An Efficient Deep Learning Model for Detection of Rice Leaf Diseases using Paddy Doctor Dataset

1st Shaveta Jain
Department of Computer Science and Engineering
MMEC, MM (Deemed to be University)
Mullana, Ambala, India
shavetajn120@gmail.com

2nd Rajneesh Kumar
Department of Computer Science and Engineering
MMEC, MM (Deemed to be University)
Mullana, Ambala, India
drrajneeshgujral@mmumullana.org

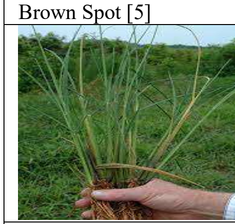
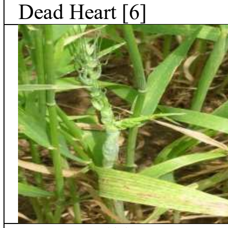
***Abstract*—Detecting diseases in rice leaves is vital for ensuring agricultural productivity and food security. This paper introduces a highly efficient deep learning model designed for the automated identification of rice leaf diseases. Traditional diagnosis methods require expert supervision, which is laborious and costly. We employed an enhanced deep learning model which is a modification over ResNet50 model, classify images of paddy leaves into nine disease categories (bacterial leaf blight, leaf streak, panicle blight, blast, brown spot, dead heart, downy mildew, hispa, tungro), plus a category for healthy leaves. Using the Paddy Doctor dataset with around 24,000 images augmented from the original 16,225, we trained and fine-tuned models to achieve high accuracy despite the complexity of ten classification categories. The proposed deep learning model was adapted with the goal of attaining precise and accurate identification of paddy diseases, the highest achieved accuracy being an impressive 98.03%.**

Keywords*—rice leaf, smart agriculture, plant disease diagnosis, deep learning, modified resnet50.

I. INTRODUCTION

Rice, as a fundamental crop globally, plays a vital role in ensuring food security and poverty alleviation, particularly in developing nations. However, the optimal yield and quality of rice crops frequently encounter obstacles due to various biological and environmental stress factors, with diseases emerging as significant challenges[1]. Among these, leaf diseases emerge as primary causes of yield reduction and financial burdens for farmers. Encouraging sustainable farming practices and managing diseases effectively depend on the timely and accurate detection of these illnesses.

TABLE I. RICE DISEASES DETECTABLE BY THE PROPOSED MODELS

Rice Leaf Disease Image	**Description**
 Bacterial Leaf Blight [3]	The Gram-negative bacterium Xanthomonas oryzae is the source of rice bacterial leaf blight. Most bacterial blight symptoms initially show up as tiny, water-soaked spots or light green patches on leaves. The tissue in the core dies and turns brown as these patches get bigger.
 Bacterial Leaf Streak [4]	Browning and drying of leaves are caused by bacterial leaf streak. In severe circumstances, grain weight may decrease as a result.
 Bacterial Panicle Blight [4]	Bacterial panicle blight has the ability to endure as a non-pathogenic surface population. These bacterial colonies may migrate upward as the plant develops. Bacteria that infect the growing grains during flowering after pollination result in grain abortion, or rotting, during grain filling.
 Rice Blast [5]	Blast is caused by the fungus Magnaporthe oryzae. It can affect every part of the above-ground portion of a rice plant, such as the sections of panicle, collar, node, neck, and infrequently the leaf sheath.
 Brown Spot [5]	A fungus called brown spot can infect both mature plants and seedlings. When seedlings are raised from heavily infected seeds, the disease can result in blight and 10–58% seedling mortality.
 Dead Heart [6]	Dead heart, a condition in which a plant's youngest partially unfolded leaf starts to turn white and die, is frequently the first sign of injury. Any type of stem borer can result in dead heart.
 Downy Mildew [6]	Regions of fields where seedlings have been growing in soggy soil are susceptible to downy mildew. The majority of infected plants are found in lowlands and flooded areas close to ditches, where the Sclerophthora fungus frequently infects other host plants.
 Hispa [7]	Only the lower epidermis of leaf blades remains after rice hispa scrapes off the upper surface. In addition, it penetrates into the leaf tissues. Plant vigour is reduced by severe injury.
 Tungro [8]	The Sequiviridae family of plant pathogenic viruses includes the rice tungro spherical virus. When combined with the Rice tungro bacilliform virus, RTSV alone only mildly manifests symptoms[9].

Conventional techniques for detecting diseases in rice leaves typically rely on visual assessments conducted by agronomists, which are time-intensive, subjective, and

2024 First International Conference on Software, Systems and Information Technology (SSITCON) | 979-8-3503-5293-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/SSITCON62437.2024.10797004

susceptible to human error. In recent years, the incorporation of machine learning methods in agriculture has demonstrated promising outcomes in automating disease detection procedures, presenting rapid, accurate, and non-destructive alternatives to traditional approaches[2]. Table 1 lists out the various rice leaf diseases with its description.

The Paddy Doctor dataset [10] is a collection of around 16,225 paddy leaf images classified into various categories of diseases and one category of healthy leaves. Our suggested model was successfully trained and tested using this dataset.

In the proposed enhanced deep learning solution, we have used the ResNet50 model framework – a machine learning model framework which was modified and fine-tuned to gain high accuracy solutions. Weights were dropped from both the ResNet50 model. Only the architecture of the ResNet50 model was imported, from which the top dense layer was dropped out and recreated with higher precision, with an output layer of 10 nodes. The model has the ability to detect and diagnose 10 different categories of paddy leaves – leaves with bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, dead heart, downy mildew, hispa, tungro and also healthy paddy leaves.

Rest of the paper is structured as follows: section II presents literature review of the researchers work in the diagnosing rice diseases, followed by description of ResNet50 model in section III. Methodology is presented in section IV. section V describes the results of the research finding followed by conclusion and future work in section VI.

II. LITERATURE REVIEW

Several techniques have been used to detect rice leaf diseases and diagnose them accurately. Most of these techniques include machine learning and deep learning algorithms and computer vision-based image processing. Researchers have presented various designs for rice leaf disease detection system.

Douaa S. Alwan [12] created a hybrid model called ResNet50 (Residual Network 50) that combines a deep convolutional neural network (CNN) and a support vector machine (SVM) to diagnose rice issues. Farmers and other agriculture workers might use this model to quickly diagnose and cure crop issues, increasing farm yield and lower the need for costly and slow manual inspection. The deep learning network ResNet50 was used to withdraw the features from photos of rice plants. ResNet-50 is an excellent model for image classification issues. SVM was then used to categorise the illnesses based on these features.

The images' complex patterns could be identified by the ResNet50, and the SVM could then accurately classify the images based on these patterns. Although the model achieved an impressive accuracy of about 99%, it is limited in its application since it only holds the capacity of classifying five different categories of rice leaf diseases.

A pipeline of three distinct lightweight CNNs is proposed by the authors of a research on the categorization of diseases using duo-layers of CNNs [13]. This pipeline is capable of identifying nine distinct paddy disorders in addition to healthy paddy. Each neural network has two unique layers from which features are collected using the "Ripa-Net" method. The dual-tree complex wavelet transform (DTCWT) is applied to the deep features of the first layer to decrease its dimensions and obtain spectral temporal information. The spatial deep features of the second layer are then combined with this data.Obtaining deep characteristics from various CNN layers offers a remarkable 97.5% accuracy and a more comprehensive approach to disease detection and classification.

The MobileNet-V2 model, which is employed in the work of Ruifan Liu [14], makes the system compatible with and appropriate for portable and mobile devices. This neural network design is perfect for handheld devices since it is built on depth-wise separable convolutions, which are more flexible in terms of model size and computational efficiency. Using the Paddy Doctor dataset, this lightweight CNN-based model was trained and evaluated, yielding an accuracy of 98.27%.

Md Mehedi Hasan and Touficur Rahman's paper [15] on illness categorization using Convolutional Neural Networks and Mobile Application Integration takes a similar technique, but with smaller, more affordable and functional CNN models. For handling pictures, the model employs segmentation and k-means clustering. It is confirmed on 1200 photos and trained on an improved dataset of 2700 images. The testing accuracy provided by the model is 97.19%.

Yunusa Haruna suggested a GAN-based data augmentation pipeline as an enhanced method for detecting rice disease [16]. As our work has shown, synthetic data augmentation works better than standard methods for object detection models, and it works especially well with tiny or imbalanced datasets. Data on rice diseases were synthesised using Style-Generative Adversarial Network Adaptive Discriminator Augmentation (SG2-ADA). The Laplacian filter is suitably tuned to remove blurring and badly created images in order to enhance the performance of the Single Shot Detector (SSD) and Faster-Region-Based Convolutional Neural Network (faster-RCNN) in the detection of severe rice illnesses. Four diseases were largely identified from imbalanced raw data: rice blast, brown spot, tungro, and blight. Faster RCN and SSD models were trained using the synthesized images.

The Efficient Channel Attention Module was incorporated into Xiaoqi Wang's ECA-ConvNeXt model [17], which enhanced feature extraction performance while utilizing fewer parameters. The model was then adjusted to lower training costs and improve performance at the same time using transfer learning to initialize the model with pretrained weights. The rice leaf disease identification dataset was used to train the model, and the experimental results showed 94.82% accuracy and 94.42% precision.

Yang Lu and Xiaoxiao Wu suggest combining a bidirectional gated recurrent unit (BiGRU) with a convolutional neural network [18] in order to enhance the rice disease classification process and lower the error percentage. A residual mechanism was added to the inception module, and the module's depth was increased. After being combined, the CNN and BiGRU outputs were sent to the classification layer, which claims a 98.21% accuracy rate in identifying four distinct rice diseases.

III. RESNET50 MODEL

One of the most widely used convolutional neural network architectures nowadays is the ResNet architecture. Residual Networks, or ResNet for short, were first presented in a paper by He et al [20] and broke multiple records when they were introduced by Microsoft Research in 2015. The six components of the ResNet-50 design are the fully-connected layer, input pre-processing, Cfg[0], Cfg[1], Cfg[2], and Cfg[3] blocks.

As seen in the Table 2 and Figure 1, ResNet50 architecture employ different numbers of Cfg blocks at different levels.

TABLE II. COMPONENTS OF RESNET50 ARCHITECTURE

Layer Name	Output Size	ResNet50 Layers
Conv1	112X112	7X7, 64, stride 2
Conv2_x	56X56	3X3 max pool, stride 2
		$\begin{bmatrix} 1X1,64 \\ 3X3,64 \\ 1x1,256 \end{bmatrix} X3$
Conv3_x	28X28	$\begin{bmatrix} 1X1,128 \\ 3X3,128 \\ 1X1,512 \end{bmatrix} X4$
Conv4_x	14X14	$\begin{bmatrix} 1X1,256 \\ 3X3,128 \\ 1X1,1024 \end{bmatrix} X6$
Conv5_x	7X7	$\begin{bmatrix} 1X1,512 \\ 3X3,512 \\ 1X1,2048 \end{bmatrix} X3$
	1X1	Average pool, 1000-d fc, softmax
FLOPs		3.8X109

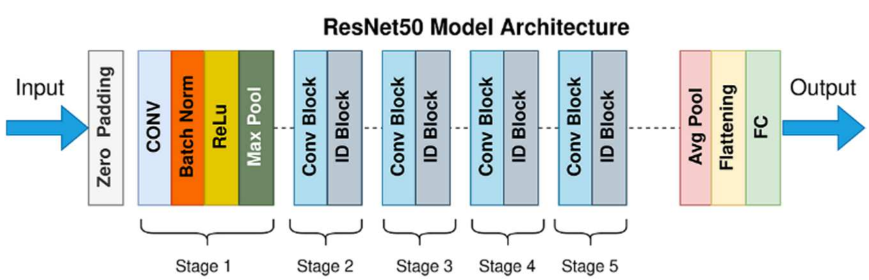


Fig. 1. Layers of the ResNet50 architecture [20]

IV. METHODOLOGY

A. Dataset

Around 16,225 paddy leaf photos from the Paddy Doctor (dataset) [10], a visual image dataset for diagnosing paddy leaf diseases, were used for this study. Images of one group of healthy rice leaves and twelve separate classes of damaged paddy leaves make up the dataset. Pictures of actual paddy fields' leaves were gathered from a village close to Tamil Nadu's Tirunelveli district. After image cleaning, the original dataset of almost 30,000 JPEG photos was reduced to a final total of 16,225 images.

B. Augmentation

Some images were augmented and modified like flipping, rotation, cropping and scalling to form new images, resulting in a dataset with a total of around 24,000 images. The dataset was divided into two parts: 80% of the dataset, around 19200 images were used for training the models. The remaining 20% of the images were used for testing the models as shown in Figure 2. The performance metrics of the models – accuracy, precision, recall value and F1-sore are based upon the results of the testing phase of the model.

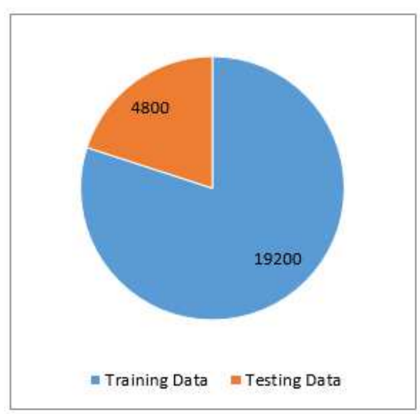


Fig. 2. Division of dataset images into training data and testing data

C. Proposed Work

Proposed model is implemented having, multiple residual blocks, each containing multiple convolutional layers, make up the ResNet-50-like architecture. After undergoing convolutional operations in each block, the input is merged with the original input via a shortcut connection. The network can learn residual information thanks to this mechanism, and it can then adjust the original input accordingly.

In proposed model, ResNet50 makes use of bottleneck architectures, which sequentially use 1x1, 3x3, and 1x1 convolutions as shown in Figure 3. This tactic preserves the expressive power of the network while lowering computational complexity. For ultimate classification, ResNet50 further has a fully linked layer and global average pooling. ResNet50's capacity to train very deep networks—networks with more than 100 layers—effectively and without compromising performance is one of its main features. This discovery has significantly changed the field of deep learning and opened the door to the creation of even more complex networks.

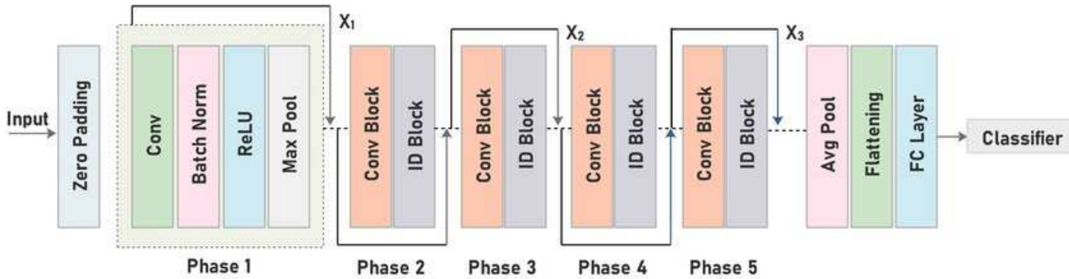


Fig. 3. Architecture of proposed model

The model was composed of six different layers – the Input Layer, the Functional Layer, the Flatten Layer, the Dense8 Layer, the Dropout Layer and the Dense9 Layer. The Functional Layer has 235,64,800 parameters, the Dense8 Layer has 167,77,728 parameters and the Dense9 Layer has 5130 parameters, bringing the total count of parameters to 403,47,658, out of which there are 403,02,218 trainable parameters.

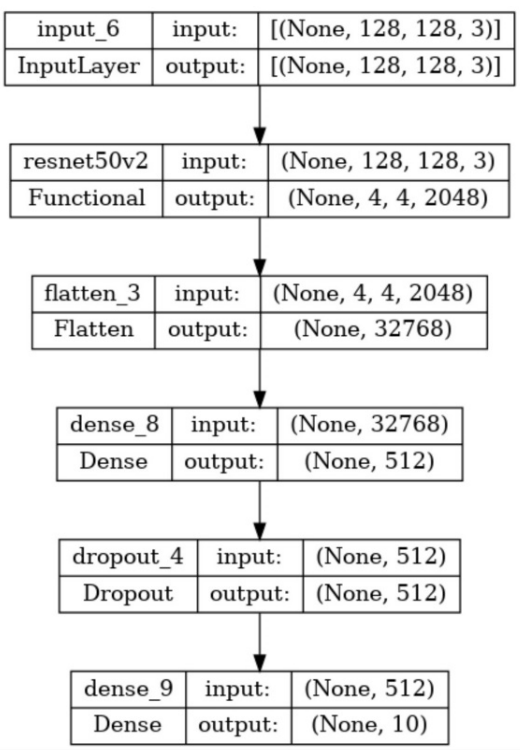


Fig. 4. Network architecture of the proposed model

The input image, having 128x128 pixels and 3 layers, is taken at the Input Layer. The Functional Layer processes the input image, following which it is flattened into a layer having 32,768 nodes.

The Dense layers and Dropout layers are added to the model after the Flatten layer. In the last stages of a neural network, a dense layer is a fully linked layer that modifies the dimensionality of the output from the layer before it.The dropout layer prevents overfitting of the training data and overtraining of the model. It nullifies or eliminates the contribution of some nodes to the next layer, while maintaining functionality of all other nodes.

The final dense layer has 10 nodes for the 10 different categories of output one can expect. The final dense layer determines the classification produced by the model as the final output as shown in Figure 4. Following is the pseudocode for the proposed model.

```
# Pseudocode for Proposed Model

# Step 1: Initialize the model

initialize model

# Step 2: Input Layer

# Input: Image of 128x128 pixels with 3 channels (RGB)

input_image = load_image(128, 128, 3)

add_input_layer(model, input_shape=(128, 128, 3))

# Step 3: Functional Layer

# Action: Process input image using a Functional Layer
with 23,564,800 parameters

# Performs convolutions, pooling, and activations

functional_layer_output = functional_layer(input_image,
parameters=23564800)

add_functional_layer(model, functional_layer_output)

# Step 4: Flatten Layer

# Action: Flatten the output from the Functional Layer into
a 1D vector of 32,768 nodes
```

```
flattened_output = flatten(functional_layer_output, nodes=32768)

add_flatten_layer(model, flattened_output)

# Step 5: Dense8 Layer

# Action: Apply Dense8 Layer with 16,777,728 parameters

dense8_output = dense_layer(flattened_output, parameters=16777228)

add_dense_layer(model, dense8_output)

# Step 6: Dropout Layer

# Action: Add Dropout Layer after Dense8 to prevent overfitting

dropout_output = dropout(dense8_output, rate=0.5) # Randomly deactivate nodes

add_dropout_layer(model, dropout_output)

# Step 7: Dense9 Layer

# Action: Apply Dense9 Layer with 5130 parameters to further reduce dimensionality

dense9_output = dense_layer(dropout_output, parameters=5130)

add_dense_layer(model, dense9_output)

# Step 8: Final Dense Layer

# Action: Apply the final Dense Layer with 10 nodes for classification

# Output: 10 categories

output_layer = dense_layer(dense9_output, nodes=10, activation='softmax')

add_dense_layer(model, output_layer)

# Step 9: Compile the model

compile_model(model, optimizer='adam', loss_function='categorical_crossentropy', metrics=['accuracy'])

# Step 10: Train the model

# Action: Train the model on the training data with the specified parameters

train_model(model, training_data, epochs=50, batch_size=32)

# Step 11: Output final classification

# Output: Predict probabilities for the 10 categories

predicted_output = predict(model, input_image)

print(predicted_output)
```

D. Evaluation Metrics

The numerical results of the predictions made in a classification problem are represented by a confusion matrix. When dealing with binary classification problems, it is usually applied to target attributes that fall into two classes: positive and negative.The quantity of data in the "Positive" class that the model predicts to be "Positive," indicating that the prediction is True, is specifically referred to as "True positive." The number of "Positive" data points that the model incorrectly forecasts as "Negative," or "False Negative," suggests that the prediction is false. For machine learning classification tasks where the output may comprise two or more classes, a confusion matrix is a performance metric. The Figure 5 displays four different combinations of the actual and expected numbers.

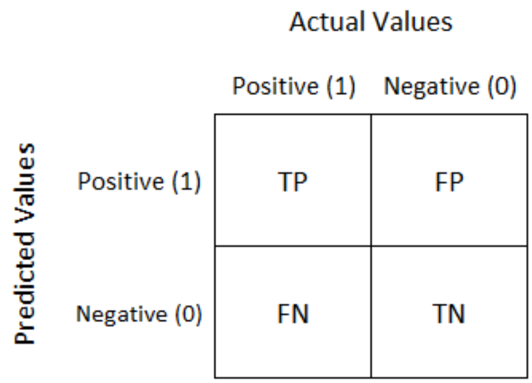


Fig. 5. Basic structure of a confusion matrix

Evaluating a classification model's performance requires the use of a confusion matrix. This tabular form succinctly expresses the predictive capacity of the model by summarising the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The confusion matrix is first created by comparing the actual and expected labels.

The resulting matrix contains the four fundamental categories (TP, TN, FP, and FN) and is arranged into two rows and two columns.

It is imperative to note that the data contained in the confusion matrix forms the basis for numerous crucial performance metrics. These metrics provide complex insights into the effectiveness of the model, ranging from accuracy to precision, recall, specificity, and the F1-score.

Accuracy is the percentage of data that is correctly classified. Its value ranges from 0 to 1. Shown in eq. (1):

$$Accuracy = \frac{True\ Positive + True\ Negative}{All\ Data} \tag{1}$$

Precision describes how accurate positive predictions are. It is the ratio between the True Positives and all the Positives. [22] It is denoted by the following formula in eq (2):

$$Precision = \frac{TruePositive}{All\ Actual\ Positives} \tag{2}$$

Recall, also known as sensitivity, describes how well the model can detect positive examples. An analogous metric for negative instances is provided by specificity. It is denoted by the formula in eq (3):

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

Since the F1-score is a harmonic mean of precision and recall, it offers a fair assessment of the model's performance shown in eq (4).

$$F1\ Score = \frac{TruePositive}{TruePositive + \frac{1}{2(FalsePositive + FalseNegetive)}} \quad (4)$$

V. Results And Discussion

One of the significant challenges faced during the research was achieving the desired level of accuracy. It was particularly challenging to secure a decent accuracy percentage with 10 different categories of classification. The models were hence continuously retrained, modified and fine-tuned until we attained the desired results. Accuracy is one of the most significant evaluation metrics for a machine learning model, and it should be properly assessed after training to determine the model's suitability. Accuracy of a model essentially denotes the degree of closeness of the predicted value to the actual correct value. Figure 6 shows the confusion matrix of proposed model respectively.

Essentially, the confusion matrix serves as the basis for a thorough assessment of the model's classification abilities. Its subtle insights, when combined with related performance metrics, offer a comprehensive view of the model's advantages and disadvantages, which helps to guide the model's further development and application. Using the AUC-ROC curve, the classification problem's performance is assessed at various threshold values. One measure of separability is the AUC. It shows the extent to which the model is capable of class discrimination. The greater the AUC, the better the model predicts 0 classes as 0 and 1 courses as 1. In a similar spirit, a greater AUC indicates a model's capacity to distinguish between disease-positive and disease-negative rice leaves. AUC values close to 1 indicate a high-quality model with good separability. An AUC close to 0 indicates a poor model, which has the lowest separability.

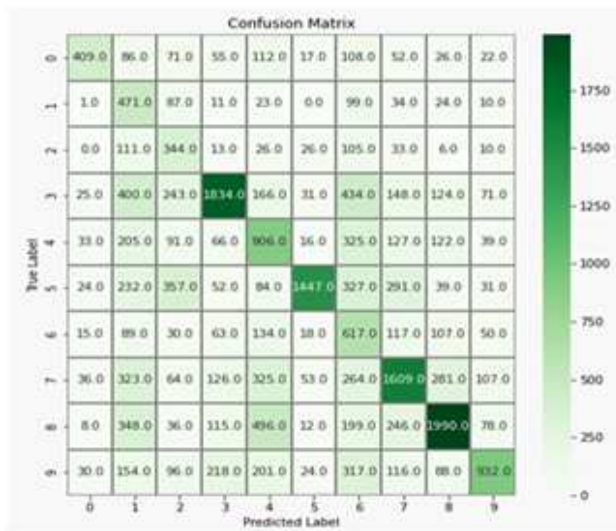


Fig. 6. Proposed enhanced deep learning model's confusion matrix

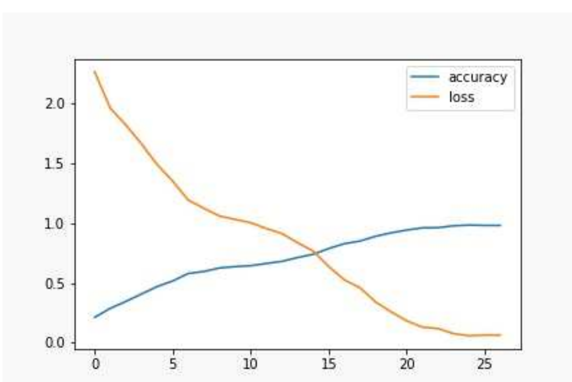


Fig. 7. AUC graph showing accuracy and loss of proposed model

Looking at the Figure 7 of the proposed model, we see that the model started from below 25% and finally topped out with an impressive accuracy of 98.03%. The model initially displayed losses of over 2.00 and at later stages, dropped down to a minimal 0.0645. This model was the latest implementation and it proved better and higher in accuracy than all the previously existing models.

TABLE III. Performance Metrics of our Proposed Model

Model	No. of disease	Accuracy	Precision	Recall Value	F1 Score
Ripa-Net [13]	10	97.5	97.39	97.07	97.22
RepVGG [21]	10	97.06	97.13	97.08	97.09
Swin Transformer [22]	10	94.34	92.52	94.30	93.43
MobileNet [23]	10	89.87	90.51	93.48	91.97
Xception	10	92.51	91.30	91.80	91.55
ResNet50	10	91.13	89.05	90.82	89.33
Proposed model	10	98.03	97.11	97.94	97.91

A thorough performance-based analysis of several deep learning-based models on the Paddy Doctor dataset is presented in Table 3 and graphically in Figure 8. Even though other models achieved high accuracy, research suggests that they are more limited in their classification since none of these previous models have a 10-category classification scheme. The proposed model prove unique in their way, as despite having been trained on 10 different categories of classification: 9 paddy diseases and one healthy paddy category, they achieved impressively high levels of accuracy. The enhanced deep learning model in our proposed solution achieved the best performance with a splendid accuracy of 98.03%.

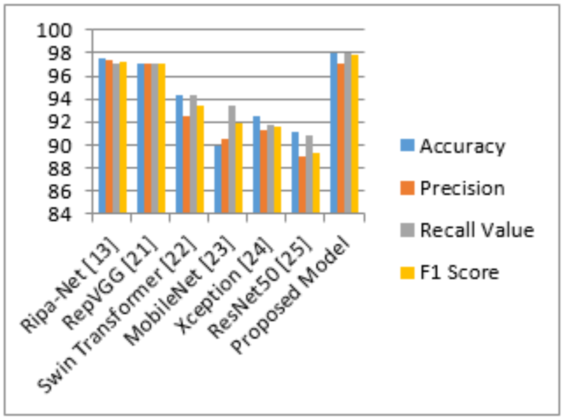


Fig. 8. Comparing the effectiveness of several deep learning models for identifying paddy leaf disease

VI. Conclusion and Future Work

Farmers find it difficult to identify paddy illnesses by hand, which is why there is a growing need for automated solutions that can be applied to a range of plants and crops. Rice leaf diseases detection and diagnosis was, and still remains, one of the most important and widespread problems that need immediate and effective attention. Thus, automated solutions using computer vision and deep learning are continuously being developed and improved. The paddy doctor dataset was used in this paper's suggested approach to train and evaluate enhanced deep learning model for the detection of rice leaf disease. The dataset was benchmarked using a variety of deep learning-based models and contrasted with one another. The proposed model achieved unprecedented accuracy of 98.03% that was higher than any previous model. The paddy doctor dataset is being planned on being improved and increased by collecting more fine-grained data about rice leaf diseases and pests. These will further be benchmarked using deep learning models.

Future work on this field essentially includes efficient and prompt deployment of these automated solutions in large scale throughout the world of agriculture, so that rice as a staple food crop can avoid these major problems and gain maximum yield.

References

[1] Al-Gaashani MS, Samee NA, Alnashwan R, Khayyat M, Muthanna MS. Using a Resnet50 with a kernel attention mechanism for rice disease diagnosis. Life. 2023 May 29;13(6):1277.

[2] Nhut TH, Khang NP, Nhan NC. An Automatic Diagnosis System of Rice Leaf Diseases Based on ResNet-50 Architecture. In2023 International Conference on Advanced Computing and Analytics (ACOMPA) 2023 Nov 22 (pp. 54-58). IEEE.

[3] Nigam S, Kumar S, Marwaha S, Chandra MS. Paddy Leaf Disease Classification using ResNet-50 integrated with Canny Edge Detection Mechanism (2023).

[4] Pothen ME, Pai ML. Detection of rice leaf diseases using image processing. In2020 fourth international conference on computing methodologies and communication (ICCMC) 2020 Mar 11 (pp. 424-430). IEEE.

[5] Bera T, Das A, Sil J, Das AK. A survey on rice plant disease identification using image processing and data mining techniques. InEmerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 3 2019 (pp. 365-376). Springer Singapore.

[6] Thakur RP, Mathur K. Downy mildews of India. Crop Protection. 2002 May 1;21(4):333-45.

[7] Sharma R, Kukreja V, Kadyan V. Hispa rice disease classification using convolutional neural network. In2021 3rd International Conference on Signal Processing and Communication (ICPSC) 2021 May 13 (pp. 377-381). IEEE.

[8] Jain S, Kumar R, Agrawal K. Original Research Article Performance analysis of various deep learning models for detecting rice diseases. Journal of Autonomous Intelligence. 2024;7(3).

[9] Asfaqur Rahman M, Shahriar Nawal Shoumik M, Mahbubur Rahman M, Hasna Hena M. Rice disease detection based on image processing technique. InSmart Trends in Computing and Communications: Proceedings of SmartCom 2020 2021 (pp. 135-145). Springer Singapore.

[10] Petchiammal, Kiruba B, Murugan, Arjunan P. Paddy doctor: A visual image dataset for automated paddy disease classification and benchmarking. InProceedings of the 6th Joint International Conference on Data Science & Management of Data (10th ACM IKDD CODS and 28th COMAD) 2023 Jan 4 (pp. 203-207).

[11] Qazi EU, Zia T, Almorjan A. Deep learning-based digital image forgery detection system. Applied Sciences. 2022 Mar 10;12(6):2851.

[12] Naji MH. Rice Diseases Classification by Residual Network 50 (RESNET50) and Support Vector Machine (SVM) Modeling. Journal of Kufa for Mathematics and Computer. 2023 Mar 31;10(1):96-101.

[13] Attallah O. RiPa-Net: Recognition of Rice Paddy Diseases with Duo-Layers of CNNs Fostered by Feature Transformation and Selection. Biomimetics. 2023 Sep 7;8(5):417.

[14] Liu R. Paddy Disease Classification Based on the Lightweight MobileNet-V2. Highlights in Science, Engineering and Technology. 2023 Jul 11;57:126-33.

[15] Hasan MM, Rahman T, Uddin AS, Galib SM, Akhond MR, Uddin MJ, Hossain MA. Enhancing Rice Crop Management: Disease Classification Using Convolutional Neural Networks and Mobile Application Integration. Agriculture. 2023 Aug 2;13(8):1549

[16] Haruna Y, Qin S, Mbyamm Kiki MJ. An improved approach to detection of rice leaf disease with gan-based data augmentation pipeline. Applied Sciences. 2023 Jan 19;13(3):1346.

[17] Wang X, Wang Y, Zhao J, Niu J. ECA-ConvNeXt: A Rice Leaf Disease Identification Model Based on ConvNeXt. InProceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2023 (pp. 6234-6242).

[18] Lu Y, Wu X, Liu P, Li H, Liu W. Rice disease identification method based on improved CNN-BiGRU. Artificial Intelligence in Agriculture. 2023 Sep 1;9:100-9.

[19] Ni, H.; Shi, Z.; Karungaru, S.; Lv, S.; Li, X.;Wang, X.; Zhang, J. Classification of Typical Pests and Diseases of Rice Based on the ECA Attention Mechanism. Agriculture 2023, 13, 1066.

[20] Wang, F.; Rao, Y.; Luo, Q.; Jin, X.; Jiang, Z.; Zhang, W.; Li, S. Practical Cucumber Leaf Disease Recognition Using Improved Swin Transformer and Small Sample Size. Comput. Electron. Agric. 2022, 199, 107163.

[21] Howard, A.G.; Zhu, M.; Chen, B.; Kalenichenko, D.; Wang, W.; Weyand, T.; Andreetto, M.; Adam, H. Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv 2017, arXiv:1704.04861.

[22] Chollet, F. Xception: Deep Learning with Depthwise Separable Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 1251–1258

[23] He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.