

SUGARCANE LEAF DISEASE CLASSIFICATION USING TENSORFLOW LITE API

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ABSTRACT

The sugarcane industry is a vital source of various products like biofuels, energy, and sugar-based ethanol, with sugarcane being a significant biomass source for biofuels globally. The Philippines is among the top producers of sugarcane, but it faces challenges, including the devastating red rot disease that affects about 10% of sugarcane-growing areas in the country. The country's productivity also lags other Southeast Asian nations due to issues like poor irrigation, soil fertility, and climate change impacts. To address these problems, researchers developed a sugarcane disease detection and classification system using artificial intelligence to help farmers improve crop yield. The primary focus was on detecting diseases like red rot, brown leaf spot, pineapple disease, and leaf scorch using a mobile application compatible with Android OS. The study aimed to provide farmers with a mobile app that could detect and classify sugarcane diseases to enable timely prevention and intervention measures, contributing to increased productivity in the Philippine sugarcane industry. The researchers evaluated the performance of a model for diagnosing sugarcane leaf diseases based on precision, recall, F1-score, and accuracy. The study focused on red rot, brown leaf spot, pineapple disease, and leaf scorch detection, excluding other plant diseases and severity assessments. The evaluation of the model's performance revealed promising results. Precision values ranged from 81.6% to 91.4%, indicating high accuracy in identifying instances within each disease category. Recall values ranged from 87.5% to 92%, demonstrating the model's ability to correctly identify actual disease instances. F1 scores, combining precision and recall, were good, ranging from 0.866 to 0.937, indicating reliable classification. The accuracy of diagnosis varied between diseases, with the highest accuracy achieved for red rot and the lowest for leaf scorch. Brown leaf spot classification trials consistently achieved accuracy scores ranging from 95.7% to 99.9%.



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1. INTRODUCTION

Over time, technology has significantly changed the world's environment and way of life. Furthermore, senior-friendly technology has created outstanding tools and services that have put valuable data at our fingertips. Smartphones are instances of versatile devices made

available by modern technology. Computers today are more powerful, portable, and rapid than ever before (Merazzo et al., 2021). All these revolutions have been facilitated by technology, which has made people's life simpler, faster, better, and more entertaining (Imamov & Semenikhina, 2021). Farmers in the agriculture industry benefit from more productive and sustainable farming

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practices enabled by modern agricultural technology (Khan et al., 2021). major headings as well as one space before and after the sub-headings.

Agriculture's viability is influenced by both tried-and-true tactics such as crop rotation and cutting-edge ones such as tracking field productivity with equipment, satellite imagery, or even specialized farming software (Haldorai et al., 2024). Sugarcane is among the members of the Poaceae grass family, which includes maize, wheat, rice, and sorghum, as well as a variety of forage crops (Nair & Sachan, 2022). It is found only in India, Southeast Asia, and the Philippines, where it thrives in moderate and tropical temperatures (Sankaran & Dinesh, 2020). Sugarcane plants are plagued by an array of conditions. Sereh, a blackening and deterioration of the fanlike tips, is caused by an East Indian virus. Mosaic is caused by virus infection and results in mottling or spotting of the foliage as well as curling, dwarfing, and narrowing of the leaves. Sugarcane growers are having difficulty correctly diagnosing what disease is in the sugarcane (Jones, 2021).

The researchers developed sugarcane detection and classification using artificial intelligence to help our sugarcane farmers improve their sugarcane crop yield by detecting and classifying diseases of sugarcane at an early stage (Canata et al. 2021; Daphal & Koli 2023; Ilyas et al. 2023; Mangrulle & Afreen, 2024). Researchers applied image processing techniques to preprocess sugarcane leaf images and used the Convolutional Neural Networks (CNNs) model MobileNetV1-SSD for classification and TensorFlow Lite API to easily deploy it on a mobile application (Hum et al., 2022; Mittapall et al., 2023).

2. MATERIALS AND METHODS

2.1 Mobile Application

A mobile application's architecture is a collection of models and technologies that are used to develop fully structured mobile apps that adhere to vendor and industry standards (Alli & Alam, 2020).

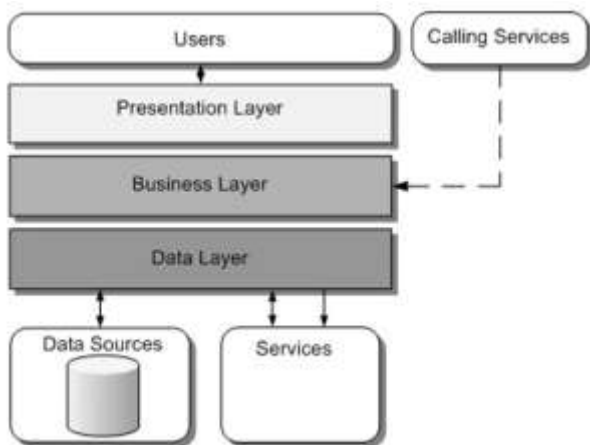


Figure 1. Architecture of Mobile Application

While developing the architecture of your app, you consider programs that run on wireless devices such as smartphones and tablets (Figure 1).

2.2 MobileNetV1-SSD

MobileNetV1-SSD refers to a specific object detection model that combines the MobileNetV1 architecture with the single-shot Multi-box Detector (SSD) framework (Vrbaski et al., 2023). The input image is resized to a fixed size to ensure consistent processing. After that, the researchers followed the next process which is feature extraction using MobileNetV1. Then MobileNetV1 architecture is employed for feature extraction and depthwise separable convolutional layers are utilized to efficiently extract meaningful features from the input image. Next, researchers proceed to hierarchical feature maps where additional convolutional layers are applied to the feature maps to create multi-scale feature maps. This process incorporates information at different scales and enables the detection of objects of various sizes.

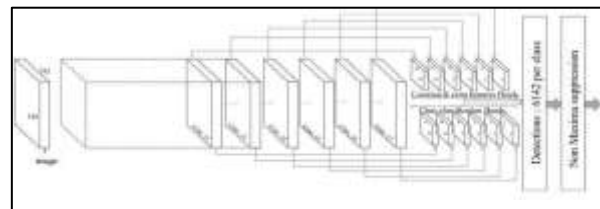


Figure 2. Architecture of MobileNetV1-SSD

In default boxes (Anchor Boxes), the SSD framework utilizes default boxes (anchor boxes) at each position in the feature maps. Default boxes have different aspect ratios and sizes, covering a range of possible objects, and are used to predict the positions and sizes of objects in the image. To better understand the components and flow of the MobileNetV1-SSD architecture, check the figure 2.

2.3 TensorFlow Lite API

TensorFlow Lite makes use of TensorFlow models that have been scaled down and optimized for machine learning (ML) models (Figure 3).

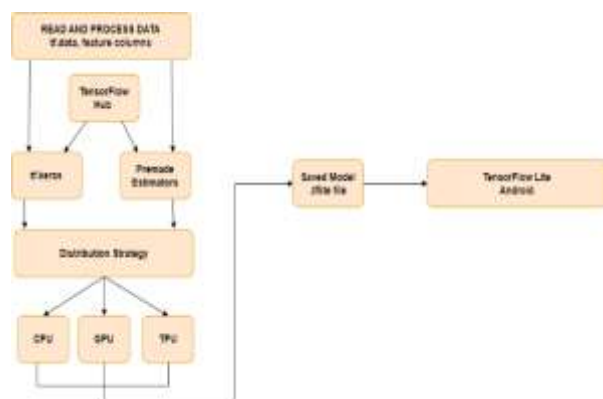


Figure 3. Architecture of TensorFlow Lite API

TensorFlow Lite allows you to use pre-trained models, modify existing models, or develop your TensorFlow models and convert them to TensorFlow Lite format.

3. RESULTS AND DISCUSSION

3.1 Developed Mobile Application using TensorFlow Lite API

Figure 4 shows the displayed result on the user's mobile application.



Figure 4. Developed Mobile Application

It shows the user the disease classification of sugarcane leaves along with the associated confidence levels, indicating the percentage of disease present in the captured leaves.

3.2 Evaluation Metrics

Table 1 depicts the results of the diagnosis of sugarcane leaf in terms of precision.

Table 1. Classification Report using the Evaluation Metrics

Diseases	Precision	Recall	FF1-Score	Accuracy
Brown Leaf Spot	0.887	0.92	00.937	0.944
Pineapple Disease	0.816	0.905	00.899	0.92
Red Rot Disease	0.902	0.875	00.91	0.956
Leaf Scorch Disease	0.85	0.89	00.866	0.885
Healthy	0.914	0.915	00.907	0.947

The researchers arrived at the data below by importing a Python library of classification that includes the evaluation metrics.

Upon analyzing the precision values provided, several observations can be made regarding the model's performance in diagnosing sugarcane leaf diseases. For Brown Leaf Spot, the model achieved a precision of 0.887, indicating that approximately 88.7% of the instances classified as Brown Leaf Spot were correctly identified. In the case of Pineapple Disease, the model achieved a precision of 0.816, suggesting that around 81.6% of the instances classified as Pineapple Disease were accurately identified. For Red Rot Disease, the precision value was 0.902, implying that roughly 90.2% of the instances classified as Red Rot Disease were correct. Regarding Leaf Scorch Disease, the model achieved a precision of 0.85, indicating that approximately 85% of the instances classified as Leaf Scorch Disease were accurately identified. Finally, for healthy sugarcane leaves, the model achieved a precision of 0.914, meaning that approximately 91.4% of the instances classified as healthy were correctly identified. These precision values provide insight into the model's accuracy and ability to distinguish between different sugarcane leaf diseases and healthy leaves.

Considering the recall scores for all the classes, it appears that the model's performance is generally in the correct manner for all correct classifications. The recall scores range from 0.875 to 0.92, indicating that the model correctly identifies a high percentage of actual instances for each disease class and for healthy leaves as well.

Analyzing the F1-scores, the model achieves an F1-score of 0.937 for detecting Brown Leaf Spot disease, indicating excellent performance in identifying instances of this disease. The predictions for this class have high precision and recall, leading to accurate classifications. For detecting Pineapple Disease, the model achieves an F1-score of 0.899, demonstrating a good performance. While not as high as Brown Leaf Spot, it still maintains a strong balance between precision and recall, ensuring accurate identification of this disease.

Based on the data provided in Table 1, the accuracy of diagnosis for each disease varies. The accuracy percentages range from 0.885 to 0.956. The highest accuracy of diagnosis is observed for the Red Rot Disease, with a value of 0.956. This suggests that the diagnostic process or application has a high level of accuracy in correctly identifying cases of Red Rot Disease in sugarcane leaves. The accuracy for other diseases is also relatively high. Brown Leaf Spot has an accuracy of 0.944, Pineapple Disease has an accuracy of 0.92, and Healthy Leaves have an accuracy of 0.947. Leaf Scorch Disease has the lowest accuracy among the listed diseases, with a value of 0.885. This indicates that the diagnostic process or application may have a slightly lower accuracy in correctly identifying cases of Leaf Scorch Disease compared to the other diseases listed in the table. Considering the accuracy scores for all the classes, it appears that the model's performance is generally in the correct manner for all correct

classifications. The accuracy scores range from 0.885 to 0.956, indicating that the model is making correct predictions for most instances in each class.

4. CONCLUSION

In conclusion, the mobile app offers a user-friendly and effective solution for sugarcane disease detection. Its simple image capture process allows users to quickly snap pictures, and the option to retake photos ensures the acquisition of clear and high-quality images crucial for accurate disease diagnosis.

The app's disease classification and informative insights, including the confidence percentage indicating disease on captured leaves, provide users with valuable information for timely and informed decision-making in sugarcane crop management. This mobile application bridges the gap between technology and agriculture, enhancing the efficiency and precision of disease diagnosis in the field.

Overall, this study significantly advances agricultural disease diagnosis, offering potential improvements in sugarcane crop management. The model consistently exhibited exceptional accuracy in classifying a variety of sugarcane diseases, ranging from Brown Leaf Spot and Red Rot to Pineapple Disease, Leaf Scorch, and healthy leaves, achieving accuracy rates between 84.5% and 100%.

These results establish the model's reliability and effectiveness in practical sugarcane disease diagnosis. Moreover, the comprehensive evaluations, which considered diverse data, independent validation, and additional performance metrics, underscore the model's robustness and its potential for real-world applications. This research represents a significant contribution to the field of agricultural disease diagnosis, offering the potential to revolutionize sugarcane crop management practices.

By providing a powerful tool for early and accurate disease detection, our model can boost crop yields, reduce losses, and ultimately benefit sugarcane farmers and the agricultural industry.

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