Intelligent Model to Detect Rice Leaves Diseases Using Transfer Learning

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Abstract: Crop diseases can have a significant impact on global agriculture, reducing yields and causing financial losses. Early identification and monitoring of these diseases is crucial for protecting human health and maintaining food security. However, detecting diseases in crops, particularly rice, can be a challenging task. Traditional methods for disease detection can be time-consuming and may not provide accurate results. In this study, we propose an intelligent system for the detection of rice leaves diseases using transfer learning. With the advancement of machine learning techniques, it is now possible to develop models that can accurately identify disease-affected rice leaves. We used transfer learning to fine-tune a pre-trained model on a dataset of images of rice leaves with different diseases and healthy leaves. The results of our study demonstrate that our proposed model can accurately detect rice leaf diseases with a 94.19% of accuracy and can be a useful tool for early disease identification and management in agriculture.

Keywords: Rice Leaves Diseases, Classification, Transfer Learning, AlexNet, Image Recognition

1 Introduction:

Rice is a staple crop that is grown and consumed worldwide. More than half of the world's population relies on rice as a food source. However, rice plants are susceptible to a variety of diseases, which can have a significant impact on yield and quality (Hussain, 2018). Leaf Blast, sheath blight, and bacterial leaf blight are a few prevalent diseases that affect rice leaves. These diseases can cause damage to the leaves, stem, and grains, leading to reduced growth and development of the plant. In severe cases, the entire crop can be lost. Additionally, disease-affected rice grains can be of poor quality and may not be suitable for consumption. Therefore, it is important to implement effective disease management strategies to protect rice crops from diseases and maintain high yield and quality (Kumar, 2017). Manually detecting plant diseases can be a time-consuming and labor-intensive process. Farmers can have trouble identifying the diseases, which results in yield losses. Processing the photos of "seemingly" infected plant leaves that have been acquired by an automatic is one of the best possible solutions for farmers (Lu, 2017). To find diseases, one looks at the leaf image that displays the symptoms. The automated technology enables farmers to quickly detect toxicities. The failure of certain plants to yield was caused by slow disease detection. In order to improve productivity, it is essential to recognize plant diseases early on (Toseef, 2018).

To increase the effectiveness and precision of disease detection, machine learning algorithms are being developed to recognize diseases of the rice plant. These algorithms can be used to automatically analyze images of rice plants and identify symptoms of diseases, such as leaf discoloration, stem lesions, and grain damage (Karthik, 2020). This can save time and effort compared to manual inspection and can also detect diseases at an early stage, when they are more easily treated. Data collection, data annotation, feature extraction, model selection, training and evaluation, and deployment are some of the phases involved in building a machine learning method for diagnosing rice plant diseases (Hassan, 2021). Although machine learning algorithms for identifying rice plant ailments are still being developed, they have the potential to completely change how diseases are found and treated. Deep learning, a kind of machine learning, is very effective at spotting diseases in rice plants because it can automatically learn complex features from images of rice plants. These features can include visual characteristics such as color, texture, and shape, which are important for identifying symptoms of diseases (Gao, 2021). Convolutional Neural Networks are one of the most often used deep learning architectures for image categorization. CNNs are particularly good at handling image data and they can automatically learn features from images by convolving the image with a set of filters. This allows CNNs to automatically learn the most discriminative features for classifying images of rice plants into healthy and diseased classes. Deep learning also has the capacity to process huge amounts of data. With deep learning algorithms, it's possible to train models with millions of images, which can provide a high level of accuracy in disease detection. Additionally, deep learning algorithms can improve their accuracy over time as they continue to learn from new images (Pouyanfar, 2018). Deep learning-based models can be used to detect diseases at an early stage, when they are more easily treated and can also detect multiple diseases at once. This can help to improve crop yields, reduce crop losses, and improve the efficiency of disease management. Therefore, in this research, we used the AlexNet model to quickly identify diseases of the rice leaves, such as brown rust and yellow rust. We trained our suggested model in Matlab for this objective. We make use of a Kaggle dataset that is divided into five different classes, including apex blast, gudi rotten, leaf blast, leaf burn, and the last one is neck blast paddy.

2 Literature review:

CNN and image processing were used to construct the system for spotting pests and ailments in rice. The searching and comparing of gathered photos to a collection of images of rice pests were done using a model based on CNN. Images that have already been edited were used to train the model. The model's ultimate training accuracy was 90.9 percent, which was a success. Given that cross-entropy was low, the trained model can categorize photographs or generate predictions with a low rate of error (Bakar, 2018).

Rice blast disease is automatically detected using K-Means Clustering, and photos of affected or healthy plants are then categorized using ANN. For training and testing purposes, the 300 photos that comprise the complete data set were partitioned. Only two classes of the dataset—healthy leaves and leaves affected by the blast disease are acquired for the proposed method. For the infected and healthy photos, the testing phase accuracy was determined to be 90% and 86%, respectively (Ramesh, 2018).

Based on image processing methods, the suggested model would correctly categorize and identify the diseases affecting rice leaves. This model is implemented using the machine learning algorithm CNN. The suggested approach divides the healthy and unhealthy traits of rice plant leaves using healthy and disease-affected leaves. 90% accuracy was obtained by the suggested model (Rahman, 2021).

They have developed a technique based on deep learning for spotting disease in rice leaves, which comprises a smartphone app and a machine learning application on a cloud service. The smartphone app works to take pictures of rice plant leaves, upload them to the cloud server application, and then obtains classification results in the form of details on the various plant illnesses. Their trained model was evaluated for effectiveness using the VGG16 architecture, which had 60% test accuracy (Andrianto, 2020).

Describe the transfer learning of deep convolutional neural networks for the detection of plant leave diseases. Take into account utilizing a model that has already been pre-trained using one of the usual large datasets before transferring it to a target that was trained using its own data. The pre-trained VGGNet model was suggested and achieved 91.83& accuracy (Chen, 2020).

A total of 1426 digital photos, with varied backgrounds and real-world scenarios, have been compiled. The two-stage compact CNN architecture that has been given has been compared to the most recent memory-efficient CNN designs, such as Mobile Net. Experimental results indicate that the proposed design may be capable of achieving the required accuracy of 93.3% (Rahman A. P., 2020). The suggested method's validity is supported by experiment results, and it effectively detects plant diseases.

They examine three different rice plant diseases—Bacterial leaf blight, Brown spot, and Leaf smut—and use a digital camera to take pictures of diseased rice plants in a plantation area. They experimentally assess three segmentation strategies and four background reduction techniques. Based on their findings, we recommend using centroid feeding with K-means clustering to accurately segment the disease section from a leaf picture, which would enable dependable feature extraction. In order to conduct multi-class classification, the researchers utilized Support Vector Machines (SVM) and achieved an accuracy rate of 93.33% during the training phase and 73.33% during the testing phase (Prajapati, 2017). By subtracting green pixels from the ailment section, they improve the outcome of the K-means clustering.

The majority of rice crop diseases apparent as spots on the leaves. To prevent substantial destruction to the rice yield, it is also important to identify the disease accurately and quickly. Applying excessive amounts of pesticides to cure illnesses in rice crops raises costs and pollutes the environment. So, it is necessary to reduce the usage of pesticides. By evaluating the severity of the illness, the affected region may be targeted with the right amount and concentration of pesticide. This study introduces the Fuzzy Logic with the K-Means segmentation approach, which is used to calculate the severity of the illness on rice crop leaves (Gurumoorthy, 2018). The accuracy of the suggested strategy is predicted to reach up to 86.35%.

Automated plant disease identification and diagnosis is a huge demand in the world of agricultural extension services. Many strategies have been proposed to address this issue, although older research had certain limitations. Some of them make use of small datasets, whereas others make use of datasets with fewer classes. Due to false positives or false negatives in the data, many automated procedures also do not produce reliable outcomes. These issues restrict their use as useful instruments in systems for producing rice. **Table 1** displays the limitations of earlier studies.

TABLE 1: Comparison and weaknesses of previous approaches.

Publication	**Method**	**Accuracy**	**Weaknesses**
(Andrianto, 2020)	deep VGG16 model trained with transfer learning	60%	Small Dataset with less no of classes
(Ramesh, 2018)	K-Means Clustering is used for Image Segmentation and artificial neuron network (ANN) is utilized for classification.	90%	Small Dataset with less no of classes
(Rahman A. P., 2020)	VGG16 and InceptionV3	93.3%	Small Dataset
(Chen J. C., 2020)	deep learning VGGNet model	92.00%	Small Dataset
(Bakar, 2018)	multi-level thresholding approach	90.90%	Small Dataset with less no of classes
(Shrivastava, 2019)	CNN as a feature extractor and SVM as classifier	91.37 %	Small Dataset with less no of classes
(Gurumoorthy, 2018)	Fuzzy Logic with K-Means segmentation technique	86.35%	Less no of classes
(Ahmed, 2021)	CNN architecture	88.92%	Small Dataset with less no of classes
(Prajapati, 2017)	Support Vector Machine (SVM) for multi-class classification.	93.33%	Small Dataset with less no of classes

2, 2.1 LIMITATIONS OF RELATED WORK:

The issues with the current identification methods are outlined in **Table 1**. At least one of the following problems affects earlier techniques:

- Large datasets are necessary for creating and enhancing deep learning models due to their accuracy. The suggested model is trained using fewer classes than usual (Andrianto, 2020). A small collection of datasets is gathered for trained the proposed model.

- Small dataset utilized in their propose study (Chen, 2020). Small datasets typically lead to over fitted models. In other words, there are too many variables present for an inference to be made from a small amount of data. As a result, the algorithm starts to remember the input dataset rather than generalizing it. Algorithms used for deep learning perform poorly with limited datasets which is used in this study (Ramesh, 2018).

Instead of using small datasets and those with less no of classes, as in other research, our approach for diagnosing rice leaves diseases utilizing a deep learning-based neural network applying efficient stretching and an effective regularization strategy. The recommended approach further increases the model's dependability by using a big and diverse range of classes and images. In our suggested study, we employ five different classes such as apex blast, gudi rotten, leaf blast, leaf burn, and the last one is neck blast paddy. The proposed approach first detects and then categorizes the relevant image to determine if the rice leaf is infected or not. In **table 2**, the number of images and classifications are displayed.

3 Proposed Methodology:

The proposed IMDRLD system model, which is based on deep learning techniques, accepts digital images that enable the disease categorization and early identification of diseases that may be in various stages. This model is organized into two distinct layers, preprocessing layer, and the application layer which work together to identify diseases from digital images. The data used to train the model was based on digital images that were accessible in the Kaggle repository. The raw data is managed by the pre-processing layer, which also scales the image to a 227 × 227 * 3 (RGB) dimension. The pre-trained model, AlexNet, is then imported and updated in the application layer for transfer learning. The suggested model must be retrained if the performance parameters are not satisfied after the trained model has been saved in the cloud.

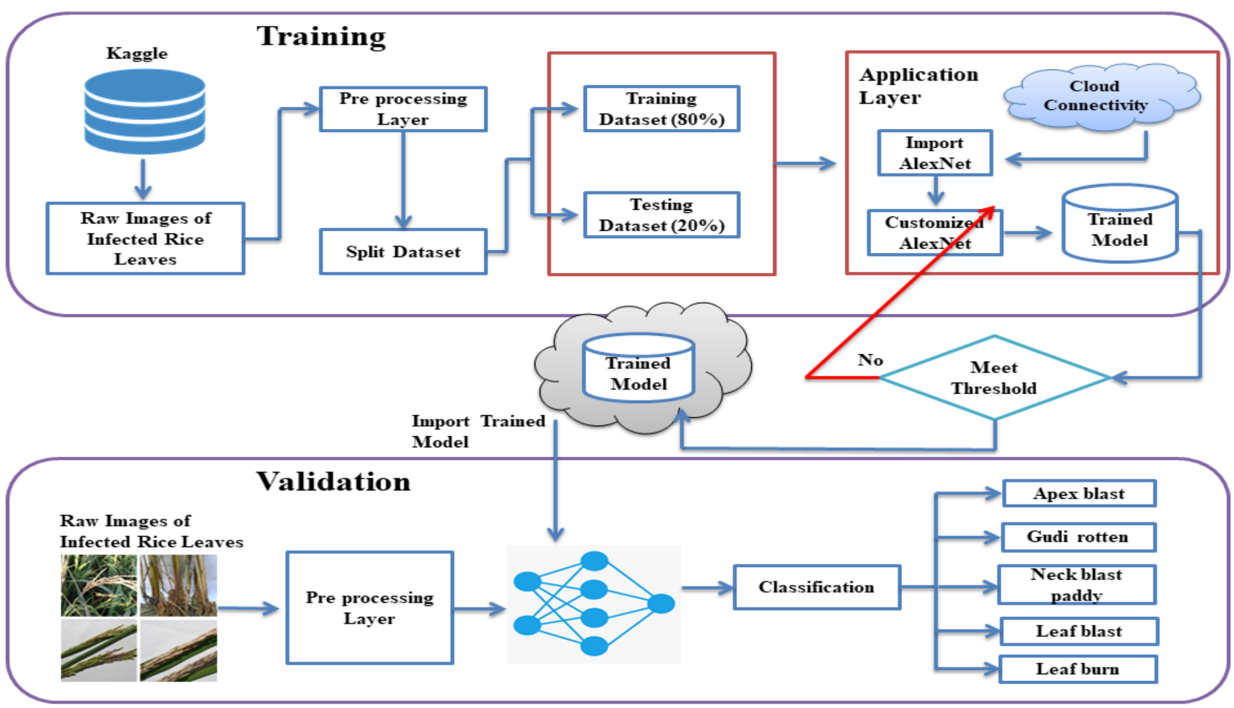

Figure 1: Proposed Model of IMDRLD

The preprocessing layer is the first layer and it is responsible for managing the raw data and preparing the data for the application layer. This layer is where the raw data is processed, scaled, and normalized to fit the requirements of the system. Following completion of the preprocessing, the suggested system model imports cloud data for the intelligent categorization of rice leaf diseases. Rice leave diseases may be

divided into five classes using this artificial intelligence approach. The technology makes sure that the rice crop is healthy and informs the farmer to take measures if it detects any unhealthy leaves in the rice crop. Our proposed model of IMDRLD is shown in **figure 1**.
In order to fulfill with the specifications of our proposed model, we first rescale all of the images in the dataset by 227,227 using Matlab image batch processor. An image batch processor is a tool that rescales images. Rescaling is a process done to optimize the size of an image file by changing its pixel dimensions (Atole, 2018). An image batch processor works by converting multiple images of different sizes into the same size. It does this by looking at the size of the images, and then calculating which pixel dimensions are necessary for each photo to maintain its aspect ratio in the new size (Ngugi, 2021). It will then rescale all photos from the first image's original dimensions to those of the second image, applying proper interpolation for both color and sharpness. We use AlexNet model to train our rice leaves dataset.
AlexNet is a multi-layer deep neural network. The first layer consists of about 25,000 neurons and filters out the background of the image. The next layer detects strokes or shapes and finds edges around each detected shape or stroke to highlight them as foreground objects in the image. The last layer then sifts through all these objects to determine what they are and classifies them into more than 100 categories like animals, buildings etc. (Alom, 2018). The AlexNet deep network is trained features from images and categorizes them into multiple groups by combining convolutional layers, max-pooling layers, and fully connected layers. By applying filters to discrete areas of the picture, the convolutional layers are utilized to extract features from the input images. These filters, which are developed through training, are employed to find particular patterns or characteristics in the image. The spatial resolution of the feature maps is decreased using the max-pooling layers, which also assists in lowering the computational complexity of the model and increases its resilience to small translations of the input. In order to determine the class of the image, the fully connected layers incorporate the characteristics discovered by the convolutional and max-pooling layers. In the ImageNet dataset, each class is represented by one unit, with the first fully connected layer having 4096 units, and the second fully connected layer having 1000 units. The final output layer generates probability scores for each class, indicating the likelihood that the input image belongs to each class. The model's final prediction is determined by selecting the class with the highest probability score. The detail AexNet layer array is shown in **figure 2**.

```
25×1 Layer array with layers:

 1   'data'     Image Input                   227×227×3 images with 'zerocenter' normalization
 2   'conv1'    Convolution                   96 11×11×3 convolutions with stride [4  4] and padding [0  0  0  0]
 3   'relu1'    ReLU                          ReLU
 4   'norm1'    Cross Channel Normalization   cross channel normalization with 5 channels per element
 5   'pool1'    Max Pooling                   3×3 max pooling with stride [2  2] and padding [0  0  0  0]
 6   'conv2'    Grouped Convolution           2 groups of 128 5×5×48 convolutions with stride [1  1] and padding [2  2  2  2]
 7   'relu2'    ReLU                          ReLU
 8   'norm2'    Cross Channel Normalization   cross channel normalization with 5 channels per element
 9   'pool2'    Max Pooling                   3×3 max pooling with stride [2  2] and padding [0  0  0  0]
10   'conv3'    Convolution                   384 3×3×256 convolutions with stride [1  1] and padding [1  1  1  1]
11   'relu3'    ReLU                          ReLU
12   'conv4'    Grouped Convolution           2 groups of 192 3×3×192 convolutions with stride [1  1] and padding [1  1  1  1]
13   'relu4'    ReLU                          ReLU
14   'conv5'    Grouped Convolution           2 groups of 128 3×3×192 convolutions with stride [1  1] and padding [1  1  1  1]
15   'relu5'    ReLU                          ReLU
16   'pool5'    Max Pooling                   3×3 max pooling with stride [2  2] and padding [0  0  0  0]
17   'fc6'      Fully Connected               4096 fully connected layer
18   'relu6'    ReLU                          ReLU
19   'drop6'    Dropout                       50% dropout
20   'fc7'      Fully Connected               4096 fully connected layer
21   'relu7'    ReLU                          ReLU
22   'drop7'    Dropout                       50% dropout
23   'fc8'      Fully Connected               1000 fully connected layer
24   'prob'     Softmax                       softmax
25   'output'   Classification Output         crossentropyex with 'tench' and 999 other classes
fx >>
```

Figure 2: AexNet layer array

3, 3.1 Transfer Learning (Modified AlexNet):

In many aspects of modern life, including agriculture, aviation, shipping, and disease forecasting, deep learning is a commonly utilized approach. Many different deep learning and trained algorithms are implemented (Dokic, 2020). We employed an AlexNet-based deep learning network that has been pre-trained for transfer learning to recognize and classify rice leaves disease.

In this study, we have implemented the AlexNet architecture for detecting rice leaves in a new dataset. Our network is modified with some changes to better suit our data needs. We will make it easier to understand by looking at the architecture of our network and how it's been modified. When we were using images from the original dataset, which only had a single type of leaves in it, we didn't need any special modifications to AlexNet. But when we used the new dataset which has different types of rice leaves, then some modification was necessary. We modified the last layer of AlexNet model because it has a lot more weights and biases than other layers, which makes it suitable for our problem statement. This is because AlexNet was not made specifically for this task and was used as a baseline model that could be easily adapted for such tasks (Sameer, 2021). A modified AlexNet layer according to our problem statement is shown in **figure 3**.

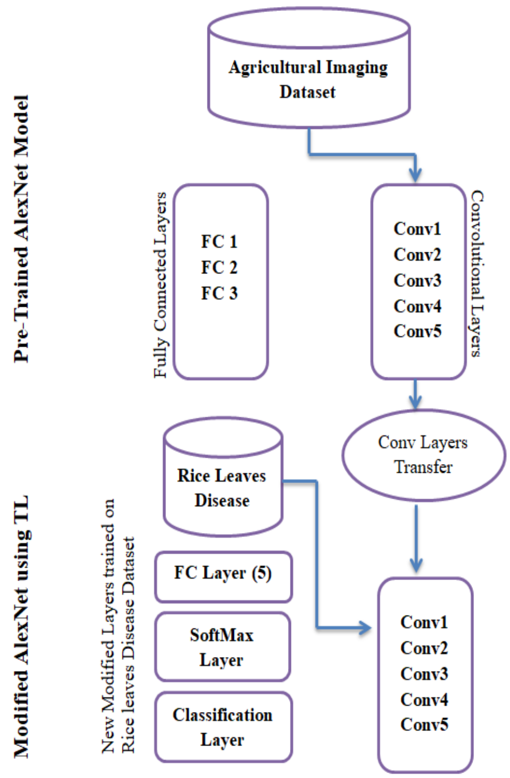

Figure 3: Modified AlexNet Architecture

Although the subsequent adaption layers are trained with rice disease leaves dataset, the first five layers of the network, which were originally trained using AlexNet (ImageNet), stay unchanged. Based on the output class labels, the last three layers are configured to classify the images into their respective labels (Singh, 2020). The output size, which is the total number of class labels, is one of the input factors for fully connected layers that deal with many classes. The output size determines the number of units in the fully connected layer and is dependent on the number of unique classes within the classification problem.

Customized trained models that may be utilized for validation are positioned on clouds. The trained model is given rice leaves images during the validation phase. The trained model evaluates the photos and classifies them according to their respective classes, which are apex blast, gudi rotten, leaf blast, leaf burn, and the last one is neck blast paddy. All of the processing features for images that the trained model learns throughout the training phase are preserved in the trained model. 20% of the original data samples from which simulations were run make up the validation data. Thus, it was determined that the effectiveness of rice diseases depends on the early identification of rice leaf diseases and the transmission of information from large datasets. Our customized dataset consist of five different classes apex blast, gudi rotten, leaf blast, leaf burn, and the last is neck blast paddy are shown in **figure 4**. Each of our classes in the dataset has 500 infected images, and all classes are identical in size. When an infected leaf is identified, the recommended system immediately notifies the farmer, classifies it as an infected leaf, and sounds an alarm. If the infected leaves are not found, however, the system assures that the rice leaves remain healthy.

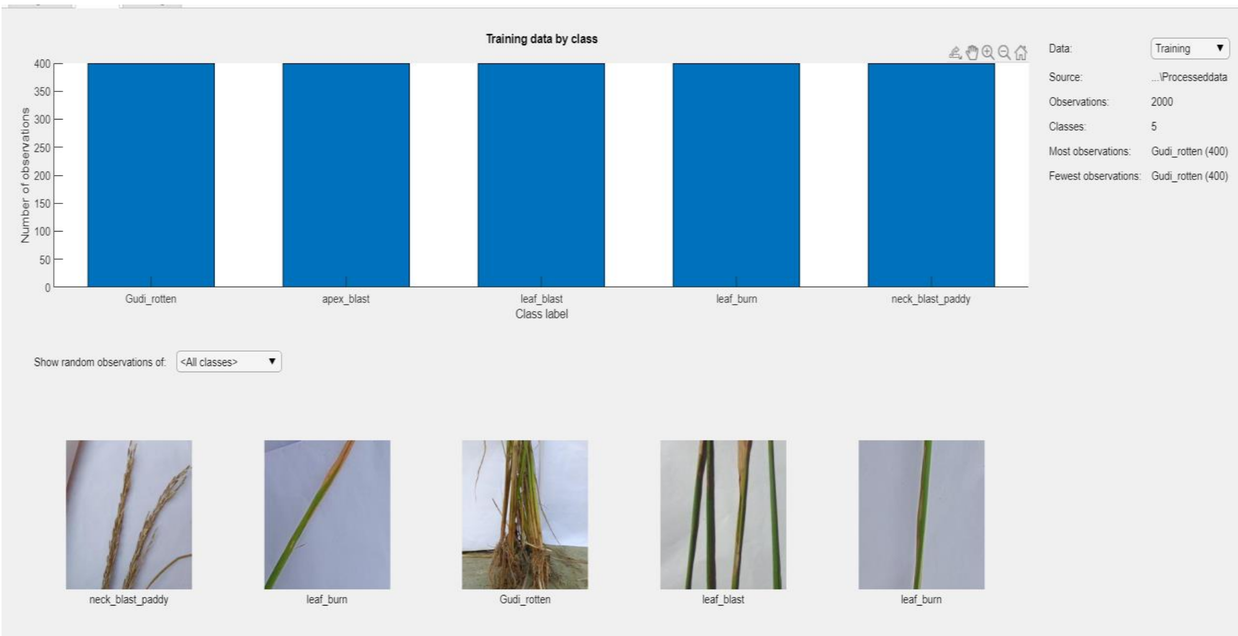

Figure 4: Customized Dataset

The network can be prepared for training using a number of different parameters, or training can be supplied in other ways. According on our dataset classes, AlexNet last three layers—fully connected, SoftMax, and output classification—have seen some modifications (Ong, 2022). During the training process, various training choices can be made, such as the learning rate, number of iterations, frequency of validation, and number of epochs. For this particular network, the training was performed with 10 iterations per epoch and a learning rate of 1e-4. The network was trained with different numbers of epochs, including 20, 30, 35, 40, and 50, to assess their impact on performance.

For training, the SGDM (stochastic gradient descent with momentum) optimization approach is utilized. The fundamental principles of SGDM involve computing the error gradient with respect to the weights and adjusting the weights in the opposite direction of the gradient (Narvekar, 2014). However, instead of updating the weights directly, SGDM maintains a velocity vector for each weight, which is used to update the weights. A component of the previous velocity and a proportion of the current gradient are added to the velocity vector at each iteration. Newly updated layers employ these training settings to take in the characteristics of the rice disease dataset (Ashwini, 2022). The training of the transfer learning algorithm was examined at several epochs, including 20, 30, 35, and 40, and it was discovered that epoch 50 was the best choice. In order to attain the best results, adjustments were made to the learning rate. The algorithm was repeatedly retrained to attain the desired level of accuracy.

3, 3.2 Dataset:

The dataset was acquired from a publicly accessible Kaggle source (S.M.NURNOBI). This dataset includes different kinds of diseases such as apex blast, gudi rotten, leaf blast, leaf burn, and the last is neck blast paddy. A collection of images that included images of several kinds of rice diseases was used to train the suggested model. The number of input samples of images that were collected following pre-processing according to their classifications is shown in **Table 2.**

Table 2: Dataset parameters		
	Classes	**No of Images (Rice Leaves)**
1	Apex blast	500
2	Gudi rotten	500
3	Leaf blast	500
4	Leaf burn	500
5	Neck blast paddy	500

3, 3.3 Simulation and Results:

The early detection of rice leaf disease is achieved through a proposed deep learning model developed with the pre-trained AlexNet architecture. MATLAB software is utilized for classification and output. The IMDRLD model consists of two phases - training and validation - and is evaluated using assessment metrics. In the training phase, 80% of the dataset is used for training, while the remaining 20% is used for validation. The IMDRLD approach categorizes rice leaf diseases into five distinct categories: apex blast, gudi rotten, leaf blast, leaf burn, and neck blast paddy. The use of deep learning models for disease detection is a rapidly growing field, with the potential to revolutionize the way we approach plant health management, leading to more sustainable and efficient agriculture practices. Training and loss rate on 50 epochs will be shown in **figure 5**.

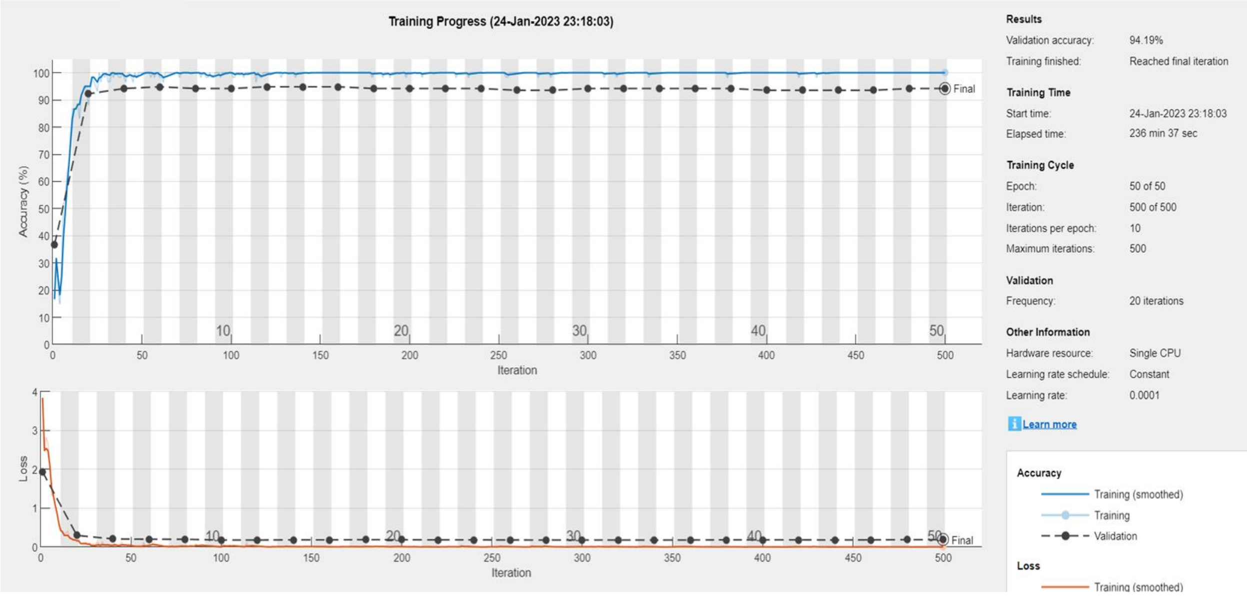

Figure 5: Training and loss rate on 50 epochs

The training accuracy plot, which includes iterations and epochs and displays the outcomes across 50 epochs, is shown in **Figure 5**. The picture displays the accuracy rate for training that lasted a total of 50 epochs, beginning at epoch 1. The accuracy was gradually improved as the number of epochs increased. This technique allows for the early detection of diseased rice leaves diseases. Values for the simulation parameters utilized in the suggested system model are shown in **Table 3**.

Table 3: Simulation parameters				
No. of epochs	**Validation Frequency**	**Solver**	**Accuracy**	**Miss rate %**
20	50	sgdm	70%	30%

30	50	sgdm	76.30%	23.70%
35	25	sgdm	87.40%	12.60%
40	20	sgdm	92.50%	7.50%
50	20	sgdm	94.19%	5.81%

The proposed model achieved a high accuracy rate of 94.19% across 50 epochs, surpassing the previous method for identifying and classifying rice leaf diseases. Training the dataset using various epochs, including 20, 30, 35, and 40, yielded increased accuracy as the number of epochs increased. The model's accuracy increased by 24% as the number of epochs rose from 20 to 50. These findings demonstrate the potential of deep learning models for detecting and managing plant diseases, which can lead to more efficient and sustainable agricultural practices. **Table 4** compares our suggested model to previous research and displays accuracy and miss classification rates.

TABLE 4: Comparison of our proposed IMDRLD model with previous approaches.

Author Name	**Method**	**Accuracy**	**Misclassification Rate (%)**
(Andrianto, 2020)	deep VGG16 model trained with transfer learning	60%	40%
(Ramesh, 2018)	K-Means Clustering is used for Image Segmentation and artificial neuron network (ANN) is utilized for classification.	90%	10%
(Rahman A. P., 2020)	VGG16 and InceptionV3	93.30%	6.70%
(Chen J. C., 2020)	deep learning VGGNet model	92.00%	8%
(Bakar, 2018)	multi-level thresholding approach	90.90%	9.10%
(Shrivastava, 2019)	CNN as a feature extractor and SVM as classifier	91.37%	8.63%
(Gurumoorthy, 2018)	Fuzzy Logic with K-Means segmentation technique	86.35%	13.65%
(Ahmed, 2021)	CNN architecture	88.92%	11.08%
(Prajapati, 2017)	Support Vector Machine (SVM) for multi-class classification.	93.33%	6.67%
Proposed ADWLD	Trained deep learning based AlexNet model	94.19%	5.81%

5 Conclusion:

Artificial intelligence is transforming the way healthcare is delivered to the world. Artificial intelligence is used to help with different tasks in healthcare especially for diagnosing the disease at an early stage. Artificial intelligence -based software can help detect disease patterns and risk factors, or it can mine data to help doctors make better diagnoses. Recent advances in artificial intelligence have also been able to improve clinical decision support. We, therefore, developed an intelligent expert system based on a fuzzy logic decision-making system to diagnose possible cardiovascular disease in patients at an early stage. The system is based on six different input variables such as blood pressure, cholesterol, sugar level, Obesity, Heart rate, and ECG. The proposed system has a single output showing the medical health of the patient. Appropriate diagnosis, management, and treatment of these patients can reduce the mortality rate and increase the survival rate.

6 Future Works:

The future work for "Intelligent Model to detect rice leaves disease using Transfer Learning" could include:

- **Improving the accuracy of the model:** The authors may wish to further improve the accuracy of the model by incorporating additional data and fine-tuning the model architecture.
- **Expanding the scope of the model:** The authors may choose to expand the scope of the model to detect additional rice diseases, or to apply the model to other crops.
- **Developing a real-time detection system:** The authors may choose to integrate the model into a real-time detection system that can be used by farmers and agricultural organizations to quickly and accurately diagnose rice diseases.
- **Exploring alternative transfer learning approaches:** The authors may choose to explore alternative transfer learning approaches, such as fine-tuning on new data or using different pre-trained models, to see if they lead to improved performance.
- **Conducting field studies:** The authors may wish to conduct field studies to validate the effectiveness of the model in real-world conditions and gather feedback from farmers and other stakeholders.

These are some examples of the future work that the authors may consider in their research on an intelligent model to detect rice leaves disease using transfer learning.

7 References:

[1] Toseef, M. and Khan, M.J., 2018. An intelligent mobile application for diagnosis of crop diseases in Pakistan using fuzzy inference system. Computers and Electronics in Agriculture, 153, pp.1-11.

[2] Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A. and Menaka, R., 2020. Attention embedded residual CNN for disease detection in tomato leaves. Applied Soft Computing, 86, p.105933.

[3] Hassan, S.M., Maji, A.K., Jasiński, M., Leonowicz, Z. and Jasińska, E., 2021. Identification of plant-leaf diseases using CNN and transfer-learning approach. *Electronics*, *10*(12), p.1388.

[4] Gao, R., Wang, R., Feng, L., Li, Q. and Wu, H., 2021. Dual-branch, efficient, channel attention-based crop disease identification. Computers and Electronics in Agriculture, 190, p.106410.

[5] Hussain, A., Ahmad, M., Mughal, I.A. and Ali, H., 2018, November. Automatic disease detection in wheat crop using convolution neural network. In The 4th International Conference on Next Generation Computing.

[6] Bakar, M.A., Abdullah, A.H., Rahim, N.A., Yazid, H., Misman, S.N. and Masnan, M.J., 2018. Rice leaf blast disease detection using multi-level colour image thresholding. Journal of Telecommunication, Electronic and Computer Engineering *(JTEC)*, *10*(1-15), pp.1-6.

[7] Shrivastava, V.K., Pradhan, M.K., Minz, S. and Thakur, M.P., 2019. Rice plant disease classification using transfer learning of deep convolution neural network. International archives of the photogrammetry, remote sensing & spatial information sciences, 3(6), pp.631-635.

[8] Gurumoorthy, S., Rao, B.N.K., Gao, X.Z., Sethy, P.K., Negi, B., Barpanda, N.K., Behera, S.K. and Rath, A.K., 2018. Measurement of disease severity of rice crop using machine learning and computational intelligence. Cognitive Science and Artificial Intelligence: Advances and Applications, pp.1-11.

[9] Ahmed, T., Rahman, C.R. and Abid, M.F.M., 2021. Rice grain disease identification using dual phase convolutional neural network based system aimed at small dataset. AgriRxiv, (2021), p.20210263534.

[10] Prajapati, H.B., Shah, J.P. and Dabhi, V.K., 2017. Detection and classification of rice plant diseases. Intelligent Decision Technologies, 11(3), pp.357-373.

[11] Ramesh, S. and Vydeki, D., 2018, September. Rice blast disease detection and classification using machine learning algorithm. In 2018 2nd International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE) (pp. 255-259). IEEE.

[12] Rahman, A., Shoumik, S.N., Rahman, M. and Hena, H., 2021. Rice Disease Detection Based on Image Processing Technique. In Smart Trends in Computing and Communications: Proceedings of SmartCom 2020 (pp. 135-145). Springer, Singapore.

[13] Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M.P., Shyu, M.L., Chen, S.C. and Iyengar, S.S., 2018. A survey on deep learning: Algorithms, techniques, and applications. ACM Computing Surveys (CSUR), 51(5), pp.1-36.

[14] Andrianto, H., Faizal, A. and Armandika, F., 2020, October. Smartphone application for deep learning-based rice plant disease detection. In 2020 international conference on information technology systems and innovation (ICITSI) (pp. 387-392). IEEE.

[15] Chen, J., Chen, J., Zhang, D., Sun, Y. and Nanehkaran, Y.A., 2020. Using deep transfer learning for image-based plant disease identification. Computers and Electronics in Agriculture, 173, p.105393.

[16] Lu, J., Hu, J., Zhao, G., Mei, F. and Zhang, C., 2017. An in-field automatic wheat disease diagnosis system. Computers and electronics in agriculture, 142, pp.369-379.

[17] Rahman, C.R., Arko, P.S., Ali, M.E., Khan, M.A.I., Apon, S.H., Nowrin, F. and Wasif, A., 2020. Identification and recognition of rice diseases and pests using convolutional neural networks. Biosystems Engineering, *194*, pp.112-120.

[18] Narvekar, P.R., Kumbhar, M.M. and Patil, S.N., 2014. Grape leaf diseases detection & analysis using SGDM matrix method. International Journal of Innovative Research in Computer and Communication Engineering, 2(3), pp.3365-3372.

[19] Dokic, K., Blaskovic, L. and Mandusic, D., 2020, December. From machine learning to deep learning in agriculture–the quantitative review of trends. In IOP Conference Series: Earth and Environmental Science (Vol. 614, No. 1, p. 012138). IOP Publishing.

[20] Atole, R.R. and Park, D., 2018. A multiclass deep convolutional neural network classifier for detection of common rice plant anomalies. International Journal of Advanced Computer Science and Applications, 9(1).

[21] Ngugi, L.C., Abelwahab, M. and Abo-Zahhad, M., 2021. Recent advances in image processing techniques for automated leaf pest and disease recognition–A review. Information processing in agriculture, 8(1), pp.27-51.

[22] Ashwini, K. and Vincent, P.D.R., 2022. A deep convolutional neural network based approach for effective neonatal cry classification. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 15(2), pp.229-239.

[23] S.M.NURNOBI, 2021, https://www.kaggle.com/datasets/nurnob101/rice-disease