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An Advanced CNN based System for Rice Plant Diseases Detection and classification in Precision Agriculture

Abstract: For the vast majority of people on the planet, agriculture is one of the most crucial industries. Rice is a vital food source, but it also faces serious risks from illnesses that can affect yield quality and quantity, potentially resulting in 20% to 40% crop losses. Reducing production losses requires early diagnosis of these disorders. For farmers, however, it is not possible to manually monitor such large areas of field. The proposed model based on a Convolutional Neural Network of Resnet50 and transfer learning model, specifically a modified TLResnet152V2. Transfer learning-based weights are used for precise identification and categorization and detection for rice leaf diseases. The proposed system demonstrates high accuracy in identifying four classes of rice diseases viz: Brown spot, Healthy, LeafBlast, NeckBlast. It achieves a remarkable accuracy of Resnet50 & TLResnet152V2 is 93.20% and 95.03 % for normalized augmented dataset respectively. Comparative analysis reveals that modified approach outperforms similar methodologies applied to the Bangladesh rice dataset or datasets of comparable size given in the existing research work. Overall findings underscore the efficacy of proposed approach in advancing the precision of rice plant disease detection, offering a promising solution to enhance agricultural practices and mitigate production losses.

Keywords: Convolutional Neural Network(CNN), Deep Neural Net Learning, Transfer-Learning, Leaf Disease-Detection

I. INTRODUCTION

Crop issues are responsible for 45 percent losses of the total yield in the world overall, rice stands as a staple food globally, catering to the dietary needs of numerous nations, particularly in densely populated countries like China, India, and Pakistan. Classified under the Orza type, which encompasses grains like wheat, corn, and cereal, rice gains popularity due to its rich nutrient content. With over three billion people considering it a fundamental dietary choice, rice undergoes varied cultivation worldwide, comprising three distinct developmental phases before harvest. Approximately 15% of global agricultural land is allocated to rice farming, primarily concentrated in East India and Pakistan.

In recent times, we can observe there is a decline in rice yield, attributed to many factors, with plant diseases emerging as a significant contributor. Brown spot, Healthy, LeafBlast, NeckBlast are detrimental diseases affecting rice production and grain quality, characterized by visible spots on plant leaves. Early detection is pivotal in mitigating damage, yet constant plant observation proves challenging. Factors such as farmers' unfamiliarity with diseases and their seasonal patterns contribute to the challenge. While diseases can strike at any time, consistent monitoring during the growth period can help control contagion.

Daily manual patrols by farmers across vast rice fields are impractical due to the farms' extensive sizes. Even if feasible, visual inspections are error-prone, damaging rice plants and incurring additional costs. Recognizing the limitations of physical diagnosis, researchers tries to use Machine Learning based systems in agriculture. Hence the advancements in digital image processing enable the fast and pre-disease detection and categorization of rice plant issues.

Despite these technological advancements, the crux of an efficient system lies in a robust ML algorithm for disease detection and diagnosis. Researchers continually seek the best possible machine learning based solution for any plant disease identification, acknowledging the ongoing exploration in various agricultural domains. Machine learning's applications in agriculture continue to evolve in many aspects like plant health, disease control, probable yield etc. While recent strides have been made, the quest for the most appropriate solution remains a challenging area for scientists actively working to achieve their targets in the respective filed.

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II. LITERATURE REVIEW

Image processing is a pivotal area in the realm of machine learning based algorithms, specifically in accurately classifying images based on shared features. Typically, ML algorithms involve three crucial parts: Image-pre-processing, its feature-extraction, and class identification, falling in two categories as supervised-learning or unsupervised-learning. Recently, deep learning-algorithms received prominence in the work area, utilizing DL models to extract features and classify images. These algorithms find extensive application across various domains such as education, healthcare, smart cities, and other areas impacting human life.

Nilam et al [1] rice leaf diseases were detected by using the machine learning techniques including Adaboost and bagging classification with the help of genetic algorithm, they achieved good accuracy as compared to earlier methods.

In a study Vimal et al [2] used CNN based transfer learning to categories the rice leaf issues, it achieves 91.37 percent categorization accuracy for 80-20 percent training- testing data partition.

In a study of Ruoling et al. [3] they found deep learning is most suitable to construct an automatic disease detection system for rice issues. They achieved ensemble learning by adding different network's sub models like Dense-Net-121, Res-NeSt-50, and SE-Res-Net-50. Due to large number of parameters, it affects the performance in terms of the speed of rice diseases detection

In the study done by Bharathi A. [4] discussed the categorization of diseases affecting rice leaves through the utilization of H-S-I unique attributes and Support Vector Machine technique. The described system does not explicitly emphasize the necessity for an expanded set of features in the feature extraction technique. Additionally, there is no indication in the study that stem cell samples are involved in assessing disease accuracy concerning color and chlorophyll content during every growth stage.

In the study of Kawcher Ahmed et al [5] utilized machine learning as a tool for identifying rice leaf diseases. Their research focused on the detection of three prevalent diseases affecting rice plants: leaf-smut, bacterial-leaf-blight, and dark-brown-spots. The input data comprised clear images of damaged rice leaves captured against a white background. The researchers employed various machine learning techniques, including KNN, J48-Decision-Tree, Naïve-Bayes, and Logistic Regression, following essential image-pre-processing steps during the training of the dataset. Notably, during the application to the test dataset, the Decision Tree algorithm demonstrated an impressive accuracy exceeding 97% after 10-fold cross-validation.

These studies collectively underscore the evolving landscape of Artificial Intelligence-Machine Learning applications in rice issues identification. However, challenges persist, and the integration of technologies like internet of things, computing based on cloud storage is very much essential for practical implementation in real-world scenarios. Ongoing efforts are directed towards the development of robust algorithms and their integration with complementary technologies to maximize effectiveness and applicability in diverse settings, as evidenced in recent work [6].

III. PROPOSE METHOD

This study introduces an innovative system for effectively identification of rice leaf issues. Illustrated in the below figure 1, this system demonstrates the capability to identify and categorises the four disease types: Brown-spot, Healthy, LeafBlast, NeckBlast. Notably, our developed technique stands out in the existing literature by addressing the classification of these four classes.

A. Convolutional Neural Networks

Convolutional Neural Networks (CNN) have witnessed significant advancements in recent years, particularly in image recognition, with diverse applications extending into agriculture. This specialized class of deep neural networks utilizes multiple blocks comprising convolutional layers, pooling layers, and fully connected layers to construct spatial-temporal hierarchies of features through adaptive and self-optimizing backpropagation. The core concept of CNN revolves around building a deeper network with fewer parameters, akin to traditional neural network models organized in layers, commencing with an input layer and concluding with an output layer interconnected by learned biases and weights. Hidden layers within this network transform the input feature space to align with the desired output, typically incorporating at least one convolutional layer to identify patterns. Unlike conventional methods requiring manual feature extraction, CNN autonomously learns these characteristics.

The convolutional layer, central to CNN functionality, employs adaptive kernels with small sizes that traverse the entire network depth. This layer executes a convolution operation on the input, passing the result to subsequent layers and applying a nonlinear function like ReLU (Rectified Linear Unit) [8-10].

Additionally, the pooling layer, synonymous with down sampling, simplifies the representation of convolved features, reducing computational requirements and image size. This reduction must maintain the effectiveness and accuracy of training while avoiding overfitting despite spatial downsizing. Finally, the fully connected layer (FC) directly links neurons without intermediate layers, generating a class score pivotal in the classification process [11].

Before initiating the training process with the convolutional and pooling layers, all CNN parameters must be fixed, with kernel weights adjusted during training. An effective activation function expedites learning, minimizing the loss function discrepancy between true and predicted outputs. Weight updates utilize optimization algorithms like gradient descent. Expanding the dataset size and regularization, achieved by randomly omitting activations, contribute to mitigating overfitting risks[12-15].

This DeepCNN (Convolutional Neural Network) Resnet-50 and layer freeze based Resnet152V2 transfer-learning (TLResnet152V2) system involves a series of pre-processing stages, where images undergo background removal, resizing, and enhancement and feature extraction.

B. ResNet-50 Model

Resnet-50, a convolutional neural network (CNN), has significantly revolutionized the field of deep learning since its inception in 2015 by Kaiming He and collaborators from Microsoft Research Asia. The term Resnet, derived from residual network, refers to the distinctive residual blocks that constitute the network's architecture.

Constructed on a profound residual learning framework, ResNet-50 facilitates the training of highly complex networks, encompassing numerous layers. The conceptualization of the ResNet architecture arose from an unforeseen observation in deep learning research – the mere addition of layers did not consistently lead to improved outcomes.

Contrary to initial expectations, the addition of layers in a neural network did not invariably result in enhanced learning beyond the capabilities of the preceding layers. In response to this challenge, the ResNet team, spearheaded by Kaiming He, introduced an inventive architecture featuring skip connections.

Resnet-50 comprises 50 layers organized into 5 blocks, each containing a series of residual blocks. These residual blocks play a pivotal role in preserving information from earlier layers, augmenting the network's capacity to acquire more effective representations of the input data[16].

C. Proposed Transfer Learning-Based Model TLResnet152V2

Similar to the Resnet50 the residual-neural-network Resnet152V2 is a CNN model consisting of 152 layers. In both the models Adam optimizer is used for the optimization purpose and it gave the highest accuracy in 50 epochs. In this proposed system transfer learning is used to for the classification of the rice leaf dataset. To tailor the model to the specific problem, certain pre-trained layers are kept frozen. The model is then trained using all twenty-one thousand images. Essential features are extracted and assigned values based on their weights. These features are subsequently transmitted to the flatten layer, responsible for converting the obtained matrix into a one-dimensional array. The output from the flatten layer is directed to a dense layer, establishing connections between each neuron in the layer five hundred and twelve times. The results from these layers are further processed by additional functions[17-21].

Fundamentally, the fine transfer learning process comprises four main steps:

a. Pre-training the CNN model.

b. Truncating the last categorisation FC layer and duplicating all the layers and arguments of existing model create modified CNN.

c. Replacing a CNN's initial part with a set of FC layers, followed by a random initialization of the CNN arguments.

d. Training the last layer (‘output layer’) from initial, fine-tuning all arguments based on the previous architecture of model.

Skip Connection for Resnet Model :

In conventional feedforward neural networks, information progresses through each layer in a sequential manner, where the output of one layer serves as the input for the subsequent layer. Residual connections introduce an alternative route for data to traverse deeper sections of the neural network by skipping certain layers. To illustrate, consider a series of layers ranging from layer i to layer i + n, with F representing the function represented by these layers. Let x denote the input for layer i. In the traditional feedforward scenario, x would sequentially pass through these layers, culminating in the outcome of layer i + n being F(x) [22]. In contrast, a residual connection that bypasses these layers typically functions in the following:

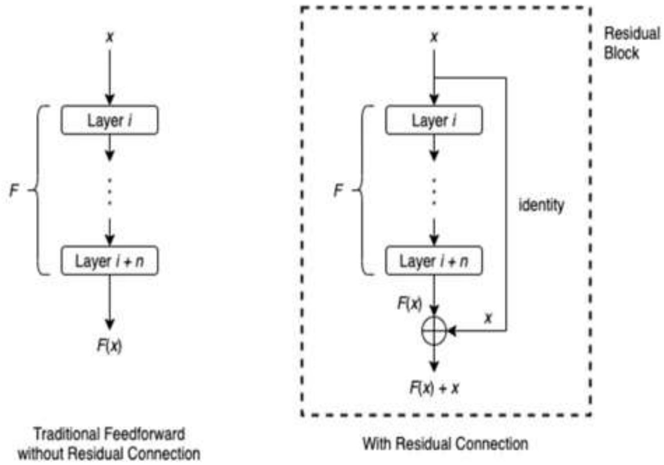

Figure 1: Schematic of Traditional Feedforward Residual Connection and Residual Block with Residual Connection [22]

To address the limitation of small datasets prevalent in existing literature, potentially leading to overfitting, we incorporate data augmentation to expand the dataset size. Unlike many studies that overlook the overfitting issue, we recognize the importance of data augmentation, introducing minor modifications like image-rotation, image-scale-in/scale-out, and image-translation to generate new distinct images[12].

Feature extraction is executed using the Resnet50 architecture and in TLResnet152V2 pretrained weights are used to extract the features, and subsequent feature-map down-sampling is done through the flatten layer followed by the dense, and softmax-layers in Resnet50. The final layers of Resnet50 model handle the categorization process.

Evaluation of our new model is conducted by checking the key parameters, including model-accuracy, model-precision, and model-F1-measure.

In summary, our proposed system addresses the classification of four distinct rice leaf disease classes, incorporating robust pre-processing techniques, data augmentation, and Resnet50 and TLResnet152V2-based feature extraction [16].

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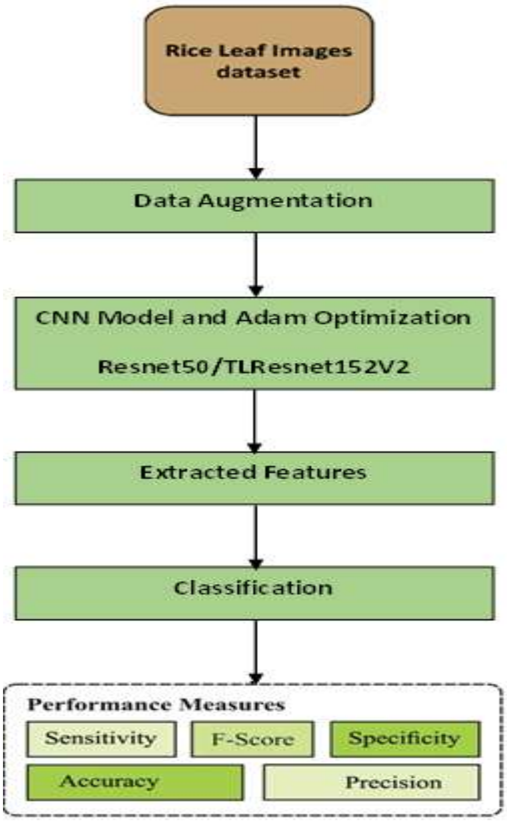


Figure 2: Proposed System for classification

D. Proposed Transfer Learning-Based Model TLResnet152V2

The dataset utilized in this study encompasses four distinct rice leaf diseases: Brown spot, Healthy, LeafBlast, NeckBlast. The image categorization is done using Resnet50 and transfer learning model TLResnet152V2. The dataset used for this study is Bangladesh rice leaf database consisting of number images as BrownSpot-613, Healthy-1488, LeafBlast-977 and NeckBlast-1000 respectively [7]. The augmentation is performed to add images to the existing dataset. Sample images of rice leaf diseases are presented in Figure 3.

BrownSpot **Healthy** **Leaf Blast** **NeckBlast**

Figure 3. Sample Images of rice leaf diseases

1)Metrics used for the Performance Checking

Various metrics are utilized to check how the model perform for given image dataset . the commonly employed metrics are model-accuracy, its-precision, model-recall, model-specificity, F1-score, loss-function, and the importantly-confusion-matrix. These metrics serve as evaluation tools to gauge the performance of the proposed method [12]. The framework's recognition accuracy is specifically measured using mean Average Precision (mAP), a crucial metric for object detection across different classes. This metric is computed by partitioning the number of correct detections for each category by the sum of correctly and incorrectly detected images. The assessment of Mean Average Precision involves considering various parameters, such as minimum-batch-size, image scale (short edge of the image), and the maximum pixel size of the scaled input image. The calculation of mean average precision is carried out for each detected class/object in the image, where average precision is determined by calculating the average-precision over a range from 0 to 1 for the recall-value, using a specific formula.

$$P=\frac{No\ of\ True\ detection}{No\ of\ True\ detections + No\ of\ False\ detections} \ldots\ldots\ldots\ldots \quad (1)$$

The assessment of CNN performance involves considering the loss function as a crucial metric. When predicting outcomes from a finite set of classes, the classification loss function comes into play. An example of such a classification loss function is Cross-Entropy, also known as logarithmic loss. In this work, Table 2 provides explanations for the different metrics utilized. It is important to highlight that TP is for True-Positive, TN stands for True-Negative, and FP used for False-Positive classification.

Table 1: Various Metrics used in Model-Evaluation

Metric	Measure
Accuracy	A metric indicating the proportion of accurate classifications relative to the overall result of categorization.
Precision	The ratio-of correctly identified positive samples to the overall number of positively categorized samples.
Recall	A measure representing actual positive samples correctly identified.
Specificity	A measure representing actual negative samples correctly identified
F1-Score	Score based on the precision and recall

IV. IV. RESULT ANALYSIS

Initially, we studied various CNN models used for image classification then conducted experiments using widely recognized Resnet50 CNN models on Bangladesh rice leaf dataset, including the normalized-dataset, normalized-augmented dataset. Then to improve the accuracy the transfer-learning technique is used using Resnet152V2 CNN models to propose TLResnet152V2 model. The performance of models based on the accuracy is given in Table 2.

Table 2. Experimental results and comparison with different CNN models.

	CNN Model	Accuracy %	Precision	Recall	Specificity	F1_score
Normalized	GoogleNet	82.03	0.8235	0.8219	0.9640	0.8158
	VGG16	82.72	0.8515	0.8279	0.9653	0.8202
	DenseNet201	83.41	0.8460	0.8364	0.9668	0.8368

	Resnet50	**92.20**	**0.8740**	**0.8610**	**0.9670**	**0.8521**
	TLResnet152V2	**93.03**	**0.8824**	**0.8722**	**0.9673**	**0.8576**
Normalized Augmented	GoogleNet	85.24	0.8492	0.8524	0.9605	0.8480
	VGG16	87.14	0.8723	0.8714	0.9643	0.8677
	DenseNet201	88.34	0.8796	0.8834	0.9677	0.8798
	Resnet50	**93.20**	**0.8870**	**0.8920**	**0.9779**	**0.8820**
	TLResnet152V2	**95.03**	**0.8923**	**0.8988**	**0.9785**	**0.8943**

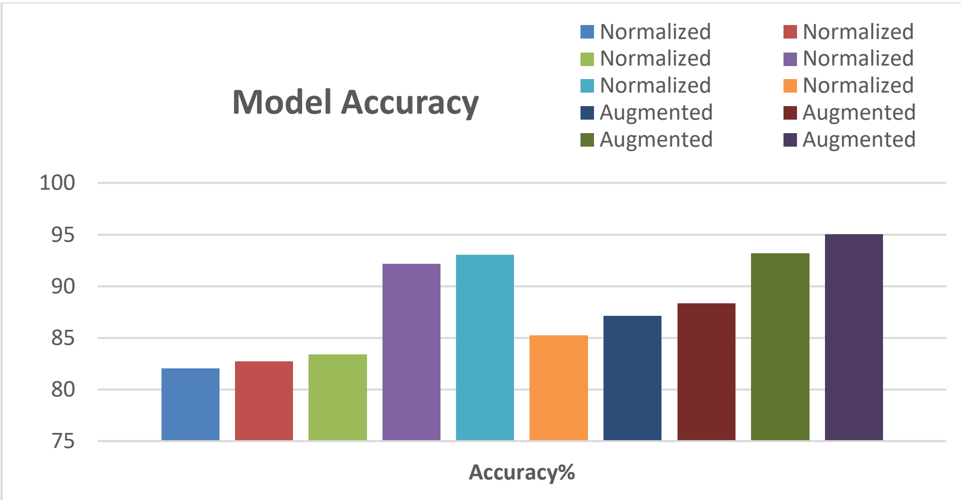


Figure 4: Accuracy of different CNN models for normalized and normalized Augmented dataset

In experimental analysis different parameters are used to evaluate the proposed and existing models for normalized and normalized-augmented dataset. The precision, recall specificity and F1 score of different CNN models for normalized and normalized-augmented dataset are depicted in figure 5 and figure 6 respectively, the proposed TLResnet152V2 model out performed than the existing models.

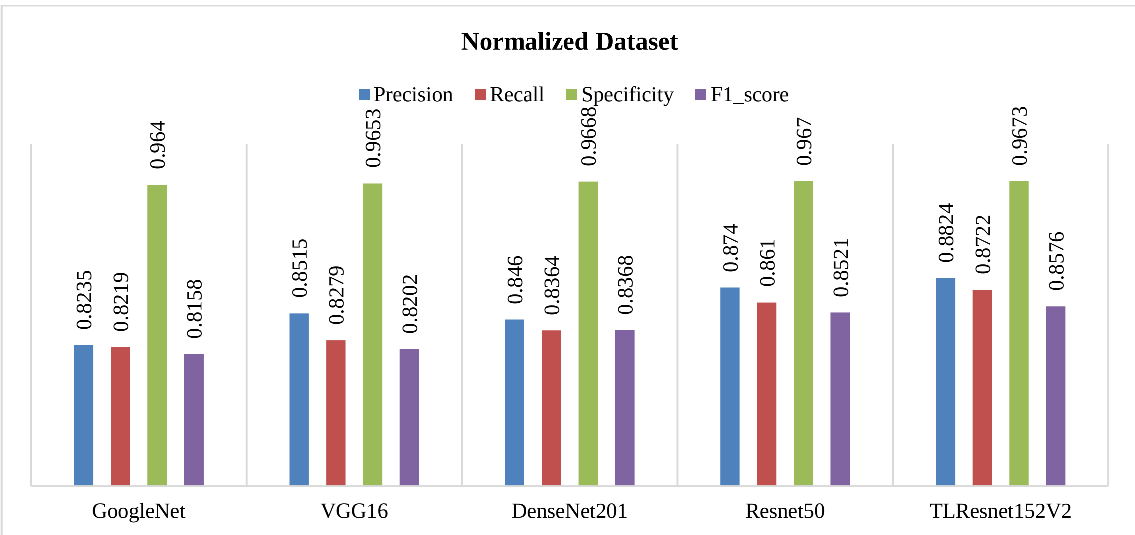


Figure 5: Precision, Recall, Specificity and F1_score of different CNN models for normalized dataset.

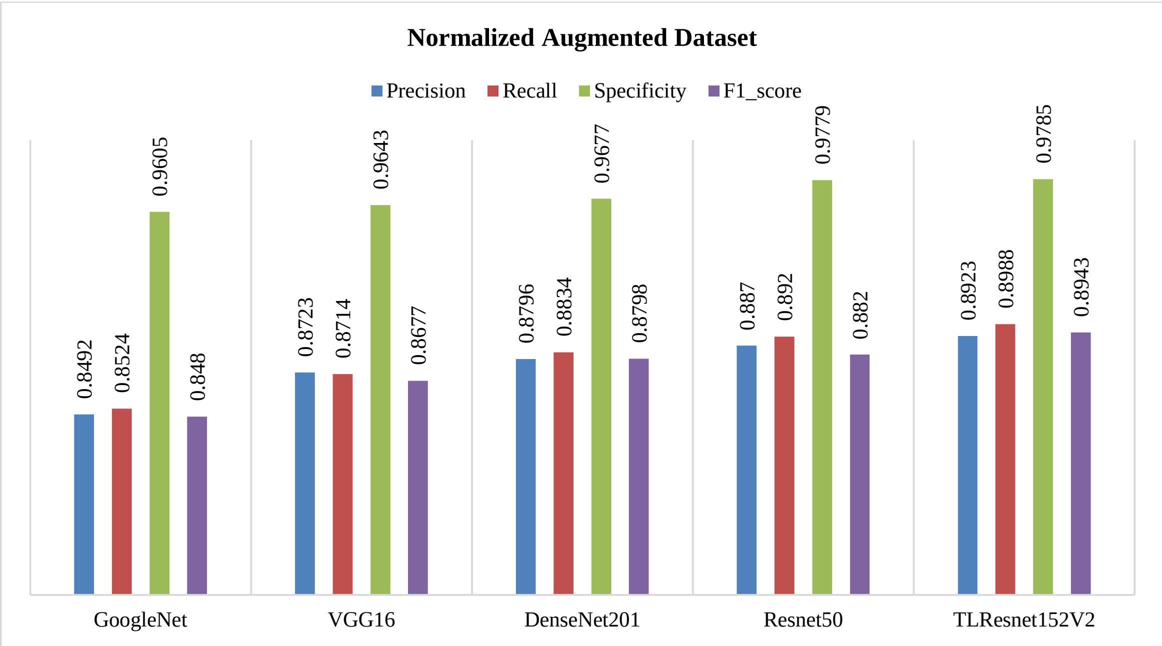
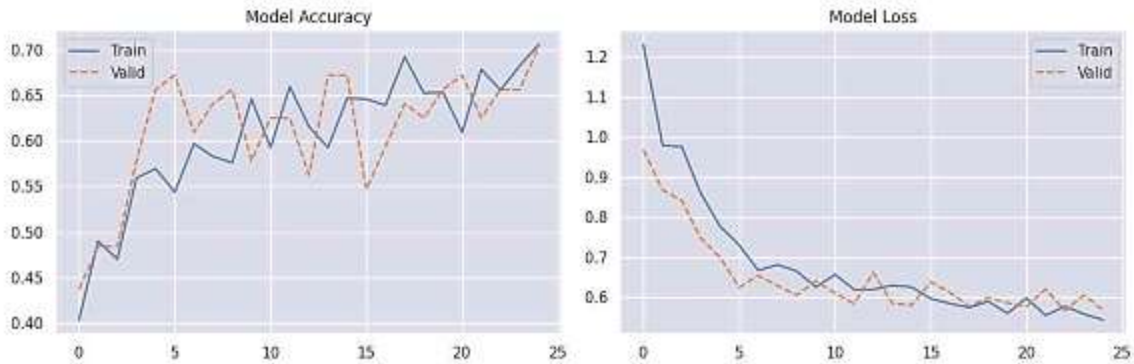
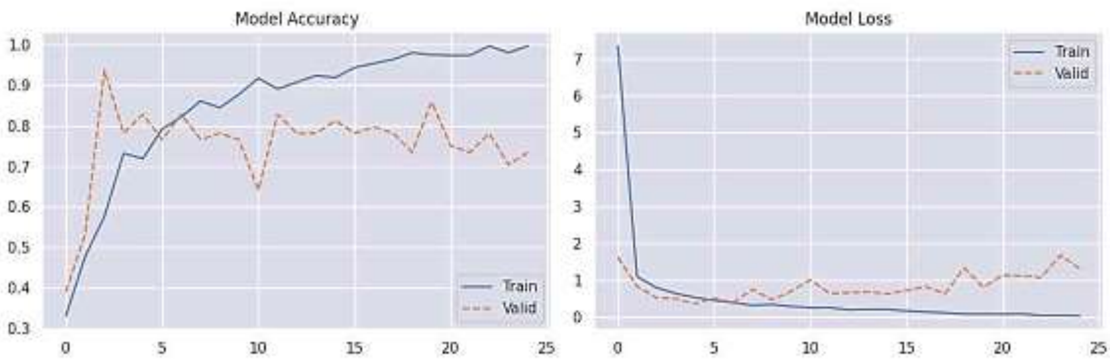


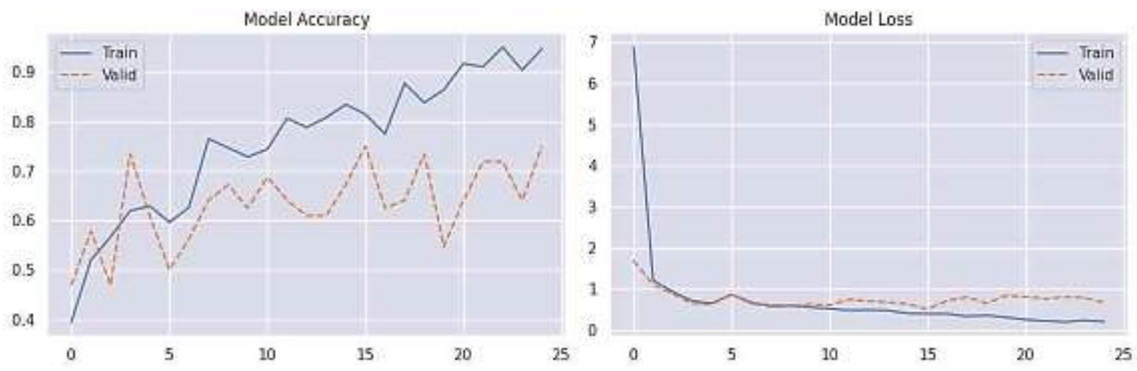
Figure 6: Precision, Recall, Specificity and F1_score of different CNN models for normalized augmented dataset.



(a)



(b)



(c)

Figure 7: (a) VGG16 Training and Validation Accuracy, Training and Validation Loss (b)ResNet50 Training and Validation Accuracy, Training and Validation Loss (c) TLResNet152V2 Training and Validation Accuracy, Training and Validation Loss

V. CONCLUSION

The leaves, being prominent components of plants, exhibit visible signs of various diseases, each manifesting in distinct ways. The significance of rice plants as a primary food source for majority of the population underscores the impact of diseases on both the quality and majorly-quantity of rice production. Annual estimates suggest that rice diseases contribute to a substantial 25–35% loss in yield of it. Manual identification of these diseases demands extensive farmer knowledge and the visual inspection of expansive farmlands, presenting a formidable challenge for early diagnosis. This task, if achievable, would be prohibitively expensive, ultimately affecting the consumer prices of rice. Alternatively, an automated method is sought to facilitate early detection and reduce costs.

Advancements in computing have significantly propelled the field of computer vision technology, offering a promising solution. Distinct visual features associated with rice leaf diseases can serve as valuable inputs for computer aided image processing based systems. This paper presents a Resnet50 architecture and modified approach based on Resnet152V2 transfer fine tuning learning, aimed at improving the accuracy of the system for detection of four types rice leaf diseases. The Resnet50 proposed method achieves an impressive average accuracy of 92.20% when utilizing the normalized dataset and 93.03 for normalized augmented dataset. The Resnet152V2 transfer fine tuning learning gives accuracy 93.20% for normalized dataset and 95.03 for normalized augmented dataset.

REFERENCES

[1] Nilam Sachin Patil and E. Kannan, “Identification of Paddy Leaf Diseases using Evolutionary and Machine Learning Methods”,Turkish Journal of Computer and Mathematics Education, Vol.12 No.2 (2021), 1672-1686, 2021, https://turcomat.org/index.php/turkbilmat/article/view/1503

[2] Vimal K. Shrivastava , Monoj K. Pradhan, Sonajharia Minz , Mahesh P. Thakur, “Rice plant disease classification using transfer learning of deep convolution neural network”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-3/W6, 2019, DOI:10.1007/s42161-020-00683-3

[3] Ruoling Deng, Ming Tao, Hang Xing , Xiuli Yang , Chuang Liu , Kaifeng Liao and Long Qi, “Automatic Diagnosis of Rice Diseases Using Deep Learning”, Front. Plant Sci., 19 August 2021, DOI: 10.3389/fpls.2021.701038

[4] D. Swathi and A. Bharathi, “Disease Classification of Paddy Leaves Using HSI Feature Extraction and SVM Technique”, IJSRD - International Journal for Scientific Research & Development| Vol. 4, Issue 02| ISSN (online): 2321-0613, 2016, https://ijsrd.com/articles/IJSRDV4I20114.pdf

[5] Kawcher Ahmed, Tasmia Rahman Shahidi, Syed Md. Irfanul Alam and Sifat Momen,” Rice Leaf Disease Detection Using Machine Learning Techniques”, International Conference on Sustainable Technologies for Industry 4.0 (STI), 24-25 December, Dhaka,2019, DOI:10.1109/STI47673.2019.9068096

[6] Bashir, K.; Rehman, M.; Bari, M. Detection and classification of rice diseases: An automated approach using textural features. Mehran Univ. Res. J. Eng. Technol. 2019, 38, 239–250, DOI:10.22581/muet1982.1901.20

[7] Liang, W.; Zhang, H.; Zhang, G.; Cao, H. Rice Blast Disease Recognition Using a Deep Convolutional Neural Network. Sci. Rep. 2019, 9, 2869., doi: 10.1038/s41598-019-38966-0
[8] Joshi, A.A.; Jadhav, B.D. Monitoring and Controlling Rice Diseases Using Image Processing Techniques. In Proceedings of the 2016 International Conference on Computing, Analytics and Security Trends (CAST), Pune, India, 19–21 December 2016, DOI: 10.1109/CAST.2016.7915015
[9] Ahmed, K.; Shahidi, T.R.; Irfanul Alam, S.M.; Momen, S. Rice Leaf Disease Detection Using Machine Learning Techniques. In Proceedings of the 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 24–25 December 2019., DOI:10.1109/STI47673.2019.9068096
[10] Latif, G.; Alghazo, J. IoT Cloud Based Rx Healthcare Expert System. In Fog Computing for Healthcare 4.0 Environments; Springer: Cham, Switzerland, 2020; pp. 251–265, DOI:10.1007/978-3-030-46197-3_10
[11] Latif, G.; Shankar, A.; Alghazo, J.M.; Kalyanasundaram, V.; Boopathi, C.S.; Arfan Jaffar, M. I-CARES: Advancing Health Diagnosis and Medication through IoT. Wirel. Netw. 2019, 26, 2375–2389, https://doi.org/10.1007/s11276-019-02165-6
[12] Ade, F. Rice Leaf Diseases Dataset. Available online: https://www.kaggle.com/datasets/adefiqri12/riceleafsv3
[13] Sanyal, P.; Patel, S.C. Pattern recognition method to detect two diseases in rice plants. Imaging Sci. J. 2008, 56, 319–325., DOI:10.1179/174313108X319397
[14] Rajan, G. Transfer-Learning Analysis for Sign Language Classification Models. Turk. J. Comput. Math. Educ. (TURCOMAT) 2021, 12, 1423–1433, https://turcomat.org/index.php/turkbilmat/article/view/3530
[15] Latif, G.; Bouchard, K.; Maitre, J.; Back, A.; Bédard, L.P. Deep-Learning-Based Automatic Mineral Grain Segmentation and Recognition. Minerals 2022, 12, 455, https://doi.org/10.3390/min12040455
[16] Nguyen, Long D., et al. "Deep CNNs for microscopic image classification by exploiting transfer learning and feature concatenation." 2018 IEEE international symposium on circuits and systems (ISCAS). IEEE, 2018, DOI: 10.1109/ISCAS.2018.8351550
[17] Dasgupta, R.; Chowdhury, Y.S.; Nanda, S. Performance Comparison of Benchmark Activation Function ReLU, Swish and Mish for Facial Mask Detection Using Convolutional Neural Network. Algorithms Intell. Syst. 2021, 31, 355–367, DOI:10.1007/978-981-16-2248-9_34
[18] Rao, A.N.; Wani, S.P.; Ramesha, M.S.; Ladha, J.K. Rice Production Systems. In Rice Production Worldwide; Springer: Cham,Switzerland, 2017; pp. 185–205., http://oar.icrisat.org/id/eprint/9895
[19] Zhang, J.; Huang, Y.; Pu, R.; Gonzalez-Moreno, P.; Yuan, L.; Wu, K.; Huang, W. Monitoring Plant Diseases and Pests through Remote Sensing Technology: A Review. Comput. Electron. Agric. 2019, 165, 104943, https://doi.org/10.1016/j.compag.2019.104943
[20] Prajapati, H.B.; Shah, J.P.; Dabhi, V.K. Detection and Classification of Rice Plant Diseases. Intell. Decis. Technol. 2017, 11, 357–373, DOI:10.3233/IDT-170301
[21] Phadikar, S.; Sil, J. Rice Disease Identification Using Pattern Recognition Techniques. In Proceedings of the 2008 11th International Conference on Computer and Information Technology, Khulna, Bangladesh, 24–27 December 2008, DOI: 10.1109/ICCITECHN.2008.4803079
[22] Priya Ujawe, Poonam Gupta, Surendra Waghmare, Identification of Rice Plant Disease Using Convolution Neural Network Inception V3 and Squeeze Net Models, International Journal of Intelligent Systems and Applications in Engineering, 2023, https://ijisae.org/index.php/IJISAE/article/view/2991
[23] Priya Ujawe, Smita Nirkhi, Comparative study of tomato crop disease detection system using deep learning techniques, Intelligent Communication Technologies and Virtual Mobile Networks: Proceedings of ICICV 2022, https://doi.org/10.1007/978-981-19-1844-5_39
[24] Surendra Waghmare, Sanjay Sanamdikar, Onion Classification using Color and Convolutional Neural Network, International Journal of Intelligent Systems and Applications in Engineering, 2024, https://www.ijisae.org/index.php/IJISAE/article/view/3876