*— Plant diseases can be quickly detected to lessen the harm they cause to crops. Convolutional neural networks are widely used in deep learning, specifically for problems related to pattern recognition and machine vision. This paper aims to provide a comprehensive overview of the numerous image processing and machine learning strategies for rice plant disease diagnosis. It does this by examining the various algorithms and machine learning techniques used to diagnose illnesses in rice plants using photographs of diseased rice plants. This study discusses several methods and offers a concise synopsis of important concepts in the fields of machine learning and image processing in relation to the classification and identification of illnesses in rice plants. This study examines and contrasts various algorithmic models and methods for classifying and identifying diseases that impact rice plants. It includes scientific results that over the last five years have been published in international review publications. In addition, this paper presents an overview and analysis of various methods used to identify agricultural illnesses, leaf health, and the image processing techniques used for the same. The framework mentioned here, can be used to more effectively detect and diagnose various rice crop diseases, which can cause the agriculture industry to experience large losses owing to rice plant diseases. These frameworks are efficient enough to safely automate repeated processes, generating enough data for additional study.**

Keywords-- Paddy leaf disease detection, deep learning, image processing, machine learning, artificial intelligence

I. INTRODUCTION

A. Motivation

The most popular, affordable, and nutrient-rich food in Asia is rice, yet demand is predicted to outpace supply in the majority of the region. Effective disease management depends on the early identification and diagnosis of plant diseases, but this can be difficult given the sheer number of crops and diseases that need to be watched after. Traditional methods of plant disease detection require expert knowledge and can be time-consuming and expensive. Every plant disease has a distinct growth stage. Farmers need to monitor the virus whenever it manifests on a plant. This method of disease detection takes time, and care must be taken while choosing insecticides.

So, farmers can make use of artificial intelligence and machine learning techniques to improve crop management efficiently. A situation like this compels society as a whole to consider using cutting-edge technology for precise and early disease detection. In order to improve yield in the future, plant disease preventive measures can be implemented with the use of technology.

It has been established that image processing methods are reliable and cost-effective ways to measure the characteristics associated with different plant diseases.

Image-based plant disease detection using machine learning algorithms has emerged as a promising approach for automating the process of disease identification. With the development of deep learning algorithms, image-based plant disease detection systems have achieved high accuracy in identifying plant diseases from images.

In this paper, we propose an algorithm for image-based plant disease detection that can accurately classify plant diseases from images. Convolutional neural networks (CNNs), which have shown success in picture classification applications, are the architecture used by the algorithm. In order for CNN to identify the characteristics that differentiate healthy from ill plants, it is trained on a sizable dataset of annotated photos of various types of plants.

In the days ahead, intelligent systems—which are learning-based and adaptable to various situations—are expected to be the most commonly utilized approaches in this field.

B. Background

A brief description of the different diseases that impact rice plants can be found in this section. The purpose of this part is to provide better knowledge of the features and image processing techniques needed to set up a system like this one for paddy leaf disease detection and classification.

1) Rice hispa: The leaf surface exhibits tiny, elongated, whitish or yellowish dots, which are indicative of damage. Frequently, these dots combine to form bigger afflicted areas. Furthermore, there may be indications of withering or browning on the afflicted leaves, which would lower the general vitality of the plant.

2) Brown spot: Brown spot causes small, dark brown to black lesions on paddy leaves, which are surrounded by yellow halos. These unevenly shaped lesions can merge to generate bigger afflicted areas.

3) Leaf blast: A paddy leaf afflicted by leaf blast usually has tiny, water-soaked lesions with a yellowish core and brown margins. As the illness continues, these lesions enlarge and take on uneven shapes.

4) Leaf scalding: Leaf scald, appears in paddy leaves as elongated, water-soaked lesions that are initially yellowish-green. As the infection spreads, these lesions form a distinct straw-colored or white center surrounded by a dark brown border.

5) Bacterial leaf blight: Bacterial leaf blight presents as water-soaked lesions that begin as narrow streaks along leaf veins. These lesions eventually grow into spindle-shaped patches with yellow halos, giving the damaged leaves a distinctive "wilting" appearance.

6) Leaf smut: A paddy leaf with leaf smut exhibits typical signs. Small, oval lesions occur on the leaf surface first, and then dark, powdery masses form.

C. *Convolutional Neural Network*

One kind of deep learning algorithm that was mainly created for image processing and detection is called a convolutional neural network (CNN). By applying filters to input images through convolutional layers, which enable the network to learn features at multiple levels of abstraction, they are particularly good at identifying hierarchical patterns and spatial correlations in data. CNN algorithms have demonstrated efficacy in a range of computer vision applications, such as object detection, facial recognition, and picture classification.

II. RELATED WORK AND METHODOLOGY

A. *Related Work*

This section summarizes previous research in many categories, including fruit grading, weed identification, plant categorization, and disease classification. The high reduction in cost, accessibility and scalabilities are other advances that make this research worth pursuing. Using the inception layer and residual connection, Mahmudul Hassan et al. offer a unique deep learning model for plant disease identification. The model reduces the number of parameters by using depthwise separable convolution, which leads to a higher accuracy when compared to the latest deep learning models. Performance accuracy was 99.39% on the plant village dataset.

Using transfer learning approaches, Gugan Kathiresan et al. offer a high-accuracy model for rice leaf disease detection. The approach is intended to give farmers and agricultural groups a mobile way to quickly identify illnesses of rice leaves. The model is compared to existing transfer learning architectures and employs an adaptive network that is able to balance the amount of disease samples. In addition, the model is evaluated on three distinct datasets in the absence of the GAN augmentation, yielding an average accuracy of 98.38% as a benchmark.

The work of Gayati i Paiasa et al. focuses on the use of Convolution Neural Networks (CNNs) with 15 layers to identify illnesses in rice crops. According to the research, a number of illnesses afflict paddy crops, which has an immediate impact on their overall output. The accuracy, precision, F-measure, and recall of the proposed model were assessed.

A segmentation-based technique utilizing deep neural networks is presented by Anam Islam et al. for the classification of rice illnesses from leaf images. The method uses local threshold-based segmentation and the Convolutional Neural Network (CNN) to identify disease-affected regions of rice leaves. Three datasets are used to test the approach, including the authors' own dataset of photographs of rice leaves that were gathered from the Bangladesh Rice Research Institute (BRRI). For the three datasets, the classification performance of the suggested technique utilizing the aforementioned CNN architectures was examined and contrasted. The findings indicate that this approach has promise for improving the performance of rice disease classification by categorizing disorders of the rice leaf.

Sandhya Venu Vasantha et. al. discusses the use of machine learning algorithms for detecting rice leaf diseases. Farmers find it difficult to determine the kind of disease that reduces crop productivity if it is not discovered quickly. The paper presents solutions using various machine learning techniques and compares algorithms diagnosing the type of disease based on image crop data.

Rutuja R. Patil et. al. presents a Convolutional Neural Network (CNN) architecture is used for diagnosing rice leaf diseases. The framework extracts numerical features from agro-meteorological data collected from sensors and visual features from captured rice images. The testing accuracy is 95.31%, outperforming other unimodal frameworks.

Some of the limitations of the applied approaches include high overfitting risks, lack of cross-checking features, scarcity of datasets, and reliance on single methodologies, which complicate the approach and make it less accessible. Resolving these problems is essential to the field's advancement.

1) Limited datasets that make it difficult to generalize and fully capture the complexity of the issue they are meant to solve.

2) Lack of cross-validation features: The absence of cross-validation reduces accuracy and dependability and increases the risk of bias and mistakes.

3) High risk of overfitting: The approaches may overfit themselves to the available data because of the small number of datasets, which would lead to poor performance with new or unexplored data.

4) Singular method dependence: The breadth and efficacy of solutions are limited when singular approaches are the only ones used.

5) Accessibility limitations: Unavailable techniques make it difficult for other academics to collaborate and validate them, which impedes advancement in the field.

III. METHODOLOGY

A. *Dataset*

The images of rice leaves used in the dataset were gathered from Kaggle. The dataset includes both healthy and diseased rice leaves. A total of 2628 photos consisting of 1 healthy leaves folder and 5 rice leaf diseases folder, in the train and validation folders, were examined. The gathered data is processed using a variety of data augmentation techniques, making it suitable for training the CNN model. The training dataset consists of 6 classes, namely, bacterial leaf blight, brown spot, healthy, leaf blast, leaf scald, narrow brown spot, each of them have 350 images. And the validation dataset has 6 classes as well, here, each class has 88 images.

TABLE I. SUMMARY OF RELATED WORK

No	Author	Dataset	Algorithm	Accuracy
1	Sk Mahmudul Hassan et. al, [2]	Plant village dataset	CNN	99.39%
2	Gugan Kathiresan et. al, [4]	GAN augmented dataset	CNN	98.79%
3	Gayati i Paiasa et. al,[8]	Kaggle & Google	CNN	95%
4	Anam Islam et. al, [10]	386 rice plant disease data	CNN	82.03%
5	Sandhya Venu Vasantha et. al, [11]	Rice plant disease dataset	CNN	99%
6	R. P. Narmadha, [12]	Camera captured images	CNN	96.52%
7	Narendra Pal Singh Rathore. et al, [16]	Kaggle dataset	CNN	99.61%
8	PallapothalaTejaswini et al, [18]	1600 rice disease dataset	CNN	78.2%
9	Vikas Sharma et al, [19]	Rice disease dataset	CNN, Naïve Bayes	81%
10	Md Taimur Ahad et al, [20]	Rice Leaf Disease Dataset, UCI Machine Learning Repository	CNN	98%

Since each image in the collected dataset contains RGB coefficients ranging from 0 to 255 and changing in height and width, image resizing and rescaling were done. Every image in the collected dataset was reduced to 256 by 256 pixels from its original dimensions. The initial dataset was enhanced using a variety of data augmentation techniques. Real-time image random rotation and flipping were achieved by the ImageDataGenerator class from the Keras deep learning package.

B. Image Processing

This stage prepares the images for the machine learning model, making them easier to evaluate and process. The obtained images are usually disorganized and come from multiple sources. The alteration of visual data for analysis, improvement, or interpretation is known as image processing. They must be standardized and cleaned before being fed into a machine learning model. Preprocessing is typically used to minimize complexity and improve the outcomes of an algorithm. The following preprocessing processes were done on the dataset's photos and are

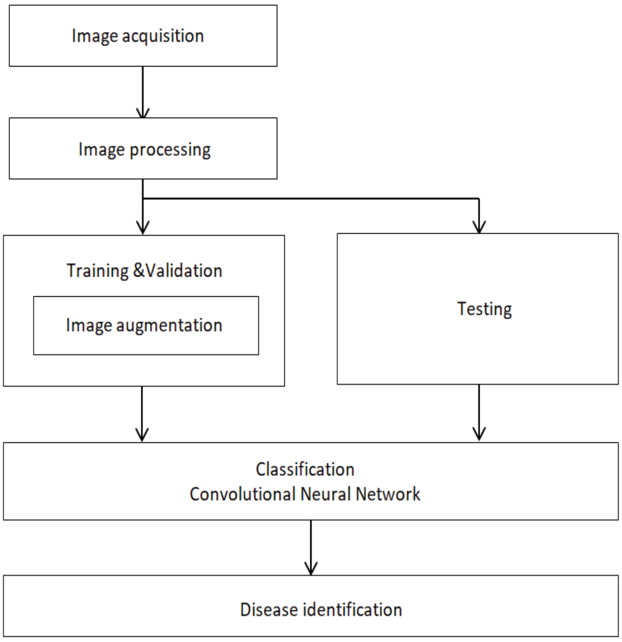

Fig. 1. Workflow diagram

explained here. It uses methods to extract or alter picture features, such as filtering, edge detection, and transformations.

C. Technology Used

Google Colab: Google Colab is pre-installed with popular ML libraries like TensorFlow and PyTorch, which simplifies the setup process for ML applications.

D. Algorithm

A Convolutional Neural Network (CNN) for image-based classification of rice leaf diseases is built using the TensorFlow and Keras frameworks.

The ImageDataGenerator class from Keras is then used to enhance the training dataset. This augmentation involves rescaling the pixel values to a range of 0 to 1, rotating the images by up to 20 degrees, and horizontal flipping. These changes seek to diversity the training dataset, hence improving the model's capacity to generalize to new data. Another ImageDataGenerator is generated for the testing dataset, but it only does rescaling to maintain consistency and avoid introducing additional differences.

The flow_from_directory method is used to load the training and testing datasets, with parameters for target size, batch size, and categorical class mode. Thus, the architecture of the CNN model can be described as a sequential model with max-pooling layers after convolutional layering with rectified linear unit (ReLU) activation functions. The last layers are an output layer with soft max activation for classification of multiple classes, a dense layer with rectified linear unit activation, and one with flattening operation. The model is built with the aid of the Adam optimizer, with accuracy serving as the evaluation measure and categorical crossentropy as the loss function.

The input layer, convolution layer, pooling layer, dense layer, and output layer are the different kinds of layers that comprise this structure. However, in order to more successfully detect the leaf diseases, the proposed structure will have more layers than before. As a result, the proposed CNN model consists of 15 layers: an input layer, five convolution layers (Convl, Conv2, Conv3, Conv4, and Conv5), five max pooling layers (Poolingl, Pooling2, Pooling3, Pooling4, and Pooling5), four dense layers (Densel, Dense2, Dense3, and Dense4), one flatten layer, and an output layer. Consequently, the SoftMax activation function is used in the output layer.

IV. RESULT

This endeavor will advance the field of agriculture as a developing technology that will help farmers make decisions pertaining to illnesses that affect rice crops. Since the system is based on a deep learning neural network technique, a substantial amount of data samples are needed for suitable model training.

Fig. 2. A subset of the utilized dataset

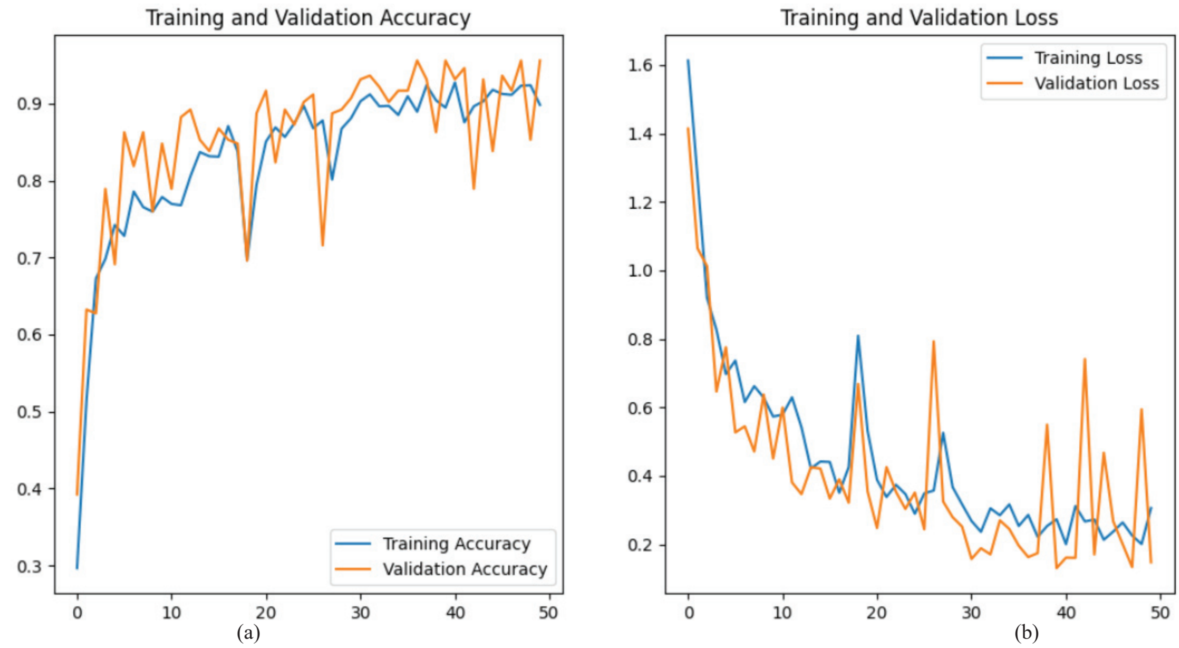

Fig. 3. . (a) Training and validation accuracy and (b) training and validation loss

TABLE II. ANALYSIS TABLE

Process	Cost	Efficiency	Accuracy	Time
Image processing deep learning model	Low	High	High (94.91)	Medium-low

V. CONCLUSION AND DISCUSSION

In the field of image pattern recognition, Deep learning is an emerging and advanced technique that has demonstrated considerable promise in the detection of plant diseases. In this research, we have suggested a CNN model that can accurately classify rice leaf diseases, based on the inception and residual connection.

Using a computer-aided technique for rice leaf disease identification and prediction has proved extremely beneficial in assessing illnesses effectively. The study considers 5 types of infections: rice hispa, bacterial leaf blight, brown spot, leaf blast, and leaf smut, as well as one type for the healthy category. Based on the paper's analysis, the image processing data technique achieves 94.91% accuracy.

VI. FUTURE SCOPE

It is critical to address the problem of data scarcity since Convolutional Neural Network (CNN) models strongly rely on the availability of large datasets. Lower accuracy levels have been linked to a significant issue with the availability of training data for image processing models. This study makes a concentrated effort to address this issue by developing methods to increase the accessibility of training data.

Future research would concentrate on compiling balanced information for various rice diseases caused by climate and geographic challenges. The results of the proposed study are very promising for real-time diagnosis of several rice illnesses in both healthy and sick leaves. However, segmenting the afflicted areas of the leaf images can be the subject of future research.

REFERENCES

[1] J. P. Shah, H. B. Prajapati and V. K. Dabhi, "A survey on detection and classification of rice plant diseases," 2016 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC), Bangalore, India, 2016, pp. 1-8, doi: 10.1109/ICCTAC.2016.7567333 https://ieeexplore.ieee.org/document/7567333

[2] S. M. Hassan and A. K. Maji, "Plant Disease Identification Using a Novel Convolutional Neural Network," in IEEE Access, vol. 10, pp. 5390-5401, 2022, doi: 10.1109/ACCESS.2022.3141371 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9674894

[3] 2- L. Li, S. Zhang and B. Wang, "Plant Disease Detection and Classification by Deep Learning—A Review," in IEEE Access, vol. 9, pp. 56683-56698, 2021, doi: 10.1109/ACCESS.2021.3069646. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9399342

[4] 1- Kathiresan, G., Anirudh, M., Nagharjun, M., & Karthik, R. (2021, May). Disease detection in rice leaves using transfer learning techniques. In Journal of Physics: Conference Series (Vol. 1911, No. 1, p. 012004). IOP Publishing. https://iopscience.iop.org/article/10.1088/1742-6596/1911/1/012004/meta

[5] Kolli, Jahnavi, Dhara Mohana Vamsi, and V. M. Manikandan. "Plant Disease Detection using Convolutional Neural Network." 2021 IEEE Bombay Section Signature Conference (IBSSC). IEEE, 2021.https://iopscience.iop.org/article/10.1088/1757-899X/1125/1/012021/pdf

[6] Shrivastava, Gaurav, and Harish Patidar. "RICE PLANT DISEASE IDENTIFICATION DECISION SUPPORT MODEL USING MACHINE LEARNING." ICTACT Journal on Soft Computing 12.3 (2022).https://ictactjournals.in/paper/IJSC_Vol_12_Iss_3_Paper_5_2619_2627.pdf

[7] R. R. Patil and S. Kumar, "Rice-Fusion: A Multimodality Data Fusion Framework for Rice Disease Diagnosis," in IEEE Access, vol. 10, pp. 5207-5222, 2022, doi: 10.1109/ACCESS.2022.3140815 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9672157

[8] Parasa, G. ., Arulselvi, M. ., & Razia, S. . (2023). Identification of Diseases in Paddy Crops Using CNN. International Journal of Intelligent Systems and Applications in Engineering, 11(6s), 548–557. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2879

[9] Li, Dengshan, et al. "A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network." Sensors 20.3 (2020): 578. https://www.mdpi.com/1424-8220/20/3/578

[10] Islam, Anam, et al. "Rice leaf disease recognition using local threshold based segmentation and deep CNN." Int. J. Intell. Syst. Appl 13.5 (2021): 35-45.

https://www.researchgate.net/profile/S_M_Rafizul_Haque/publication/355031837_Rice_Leaf_Disease_Recognition_using_Local_Threshold_Based_Segmentation_and_Deep_CNN/links/6158a67ae7bb415a5d50c8bd/Rice-Leaf-Disease-Recognition-using-Local-Threshold-Based-Segmentation-and-Deep-CNN.pdf

[11] Vasantha, Sandhya Venu, Bejjam Kiranmai, and S. Rama Krishna. "Techniques for Rice Leaf Disease Detection using Machine LearningAlgorithms." Int. J. Eng. Res. Technol 9.8 (2021): 162-166.

https://www.researchgate.net/profile/S-Rama-Krishna/publication/352881940_Techniques_for_Rice_Leaf_Disease_Detection_using_Machine_learning_algorithms/links/60ddcf4792851ca9449e9e49/Techniques-for-Rice-Leaf-Disease-Detection-using-Machine-learning-algorithms.pdf

[12] Narmadha, R. P., N. Sengottaiyan, and R. J. Kavitha. "Deep Transfer Learning Based Rice Plant Disease Detection Model." Intelligent Automation & Soft Computing 31.2 (2022). https://cdn.techscience.cn/ueditor/files/iasc/TSP_IASC-31-2/TSP_IASC_20679/TSP_IASC_20679.pdf

[13] Agrawal, Mr Manoj, and Shweta Agrawal. "Rice plant diseases detection & classification using deep learning models: a systematic review." J Crit Rev 7.11 (2020): 4376-4390. https://www.jcreview.com/admin/Uploads/Files/61fce2417dfdd2.41728047.pdf

[14] Poornappriya, T. S., and R. Gopinath. "Rice plant disease identification using artificial intelligence approaches." International Journal of Electrical Engineering and Technology 11.10 (2022): 392-402. https://www.researchgate.net/profile/Dr-Gopinath-R/publication/358634753_RICE_PLANT_DISEASE_IDENTIFICATION_USING_ARTIFICIAL_INTELLIGENCE_APPROACHES/links/620c8bc787866404a16e1442/RICE-PLANT-DISEASE-IDENTIFICATION-USING-ARTIFICIAL-INTELLIGENCE-APPROACHES.pdf

[15] Prottasha, Sazzadul Islam, and Sayed Mohsin Salim Reza. "A classification model based on depthwise separable convolutional neural network to identify rice plant diseases." International Journal of Electrical & Computer Engineering (2088-8708) 12.4 (2022). https://www.researchgate.net/profile/Md-Sazzadul-Islam-Prottasha/publication/359973731_A_classification_model_based_on_depthwise_separable_convolutional_neural_network_to_identify_rice_plant_diseases/links/62593d93709c5c2adb7d8338/A-classification-model-based-on-depthwise-separable-convolutional-neural-network-to-identify-rice-plant-diseases.pdf

[16] Rathore, Narendra Pal Singh, and Lalji Prasad. "Automatic rice plant disease recognition and identification using convolutional neural network." Journal of critical reviews 7.15 (2020): 6076-6086. https://jcreview.com/admin/Uploads/Files/61f2bb06b794d6.51115459.pdf

[17] Sharma, Mayuri, Chandan Jyoti Kumar, and Aniruddha Deka. "Early diagnosis of rice plant disease using machine learning techniques." Archives of Phytopathology and Plant Protection 55.3 (2022): 259-283. https://www.mdpi.com/2223-7747/11/17/2230

[18] Tejaswini, Pallapothala, et al. "Rice leaf disease classification using CNN." IOP Conference Series: Earth and Environmental Science. Vol. 1032. No. 1. IOP Publishing, 2022. https://iopscience.iop.org/article/10.1088/1755-1315/1032/1/012017/pdf

[19] Sharma, Vikas, Aftab Ahmad Mir, and Abid Sarwr. "Detection of rice disease using bayes' classifier and minimum distance classifier." Journal of Multimedia Information System 7.1 (2020): 17-24. https://koreascience.kr/article/JAKO202009863559891.page

[20] Su, Nguyen Tien, et al. "Rice leaf disease classification using deep learning and target for mobile devices." Proceedings of International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2021 (Volume 1). Springer International Publishing, 2022. https://www.sciencedirect.com/science/article/pii/S2589721723000235