



Sugarcane Disease Identification Using Mobile Deep Learning Solutions

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Abstract

To minimize losses in the agricultural sector and ensure food security, early diagnosis and identification of sugarcane diseases are essential. Conventional diagnostic approaches are often costly, labor-intensive, and reliant on the subjective expertise of individuals in recognizing pathogenic microorganisms. Recent improvements in machine learning and deep learning provide viable solutions for automating the data analysis and classification of plant diseases through image-based analysis. This study presents a comprehensive analysis of image-based sugarcane disease identification systems, emphasizing various computational techniques to achieve optimal results, and applies these methods in a mobile application. In this study, the authors review relevant case studies, highlighting key developments in disease detection using computer vision technologies, and demonstrating how these approaches improve diagnostic accuracy while enhancing computational efficiency and reducing resource consumption. The authors aim to guide future research and development by offering methods to overcome existing challenges. This assessment serves as a resource for academics and practitioners, providing insights into current practices and suggesting ways to enhance automated plant disease detection systems for mobile and handheld devices.

Keywords: Early Detection, Sugarcane Disease, Machine Learning (ML), Deep Learning (DL), Plant Datasets, Disease Category, Object Detection, Mobile Application.

Introduction

The global population is projected to reach 9.8 billion by 2050. This growth poses a significant challenge for agriculture. The sector needs to boost food production to support a quickly growing and increasingly urban population. Climate change also poses a challenge by causing more unpredictability in farming conditions. Due to this, there is a need for new and sustainable solutions to enhance agricultural productivity and secure food for future generations.

One promising method is precision agriculture, which leverages advanced technologies to optimize farming operations. Precision agriculture utilizes virtual analytics and next-generation sensors to enhance crop yields by providing specific, actionable insights. Advanced sensing technologies have become imperative to this technique. Applications like weed detection, plant disease identification, and pest tracking have significantly benefited from these technologies. Conventionally, plant disease monitoring has relied on manual examination, which was labor-intensive and challenging to scale for large plantations. To overcome, researchers and practitioners have employed various techniques, including molecular biology, biotechnology, and manual diagnostic technologies. However, these methods often encompass high costs and complexity.

The incorporation of Internet of Things (IoT) devices, sensors, drones, AI, and blockchain technology is bringing a significant transformation in agriculture. IoT devices and sensors continuously accumulate data on machinery performance, soil conditions, and environmental factors. Drones equipped with advanced cameras and multispectral sensors deliver specific information on crop health and potential. Blockchain technology works with transparency and traceability in the agricultural supply chain, assuring the authenticity and safety of food products. By minimizing resource waste, enabling real-time decision-making, and optimizing inputs according to particular requirements, the merging of artificial intelligence not only supports sustainability but also increases agricultural productivity.

Machine learning and Deep Learning are at the forefront of this technological revolution. ML is a branch of AI that uses algorithms to classify patterns in the data and then improve the overall performance. Researchers have been using standard ML algorithms such as “Support Vector Machine (SVM)”, “K-nearest Neighbor (K-NN)”, and “Artificial Neural Network (ANN)” to detect plant diseases. However, these standard algorithms usually work with tabular data, not image-based information.

Deep Learning, a more advanced subfield of AI, typically uses CNN architecture, which utilizes multiple layers of a neural network system to classify image data and recognize

patterns of interest. This approach has proven powerful in detecting plant diseases through the analysis of leaf images to classify disease signs and symptoms with high accuracy. Modern computer vision tools based on DL have extensively advanced the field of plant disease detection, providing automated and precise evaluation. Some practices, such as data augmentation and transfer learning, have also uplifted the capabilities of DL in this domain.

Literature Review

Image pre-processing is crucial for improving data quality and making images usable for model training. Researchers utilize numerous pre-processing techniques, including noise elimination, brightness adjustment, contrast leveling, and normalization. Pre-processing techniques used by Zhang et al. (2020) and Goyal et al. (2024) incorporated simple image enhancement techniques like blur reduction and geometric corrections, which significantly improved the performance of machine learning models by eliminating image artifacts and standardizing input data. Sachi et al. (2024) explored a higher level of pre-processing, which utilized methods like histogram equalization and adaptive thresholding to improve the readability of images. Kolli et al. (2024) enlightened that segmentation involves partitioning the image into meaningful regions to extract features related to plant diseases. Chakravarty et al. (2022) enlightened that the traditional methods use thresholding and field observations. In contrast, cutting-edge procedures use deep learning to identify patterns in a dataset. Chen et al. (2022) introduced an optimized version of YOLOv5 that classifies disease in the rubber tree. They used a dataset that contained images of rubber trees and achieved an accuracy of 86.6%. Singh and Kumar (2023) explained the deep convolutional neural network advancements in cucumber leaf diseases, incorporating the ResNet50 architecture, which has shown high accuracy in segmenting plant images while keeping spatial data.

Feature extraction involves identifying and quantifying different features or attributes from segmented images. Researchers have historically used hand-crafted features like texture, colour, and shape descriptors. Wang et al. (2021) emphasized the efficiency of deep learning models in automating feature extraction and directly accessing features from raw image data and proposed a method that combines conventional feature extraction with deep learning strategies to improve the accuracy. Sudhakar et al. (2024) discussed CNN- and SVM-based models that pre-process data to train ML models, typically employing supervised learning techniques for accurate brain tumor identification. Mohanty et al. (2016) explored a technique that incorporated a CNN-based model, which worked on smartphones and was successfully tested on various datasets, to leverage existing model knowledge through transfer learning. Kapida and Arul (2025) explained about the automated rice disease detection system, which recognized the disease at its early stages. Testing evaluates the model's overall accuracy on unseen data, using metrics such as precision, accuracy, recall, and F1-score, emphasizing the need for strong testing protocols to ensure that models perform well on new and diverse datasets.

The development of ML models for plant disease detection is a multi-stage pipeline involving data acquisition, pre-processing, segmentation, and feature extraction, culminating in the training and testing phase. Recent improvements in Deep Learning and Machine Learning have drastically improved these steps, making it easier to detect disease in plants. Ongoing research continues to refine these methodologies, with a focal point on improving data quality, model robustness, and practical deployment in real-world agricultural areas.

Methodology

Data Collection: This step comprised preparing image data, which included the collection of images representing common diseases present in sugarcane plants. In this study, the sugarcane image dataset was divided into two classes. The first class contained healthy samples, and the second contained unhealthy samples. Table 1 presents the overall distribution.

Table 1. Distribution of the sugarcane disease dataset for the healthy and unhealthy classes.

S. No.	Type of Disease		Count of Images	Distribution
1	Healthy		1200	50
2	Unhealthy	Red root	845	25
3	Unhealthy	Red Rust	678	25
4	Total		2723	100

The dataset consisted of two major classes: Healthy and Unhealthy, which were collected from the village Dhakera, district Moradabad, state Uttar Pradesh, India.

Data Augmentation: The application of data augmentation over the dataset provides additional variation. Augmentation included rotation, flipping, scaling, and colour adjustment, which enhanced the dataset with a diverse set of images. Augmentation helps the model generalize better and improves its performance on unseen data. The dataset contains a variety of images from two classes, including disease-affected and healthy samples. Data augmentation techniques create a dataset that consists of images with different geometric transformations. Figure 1 shows a set of images from the image dataset after the application of augmentation techniques.



Figure 1. Various images from the sugarcane dataset after successful augmentation.

Image pre-processing: Image pre-processing refers to the operations performed on images at the lowest level of processing. Using a smaller image size enables Deep Learning-based models to train more efficiently with low computational cost. Furthermore, the size of the collected raw images varies; most Deep Learning architectures require the images to have uniform dimensions. Moreover, YOLO's performance degrades if the training images and the testing images differ in dimensions. To ensure compatibility and optimal performance, researchers resize the raw collected images to 416×416 .

System Design: The system operates as illustrated in Figure 2. It accepts input images either captured using the camera or selected from the device's storage. The proposed system then analyzes the input using the model to detect the presence of any disease. Subsequently, it displays the results to the end user. Model development and its deployment in an application require a high level of effectiveness in all phases. Hyperparameter tuning, a dataset for training purposes, and high-end computational resources for analyzing high-resolution image data are crucial for system development. The proposed system requires minimal computational resources in dataset preparation. The proposed system directly identifies the class of disease. A key advantage of the proposed system is that it does not require a backend server for analysis.

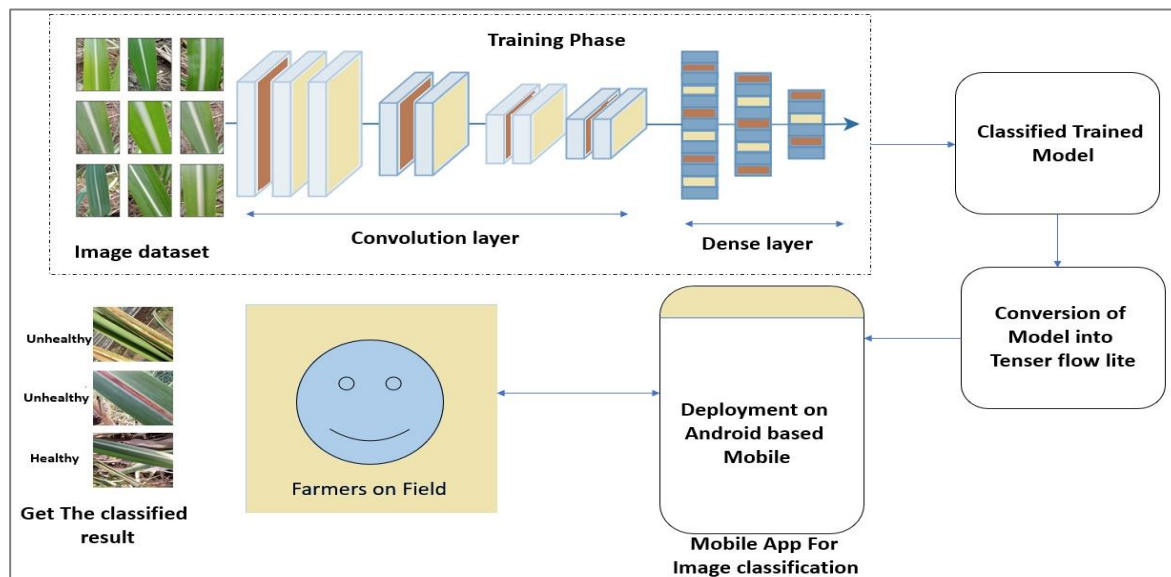


Figure 2. Architecture of the sugarcane disease identification system.

1. Model Evaluation and Testing:

The test set was kept separate to ensure that no image from the training phase entered the evaluation. YOLOv8n achieved the highest performance, while all YOLO models generally performed well in aiding the diagnosis of sugarcane disease. The study employed various performance parameters such as recall, precision, mAP, and loss. A relative assessment was used to evaluate the performance of different models. Precision refers to the ability to identify an object correctly. False Negative (FN) indicates that the model fails to detect the correct disease class. In contrast, True Positive (TP) indicates that our model accurately predicts the correct disease class. Equation (1) illustrates the formula used for calculating the accuracy.

$$Precision = \frac{TP}{TP+FN} \quad (1)$$

The model's effectiveness depends on its ability to identify all target objects relevant to the current analysis. Recall includes all bounding boxes identified by the model in the validation dataset. When the model incorrectly predicted the presence of a class that was absent, then a False Positive (FP) occurred. Equation (2) provides the equation for calculating recall.

$$Recall = \frac{TP}{TP+FP} \quad (2)$$

mAP is the mean Average Precision (AP) values computed across all classes. It accounts for both FN and FP by summarizing the precision and recall trade-off, as expressed mathematically in Equation (3), where N represents the number of classes. AP measures the average precision across dissimilar recall levels with a value ranging from 0 to 1.

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (3)$$

2. Data Analysis

Almost 2,723 images were collected from a video of 3,000 seconds using the image framing technique and then augmented. This growth highlights the significant effect of augmentation strategies in diversifying the dataset. In the proposed study, horizontal and vertical flips were used to double the dataset size. These augmentation techniques significantly improved the diversity of samples, which is essential for training robust and generalized models. Moreover, it contributed to alleviating underrepresented classes, thereby ensuring a more equitable distribution across the dataset.

3. Class Distribution

Healthy: The primary dataset comprises images of healthy sugarcane plants taken from multiple angles and covering various plant parts. It was developed specifically for this study from a 3,000-second video recording. To further assess model performance, an independent secondary dataset was also used for evaluation.

Unhealthy: This class includes two types of sugarcane disease-affected images for model development and testing.

Results

Figure 3 illustrates the training performance trends of the YOLOv8n compared to others. The YOLOv8n model exhibited superior detection accuracy and robustness, with confidence scores significantly higher than those of earlier models tested on unseen data.

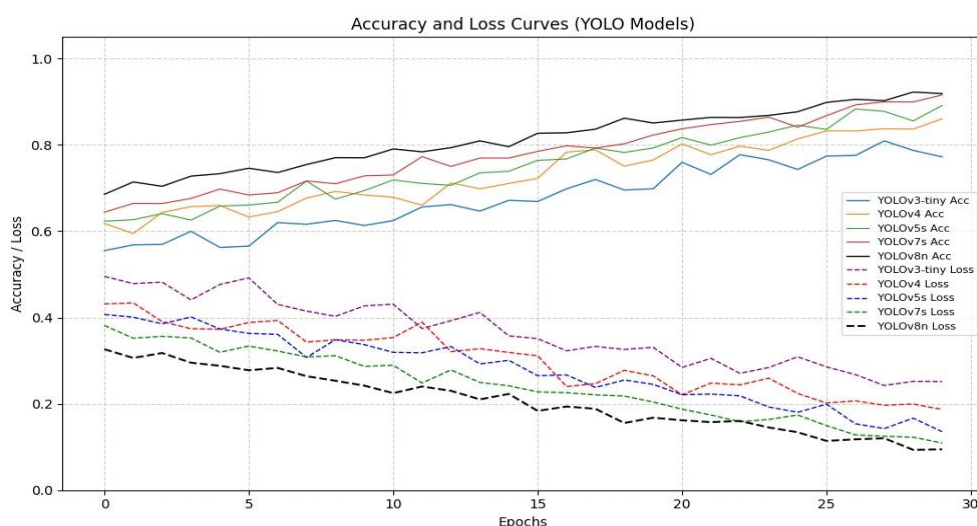


Figure 3. Comparative analysis of different YOLO models through performance visualization.

To monitor the training process, Weights and Biases were integrated into the workflow. This process enables real-time monitoring of model performance and training progress over multiple epochs. The model parameters fluctuated significantly throughout the initial 0-5

iterations. Performance improved progressively each time as the number of iterations increased, and the precision ultimately reached 0.92. The YOLOv8n model's effectiveness on the sugarcane dataset was evaluated by using the loss function. The model not only classified diseases into their correct categories but also supported detection, segmentation, and tracking tasks. The loss function evaluates how well the models learn the mapping between input data and expected output. A lower loss value indicates better performance, while a higher loss suggests reduced accuracy. This study tracked validation segmentation loss for individual objects as a component of the total training segmentation loss and recorded loss values at the end of each training epoch. Table 2 presents the various classification metrics for different versions of "YOLO".

Table 2. Performance Analysis of different YOLO versions on the sugarcane dataset.

Model Name	Precision value	Recall value	F1-Score	Accuracy
"YOLOv3-tiny"	0.81	0.82	0.81	0.82
"YOLOv4"	0.85	0.86	0.85	0.86
"YOLOv5s"	0.87	0.88	0.87	0.88
"YOLOv7s"	0.90	0.91	0.90	0.91
"YOLOv8n"	0.92	0.93	0.92	0.93

CNN-based Model: This study also evaluated the performance of an optimized CNN-based model, which proved encouraging results. Figures 4a and 4b illustrate the CNN-based model's training accuracy and loss curves, highlighting its learning progress over time.

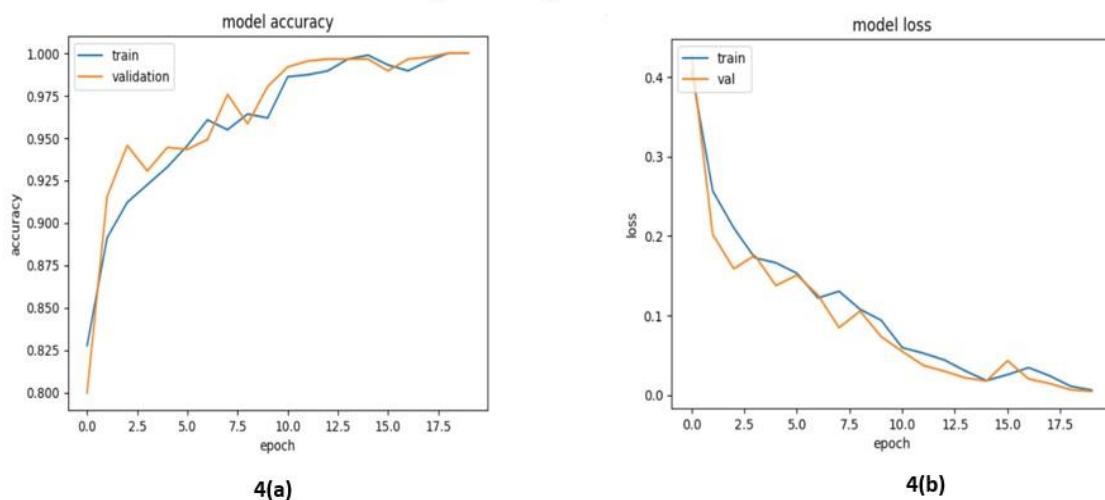


Figure 4(a),4(b). Accuracy and loss analysis of CNN based model

The same dataset was used for training purposes. The model achieved an accuracy of approximately 98.0% as shown in Figure 4(a), and minimal loss was presented by Figure 4(b). A comprehensive summary of the optimized CNN-based model is presented in Figure 5. The optimized CNN-based model consists of a total of ten layers, including three convolutional layers, three max-pooling layers, one flattened layer, and two fully connected (dense) layers.

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 32, 32, 3)	0
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 32)	0
conv2d_2 (Conv2D)	(None, 4, 4, 32)	9248
max_pooling2d_2 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 128)	16512
dense_1 (Dense)	(None, 3)	387
Total params: 36291 (141.76 KB)		
Trainable params: 36291 (141.76 KB)		
Non-trainable params: 0 (0.00 Byte)		

Figure 5. The optimized CNN-based model's summary.

The performance evaluation of the proposed model revealed its excellent reliability in classifying between the Healthy and Unhealthy classes. The model recorded an overall accuracy value of 98% in the test set, showing a good generalization capacity for the entire dataset. Table 3 illustrates the detailed classification metrics for the optimized CNN-based model.

Table 3. Performance metrics for the proposed CNN-based model.

Class	Precision	Recall	F1-score
Healthy	0.98	0.96	0.97
Unhealthy	0.98	1.00	0.99
Accuracy			0.98
Macro Avg	0.98	0.98	0.98
Weighted Avg	0.98	0.98	0.98

For the Healthy class, the model obtained a precision value of 0.98, a recall of 0.96, and an F1-score of 0.97, indicating a very low rate of false positives and slightly higher but minimal false negatives. For the Unhealthy class, the precision and recall were 0.98 and 1.00, respectively, with an F1-score of 0.99, proving that almost all of the diseased samples were identified correctly without any significant misclassification. A macro-average and weighted-average score of 0.98 in precision, recall, and F1-score further guaranteed that the model equally maintained its performance in both classes rather than favoring one over the other. These results collectively emphasized the robustness and efficiency of the model that delivered a high performance in the classification task.

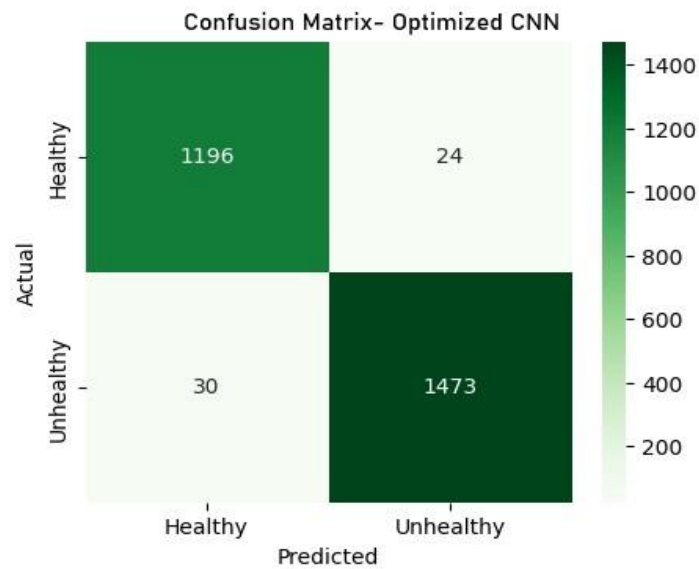


Figure 6. Confusion matrix for proposed CNN-based model.

Figure 6 shows a confusion matrix of the CNN-based proposed model. The consistency of results from one class to another highlighted the robustness of the model in classifying Healthy from Unhealthy samples. The close agreement of precision, recall, and F1-scores further indicated that the model demonstrated a balanced performance in the sense that it equally minimized false positives and false negatives.

Deployment and Application

Architecture: To enable real-time disease detection, segmentation, and tracking in sugarcane crops, the most accurate trained model was embedded into a mobile application.

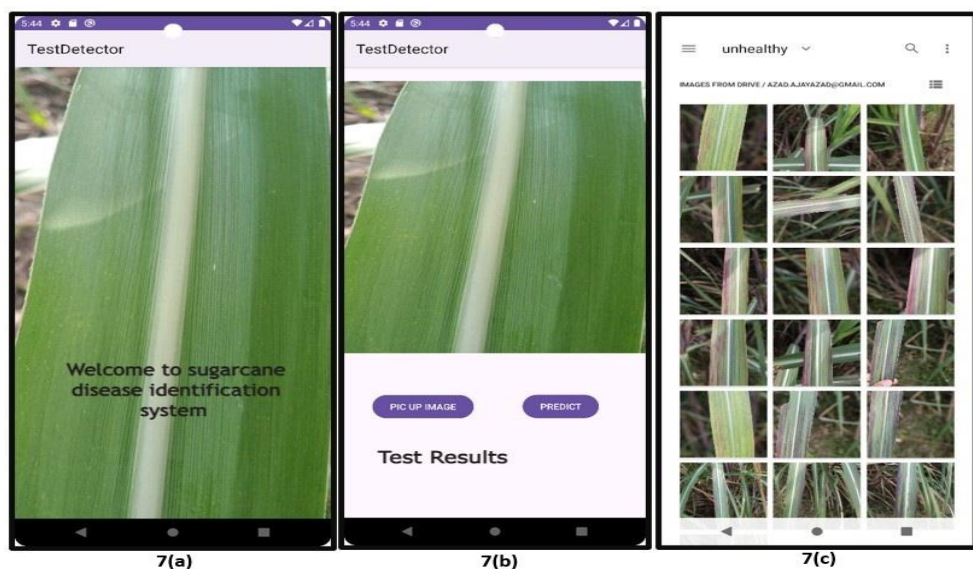


Figure 7(a), 7(b), 7(c). Mobile application interface of Sugarcane disease identification system

Figure 7(a) illustrates the application launcher interface. Figure 7(b) provides two options: selecting an image from the device's storage or capturing it from the camera. Figure 7(c) shows a grid of images for selection purposes.

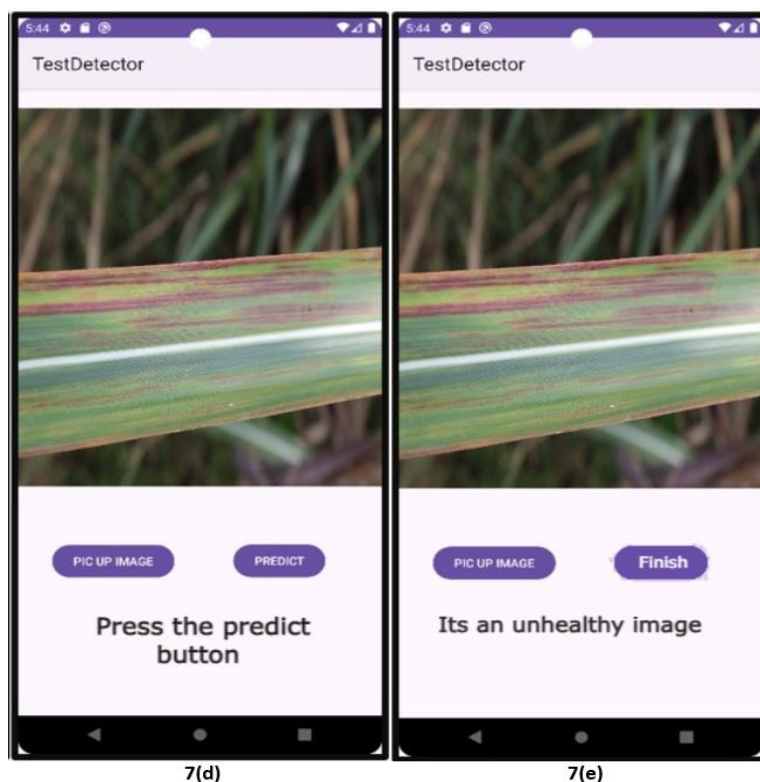


Figure 7(d), 7(e). Disease classification interface of Sugarcane disease identification system

Figure 7(d) displays the image chosen by the user, while Figure 7(e) indicates the classification results, specifying whether the selected image is healthy or unhealthy.

The best-trained model was converted into a TensorFlow Lite (.tflite) setup using the TensorFlow Lite Converter and deployed as an Android application. The mobile application was built using the Java programming language and Android Studio IDE, which consists of the Android SDK and Java Development Kit (JDK).

Sugarcane disease detection pseudocode: As the following pseudocode explains, the user selects an image from device storage or directly through the device camera. The model then analyzes the input image data and displays the classification results. After completion, the system prompts the user to provide a new image, and the same procedure repeats. Figure 8 illustrates the pseudocode outlining the workflow of the proposed sugarcane disease identification system.

```

BEGIN
  DISPLAY "Welcome to Plant Disease Identification App"
  PROMPT "Select Image Source: [1] Camera [2] Gallery"
  INPUT source_choice
  IF source_choice == 1 THEN
    image ← CaptureImageFromCamera()
  ELSE IF source_choice == 2 THEN
    image ← SelectImageFromGallery()
  ELSE
    DISPLAY "Invalid choice. Restarting..."
    GOTO BEGIN
  END IF
  result ← RunModel(image)
  IF result IS NOT NULL THEN
    IF result == "Healthy" THEN
      DISPLAY "Plant is Healthy"
    ELSE IF result == "Unhealthy" THEN
      DISPLAY "Plant is Unhealthy"
    ELSE
      DISPLAY "Unknown result"
    END IF
  ELSE
    DISPLAY "Detection failed. Please try another image."
    GOTO BEGIN
  END IF
  PROMPT "Do you want to test another image? [Y/N]"
  INPUT repeat_choice
  IF repeat_choice == "Y" OR repeat_choice == "y" THEN
    GOTO BEGIN
  ELSE
    DISPLAY "Thank you for using the app!"
    EXIT
  END IF
END

```

Figure 8. Pseudocode of the sugarcane disease identification application.

Figure 9 illustrates the system flow diagram, which outlines the sequences of operations and flow of information.

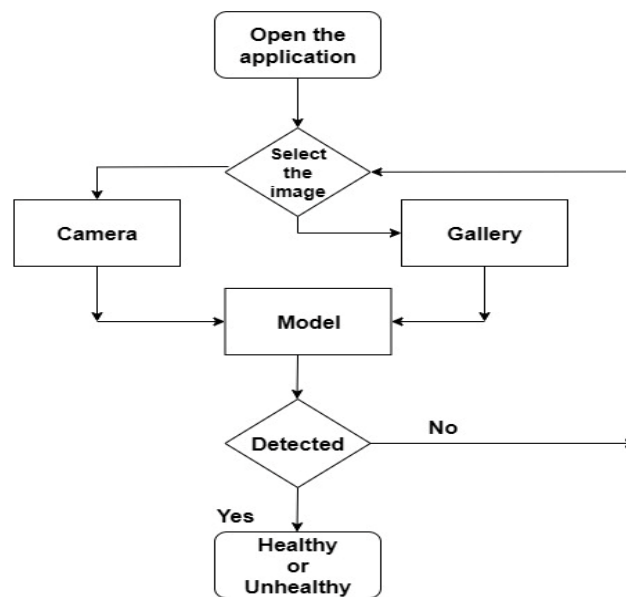


Figure 9. Flow chart for the implementation of the proposed model for mobile application development.

Challenges and Observations

Annotating high-quality data proved to be both time-consuming and dependent on professional expertise, as the accuracy of annotations directly influenced the performance of the model. Variations in the quality of the image and different environmental conditions posed challenges in ensuring uniform annotations and achieving stable training outcomes. YOLOv8 demonstrated strong accuracy under agricultural conditions; extensive testing across diverse environments remains essential to validate its robustness. Incorporating automated or semi-automated annotation tools could significantly reduce the manual effort and accelerate large-scale dataset processing. One key observation is that integrating real-time environmental data has the potential to further increase prediction accuracy and support farmers in making data-driven decisions.

Discussion

Dataset Quality and Diversity

Image Acquisition: In this study, a dataset of 2,723 original sugarcane images was used and further expanded through data augmentation to enhance its quality and diversity. Images were collected from several disease-prone areas across different growth stages and using various cameras, thereby ensuring a comprehensive dataset. This approach yielded a dataset that closely reflects real-world agricultural conditions.

Micro-Annotated Details: The inclusion of micro-annotations significantly improved the dataset's granularity by capturing fine facts of disease symptoms. The detailed labeling

process aided the precise identification of suitable visual patterns, thereby refining the model's sensitivity and overall predictive accuracy.

Effectiveness of Data Augmentation

Augmentation Strategies: This study used data augmentation practices such as horizontal or vertical flipping and brightness adjustment to increase dataset diversity. Augmentation was especially valuable for the cases with insufficient class representation, including Yellow, Yellow Rust, Red Leaf, and healthy pods. These techniques reduced overfitting, improved the generalization performance of the Deep Learning models, and significantly increased the volume of annotated data, thereby enhancing model performance.

Model Evaluation and Performance

Model Comparison: The study compared different YOLO models, with an optimized CNN-based model outperforming others in both detection accuracy and inference speed, highlighting its potential for real-time agricultural applications.

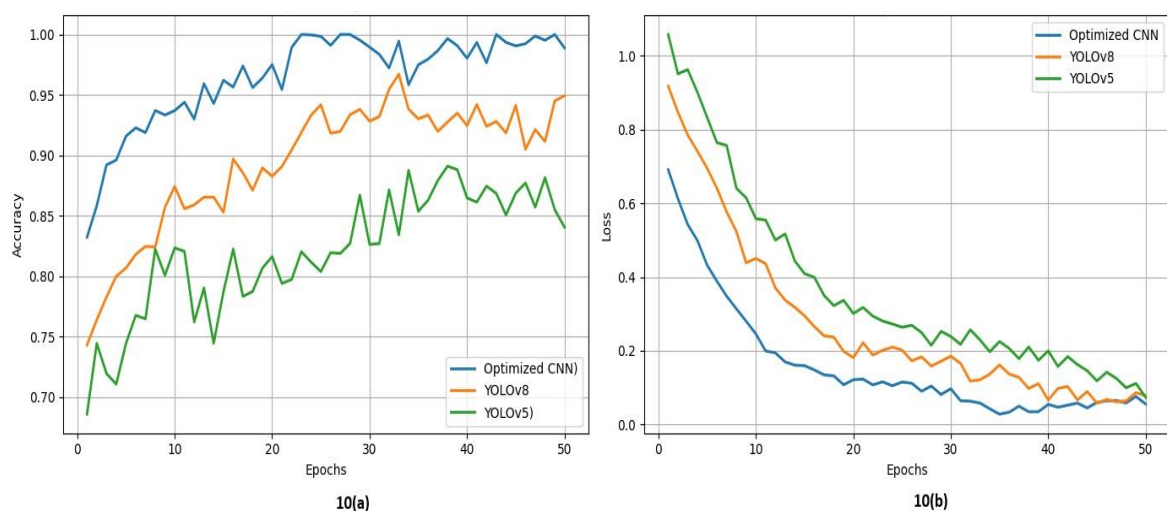


Figure 10(a),10(b). Performance comparison: optimized CNN with others

Figure 10(a) illustrates the overall accuracy comparison, while Figure 10(b) presents loss values obtained during the comparative analysis of different Yolo versions with the optimized CNN model.

Table 4. Performance metrics table

Model Name	Precision	Recall	F1-Score
Optimized CNN	0.98	0.97	0.98
YOLOv8	0.95	0.94	0.95
YOLOv5	0.91	0.89	0.90

Table 4 illustrates the comparison results. The comparative evaluation showed that the highest performance was achieved by the optimized CNN, with a precision of 0.98, a recall of 0.97, and an F1-score of 0.98. These results suggested that the optimized CNN outperformed the YOLO family for sugarcane disease identification, making it a dependable option for real-time sugarcane disease classification.

Resolution Analysis: Performance metrics varied across different annotated resolutions (entire leaf vs. micro-annotation) and plant parts. The results showed significant advantages in accurately detecting both complete and micro-annotations, demonstrating the model's suitability for real-time applications across diverse regions and conditions.

Challenges and Future Directions

The application of micro-annotation within a dataset proved challenging, as the quality and consistency of annotations directly influenced model performance. Future work should prioritize the development of computerized or semi-automated annotation tools to reduce manual effort and improve efficiency. Additionally, integrating model predictions with real-time environmental data could enhance detection accuracy and generate actionable insights for farmers. Achieving fast application development with reliable results requires not only a high-quality and diverse image set but also micro-level analysis to capture subtle disease patterns. Future research directions may include the creation of larger and more diverse datasets, the design and development of lightweight and efficient models, the adoption of a multimodal approach, and the incorporation of explainable AI to ensure transparency and trust in agricultural applications.

Conclusion

This study highlighted that Deep Learning models can significantly improve the accuracy of real-time disease identification in sugarcane crops. The study achieved excellent results using YOLO frameworks like YOLOv5 and YOLOv8, along with an optimized CNN model. The CNN-based model outperformed some versions of YOLO. The collected field datasets included diverse and high-quality images, which allowed for accurate disease classification, achieving 98% accuracy in sugarcane disease identification. In addition to model development, a mobile application was also created, which integrated the best-trained model and provided an easy-to-use disease detection platform for farmers.

Through these findings, it was confirmed that the proposed system was both technically sound and practically valuable, as actionable insights for effective disease management were made available to farmers. The integration of AI-driven solutions marked a transformative shift towards data-driven and sustainable agricultural practices. For future work, it was suggested that datasets should be expanded to cover more diverse environmental conditions, contextual information such as weather and soil factors should be incorporated, and

lightweight models optimized for mobile and edge deployment should be developed. Such advancements were expected to enhance scalability and usability, thereby amplifying the system's impact and supporting resilience and sustainability in agriculture.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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