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Deep Learning-Based Jute Leaf Disease Identification

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***Abstract*—One of the most valuable crops which has potential in environmental concern as well as in economic revolutions is jute. However, significant losses come from the inability to spot jute leaf diseases using hand observations alone. Deep learning and machine learning prove good strategies to solve this issue. For disease detection, the sample set was collected of 1820 jute leaf images, consisting of both normal and diseased observations. SVM, Random Forest, XGBoost and custom pre-trained CNN classifier were combined with DenseNet121, ResNet152, Xception, VGG19 feature extractors. To enhance the given dataset, additional techniques like CLAHE, normalization and Laplacian filtering were applied. The performance was evaluated using AUC-ROC, F1 score, recall rate, accuracy and precision. Resnet152 with the Custom Classifier was determined to be the model with the highest accuracy of 98.41%, and AUC of 0.9988 with custom classifier and DenseNet121.This research proves that deep learning can successfully diagnose Jute leaf disease and therefore improve disease management and consequently improve agricultural yields. We contribute in enhancing different methods of disease control and overall jute farming yields.**

***Index Terms*—Image Classification, Deep Learning, Agriculture, Computer Vision, Jute.**

I. Introduction

Corchorus is a species of jute,also known as the “golden fiber” which is very important to the Bangladeshi economy.Its product is biodegradable,causing less pollution and helping clean our earth.Researchers believe that 40–50% of jute plants could be damaged in fields affected by jute leaf disease [1].In the past,people visually examined crops for disease by touching,an approach that was time consuming,intensive in terms of manpower and skills,and inconsistent.Today,these tasks are made easy with DL & ML models.However,many existing models struggle due to small,imbalanced datasets and insufficient preprocessing,which leads to errors in classification and low performance.That’s why,in this work,we focused on creating a wide collection of jute leaf images and applying advanced preprocessing techniques to enhance image quality,minimize model errors,and maximize performance.

ML & DL can solve many problems like object detection,recognition,and categorization with high efficiency [2].Our data consists of high quality images of jute leaves used to train a model to differentiate between healthy and diseased leaves.To overcome the absence of large, high quality datasets we generated an exhaustive set of images including major jute leaf diseases.This paper also compares different deep learning models and shows that our approach achieves high accuracy in detecting jute leaf diseases,making our method a dependable tool for managing jute production.

This paper is organized as follows:Section III explains the Jute Leaf Disease dataset and the overall architecture of the deep learning based detection algorithm, and Section IV evaluates the model and offers suggestions for future developments in jute leaf disease classification.

II. Related work/Literature review

With advanced technology using DL & ML , it is easier to identify, classify, and categorize objects. In identifying the jute diseases and pests from 4418 photos with a fixed resolution of 640 × 640, Li et al acquired a 96.63% mAP(mean Average Precesion) and F1-score of 95.83 % using YOLO-JD models [3]. Wagle et al proposed a paper where they focused on crop safety using plant detection. They use PlantVillage (9 plant species) and Flavia (32 classes)

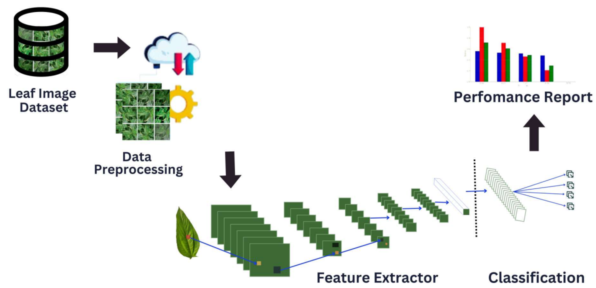

Fig. 1: Methodology Overview

Fig. 2: Jute Leaves(Healthy & Disease)

datasets. They use four CNN models with accuracy N1:99.45%, N2:99.65%, N3:99.55%, AlexNet:99.73% on the PlantVillage dataset [4]. Harakannanavar et al represent a study about tomato leaf diseases detection where they used PlantVillage dataset with 600 samples. For feature extractor they used Contour Tracing ,DWT,PCA,GLCM . As a classifier they used SVM, K-NN,CNN with accuracy achieved 88%,97%, and 99.6% [5]. Kulkarni et al shows that for Rice Leaf Diseases Detection , they used kaggle dataset with both healthy and diseases rice leaves.They use Convolutional Neural Networks (CNNs) and VGG16 as feature extractor.For preprocessing used images undergo.They used CNN based classifier with training 25 epochs with a batch size 10.They achieved total accuracy of 95% on the test dataset [6]. Soeb et al presenting a scientific report that is Tea leaf disease detection and identification.They used 4000 digital images with five types of disease.They used YOLOv7 as feature extractor and also classifier both.To used YOLOv7 they performance metrics are Accuracy:97.3,%Precision:96.7%,Recall:96.4%,Mean Average Precision(mAP):98.2%,F1-Score:0.965 [7].

III. Methodology

The first figure shown in this paper represents a process flow chart of the disease identification of jute leaves and is presented in **Fig.1**.

A. Data Collection

The detailed source of the data in this study is the “Jute Leaf Disease Detection” public dataset on Kaggle.The images were captured during extensive research in Dinajpur and Brahmanbaria,two premier agricultural districts in Bangladesh [8].An illustration of the gathered jute leaves is shown in **Fig.2**.This paper introduces Jute Leaf Disease Detection through Image Classification.It consists of jute leaf images in two classes,0(Healthy) and 1(Diseased),as detailed in **Table-I**.The data is divided into folders by these labels,and the images are in JPG or PNG formats.Analysts can use this dataset to design accurate AI powered algorithms for plant disease detection,crop monitoring, and management.The dataset comprises 1,820 images:564 Healthy Leaves and 1,256 Diseased Leaves,including 609 images of Cercospora Leaf Spot and 647 of Golden Mosaic. Two diseases most threatening to jute crops are Cercospora Leaf Spot and Golden Mosaic(shown as the last two images in **Fig. 2**).Golden Mosaic begomovirus(a genus of viruses in the family Geminivirida) causes yellowing of the leaves,stunted growth,and reduced output,while the fungal disease Cercospora Leaf Spot causes leaf fall and spots on leaves.Uncontrolled,these diseases can lead to huge losses in crop yields.

TABLE I: Class-wise distribution of Jute Leaf Disease Detection dataset

Class	Category	Number of Images
Healthy Leaves	0	564
Diseased Leaves	1	1,256
Cercospora Leaf Spot	1.1	609
Golden Mosaic	1.2	647
Total	**-**	**1,820**

B. Image Preprocessing

A couple of preprocessing techniques were applied in the Jute Leaf Disease Identification study to solve the problem.The use of CLAHE enhanced image contrast, making subtle details clearer for disease detection and the Lab color space involved alteration of brightness levels in the images.Edges and diseases were made more prominent by applying Laplacian filter to acuteness of the images.Random resizing was performed to ensure all images were resized to 224×224 pixel resolution and pixel values scaled between 0 and 1.Besides,to balance the given dataset,the SMOTE technique was implemented to ensure that healthy and disease samples were almost equally represented.The combination of CLAHE and Laplacian filtering ensures optimal feature extraction.These techniques collectively contribute to a more robust and accurate disease classification model.These procedures provided accurate input for the evaluation and training of the model.

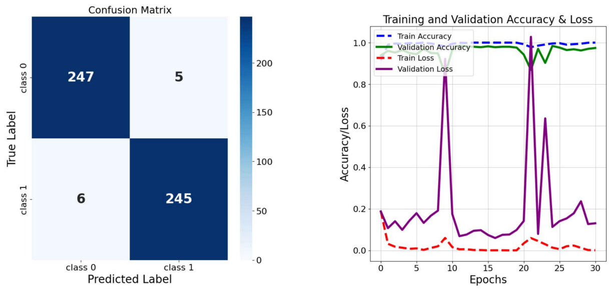

Fig. 3: (a) Confusion Matrix and (b) Training/Validation Accuracy & Loss.

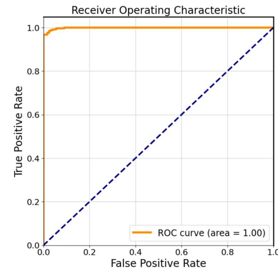

Fig. 4: Receiver Operating Characteristic

C. Feature Extractor

In this study,four advanced deep-learning feature extractors—DenseNet121,ResNet152,Xception and VGG19 were used to separate the jute leaves into healthy and unhealthy types.The layers connected end-to-end by the DenseNet121 ensure full reuse of features and better flow of gradients which reduces the expenses hence yielding better results.ResNet152 deals with the vanishing gradient problem since they use residual connections in the networks hence minimizing on depths of training with depthwise separable convolutions.Xception,which is derived from the introduction architecture,reduces the computing burden but retains special spatial relationships.The typical convolutional neural network is the VGG19,which has an extremely clear and regular framework and 19 layers that effectively collect features of different levels.For evaluation purposes,some feature extractors were compiled with classifiers such as XGBoost,SVM,Random Forest and Custom classifier. ResNet152 with a Custom Classifier returned the highest classification of 97.81% accuracy and DenseNet121 with Custom classifier an AUC of 0.9988.This work shows how the use of deep learning can lead to development of a program that can be used to identify jute leaf disease thus helping control of the disease and as well as enhancing agricultural production.

D. Classification

Several classifying tools such Custom Classifier,SVM,Random Forest,and XGBoost were used in the present work to differentiate healthy and diseased jute leaves(shown in **Table-II**).With a convolutional neural network (CNN) with pre-training with the ImageNet dataset, the Custom Classifier achieved high accuracy.The model was created with the Adam optimizer using an initial learning rate of 1e-4 and a learning rate scheduler that increases the rate by a factor of 1.04 per epoch.Class weights were computed to balance the training data and early stopping was implemented with a patience of 20 epochs and a minimum delta of 1e-3 to prevent overfitting.Fine tuning was performed on the last 80 layers of DenseNet121 to ensure efficient feature extraction.Specifically,the Support Vector Machine(SVM) classifier,requires the use of kernel functions for operating on non-linearly separable data for defining the best hyperplane for distinguishing between healthy and diseased leaves. While it has produced relatively lower performance in this work, Random Forest, which is an example of cooperative learning, creates several decision trees and attempts to merge their results in order to improve the rate of classification. Another element of experimental techniques is XGBoost, where instead of using boosting factors, individual decision trees are constructed as a gradient-boosted model where new trees are trained to minimize the error of the previous tree. The Custom Classifier outperformed the other four classifiers consistently excelling to the maximum accuracy despite the performance of RF, XGBoost and SVM. The study ensured that any classification approaches can be used to well and hardly identify jute leaf diseases.

E. Performance Evaluation

The performance analysis proved that when using the Custom Classifier, the models that had the higher accuracy of were: ResNet152,DenseNet121, Xception, and VGG19 with an accuracy of 0.9841, 0.9781, 0.9702, and 0.9721 respectively (from **Table-II**) with Custom Classifier. These combinations also achieved high F1-scores, and AUC- values; DenseNet 121 and ResNet152 achieved AUC- 0.9988 and 0.9975 respectively(from **Table-II**) with Custom Classifier. Along with SVM, Random Forest, and XGBoost classifier, DenseNet121 performs the second highest AUC that is 0.9896 and Accuracy is 0.9543,0.9324,0.9423 respectively. The capability of the Custom Classifier was further validated through its higher performance for different jute leaf diseases and all the classifiers selected for feature extraction(shown in

Table-II).

IV. Result & Discussion

The current work shows the possibility of deep learning in categorizing jute leaf diseases without human

TABLE II: Performance of classifiers with various feature extractors

Feature Extractor	Classifier	Accuracy	Precision				Recall				F1 Score				AUC
			Healthy	Disease	Mac. AVG	Wtd AVG	Healthy	Disease	Mac. AVG	Wtd AVG	Healthy	Disease	Mac. AVG	Wtd AVG	
DenseNet121	Custom Classifier	0.9781	0.9763	0.9800	0.9781	0.9781	0.9802	0.9761	0.9781	0.9781	0.9782	0.9780	0.9781	0.9781	0.9988
	SVM	0.9543	0.9321	0.9790	0.9555	0.9555	0.9802	0.9283	0.9542	0.9543	0.9555	0.9530	0.9542	0.9542	0.9896
	Random Forest	0.9324	0.8838	0.9954	0.9396	0.9395	0.9960	0.8685	0.9323	0.9324	0.9366	0.9277	0.9321	0.9321	0.9839
	XGBoost	0.9423	0.9240	0.9625	0.9432	0.9432	0.9643	0.9203	0.9423	0.9423	0.9437	0.9409	0.9423	0.9423	0.9876
Resnet152	Custom Classifier	**0.9841**	0.9803	0.9880	0.9841	0.9841	0.9881	0.9801	0.9841	0.9841	0.9842	0.9840	0.9841	0.9841	0.9982
	SVM	0.8648	0.8566	0.8735	0.8650	0.8650	0.8770	0.8526	0.8648	0.8648	0.8667	0.8629	0.8648	0.8648	0.9385
	Random Forest	0.8628	0.8144	0.9292	0.8718	0.8717	0.9405	0.7849	0.8627	0.8628	0.8729	0.8510	0.8620	0.8620	0.9448
	XGBoost	0.8926	0.8587	0.9339	0.8963	0.8962	0.9405	0.9405	0.8925	0.8926	0.8977	0.8870	0.8924	0.8924	0.9649
Xception	Custom Classifier	0.9702	0.9611	0.9797	0.9704	0.9704	0.9802	0.9602	0.9702	0.9702	0.9705	0.9698	0.9702	0.9702	0.9975
	SVM	0.9324	0.9192	0.9465	0.9329	0.9328	0.9484	0.9163	0.9324	0.9324	0.9336	0.9312	0.9324	0.9324	0.9820
	Random Forest	0.9165	0.8723	0.9729	0.9226	0.9225	0.9762	0.8566	0.9164	0.9165	0.9213	0.9110	0.9162	0.9162	0.9668
	XGBoost	0.9284	0.9060	0.9536	0.9298	0.9298	0.9563	0.9004	0.9284	0.9284	0.9305	0.9262	0.9284	0.9284	0.9814
VGG19	Custom Classifier	0.9721	0.9722	0.9721	0.9722	0.9722	0.9722	0.9721	0.9722	0.9722	0.9722	0.9721	0.9722	0.9722	0.9979
	SVM	0.9324	0.9225	0.9429	0.9327	0.9326	0.9444	0.9203	0.9324	0.9324	0.9333	0.9315	0.9324	0.9324	0.9797
	Random Forest	0.9026	0.8512	0.9720	0.9116	0.9115	0.9762	0.8287	0.9024	0.9026	0.9094	0.8946	0.9020	0.9020	0.9774
	XGBoost	0.9304	0.9064	0.9576	0.9320	0.9319	0.9603	0.9004	0.9304	0.9304	0.9326	0.9281	0.9303	0.9304	0.9834

intervention.ReseNet152 along with a Custom Classifier with accuracy of 98.41 %, AUC of 0.9988 using DenseNet121 with custom classifier shows our highest performance. To enhance the strength of the data set, CLAHE, normalization, and Laplacian filtering were integrated into the preprocessing phase, these methods maintained stable performance for the high classification metrics including precision, recall, F1 score, and AUC. Altogether, these findings demonstrate how well deep learning techniques can contribute to proper identification and classification of the jute leaf diseases.

V. Future Work & Limitation

Despite the promising results,this study has a few limitations that SMOTE may introduce noise as synthetic data may not reflect real disease variations,potentially introducing noise.Deep learning models(CNNs),operate as black boxes,making it challenging to interpret their decision making process.Also real time performance in varying field conditions such as lighting changes,occlusions,and image quality differences remains untested.

According to the limitations,in future work we can explore advanced data augmentation techniques to better simulate real world disease patterns and reduce synthetic data limitations.Explainable AI methods(such as Grad-CAM) can improve model understandability by highlighting key decision making areas.Although they also have some limitations.Furthermore real world testing can ensure practical deployment.Also,the proposed approach can be extended to identify diseases in other crops such as rice,wheat,cotton etc.to enhancing its agricultural utility.

VI. Conclusion

In this work using large high quality jute leaf images with several model and classifier(**Table-II**) with best combination of Resnet152 with Custom Classifier (accuracy **98.41%**). The findings of this study reveal that plant diseases can be distinguished effectively using Machine learning Classifier with high accuracy, where the Custom Classifier supply high results and has shown an optimum accuracy as compared to other classifiers. **Table-III** shows the comparison of other work model between our proposed work model where we see that our model as good as them and in some cases better than them. The future work may include more sophisticated models, real-time identification and the extension of the database to various diseases for wider precision agriculture.

TABLE III: Comparison of Existing Models with Proposed Model

Authors	Description	Accuracy
Li et al. [3]	YOLO-JD on 4418 images	96.63%
Wagle et al. [4]	CNN on PlantVillage & Flavia datasets	99.73%
Harakannanavar et al. [5]	Detection using 600 PlantVillage images	99.6%
Kulkarni et al. [6]	CNN/VGG16 on Kaggle for rice diseases	95%
Soeb et al. [7]	YOLOv7 on 4000 images for tea diseases	97.3%
Proposed work	Jute leaf disease detection (1820 images, ResNet152 + Custom CNN)	**98.41%**

References

[1] M. A. Islam, M. S. Sharif, M. A. Kafi, and M. S. Arefin, "Jute leaf disease prediction using deep neural network," 2018.

[2] "Introduction to object detection with deep learning," SuperAnnotate. [Online]. Available: https://www.superannotate.com/blog/object-detection-with-deep-learning. [Accessed: 14-Jan-2025].

[3] D. Li, F. Ahmed, N. Wu, and A. I. Sethi, "YOLO-JD: A deep learning network for jute diseases and pests detection from images," Plants, vol. 11, no. 7, p. 937, 2022.

[4] S. A. Wagle, R. Harikrishnan, S. H. M. Ali, and M. Faseehuddin, "Classification of plant leaves using new compact convolutional neural network models," Plants, vol. 11, no. 1, p. 24, 2021.

[5] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," Global Transitions Proceedings, vol. 3, no. 1, pp. 305–310, 2022.

[6] P. Kulkarni and D. S. Shastri, "Rice leaf diseases detection using machine learning," Journal of Scientific Research and Technology, pp. 17–22, 2024.

[7] M. J. A. Soeb et al., "Tea leaf disease detection and identification based on YOLOv7 (YOLO-T)," Sci. Rep., vol. 13, no. 1, pp. 1–16, 2023.

[8] Kaggle.com. [Online]. Available: https://www.kaggle.com/datasets/mdsaimunalam/jute-leaf-disease-detection [Accessed: 14-Jan-2025].