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Sugarcane Crop Disease Detection

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Abstract

Sugarcane is the crucial crop in the world, and the many diseases are impacted on this crop. Early disease detection of the crop is the important for the preventing losses of the yield. This research proposes a deep learning based approach for the detecting diseases of the sugarcane using the DenseNet and Sequential models. This pre-trained model uses the convolutional neural networks (CNNs) to extract features from the sugarcane images and classify them into the different diseases based on their features. The Sequential model achieves the high accuracy i.e. 94% while the DenseNet achieves the 75% accuracy. These result shows that this models can effectively detect the diseases of the sugarcane crop which is helpful for the preventing the disease spread and the reduce the yield losses. Sugarcane is a vital crop worldwide, and its production is severely impacted by various diseases. Early detection of these diseases is crucial for preventing significant yield losses. This research proposes a deep learning-based approach for detecting sugarcane crop diseases using DenseNet and Sequential models. The proposed models utilize convolutional neural networks (CNNs) to extract features from sugarcane images and classify them into different disease categories. The DenseNet model achieves a high accuracy of 75%, while the Sequential model attains an accuracy of 94%. The results demonstrate that the proposed models can effectively detect sugarcane crop diseases, enabling farmers and agricultural experts to take timely measures to prevent disease spread and reduce yield losses. This research contributes to the development of precision agriculture techniques, promoting sustainable and efficient sugarcane production.

Introduction

Sugarcane is a fundamental crop for the many countries, which are farmers can faces a many challenges, including the diseases that reduces the yields and affects on the crop quality. For the reducing financial loss, food quality and supporting the farmers it is essential to detect the diseases at the early stage. Traditional methods such as visual inspections, can takes longer time to detect the diseases due to that the farmers suffer from the financial loss. However, Now-a-days the advanced technologies are available to detecting the diseases using the image classification by deep learning. In deep learning the images are analyzed for identifying the diseases such as rust, leaf spot, red rot and etc. By analyzing the images of the infected plants, models can learn patterns and detect diseases correctly. So, the farmers can takes early actions for reducing the crop losses and enhancing the healthy sugarcane growth. For some reasons it is important to detecting the sugarcane disease in early stage. Firstly it helps to prevent the spread of the disease and also maintaining the ecosystem health. Secondly early detection is helps for getting the solution and treatment and minimizing the economical losses for the farmers. This research shows a deep learning based approach for detection sugarcane crop diseases using CNN architectures such as DenseNet and Sequential models. The main aim is to identify accurately the sugarcane diseases by passing images. Also this research contributes to the development of the agriculture techniques, and improving the sustainable and efficient sugarcane production. The performance of the models can be evaluated by the dataset of the sugarcane images, and result will be compared to existing methods.

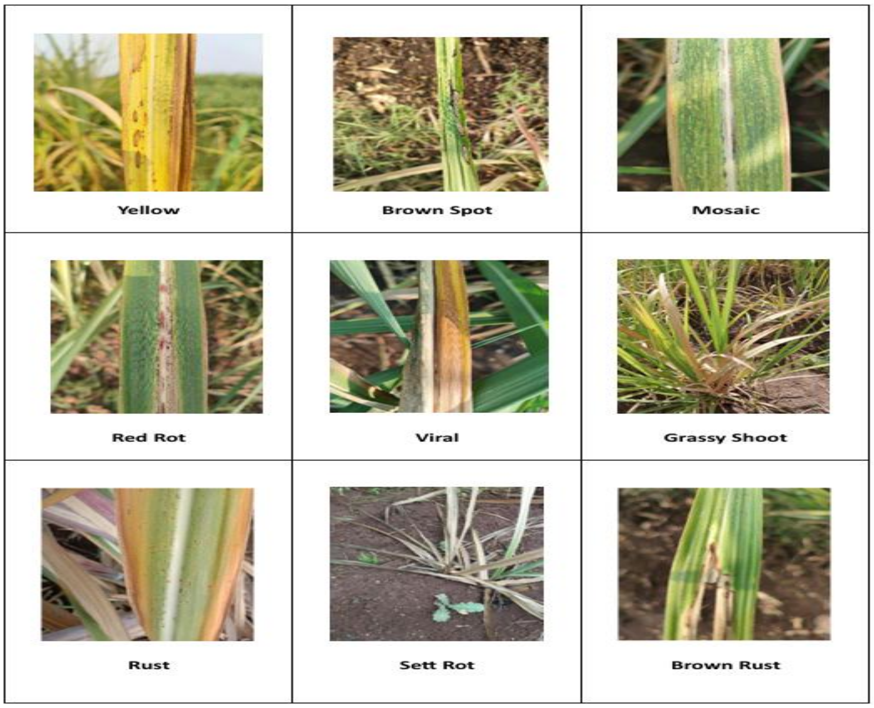


Fig (1): Sugarcane various diseases image

Literature Review

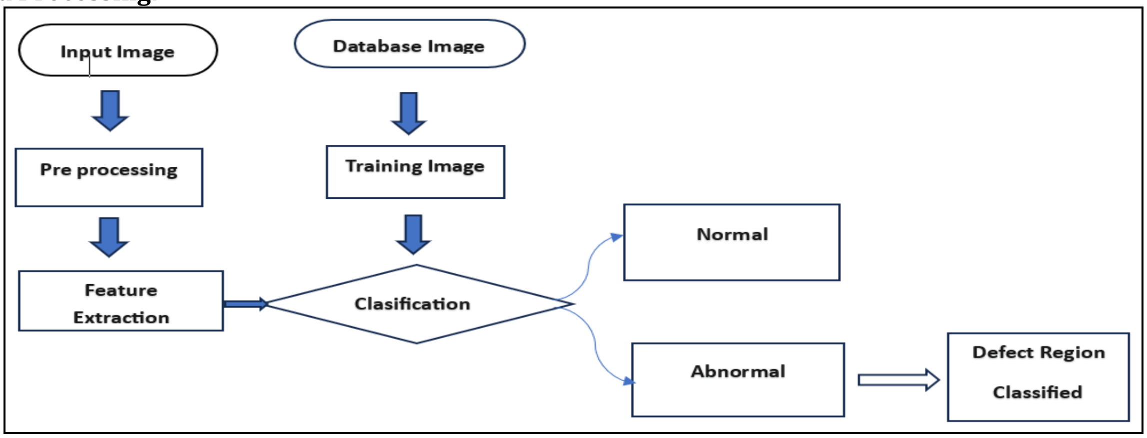
Ruddy decay illness, caused by Colletotrichum falcatum, essentially impacts sugarcane generation, coming about in 5-50% financial misfortune and as it were 31% sugar recuperation. Current prevalent sugarcane assortments are helpless to C. The adequacy of these control strategies is evaluated, and modern proposition are made to relieve the spread of C. falcatum. Actualizing these recommendations seem altogether contribute to feasible sugarcane development, guaranteeing the long-term practicality of the sugar industry in tropical and subtropical locales [1]. This consider presents a profound learning system to distinguish sugarcane illnesses by analyzing plant highlights. Three scenarios utilizing Beginning v3, VGG-16, and VGG-19 models are assessed, and the best combination (VGG-16 and SVM) accomplishes 90.2% exactness. This robotized location framework empowers early recognizable proof of unhealthy plants, vital for sugarcane surrender and sugar generation. [2] Sugarcane muck, caused by the organism Sporisorium scitamineum, is a major illness influencing sugarcane around the world, driving to noteworthy misfortunes in efficiency and productivity. The infection is spread through airborne teliospores, which can survive unforgiving conditions. Breeding safe assortments is the most viable administration strategy, but sugarcane's complex genome makes it challenging. Later progresses in atomic markers and omics innovations have distinguished resistance loci and given experiences into the instrument of resistance, clearing the way for creating strong safe assortments. [3] Sugarcane mosaic malady is a huge issue for sugarcane agriculturists, diminishing trim yields and sugar substance. This survey talks about the current circumstance, how the illness spreads, and ways to recognize and control it. The objective is to offer assistance agriculturists and researchers discover successful arrangements to oversee the malady and breed safe sugarcane assortments. [4] Sugarcane white leaf malady is a major issue for sugarcane agriculturists, particularly in Sri Lanka. This investigate utilized rambles and machine learning to identify the malady early, some time recently it's unmistakable to the eye. The rambles took high-resolution photographs of sugarcane areas, which were at that point analyzed by machine learning calculations to distinguish sound and tainted plants. The comes about appeared a 94% precision rate in recognizing the infection, making this strategy a dependable, cost-effective, and speedy way to identify sugarcane white leaf infection. [5] This investigate created a Sugar Cane Leaf Malady Conclusion Framework utilizing Convolutional Neural Arrange (CNN) calculation YOLO, accomplishing tall precision in recognizing sugarcane infections. The framework was prepared on 4,000 pictures and tried on three bunches, coming about in normal exactness rates of 95.90%, 91.30%, and 98.45%, with most noteworthy precision rates of 98.45% and 97.26%, and normal handling times of 1.46 and 1.53 seconds. This framework illustrates tall precision and proficiency in identifying sugarcane maladies, making it a important instrument for agriculturists and analysts. [6] This investigate paper addresses the issue of sugarcane illnesses influencing edit efficiency. Existing strategies for recognizing sugarcane infections are not exact. To illuminate this, the paper proposes a modern approach called QBPSO-DTL (quantum carried on molecule swarm optimization based profound exchange learning) which employments fake insights (AI) and machine learning to identify and classify sugarcane leaf maladies with tall precision. [7] This consider creates a web application for recognizing sugarcane leaf maladies utilizing picture preparing methods, accomplishing an normal exactness of 95% by utilizing the SVM . The framework collects leaf pictures, applies Versatile Histogram Equalization (AHE) and k-means clustering division, extricates measurable highlights utilizing Gray Level Co-occurrence Network (GLCM) and Central Component Examination (PCA), and classifies maladies utilizing Back Vector Machine (SVM).[8] Sugarcane illnesses can significantly diminish edit yields. Conventional determination strategies are moderate and wrong. This ponder employments profound learning to distinguish sugarcane infections from leaf pictures, accomplishing 93% precision. This innovation can offer assistance ranchers make opportune choices, decrease trim misfortune, and increment yields.[9] This consider investigates modern advances to distinguish and oversee sugarcane infections. Machine learning, farther detecting, and hereditary building have made strides malady location and control. These advances offer assistance recognize illnesses early, diminish chemical utilize, and make disease-resistant crops. This leads to more beneficial crops, expanded yields, and feasible horticulture practices.[10]

Sugarcane, a basic edit for the worldwide sugar industry, is powerless to different infections that essentially affect its abdicate and quality. To address this challenge, we present the "Sugarcane Leaf Dataset," a comprehensive collection of 6748 high-resolution leaf pictures categorized into 11 classes, counting 9 illness categories, solid takes off, and dried takes off. This dataset gives a profitable asset for creating machine learning calculations for malady location and classification in sugarcane takes off. By leveraging this dataset, analysts and professionals can progress mechanized illness distinguishing proof frameworks, improving precision and effectiveness. The open accessibility of this dataset cultivates collaboration, assisting inquire about on malady control procedures and progressing sugarcane production.[11] Crop illness discovery is basic for avoiding abdicate misfortune, and later progressions in exactness horticulture have driven to imaginative strategies for infection distinguishing proof. This survey centers on sugarcane edit illness discovery, highlighting different methods and input information sorts, counting RGB, multispectral, and hyperspectral symbolism. We examine machine learning, profound learning, exchange learning, and unearthly data dissimilarity approaches, giving an outline of the comes about accomplished with each strategy. This comprehensive survey points to encourage the advancement of proficient and precise sugarcane malady location frameworks, eventually contributing to made strides trim yields and diminished losses.[12]

Dataset:

Data was collected from Panhala Taluka in Kolhapur district, covering five farms with a total area of 8 acres. A Cannon Mark 3 camera device was used to capture images. The preprocessing of images was done using the Scikit-Image library, which helped reduce noise, detect edges, and correct colour. The dataset includes images of 10 different sugarcane diseases, with 300 to 500 images for each disease. The diseases in the dataset are Red Rot, Brown Spot, Brown Rust, Grassy Shoot, Mosaic, Rust, Sett Rot, Viral Disease, and Yellow Leaf

Data Processing:



Fig(2): Data Precessing

Input Image and Database Image: The process consists of two types of images:

- **Input Image**: The image which is passing for analyzing the disease.
- **Database Image**: A reference image used to train the classification model.

Pre-processing: The input image is enhanced to improve its quality. This may include techniques like reducing noise or adjusting contrast to make the image clearer.

Training Image: The database image is used to create a set of training images that help teach the classification model what to look for in the input image.

Feature Extraction: Important details (features) from the input image are extracted, such as texture, shape, edges, or color, which help identify the differences between normal and defective areas.

Classification: The classification model uses the extracted features to determine whether the image contains normal or abnormal (defective) regions.

Output:

- **Normal**: If the region is healthy, it is classified as normal (no defect).
- **Abnormal**: If the region shows signs of a defect, it is classified as abnormal.
- **Defect Region Classified**: The defect is identified.

Models-

Sequential- Sequential Model for Image Classification

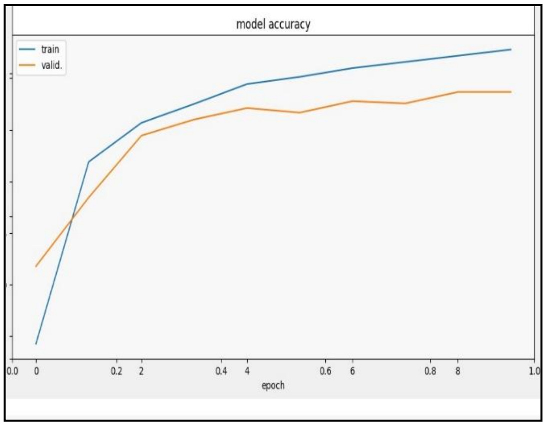
A Sequential model is used the image processing and classify this into different categories. This model consist of different layers and that are work together to extract the features and make predictions. It is start with the convolutional layer that helps for detecting the edges, textures and other features which are followed by the activation functions that can introduce the non-linearity. The pooling layer that helps for the down sample the images to retain key features. The output is then flattened and passes to the fully connected layers to learn and understand the complex relationships, before producing the output the softmax activation function is used to produce a probability distribution over the possible classes.

With the help of Adam optimizer, categorical cross-entropy loss function, and accuracy metric the model is compiled. The model is trained using the data which is present in the training set with 10 epochs and validated on the validation data. This model achieves the 89.11 accuracy.

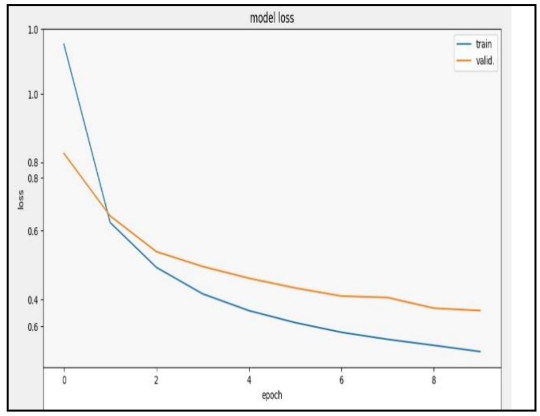
Model Accuracy:

Sequential Model	
Training Accuracy	**0.9287**
Testing Accuracy	**0.8998**

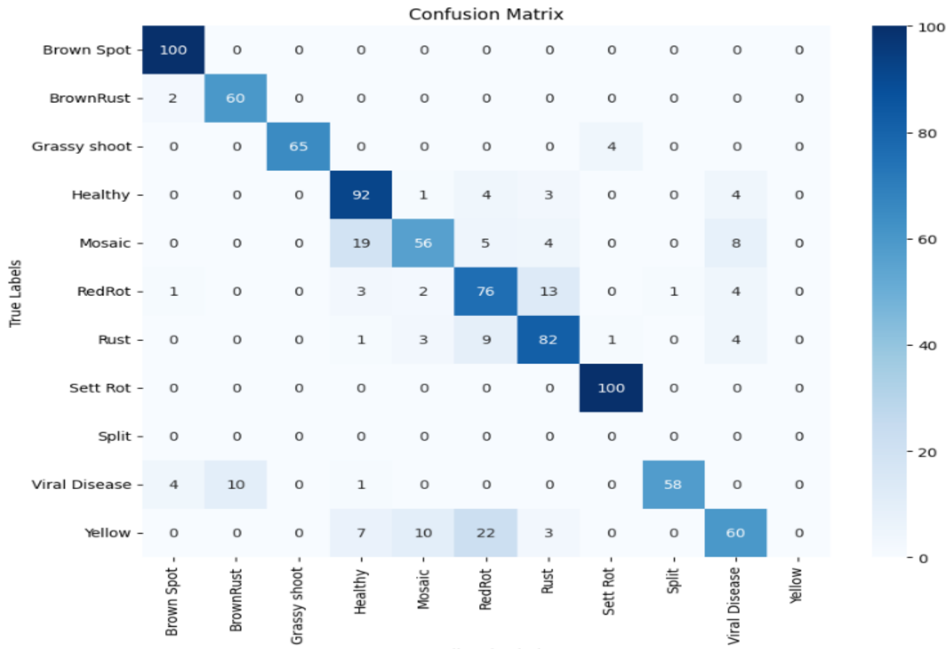
(a) Model Accuracy



(b) Model Loss



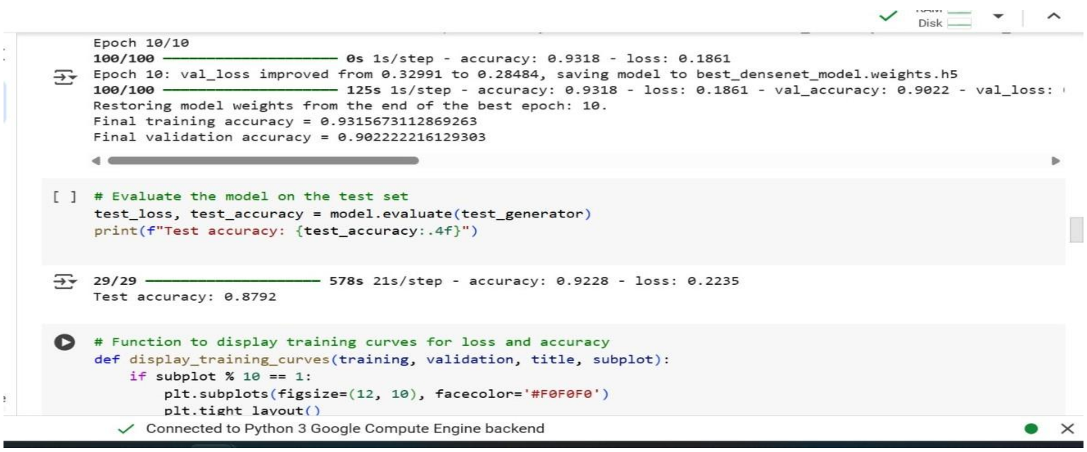
Fig(3): Model accuracy and loss of Sequential Model



confusion matrix- Sequential

DenseNet121:

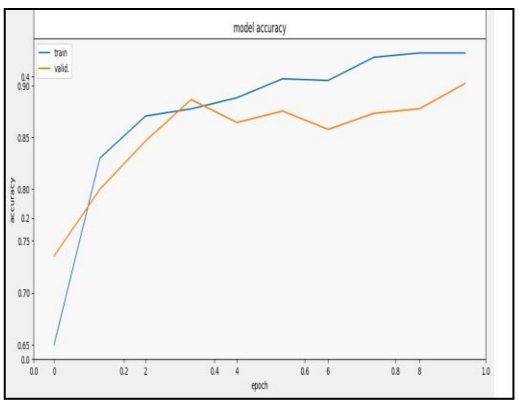
DenseNet, a type of convolutional neural network (CNN), works with image processing by leveraging its unique architecture to extract features from images. The pre-trained DenseNet121 model used in this code is initially trained on the large ImageNet dataset, allowing it to learn general features such as edges, lines, and textures. When applied to image processing tasks, Dense Net's architecture, which consists of dense blocks, transition layers, and a classification layer, enables it to capture complex features and patterns in images. The dense blocks, comprising multiple convolutional layers, allow for feature reuse and efficient extraction of features at different scales. The transition layers, which consist of batch normalization, 1x1 convolution, and average pooling, help to reduce spatial dimensions and retain the most important features. Finally, the classification layer outputs probabilities for each class, enabling the model to accurately classify images. By fine-tuning the pre-trained DenseNet model on the specific image processing task, it can learn task-specific features and achieve 90.22 accuracy in image classification.



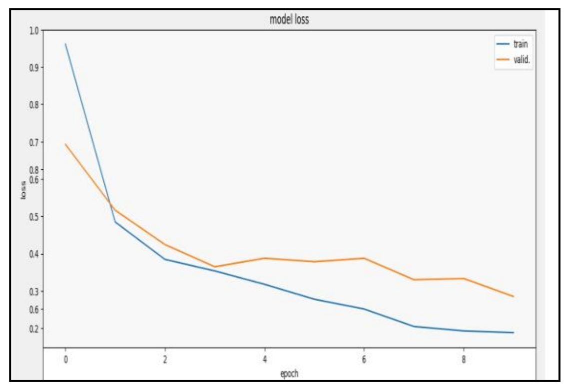
```
Epoch 10/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 0.9318 - loss: 0.1861
Epoch 10: val_loss improved from 0.32991 to 0.28484, saving model to best_densenet_model.weights.h5
100/100 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.9318 - loss: 0.1861 - val_accuracy: 0.9022 - val_loss:
Restoring model weights from the end of the best epoch: 10.
Final training accuracy = 0.9315673112869263
Final validation accuracy = 0.902222216129303

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(test_generator)
print(f"Test accuracy: {test_accuracy:.4f}")

29/29 ━━━━━━━━━━━━━━━━━━━━ 578s 21s/step - accuracy: 0.9228 - loss: 0.2235
Test accuracy: 0.8792

# Function to display training curves for loss and accuracy
def display_training_curves(training, validation, title, subplot):
    if subplot % 10 == 1:
        plt.subplots(figsize=(12, 10), facecolor='#F0F0F0')
        plt.tight_layout()
```


Model Accuracy

Dense121 Model	
Training Accuracy	**0.7496**
Testing Accuracy	**0.7328**

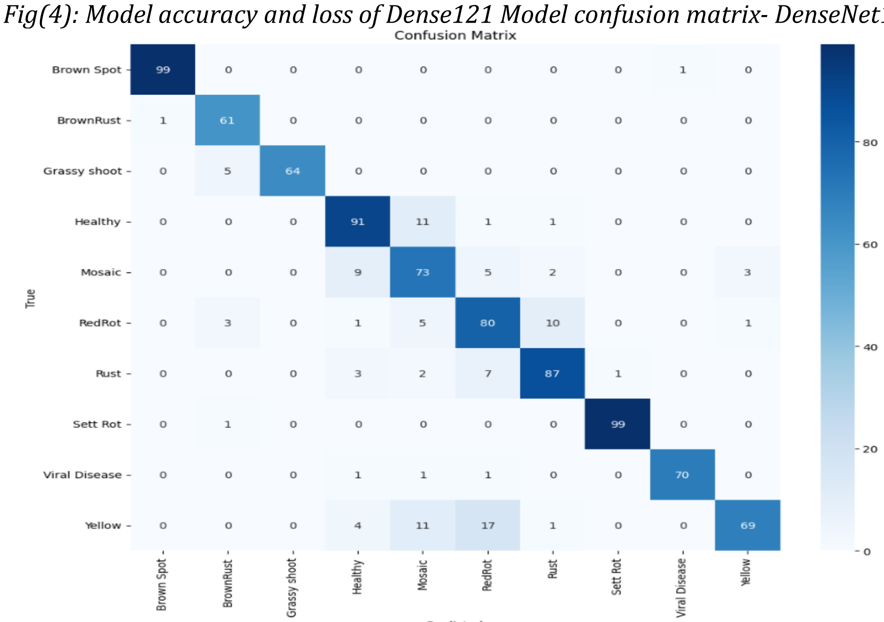


(a) *Model Accuracy*



(b) *Model Loss*

Fig(4): Model accuracy and loss of Dense121 Model confusion matrix- DenseNet121



Comparison: Testing Accuracy

Model	Accuracy
Sequential	**0.8998**
DenseNet121	**0.7328**

Conclusion

The sugarcane crop disease detection application using deep learning and machine learning techniques has demonstrated high accuracy and efficiency in detecting and classifying sugarcane diseases. This application has the potential to revolutionize the sugarcane industry by enabling early disease detection, reducing crop losses, and promoting sustainable agriculture practices. With further development and deployment, this technology can benefit sugarcane farmers, agricultural stakeholders, and the environment, contributing to food security and a more sustainable future.

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