Sugarcane Leaf Disease Detection: A Comparative Analysis Using Deep Learning

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Abstract

In this paper, sugarcane leaf diseases were detected through image analysis. This research investigated the effectiveness of four deep learning models, ResNet101, DenseNet161, MobileNetV2, and AlexNet, for sugarcane leaf disease detection. A dataset of sugarcane leaf images was categorized into healthy and various disease classes, and those models were trained and validated on that dataset. The result demonstrated a superior performance which achieved a validation accuracy of 97.41% and a validation loss of 0.0902 by DenseNet161, whereas ResNet101 attained a slightly lower outcome with a validation accuracy of 97.21% and a validation loss of 0.0971. A validation accuracy of 95.82% and a validation loss of 0.1541 were obtained using MobileNetV2. AlexNet obtained the lowest performance with a validation accuracy of 91.43%, and a validation loss of 0.2505, and its performance evaluation was the lowest compared to other models. DenseNet161 and ResNet101 showed high accuracy and low loss for sugarcane leaf disease detection.

CCS Concepts

• **Computing methodologies → Interest point and salient region detections**; *Artificial intelligence*; *Computer vision*; Computer vision problems; Interest point and salient region detections.

Keywords

Agriculture, AlexNet, CNN, DenseNet161, Deep learning, Disease Detection, Leaf Disease, MobileNetV2, ResNet101, Sugarcane Leaf

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1 Introduction

Sugarcane has an economic influence as a cash crop and timely detection of sugarcane leaf diseases is vital for crop production. This study aims to use pre-trained models to execute comparative deep-learning model training to detect sugarcane leaf diseases through image pattern analysis. Early detection prevents pesticide control and saves yield loss ensuring better sustainability for sugarcane farming.

Moreover, Sugarcane diseases have been diagnosed using different methods, such as Artificial Neural Networks, Case-Based Reasoning, and Neuro-Fuzzy. These methods produce instant solutions for farmers and enrich crop yield production [1].

This paper introduces a pre-trained model to detect sugarcane leaf diseases with the highest accuracy and efficiency. The majority of the research has focused on a single model. Here, multiple models have been introduced to evaluate the result and produce a comparative analysis for the optimum result. Deep learning techniques such as ResNet101, DenseNet161, MobileNetV2, and AlexNet models have been applied over a comprehensive dataset to achieve high precision in disease identification. This dataset is a manually collected image dataset of sugarcane leaf disease in Maharashtra, India. It has five main categories, those are Healthy, Mosaic, Redrot, Rust and Yellow Disease. Moreover, a web application has been integrated to detect sugarcane leaf diseases in the real world.

The rest of the paper is organized as follows: Section 2 describes the related works. The methodology is briefly discussed in Section 3, and results and discussion are presented in Section 4. Finally, the conclusion is in Section 5.

2 Related Work

In this literature section, numerous models have been applied and studied to explore sugarcane leaf disease based on different research works. Enormous progress has been noticeable in this field at current times.

Simoes et al. represent an automated identification and classification method for image analysis of rust on sugarcane leaves. It overcomes the limitations of visual approximation [2]. Daphal and Koli et al. propose an integrated model with transfer learning methods and an ensemble deep learning tactic. It improves disease classification accuracy and minimizes computational expenses [3]. Demilie et al. present the detection mechanism of plant disease using the CNNs architecture to improve farming by independently extracting relevant patterns [4]. Kotekan et al. present ConvNet, a sophisticated deep-learning model that transforms disease management and mitigates yield losses via automated detection of sugarcane diseases [5]. Li et al. explore a fusion network and lightweight Vision Transformer called SLViT, that integrates with a Shuffle-convolution-based lightweight CNN. It is recognized for its speed, efficacy and precision in sugarcane leaf disease identification [6]. Murugeswari et al. introduce the combined approach of Faster RCNN with CNN architectures for automatic sugarcane disease detection that boosts the accuracy of disease recognition and decreases possible threats in the sugarcane industry [7].

Pawar et al. present a CNN algorithm with 15 layers that accurately detects and classifies leaf diseases. It offers custom-made smart pesticide recommendations[8]. Saxena and Rathor et al. introduce ensemble frameworks by integrating CNN and Random Forest classifier. It produces robust agricultural solutions and automates plant disease detection in India [10]. Sharma and Kukreja et al. propose an MLP-based model for Sugarcane Red Rot (SRR) disease that is significant for crop management [11]. Tanwar et al. introduce a yield prediction model for sugarcane diseases that merges CNN and SVM [12]. Tanwar et al. represent a deep learning model with robust architecture and categorizes sugarcane leaf diseases precisely. This works as a tool for disease identification [13]. Vignesh and Chokkalingam et al. introduce a hybrid model by integrating CNN and SVM. With an accuracy of 97.45%, it can play a vital role in reducing crop loss and ensuring food security [14].

3 Methodology

The dataset contains a manual collection of images including several types of sugarcane leaf diseases and their categories such as Healthy, Mosaic, Redrot, Rust, and Yellow disease. The dataset has 2,521 images which are captured using smartphones of varied configurations to ensure diversity [9]. Originating from Maharashtra, India, the dataset is well-balanced and offers various samples. Multiple devices have been used to capture the image resulting in variations of image size but all in RGB format.

The below steps have been followed during the training and validation. A flowchart of sugarcane leaf disease detection is given in figure 1.

- `Data Partitioning`: The dataset is split into 80% training and 20% validation.
- `Model Training`: SGD optimization has been used to train the models.
- `Hyperparameter Tuning`: It makes sure optimal performance. A learning rate of 0.001 is used to provide stable convergence and a momentum of 0.9 is selected for quick optimization and it reduces gradient descent instability. Hyperparameter adjustment is essential to maximize model performance through effective learning and enhanced generalization.
- `Validation`: It checks the performance on the validation set to avoid the impact of over-fitting.

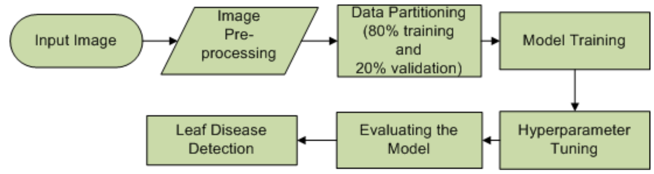

Figure 1: Flowchart of Sugarcane Leaf Disease Detection

Table 1: Dataset Description

Sugarcane leaf disease Category	No. of images
`Healthy`	522 files
`Mosaic`	462 files
`RedRot`	518 files
`Rust`	514 files
`Yellow`	505 files
Total	2521 images

Model preprocessing is very crucial before performing any model training. Images have been resized to 256x256 pixels and then center-cropped to 224x224 pixels for consistency. Pixel values are normalized using the mean of [0.485, 0.456, 0.406] and a standard deviation of [0.229, 0.224, 0.225] from the ImageNet dataset. The DenseNet161, ResNet101, MobileNetV2, and AlexNet models have been preferred as the deep learning architecture for disease detection. Chosen models are renowned for their dense connectivity pattern, which facilitates efficient feature reuse and enables deeper networks without encountering vanishing-gradient problems. And they perform top-notch.

DenseNet161 is selected for its dense connectivity pattern which enables efficient feature reuse and deeper network training without the issue of vanishing gradients and captures complex representations of sugarcane leaf diseases.

ResNet101, a chosen architecture for disease detection, is a CNN acclaimed for its deep structure and skip connections. It addresses the vanishing-gradient issues and enables the training of deep networks. This neural network is good for sugarcane leaf diseases, where capturing complex patterns is crucial.

AlexNet, is a deep learning model structure that is constructed with convolutional layers followed by max-pooling layers. It allows the capture of hierarchical features. This supports its learning and recognition of small differences in sugarcane leaf diseases more accurately which makes it better at spotting these diseases.

MobileNetV2 has a lightweight architecture with depth-wise separable convolutions and linear bottlenecks which optimizes computational efficiency. It is 53 layers deep. It employs an inverted residual structure that helps maintain accuracy and reduces the number of parameters and computations. This architecture helps for real-time, on-device detection and classification of sugarcane leaf diseases, resulting in prompt and accurate management of crop health.

The DenseNet161, ResNet101, MobileNetV2, and AlexNet models are trained on a sugarcane leaf disease dataset and classify the images into various diseases. Training involves providing the image batches with corresponding labels. The model learns through backpropagation and gradient descent. DenseNet161, ResNet101, MobileNetV2 and AlexNet have been trained and evaluated effectively by applying those methods while training for sugarcane leaf disease detection.

4 Results and Discussion

The dataset splits into training and validation. During training, selected hyperparameters are learning rate (lr=0.001), momentum (0.9), and batch size (32). It provides optimized performance and prevents over-fitting with these fine-tuned values. The learning rate makes sure better convergence and momentum speed up optimization. 10 epochs have been executed to achieve sufficient training without excessive over-fitting. To reduce over-fitting, dropout rates (p=0.5, inplace=False) in AlexNet and (p=0.2, inplace=False) in MobileNetV2 are used. Neurons are randomly deactivated via dropout rates, which vary according to the network's capacity and complexities. Because AlexNet has more parameters than other networks, it has a greater dropout rate in this case, which reduces over-fitting. Collaborating with over-fitting techniques and hyper-parameter tuning has played a crucial role in ensuring model performance and robustness.

In Figure 2, the graph shows the training and validation accuracy over ten epochs of four models (AlexNet, DenseNet161, ResNet101, and MobileNetV2). The accuracy (%) is shown on the y-axis, while the number of epochs is indicated on the x-axis. AlexNet train accuracy (blue line) starts at 65.82% at the initial epoch, improves over epochs, and finally achieves 99.46%, whereas AlexNet validation accuracy (orange line) steadily achieves 91.43% by the 10th epoch. DenseNet161 train accuracy (green line) begins around 66.82%, improves quickly, and achieves 99.55%, whereas DenseNet161 validation accuracy (red line) is 97.41% by the 10th epoch. ResNet101 train accuracy (purple line) starts at about 66.77%, rises steadily over epochs, and achieves 99.46% whereas ResNet101 validation accuracy (brown line) is 97.21% by the 10th epoch. MobileNetV2 train accuracy (pink line) initially starts at 44.63%, increases steadily over epochs, and reaches 96.98% whereas MobileNetV2 validation accuracy (ash line) is 95.82% by the 10th epoch. From here, ResNet101 and DenseNet161 exhibit the highest validation accuracy compared to other models.

In Figure 3, the graph shows the training and validation loss over ten epochs of the above four models. In y-axis, the loss is shown and in x-axis, the number of epochs is shown. Initially, the AlexNet train loss (blue line) starts at 0.8474, and the loss reduces to 0.0180. The AlexNet validation loss (orange line) stabilizes around 0.2505. Initially, the DenseNet161 train loss (green line) begins at 0.9449, and the loss reduces to 0.0277. The DenseNet161 validation loss (red line) is very low and remains around 0.0902. Initially, the ResNet101 train loss (purple line) is 0.9431, and the loss reduces to 0.0379. The ResNet101 validation loss (brown line) stabilizes around 0.0971. Initially, the MobileNetV2 train loss (pink line) is 1.4660, and the loss reduces to 0.1196. The MobileNetV2 validation loss (ash line) fluctuates and is around 0.1541. DenseNet161 and ResNet101 exhibit the lowest validation loss by the last epoch.

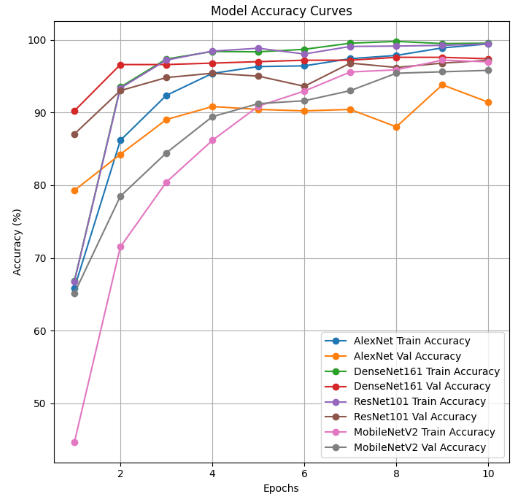

Figure 2: Accuracy over Epochs using Different Models

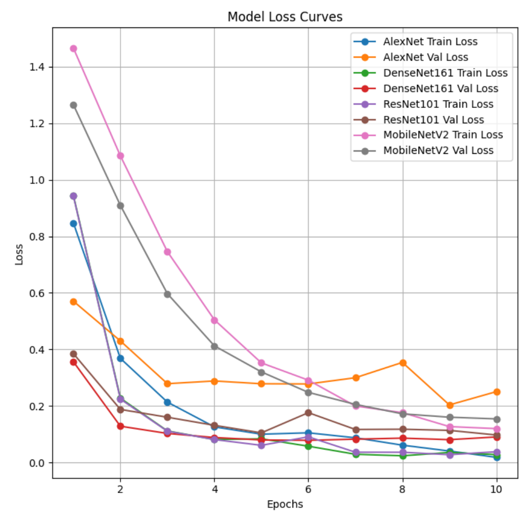

Figure 3: Loss over Epochs using Different Models

In Table 2, the classification report is shown.

Train Accuracy: This metric generates the ratio of accurately predicted training instances to the total number of train instances. The accuracy of DenseNet161 (99.55%) is performing slightly better compared to ResNet101 (99.46%) and AlexNet (99.46%). MobileNetV2 has the lowest training accuracy of 96.98%.

Train Loss: This is the way to measure the error between predicted and actual values during model training. The loss of AlexNet (1.80%) has been reduced better compared to DenseNet161 (2.77%), ResNet101 (3.79%), and MobileNetV2 (11.96%).

Validation Accuracy: This metric generates the ratio of accurately predicted validation instances to the total number of validation instances. The accuracy of DenseNet161 (97.41%) is slightly better

Table 2: Classification Report

Parameters	DenseNet161(%)	ResNet101(%)	AlexNet(%)	MobileNetV2(%)
Train Accuracy	99.55%	99.46%	99.46%	96.98%
Train Loss	2.77%	3.79%	1.80%	11.96%
Validation Accuracy	97.41%	97.21%	91.43%	95.82%
Validation Loss	9.02%	9.71%	25.05%	15.41%
Precision (wgt. avg)	98.00%	97.00%	92.00%	96.00%
Recall (wgt. avg)	97.00%	97.00%	91.00%	96.00%
F1-Score (wgt. avg)	97.00%	97.00%	91.00%	96.00%

as compared to ResNet101 (97.21%), MobileNetV2 (95.82%) and AlexNet (91.43%) is the lowest.

Validation Loss: The measure of error between predicted and actual values during model testing/validating. The loss of DenseNet161 (9.02%) has been reduced better compared to ResNet101 (9.71%), MobileNetV2 (15.41%), and AlexNet (25.05%).

Precision: Proportion of true positives among all positive predictions for a class. The weighted average precision is 98% in DenseNet161, 97% in ResNet101, 92% in AlexNet, and 96% in MobileNetV2.

Recall: This is the way to calculate the proportion of true positives for a class out of all actual positives. The weighted average recall is 97% for both DenseNet161 and ResNet101. The weighted average recall of AlexNet and MobileNetV2 is 91% and 96% respectively.

F1-score: This is the way to calculate the harmonic mean of precision and recall, indicating a balance between the two metrics. Both DenseNet161 and ResNet101 have 97% weighted avg. F1-Score. In the case of AlexNet, it is 91% and MobileNetV2 has 96%.

Confusion Matrix:

The confusion matrix table represents the performance of the model prediction of each class accurately or not. The confusion matrix breakdown is given below:

Classes: The rows and columns represent the five classes of sugarcane leaf disease: healthy, mosaic, red, rot, rust, and yellow. Here, the x-axis refers to predicted classes, and the y-axis refers to actual classes.

Diagonal: The highest values represent diagonally, specifying correct classifications. In this matrix, good numbers have been observed on the diagonal section, and there are also some off-diagonal values.

Off-diagonal: These cells represent the count of misclassified images.

Confusion Matrix for DenseNet161 Model:

In Figure 4, the confusion matrix displays classification performance for five sugarcane leaf disease classes. That shows the accurate classification of healthy (104/104), mosaic (89/92), red rot (101/103), rust (101/102) and yellow (94/101) images. However, most of the misclassified images(7) of different classes exhibit confusion with the yellow class.

Confusion Matrix for ResNet101 Model:

In Figure 5, the confusion matrix displays classification performance for five sugarcane leaf disease classes. That shows the accurate classification of Healthy (104/104), Mosaic (87/92), Red Rot (102/103), Rust (98/102) and Yellow (97/101) images. However, most of the misclassified images (5) of the Mosaic class exhibit confusion with the Healthy class.

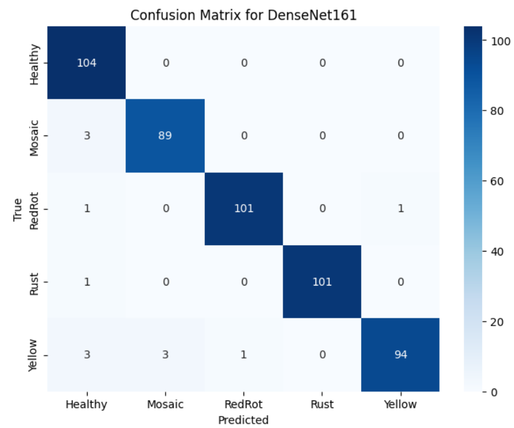

Figure 4: Confusion Matrix using DenseNet161 Model

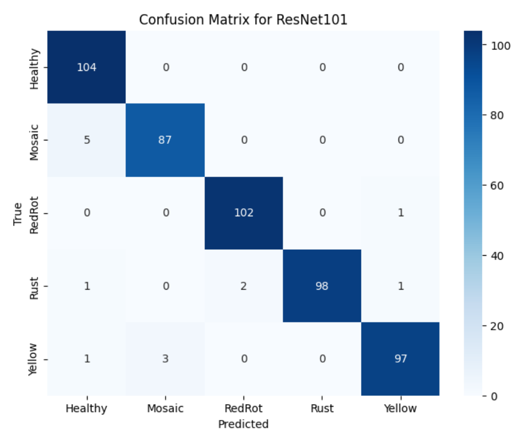

Figure 5: Confusion Matrix using ResNet101 Model

Confusion Matrix for AlexNet Model:

In Figure 6, the confusion matrix displays classification performance for five sugarcane leaf disease classes. That shows the accurate classification of Healthy (95/104), Mosaic (79/92), Red Rot (98/103), Rust (94/102) and Yellow (93/101) images. However, most of the misclassified images (13) of different classes exhibit confusion with Mosaic. However, there are misclassified images for the Healthy (9) class. Misclassified images of Rust (8) and Yellow (8) also display confusion with different classes and there are 43 misclassified images overall.

Confusion Matrix for MobileNetV2 Model:

In figure 7, the confusion matrix displays classification performance for five different classes of sugarcane leaf diseases. That shows the accurate classification of Healthy (104/104), Mosaic (82/92), Red Rot (101/103), Rust (99/102) and Yellow (95/101) images. However, most of the misclassified images (9) of the Mosaic class exhibit confusion with the Healthy class and Mosaic has 10 misclassified images. Misclassified images (6) of Yellow are showing confusion with multiple classes.

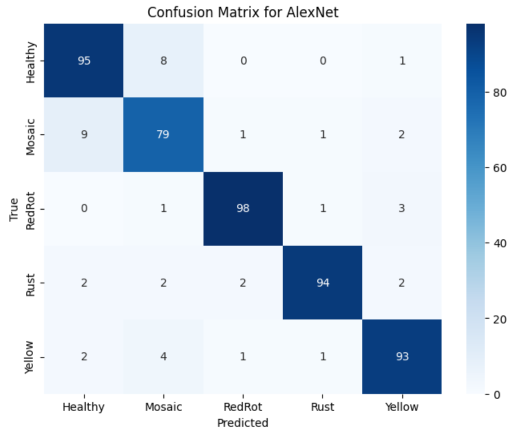

Figure 6: Confusion Matrix using AlexNet Model

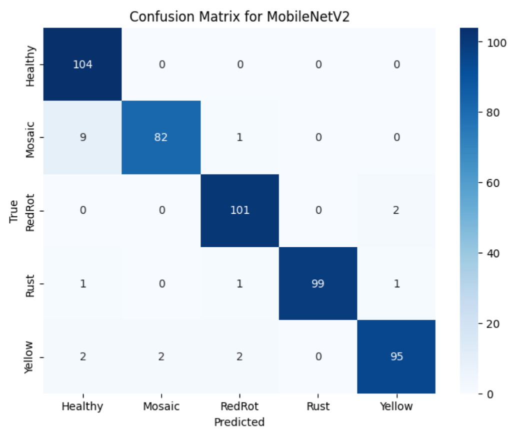

Figure 7: Confusion Matrix using MobileNetV2 Model

An enhanced investigation could be performed to identify the confusion caused by misclassification. Furthermore, accuracy can be enhanced by collecting additional data.

Comparison Report:

In Figure 8, the comparison graph shows the performance of four different deep-learning model models (DenseNet161, AlexNet, ResNet101 and MobileNetV2). The x-axis represents the evaluation metrics such as precision, recall, F1-score, and accuracy of all four models for sugarcane leaf disease detection. The y-axis shows the score for each metric of those corresponding models in different colors.

DenseNet161 has achieved the highest accuracy (97.41%) and the highest F1-Score (97.00%). ResNet101 achieves the second-highest accuracy (97.21%) with the highest F1-Score (97.00%), like DenseNet161. MobileNetV2 has the third-highest accuracy (95.82%) and F1-Score is 96%. However, AlexNet is among the lowest with an accuracy of 91.43% and F1-Score of 91.00%. Finally, DenseNet161 outperforms the other 3 models.

Implementation of web Application:

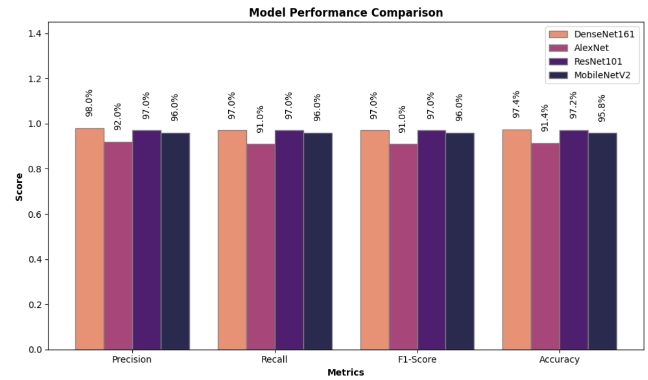

Figure 8: Comparison Report between DenseNet161, AlexNet, ResNet101 and MobileNetV2 Models

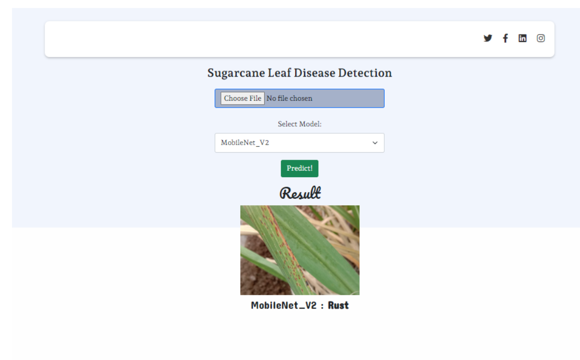

Figure 9: Implementation of web Application

A web application has been developed to upload images of a sugarcane leaf for disease prediction. Here, a user has chosen the MobileNetV2 model, and the outcome is "Rust". MobileNetV2 has successfully detected that disease in the sugarcane leaf. Hence, the application has the ability to detect sugarcane leaf diseases.

This application has been implemented for four models, such as ResNet10, DenseNet161, MobileNetV2, and AlexNet, for sugarcane leaf disease detection and offers significant advantages to farming. Early disease identification (accurately) can help farmers with timely interventions, protect crops, and improve yield quality. Financial sustainability of Sugarcane farming and food safety are very crucial and this can make sure that process. The application reveals the ability to detect sugarcane leaf diseases. This research can be extended further for other crops and inspire the development of similar types of applications across the farming sectors.

5 Conclusion

This research paper demonstrates the performance and effectiveness of ResNet101, DenseNet161, MobileNetV2, and AlexNet deep learning models for detecting sugarcane leaf disease. DenseNet161 produces the highest validation accuracy at 97.41% with a low validation loss of 0.0902. ResNet101 represents better performance as well, where the validation accuracy is 97.21% with a validation loss of 0.0971. It is also mentionable here that MobileNetV2 achieves a validation accuracy and validation loss of 95.82% and 0.1541 accordingly. In comparison, AlexNet has a lower accuracy (91.43%) and a higher validation loss (0.2505). Therefore, these particular outcomes referred to the extraordinary potentiality of DenseNet161 and ResNet101 for real-world applications in sugarcane disease detection. In addition, with this achievement of better accuracy, they could accurately distinguish between healthy and diseased leaves. Furthermore, model performance can be enhanced by introducing dropout and data augmentation methods. Dropout deactivates certain neurons whereas data augmentation generates images on the fly based on existing samples while training. Future research can be extended further by integrating more classes and high-resolution photos. In addition, transfer learning with pre-trained models can be introduced to see the influence of their performance.

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