# Improving Sugarcane Disease Identification with L1-Regularized Transfer Learning Approach

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**Abstract** — Sugarcane is a crucial cash crop in India, significantly impacting the country's economy through its extensive use in the sugar industry. However, various diseases are hindering sugarcane production. Effective identification and management of these diseases can substantially improve yields. In this study, we developed a modified and regularized transfer learning model to diagnose sugarcane diseases early and accurately by processing leaf images. We enhanced two well-known pre-trained models, DenseNet121 and InceptionV3, by adding nine extra layers at the end. These include three layers of batch normalization, three dropout layers, and three dense layers using LASSO regularization. The models were trained using an appropriate optimizer and early-stop regularization. The customized models effectively identified sugarcane diseases. Our evaluation metrics included recall, precision, f1-score, roc curves, and confusion matrices. The results indicate that the modified and regularized InceptionV3 outperformed previous approaches, achieving 97% of the matrices. Similarly, the modified DenseNet121 also showed improved performance, with 96% accuracy, precision, recall, and F1-score.

**Keywords:** sugarcane; DenseNet121, InceptionNetv3, Deep Learning.

## 1 Introduction

Plant diseases have long threatened agricultural productivity and plant growth worldwide, negatively impacting human food availability. Sugarcane farming is a structured sector of agriculture and is crucial globally due to its extensive applications. It is widely cultivated in Brazil, India, China, Thailand, Pakistan, Mexico, Colombia, and other countries, playing a major role in their economies [1]. In 2022, the global production of sugarcane reached 1.92 billion tons, with Brazil contributing 38%, India 23%, and China 5% [2]. Sugarcane provides a wealth of products, including food (sucrose,


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jiggery, and syrups), fiber (cellulose), fuel (bagasse, molasses, and green tops), and chemicals (alcohol and bagasse molasses). The primary byproducts of the cane sugar industry during sugar production are press mud, bagasse, and molasses [3]. However, diseases present a significant challenge, threatening global food security by negatively affecting production in agriculture.

Quick identification and proper management of these diseases are crucial to reducing their detrimental impact on production [4]. However, the lack of agriculturists and the prevalence of uneducated farmers often hinder timely intervention [5]. Deep learning-based artificial intelligence systems have emerged as an automatic technology for detecting sugarcane diseases.

In this research, we conducted an extensive analysis of sugarcane diseases and proposed an enhanced, accurate, and robust deep learning approach to identify sugarcane leaf diseases. Our study focused on four types of sugarcane diseases that severely affect crops in the Indian subcontinent: Mosaic, Red Rot, Rust, and Yellow [6]. We modified two prominent pre-trained models, DenseNet121 and InceptionV3, by incorporating nine additional layers. Hyperparameter tuning of LASSO regularization, batch normalization, dropout layers, and their optimal combination significantly improved our proposed model's performance. Early stopping and appropriate optimization techniques were employed during model training. By integrating these strategies, our proposed model achieved a 97% accuracy in classifying sugarcane diseases, the best results in our study when compared to the most advanced techniques. The following are this study's primary contributions:

- Scaling the dataset.
- Proposing a highly efficient L1-regularized model.
- Modifying the DesneNet121 & InceptionV3 by fine tuning and adding extra 9 layers.
- Introducing Early Stop, LASS, dropout regularization.
- Comparison between the modified DenseNet121 and InceptionV3.

A review of the literature on the classification of sugarcane diseases is included in the next portion of the manuscript. The third portion provided a review of the methodology employed along with a detailed description of the real sugarcane dataset that was used in this investigation. The experimental evaluation's results and analysis were provided in the fourth section. Section Five discusses conclusions and directions for future study.

## 2 Literature Review

Advanced deep learning and computer vision technologies have emerged as various promising solutions to the challenges of achieving the sustainability of agriculture. The researchers have been continuing their research in agriculture from a variety of angles, such as pest identification [7] and disease classification [8]. Similarly, several works on sugarcane disease classification have been performed by the researchers. Süleyman Öğrekçi et al. [9] compared three models, namely DenseNet121, ViT, and a hybrid of them, in the classification of sugar diseases. The models exhibited precisions of

92.87%, 93.34%, and 87.37%, respectively. The hybrid approach degraded the performance of classification. Cuimin et. al. [10] introduced SE-ViT, where the SE attention module was incorporated, and the models demonstrated 89.57% accuracy. Rahul Maurya et. al. [11] proposed a customized VGG16 model that attained an accuracy of 94.47% using the Adam optimizer. P. Aakash Kumar et. al. [12] classified sugarcane by whether the leaf is healthy or not. The author suggested VGG-16 and VGG-19, where VGG19 performed the best with an accuracy of 92% and precision of 90%. Deepak Banerjee et al. [13] used a three-layer CNN model for feature extraction of sugarcane diseases, and later SVM was used to classify. The approach achieved 81.53% accuracy. Ivan Grijalva et. al. [14] employed DenseNet 121, Resnet 50, Xception, and Inception v3 models to identify sugarcane leaf diseases, and with an accuracy rating of 86%, Inception v3 and Xception fared the best.

Recently, Swapnil et. al. [15] conducted a wide study on sugarcane disease dentification on a self-created dataset. The dataset has five categories (healthy, mosaic, redrot, rust, and yellow) with a total of 2569 images. The study concluded that the MobileNet-V2 model achieved 84% accuracy and the ensemble approach attained 86.53% accuracy. The accuracy and loss curves of this research showed overfitting. Later in April 2024, Swapnil et. al. [16] further conducted another analysis on the same dataset. The author proposed an attention-based multi-level residual convolutional neural network (AMRCNN) model to classify sugarcane diseases, which outperformed models such as XceptionNet, VGG19, ResNet50, and EfficientNet_B7 with an 86.53% accuracy rate. They also deployed the model in Android mobile applications.

The authors did not use any regularized techniques to reduce the overfitting. The DenseNet and Inception models were not applied to evaluate classification performance. The sensitivity analysis of those models was not included as well. Ensemble techniques are also time-consuming. There is also scope for performance improvement.

In our study, we addressed all those issues by applying L1, dropout, early stop regularization, the extra nine layers, and fine tuning of InceptionV3. A comparison has also been conducted with DenseNet 121. The modified version of that model has outperformed the previous study.

## 3 Research Methodology

Modified L1 regularized DenseNet121 and InceptionV3 models were developed, implemented, and evaluated in several stages. Data collection, pre-processing, training, and testing were managed using different techniques. The procedures are illustrated in Fig. 1.

### 3.1 Dataset Collection

The dataset is the key element in the deployment of machine learning models. In our study, we collected the dataset from a Kaggle trustworthy repository [17]. The five primary types of sugarcane leaf diseases—healthy, mosaic, red rot, rust, and yellow disease—have been painstakingly compiled into this collection. 2,569 images in all, spanning all categories, were taken using smartphones in a variety of setups to guarantee diversity. Maharashtra, India, was the location of this collection. The collection of images is well-balanced and has a wide range of images. The images are not all the same size since different technologies were used to capture them. Every image is in RGB format. The distribution of the sugarcane disease dataset is listed in Table 1, and visualization is shown in Fig. 2.

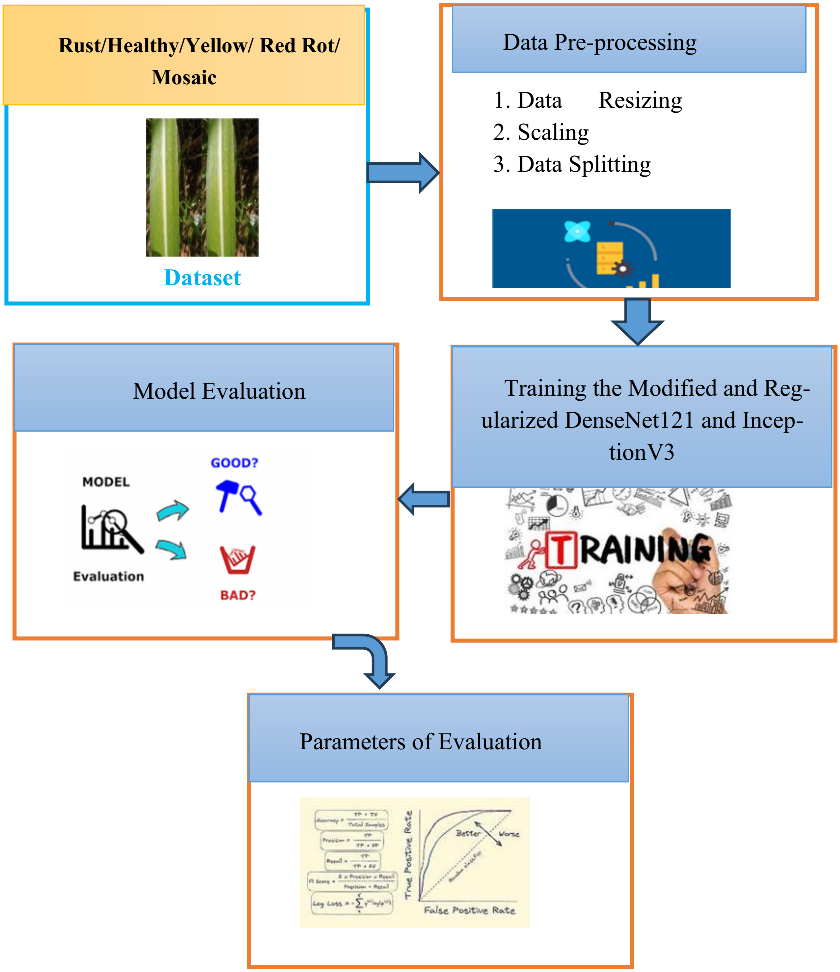


Fig. 1. Workflow our approach (created by author(s))

Fig.2. Physical appearance of our dataset (created by author(s))

Table 1. Distribution of sugarcane dataset (created by author(s))

| Class Name | Number of Images | % of amount |
|---|---|---|
| Healthy | 520 | 20.24 |
| Mosaic | 514 | 20.7 |
| RedRot | 519 | 20.20 |
| Rust | 505 | 19.65 |
| Yellow | 511 | 19.89 |
| Total | 2569 | 100 |

### 3.2 Data Pre-processing

Data pre-processing is an important phase of machine learning model implementation. In our study, data resizing, scaling, and data splitting were performed. The images of each class were resized to 224 x 224 by using the image.resize() function of Python. Then the image was scaled by dividing 255 by each. Finally, the dataset was divided 70:30 into training and testing groups.

### 3.3 Proposed Approach

In our study, a modified transfer learning approach was applied to classify sugarcane diseases. Transfer learning is a strategy that solves a similar type of problem by

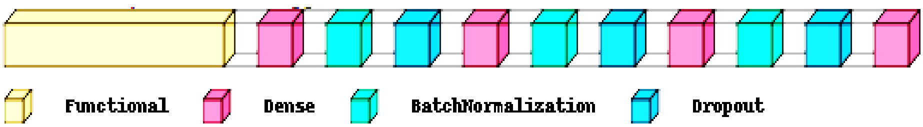


Fig.3. Proposed Modified TL model (created by author(s))

using the knowledge that has already been gained in solving other issues. We customized two prominent pre-trained models called DesneNet121 and InceptionV3 by adding an extra nine layers beneath the models. Three batch normalization layers, three dense layers with LASSO regularization (0.0001), and three dropout layers (0.3) are the additional layers that are widely impacted to reduce model overfitting and optimize the training processing. The modified version of the TL model is illustrated in Fig. 3. The models were learned using RMSprop optimization (learning rate 0.001) and categorical cross-entropy. The equation of the loss function can be defined as follows:

$$CE = -\sum_{i}^{C} t_i \log\left(\sigma(z)_i\right) \quad (1)$$

Where, $t_i$ is the ground truth and the CNN score for each class $i$ in $C$. $\sigma(z)_i$ is the activation function.

Additionally, the models were trained up to 100 epochs using early stop regularization, where the monitor was validation loss. And patience was 7. The model parameters are summarized in Tables 2 and 3. Trainable and non-trainable parameters of the customized model are presented in Table 4.

Table 2. Parameter modified inceptonv3 (created by author(s))

| Name of the Layer (type) | Output Shape | Parameters |
|---|---|---|
| Inception_v3 (Functional) | (None, 2048) | 21,802,784 |
| dense_19 (Dense) | (None, 128) | 262,272 |
| batch_normalization_579 (BatchNormalization) | (None, 128) | 512 |
| dropout_12 (Dropout) | (None, 128) | 0 |
| dense_20 (Dense) | (None, 64) | 8,256 |
| batch_normalization_580 (BatchNormalization) | (None, 64) | 256 |
| dropout_13 (Dropout) | (None, 64) | 0 |
| dense_21 (Dense) | (None, 32) | 2,080 |
| batch_normalization_581 (BatchNormalization) | (None, 32) | 128 |
| dropout_14 (Dropout) | (None, 32) | 0 |
| dense_22 (Dense) | (None, 5) | 165 |

Table 3. Parameter modified densenet121 (created by author(s))

| Name of the Layer (type) | Output Shape | Parameters |
|---|---|---|
| densenet121 (Functional) | (None, 2048) | 7,037,504 |
| dense_19 (Dense) | (None, 128) | 131,200 |
| batch_normalization_579 (BatchNormalization) | (None, 128) | 512 |
| dropout_12 (Dropout) | (None, 128) | 0 |
| dense_20 (Dense) | (None, 64) | 8,256 |
| batch_normalization_580 (BatchNormalization) | (None, 64) | 256 |
| dropout_13 (Dropout) | (None, 64) | 0 |
| dense_21 (Dense) | (None, 32) | 2,080 |
| batch_normalization_581 (BatchNormalization) | (None, 32) | 128 |
| dropout_14 (Dropout) | (None, 32) | 0 |
| dense_22 (Dense) | (None, 5) | 165 |

Table 4. Transfer learning parameters (created by author(s))

| Model Names | Trainable parameters | Non-trainable parameter | Optimizer parameter | Total |
|---|---|---|---|---|
| Modified Dense-Net121 | 7,096,005 | 84,096 | 7,096,005 | 14,276,108 |
| Modified InceptionV3 | 22,041,575 | 34,880 | 22,041,575 | 44,118,028 |

## 3.4 Evaluation Parameter

The models were evaluated using the following parameters from equation (2-5).

$$\text{Accuracy} = \frac{True\ Positive + False\ Negative}{all} \tag{2}$$

$$\text{F1 score} = 2 * \frac{1}{\frac{1}{\text{precision}} + \frac{1}{\text{Recall}}} \tag{3}$$

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ positive} \tag{4}$$

$$\text{Recall}=\frac{True\ Positive}{True\ Positive+False\ negative} \tag{5}$$

# 4 Data Analysis

The research has been performed in the Google Collaboratory using Python programming, integrating TensorFlow, Keras, Pandas, and the OpenCV library. The findings from the experiment have been analyzed and discussed in this section.

## 4.1 Results from Modified DesNet121

The modified DenseNet121 model was trained over 100 epochs, but early stop regularization allowed us to reach 43 epochs. The accuracy and loss curves for training and validation are depicted in Fig. 4. The accuracy curves for both training and validation increased exponentially, reaching 99.26% and 96.04%, respectively. The loss curves showed a reduction, with training loss at 0.4069 and validation loss at 0.4492, indicating that the model trained the data to the desired level.

The class-wise and overall performance of the model were calculated using available metrics, as listed in Tables 5 and 6, respectively. Recall, precision, F1-score, and accuracy for each class ranged from 94% to 98%. Overall, both micro and weighted average recall, precision, accuracy and F1-score were 96% for classifying sugarcane diseases. The confusion matrix for this model, shown in Fig. 5, indicates that the model correctly classified 730 out of 757 cases. The true positive and false positive rates, along with the visual output of the model's predictions, were analyzed in Figs. 6 and 7. The ROC curves approach (0,1), and the prediction confidence is also at a significant level.

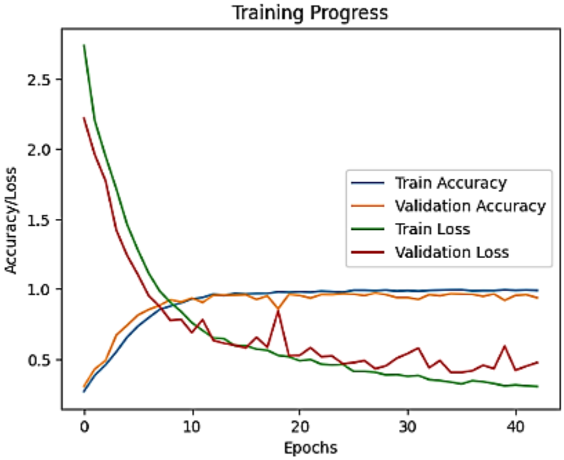


Fig.4. Accuracy and loss curves of modified DenseNet121 (created by author(s))

Table 5. Performance of modified desnenet121 in class wise (created by author(s))

| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Class 0-(healthy) | 0.97 | 0.99 | 0.98 |
| Class 1-(Mosaic) | 0.94 | 0.96 | 0.95 |
| Class 2-(RedRot) | 0.98 | 0.97 | 0.97 |
| Class 3-(Rust) | 0.98 | 0.96 | 0.97 |
| Class 4-(Yellow) | 0.95 | 0.95 | 0.95 |

Table 6. Overall performance of modified densenet121 (created by author(s))

| Average | Precision | Recall | F1-Score | Accuracy | Sup-port |
|---|---|---|---|---|---|
| Micro Avg. | 0.96 | 0.96 | 0.96 | 0.96 | 757 |
| Weighted Avg. | 0.96 | 0.96 | 0.96 | | 757 |

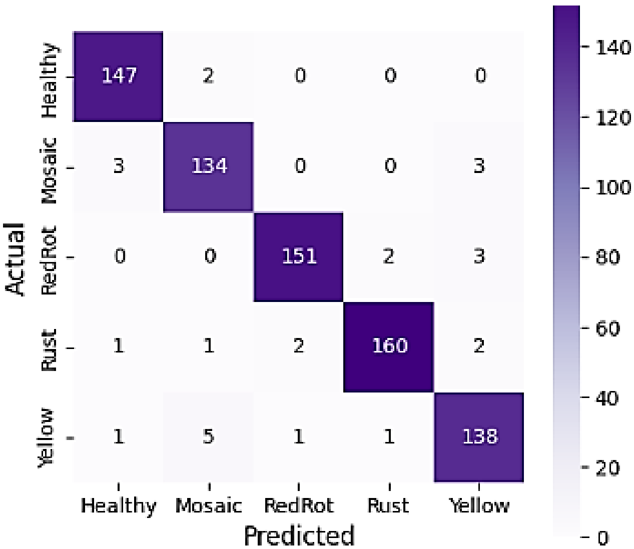


Fig.5. Confusion Matrix of Modified densenet121 (created by author(s))

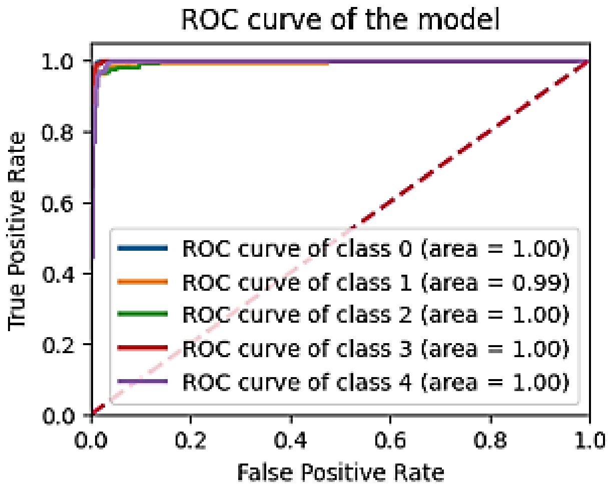


Fig. 6. ROC curve of Modified densenet121 (created by author(s))

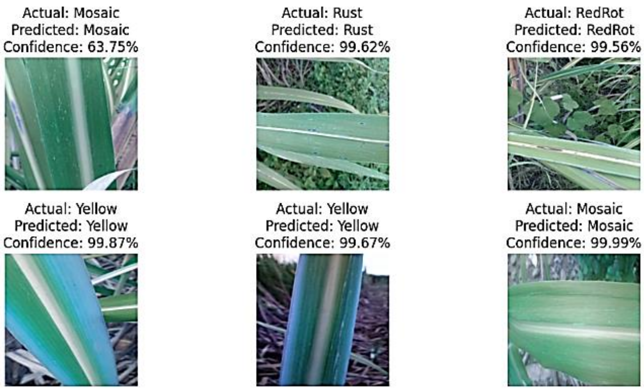


Fig. 7. Visual prediction output of Modified DenseNet121 (created by author(s))

### 4.2 Results of Modified InceptionV3

The outcomes of the modified InceptionV3 model are analyzed in this subsection. The model was trained for up to 100 epochs, but early stop regularization terminated it at 76 epochs. The loss and accuracy curves of the modified InceptionV3 are illustrated in Fig. 8. The curves are optimally fitted, with accuracy reaching 0.9952 (training) and 0.9709 (validation). The loss curves decreased to 0.2674 (training) and 0.3564 (validation). Class-wise and overall performance metrics are shown in Tables 7 and 8. Class-wise performance ranges from 95% to 99%. Overall, recall, precision, F1-score, and accuracy are 97%, which is the highest compared to the modified DenseNet121 and previous studies. The confusion matrix of the model, depicted in Fig. 9, indicates that the model correctly classified 738 out of 757 cases, demonstrating impressive performance. The sensitivity is analyzed using ROC curves, shown in Fig. 10, presenting the true positive and false positive rates. The curve is close to the (0,1) coordinate, indicating high sensitivity. The visual output of predictions in Fig. 11 displays the prediction confidence and classification correctness. A comparative summary with previous studies is presented in Table 9, clearly demonstrating the superior performance of our proposed approach on the same dataset.

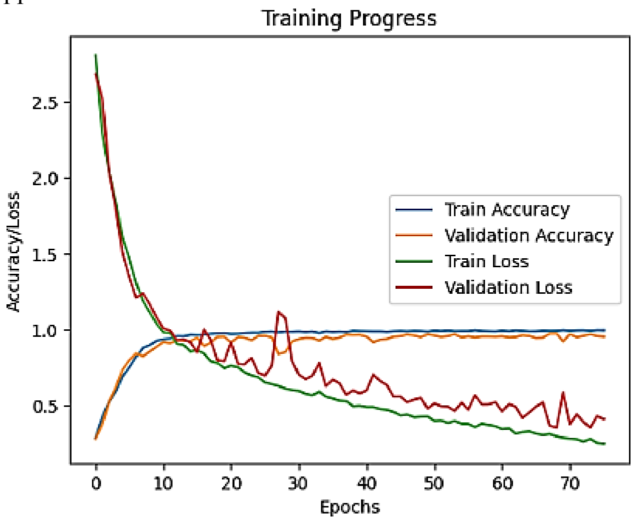


Fig.8. Accuracy and loss curves of modified InceptionV3 (created by author(s))

Table 7. Performance of modified inceptionv3 in class wise (created by author(s))

| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Class 0-(healthy) | 0.95 | 0.99 | 0.97 |
| Class 1-(Mosaic) | 0.98 | 0.97 | 0.97 |
| Class 2-(RedRot) | 0.99 | 0.97 | 0.98 |
| Class 3-(Rust) | 0.98 | 0.99 | 0.98 |
| Class 4-(Yellow) | 0.97 | 0.96 | 0.97 |

Table 8. Overall performance of modified inceptionv3 (created by author(s))

| Average | Precision | Recall | F1-Score | Accuracy | Support |
|---|---|---|---|---|---|
| Micro Avg. | 0. 97 | 0.97 | 0.97 | 0.97 | 757 |
| Weighted Avg | 0. 98 | 0.97 | 0.97 | | 757 |

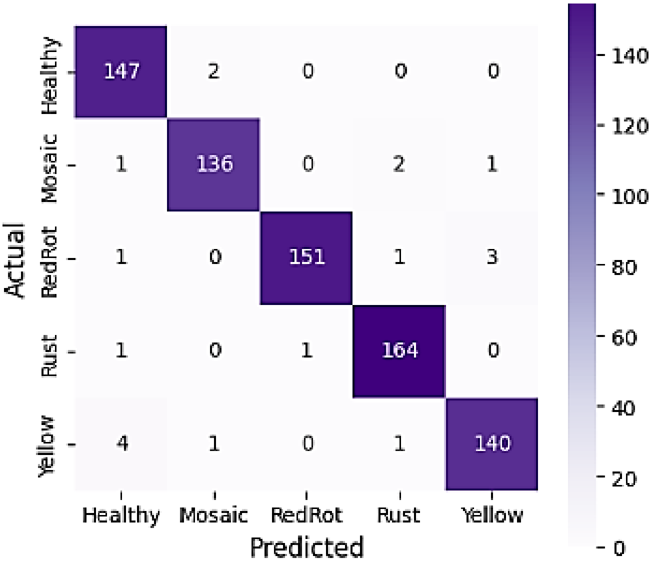


Fig.9. Confusion Matrix of Modified InceptionV3 (created by author(s))

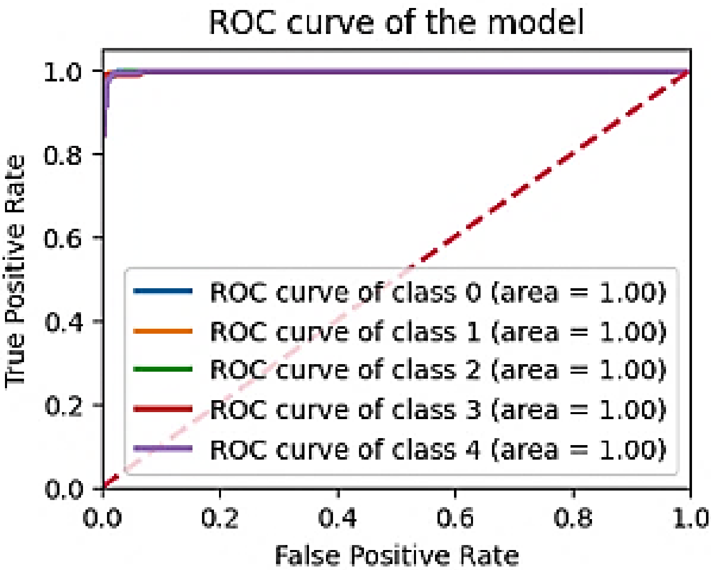


Fig. 10. ROC curves of Modified InceptionV3 (created by author(s)

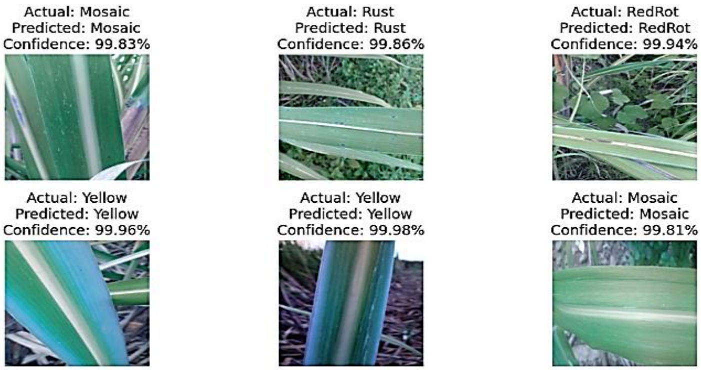


Fig.11. Visual prediction output of Modified InceptionV3.

Table 9. Comparison of our study with the previous (created by author(s))

| **Model** | **Published Time** | **Preci-sion (%)** | **Re-call (%)** | **F1-Score (%)** | **Accu-racy (%)** |
|---|---|---|---|---|---|
| [15] | 24 July 2023 | - | - | - | **86.53** |
| [16] | 16 April 2024 | 86.34 | 82.32 | 83.15 | 86.53 |
| Our proposed (Modified dense-Net121 | - | 96.00 | 96.00 | 96.00 | 96.00 |
| Our proposed (Modified Incep-tionV3) | - | 97.00 | 97.00 | 97.00 | 97.00 |

## 5 Conclusion and Discussion

The study on sugarcane disease classification has yielded successful results. Our proposed modifications to DenseNet121 and InceptionV3 have demonstrated impressive performance in classifying the test data. Specifically, the recall, precision, F1-score, and accuracy for modified DenseNet121 and InceptionV3 are 96% and 97%, respectively. These results were achieved by incorporating nine additional layers, LASSO regularization, dropout layers, normalization, optimization, and early stopping regularization. The models were thoroughly evaluated using the confusion matrix, ROC curve, and output visualization with confidence scores. A comparative analysis with recent studies further highlights the effectiveness of our approach.

## 6 Future Work

Limitations are an intrinsic feature of research, and our work is no exception. We did not perform clinical testing as part of this investigation, and our data size is limited. For future work, the dataset can be expanded and diversified, and efforts can be made to incorporate explainable AI techniques. Additionally, researchers can explore the development of industry-specific mobile applications based on this study and can conduct an extensive test in real time.

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