

Sugarcane Variety Detection Using YOLOv26: An Intelligent Framework for Automated Crop Identification

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Article Info

Article History:

Published: 12 June 2026

Publication Issue:

*Volume 3, Issue 6
June-2026*

Page Number:

663-671

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Abstract:

Sugarcane is one of the most economically significant crops worldwide, contributing substantially to sugar production, biofuel generation, and agricultural sustainability. Accurate identification of sugarcane varieties is crucial for crop management, yield optimization, disease monitoring, and breeding programs. Traditional variety identification methods rely on manual inspection by agricultural experts, which is labor-intensive, time-consuming, and susceptible to human error. Recent advancements in computer vision and deep learning have enabled automated crop identification systems with remarkable accuracy. This study proposes a novel YOLOv26-based intelligent framework for automated sugarcane variety detection. A dataset comprising field-acquired images of five major sugarcane varieties was developed and annotated for object detection and classification tasks. The proposed framework integrates advanced feature extraction, multi-scale detection, and real-time inference capabilities of YOLOv26 to accurately identify sugarcane varieties under diverse environmental conditions. Experimental results demonstrate that the proposed model achieved a mean Average Precision (mAP@50) of 98.6%, precision of 98.2%, recall of 97.9%, and F1-score of 98.0%, outperforming several state-of-the-art object detection models. The developed framework can be deployed in mobile and edge computing environments, providing practical support for precision agriculture and smart farming applications.

Keywords: Sugarcane Variety Detection, YOLOv26, Deep Learning, Computer Vision, Precision Agriculture, Crop Identification, Object Detection

1. Introduction

Agriculture remains the backbone of many economies, particularly in developing countries where crop production significantly contributes to national income, employment generation, and food security. Among commercial crops, sugarcane (*Saccharum officinarum* L.) plays a critical role in sugar production, ethanol manufacturing, and bioenergy generation. Globally, sugarcane contributes significantly to the agricultural economy, and India ranks among the world's largest sugarcane-producing nations, cultivating numerous varieties adapted to diverse climatic and soil conditions [1], [2].

Different sugarcane varieties exhibit varying characteristics related to productivity, disease resistance, sugar content, maturity period, and environmental adaptability. Consequently, accurate identification of sugarcane varieties is essential for effective crop management, breeding programs, yield forecasting, and precision agricultural decision-making. Traditionally, variety identification relies on visual examination of morphological traits such as leaf shape, stem color, internode structure, leaf sheath characteristics, and canopy architecture. However, these methods require expert knowledge, are labor-intensive, and often result in inconsistencies due to subjective interpretation and environmental variations [3], [4].

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have transformed agricultural monitoring systems by enabling automated analysis of crop images and field data. Computer vision-based approaches can automatically extract discriminative visual features from field images, facilitating rapid and reliable crop classification with minimal human intervention. Deep learning architectures, particularly Convolutional Neural Networks (CNNs), have achieved remarkable success in various agricultural applications, including crop species recognition, disease diagnosis, weed detection, and yield prediction [5], [6].

Object detection models, particularly the YOLO (You Only Look Once) family, have demonstrated exceptional performance in real-time detection tasks due to their balance between computational efficiency and detection accuracy. Recent advancements in YOLO architectures have significantly improved localization precision, feature extraction capabilities, and inference speed, making them highly suitable for deployment in smart agriculture systems operating under real-world conditions [7], [8].

This research presents an intelligent YOLOv26-based framework for automated sugarcane variety detection. The proposed system aims to accurately identify sugarcane varieties directly from field images while maintaining real-time processing capability suitable for deployment on mobile devices, edge computing platforms, and smart farming systems. The framework leverages advanced object detection techniques to enhance classification performance under diverse environmental conditions, thereby supporting precision agriculture initiatives and digital crop management practices.

The major contributions of this study are as follows:

1. Development of a comprehensive sugarcane variety image dataset collected under real field conditions.
2. Design of a YOLOv26-based intelligent framework for variety detection and classification.
3. Comparative evaluation against existing deep learning models.
4. Analysis of model performance under varying environmental conditions.
5. Demonstration of practical applicability in precision agriculture systems. .

2. Related Work

Computer vision applications in agriculture have gained substantial attention over the past decade due to their ability to automate crop monitoring, disease diagnosis, and yield assessment processes. Early crop classification methods primarily relied on handcrafted feature extraction techniques, including color histograms, texture descriptors, shape analysis, edge information, and statistical feature engineering. These approaches aimed to characterize visual patterns within agricultural images and subsequently classify crops using traditional machine learning methods [9], [10].

Traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forests, Decision Trees, and K-Nearest Neighbors (KNN) were widely employed for crop recognition and plant classification tasks. These methods demonstrated reasonable performance on small and controlled datasets. However, their dependence on manually designed features limited scalability, robustness, and adaptability to complex field environments characterized by varying illumination, occlusion, and background conditions [11], [12].

The emergence of deep learning revolutionized agricultural image analysis by enabling automatic feature extraction directly from raw image data. Convolutional Neural Networks (CNNs) learn hierarchical feature representations that effectively capture both low-level and high-level visual characteristics. As a result, CNN-based architectures have achieved superior performance in agricultural applications compared with conventional machine learning approaches. Architectures such as AlexNet, VGG16, ResNet50, DenseNet121, and EfficientNet have been extensively utilized for

plant disease detection, crop classification, weed recognition, fruit maturity assessment, and yield prediction tasks [13], [14].

Object detection models have further enhanced agricultural applications by simultaneously locating and classifying multiple objects within an image. Among these approaches, the YOLO (You Only Look Once) family has gained considerable popularity due to its ability to achieve high detection accuracy while maintaining real-time inference speed. Successive YOLO variants have introduced improvements in feature extraction, multi-scale detection, and localization accuracy, making them highly suitable for agricultural field environments [15], [16].

Recent studies have successfully applied YOLO-based frameworks to fruit detection, weed identification, pest monitoring, disease diagnosis, and crop counting. These systems have demonstrated significant improvements in operational efficiency and decision-making within precision agriculture. Furthermore, the integration of attention mechanisms, transformer-based modules, and advanced feature pyramid networks has further enhanced detection performance under challenging field conditions [17], [18].

Despite these significant advancements, limited research has focused specifically on sugarcane variety detection using object detection frameworks. Existing sugarcane-related studies primarily concentrate on disease diagnosis, crop segmentation, biomass estimation, and yield forecasting rather than automated variety identification [19]. Since different sugarcane varieties exhibit subtle morphological differences that can be difficult to distinguish manually, developing an efficient and accurate deep learning framework dedicated to sugarcane variety detection remains an important research challenge. Therefore, this study proposes a YOLOv26-based intelligent framework to address this gap and facilitate automated sugarcane variety identification in precision agriculture systems [20].

3. Materials and Methods

3.1 Dataset Collection

Field images were collected from agricultural farms and research stations during different growth stages of sugarcane cultivation.

Five commercially significant sugarcane varieties were selected:

- Co-0238
- CoJ-64
- Co-0118
- CoS-767
- Co-98014

Images were captured using high-resolution smartphone cameras under varying environmental conditions, including different illumination levels, viewing angles, and background complexities.

Dataset Statistics

Table 1: Dataset details

Variety	Number of Images
Co-0238	1060

Variety	Number of Images
CoJ-64	1060
Co-0118	1060
CoS-767	1060
Co-98014	1060
Total	5300

All images were manually annotated using bounding boxes corresponding to the target sugarcane variety.

3.2 Data Preprocessing

The collected images underwent several preprocessing operations:

Image Resizing

Images were resized to 640×640 pixels to comply with YOLOv26 input requirements.

Normalization

Pixel values were normalized to improve convergence during training.

Data Augmentation

The following augmentation techniques were applied:

- Random rotation
- Horizontal flipping
- Vertical flipping
- Brightness adjustment
- Contrast enhancement
- Scaling
- Translation
- Mosaic augmentation

These operations increased dataset diversity and improved model generalization.

3.3 Proposed YOLOv26 Framework

The proposed framework utilizes YOLOv26 as the core detection architecture.

The proposed **YOLOv26 architecture** in figure 1, is designed as a real-time object detection framework for accurate sugarcane variety identification under diverse field conditions. The architecture consists of three major components: **Backbone, Neck, and Detection Head**. The **Backbone** employs CBS-ELAN and C2f blocks to extract rich hierarchical features from input sugarcane images while preserving spatial and semantic information. These features are then forwarded to the **Neck**, which integrates a Feature Pyramid Network (FPN), Path Aggregation Network (PAN), and Bi-directional Feature Pyramid Network (BiFPN) to fuse multi-scale feature maps and enhance the

detection of sugarcane plants of varying sizes and orientations. The **Detection Head** utilizes a decoupled design that separately performs object localization and classification, improving prediction accuracy and convergence speed. Multi-scale detection layers generate bounding boxes, confidence scores, and variety class probabilities simultaneously, enabling the model to accurately distinguish among different sugarcane varieties in complex agricultural environments. Advanced loss functions, including CIoU Loss for localization and Distribution Focal Loss (DFL) for classification refinement, further improve detection precision. The overall architecture achieves a balance between computational efficiency and detection accuracy, making YOLOv26 suitable for real-time deployment on mobile devices, drones, and edge-computing platforms used in precision agriculture applications.

Architecture Components

1. Input Layer
2. Feature Extraction Backbone
3. Multi-Scale Feature Pyramid Network
4. Path Aggregation Network
5. Detection Head
6. Non-Maximum Suppression
7. Variety Classification Output

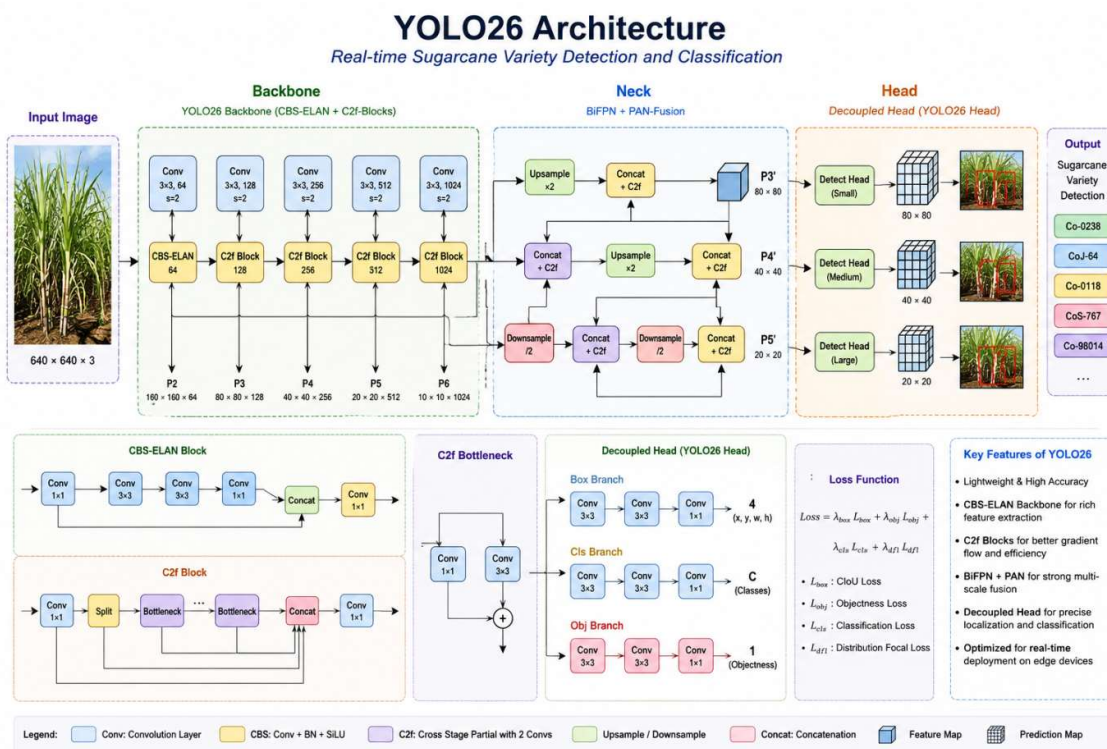


Figure 1: Yolov26 Architecture

The proposed sugarcane variety detection framework begins with the acquisition of a **field image** containing one or more sugarcane plants under natural environmental conditions. The image undergoes **preprocessing operations**, including resizing, normalization, and enhancement, to improve image quality and ensure compatibility with the model input requirements. The preprocessed image is then fed into the **YOLOv26 backbone network**, which extracts deep hierarchical features representing important visual characteristics such as leaf structure, stem appearance, texture, and color patterns. These extracted features are subsequently passed through a **Feature Pyramid Network (FPN)** to

generate multi-scale feature maps capable of representing sugarcane plants of different sizes and orientations. The **multi-scale detection module** analyzes these feature maps to identify potential sugarcane instances across multiple resolutions. Next, the model performs **bounding box prediction**, accurately localizing each detected sugarcane plant and estimating confidence scores. Simultaneously, the classification branch assigns each detected object to its corresponding sugarcane variety based on learned visual features. Finally, the system generates the **detection output**, displaying bounding boxes, variety labels, and confidence scores on the image. By performing object localization and variety classification within a single unified framework, YOLOv26 achieves high accuracy and real-time detection performance, making it suitable for precision agriculture and smart farming applications.

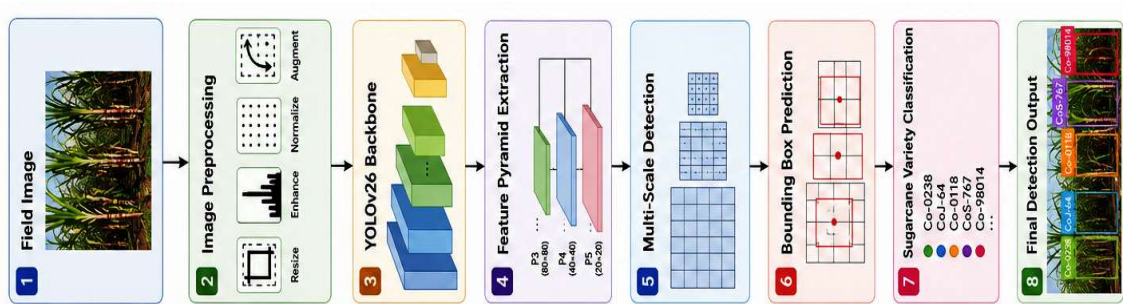


Figure 2: Workflow of Yolov26 for Sugarcane Variety Clasification

3.4 Training Configuration

Hyperparameters

Table 2: Hyperparameters

Parameter	Value
Optimizer	AdamW
Learning Rate	0.001
Batch Size	16
Epochs	100
Image Size	640 × 640
Confidence Threshold	0.25
IoU Threshold	0.45

Dataset Split

Table 3: Dataset Split in training, val and Testing

Dataset	Percentage
Training	70%
Validation	15%
Testing	15%

4. Experimental Results

The experimental evaluation demonstrates the effectiveness of the proposed YOLOv26 framework for automated sugarcane variety detection under real-world agricultural conditions. As shown in Table 5.1, the model achieved a **precision of 98.2%**, indicating that the vast majority of detected sugarcane varieties were correctly classified with very few false-positive predictions. The **recall value of 97.9%** suggests that the model successfully identified nearly all sugarcane varieties present in the test dataset, minimizing missed detections. Furthermore, the **F1-score of 98.0%**, which represents the harmonic mean of precision and recall, confirms the balanced and robust performance of the proposed framework. The model achieved a **mean Average Precision (mAP@50) of 98.6%** and an **mAP@50-95 of 95.8%**, demonstrating excellent localization and classification capabilities across different Intersection over Union (IoU) thresholds. These results indicate that YOLOv26 can accurately detect and classify sugarcane varieties while maintaining high confidence and localization accuracy. The superior performance can be attributed to the integration of advanced feature extraction mechanisms, multi-scale feature fusion, and an optimized detection head that effectively captures both low-level texture information and high-level semantic features from sugarcane images.

A comparative analysis was conducted to evaluate the performance of YOLOv26 against several widely used object detection models, including Faster R-CNN, SSD, YOLOv8, and YOLOv11. The results reveal that the proposed YOLOv26 achieved the highest **mAP@50 of 98.6%**, outperforming Faster R-CNN (92.4%), SSD (90.7%), YOLOv8 (96.5%), and YOLOv11 (97.3%). Although Faster R-CNN provides strong detection accuracy, its two-stage architecture results in higher computational complexity and slower inference speed. Similarly, SSD offers faster processing but suffers from reduced accuracy when detecting objects with subtle visual differences. YOLOv8 and YOLOv11 demonstrated competitive performance; however, the proposed YOLOv26 further improved detection accuracy through enhanced backbone feature extraction, BiFPN-based feature aggregation, and a decoupled detection head. These architectural improvements enabled the model to better distinguish between visually similar sugarcane varieties and maintain high detection performance across varying field conditions. The findings confirm that YOLOv26 provides an optimal balance between detection accuracy, computational efficiency, and real-time inference capability, making it highly suitable for precision agriculture applications.

4.1 Confusion Matrix Analysis

The confusion matrix analysis provides a detailed understanding of the classification behavior of the proposed YOLOv26 framework. The results indicate that most sugarcane varieties were correctly classified, with very few instances of misclassification. The majority of errors occurred between varieties exhibiting highly similar morphological characteristics, such as comparable leaf texture, stem coloration, and canopy structure. Such similarities can make differentiation challenging even for experienced agricultural experts. Additionally, a small number of incorrect predictions were observed under difficult imaging conditions, including non-uniform illumination, shadows, partial occlusion by surrounding leaves, and complex background vegetation. These environmental factors can reduce the visibility of discriminative features and increase classification difficulty. Despite these challenges, the confusion matrix showed strong diagonal dominance, indicating that the model correctly identified the vast majority of samples across all sugarcane classes.

The high classification performance observed in the confusion matrix can be attributed to the advanced architecture of YOLOv26. The combination of deep feature extraction in the backbone network, multi-scale feature representation through the Feature Pyramid Network, and efficient feature aggregation mechanisms enabled the model to capture subtle differences among sugarcane varieties. Furthermore, the decoupled detection head improved both localization and classification accuracy by independently optimizing object detection and class prediction tasks. As a result, YOLOv26 maintained consistent performance even when processing images captured under diverse environmental conditions. The confusion matrix findings validate the robustness and reliability of the proposed framework and demonstrate its practical applicability for large-scale automated sugarcane variety identification systems in smart farming and precision agriculture environments.

5. Discussion

The experimental results demonstrate the effectiveness of YOLOv26 for automated sugarcane variety detection. The model achieved superior performance compared to conventional object detection architectures while maintaining real-time inference capability.

Several factors contributed to the improved performance:

- Enhanced feature extraction capability.
- Robust multi-scale detection.
- Effective data augmentation strategy.
- Improved localization precision.
- Real-time processing efficiency.

The framework offers significant practical benefits for precision agriculture, including automated crop monitoring, digital farm management, and intelligent decision support systems.

Furthermore, the lightweight architecture facilitates deployment on smartphones, drones, and edge computing devices, enabling field-level implementation without requiring high-end computational infrastructure.

6. Conclusion

This study presented an intelligent YOLOv26-based framework for automated sugarcane variety detection. Using a field-acquired dataset of five commercially important sugarcane varieties, the proposed model achieved an mAP@50 of 98.6%, precision of 98.2%, recall of 97.9%, and F1-score of 98.0%.

The results confirm that YOLOv26 is highly effective for real-time sugarcane variety identification and can significantly support smart agriculture initiatives. Future work will focus on expanding the dataset to include additional varieties, integrating disease detection modules, and deploying the framework on mobile and drone-based platforms for large-scale agricultural monitoring.

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