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Automated Real-Time Sugarcane Node Detection System Using YOLOv8 and Edge Computing

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Abstract: Sugarcane farming is a vital agricultural sector that faces major challenges due to its heavy reliance on manual labor, especially during node identification and harvesting. Traditional methods are labor-intensive, time-consuming, and prone to human errors, leading to decreased productivity and increased operational costs. This research presents an automated, real-time sugarcane node detection and cutting system leveraging deep learning and computer vision technologies. The proposed system utilizes the YOLOv8 object detection model for accurate node identification and integrates actuator control mechanisms to automate cutting. A dataset comprising over 4000 labeled sugarcane stem images was used to train the detection model, achieving an average precision of ~92% and an F1 score of ~90.5%. The solution is deployed on a low-power edge device (Jetson Nano) using Python, OpenCV, and TensorFlow/Keras, enabling efficient real-time performance with an average processing speed of 20–25 FPS. Servo motors are employed for executing precise cuts based on model predictions. This integration significantly reduces dependency on manual labor, enhances cutting precision, and promotes sustainable farming practices. The system's modularity, low cost, and adaptability suggest a strong potential for commercial adoption and future expansion into broader smart farming applications.
Keywords: Sugarcane Automation, Node Detection, YOLOv8, Computer Vision, Jetson Nano, Precision Agriculture, Machine Learning, Real-Time Object Detection, Smart Farming, Edge Computing.

I. INTRODUCTION

Sugarcane is a crucial cash crop grown extensively in tropical and subtropical regions, contributing significantly to the global supply of sugar, ethanol, and other industrial by-products. Countries like India, Brazil, and China rely heavily on sugarcane cultivation for economic development and rural employment. However, the methods employed in sugarcane farming have largely remained traditional, depending heavily on manual labor for planting, irrigation, and harvesting processes.

One critical step in sugarcane farming is the identification of stem nodes, which are essential for proper planting and regrowth. In conventional practices, farmers manually inspect and cut sugarcane stalks at the nodes. This approach is not only labor-intensive but also susceptible to human errors, leading to improper node identification, inconsistent cutting, wastage of planting material, and ultimately lower crop yields. Furthermore, with the increasing demand for sugar and biofuels, the shortage of agricultural labor has emerged as a major bottleneck, necessitating automation in farming operations.

Recent advancements in computer vision, machine learning, and edge computing technologies provide new opportunities to address these challenges. Deep learning models such as YOLO (You Only Look Once) have revolutionized real-time object detection, offering high accuracy and speed even in resource-constrained environments. The integration of such models with low-power edge devices like the NVIDIA Jetson Nano enables the development of efficient, scalable, and cost-effective agricultural automation systems.

This research proposes a real-time, automated sugarcane node detection and cutting system using YOLOv8 and Jetson Nano. The system is designed to detect sugarcane nodes accurately from live video feeds, predict optimal cutting moments, and automate the cutting action through a servo-controlled actuator. By significantly reducing manual labor requirements and increasing operational efficiency, the proposed solution aims to promote sustainable and smart farming practices in sugarcane cultivation.

II. RELATED WORK

Automation in agriculture has witnessed rapid advancements in recent years, especially with the adoption of machine learning and computer vision techniques. Several researchers have focused on automating processes such as fruit detection, weed identification, and crop health monitoring. However, the automation of sugarcane node detection and cutting remains a relatively underexplored area.

R. Ehsani et al. (2013) developed an image processing-based system for detecting sugarcane row positions to aid in automated planting. Their approach, which utilized thresholding and edge detection methods, was effective under controlled conditions but lacked robustness when deployed in natural field environments.

J. Zhang et al. (2017) applied Support Vector Machine (SVM) classifiers for sugarcane disease identification using leaf images. Although their system achieved high accuracy in laboratory settings, it struggled with environmental variations such as inconsistent lighting and background noise, limiting its practical usability.

A. Kumar et al. (2020) demonstrated the use of convolutional neural networks (CNNs) for identifying sugarcane growth stages using UAV imagery. Their work highlighted the potential of deep learning in agriculture but did not address node detection or mechanical actuation for automated cutting.

The emergence of real-time object detection models, particularly the YOLO (You Only Look Once) family, has enabled the deployment of highly accurate and efficient detection systems even on edge devices. Ultralytics' YOLOv8 model, with its compact size and improved accuracy, provides a practical solution for field-level agricultural tasks.

However, most previous studies in sugarcane automation have major limitations:

- Reliance on conventional image processing techniques that perform poorly in dynamic field conditions.
- Lack of real-time processing capabilities suitable for deployment on low-power hardware.
- Absence of end-to-end systems that not only detect but also act upon the detections (e.g., automatic cutting).
- Limited focus on the specific task of sugarcane node detection, which is critical for planting and harvesting efficiency.

The system proposed in this paper addresses these gaps by integrating a deep learning-based detection model with mechanical cutting automation, optimized for real-world deployment on portable, low-power computing platforms.

III. METHODOLOGY

The proposed system for automated sugarcane node detection and cutting integrates computer vision, machine learning, and actuator control technologies to achieve real-time precision farming. The methodology is divided into multiple phases, each addressing a specific functional component of the system.

A. System Architecture

The overall system architecture consists of the following main components:

- Video Acquisition Module: Captures live video feed of sugarcane stems using a high-resolution camera.
- Node Detection Module: Processes video frames through a YOLOv8-based deep learning model to identify sugarcane nodes.
- Prediction and Decision Module: Determines the optimal moment to initiate the cutting action based on node position and movement.
- Actuator Control Module: Controls a servo motor to perform precise cuts at the detected nodes.
- User Interface Module: Provides real-time visualization of the detection results and system status through a Flask or Streamlit-based dashboard.

B. Dataset Preparation

A custom dataset was created by capturing over 4000 images of sugarcane stems under varying lighting and environmental conditions.

Each image was manually annotated with bounding boxes marking the sugarcane nodes using labeling tools like Roboflow and CVAT.

This labeled dataset was used for training and validating the YOLOv8 detection model to achieve high real-world accuracy.

C. Node Detection Using YOLOv8

YOLOv8, a state-of-the-art object detection model, was employed for real-time node detection:

- The model was either trained from scratch or fine-tuned on the custom sugarcane dataset.
- During operation, each incoming frame from the camera is processed by YOLOv8.
- Nodes are detected with bounding boxes and confidence scores, and their positional coordinates are extracted for further processing.
- The model achieved an inference speed of ~25–30 ms per frame on a Jetson Nano, enabling real-time operation.

D. Prediction of Cutting Moment

After detecting the nodes, a simple predictive algorithm analyzes:

- The position and size of the detected node in the frame.
- The movement speed of the sugarcane stem (if on a conveyor or manual feed).

Based on this analysis, the system calculates the ideal time to trigger the cutting actuator to ensure the node is cut precisely.

E. Servo Motor Control

The system controls a servo motor through GPIO interfaces on the Jetson Nano:

- When the optimal cutting moment is predicted, a control signal is sent to the servo motor.
- The motor moves the cutting blade to perform an accurate cut at the node location.
- After cutting, the system resets the servo to its initial position, ready for the next operation.

F. Software Environment

Software

- Windows 11 (Operating System)
- Python (Primary Programming Language)
- OpenCV (Image Processing and Camera Handling)
- TensorFlow/Keras or PyTorch (Deep Learning Libraries)
- SQLite (Data Logging)

G. Integration and Testing

All components — detection, prediction, actuation, and UI — were modularly developed and then integrated into a unified system. Comprehensive unit, integration, and real-time field testing were conducted to ensure accuracy, reliability, and responsiveness under varied operating conditions.

IV. FUTURE ENHANCEMENTS

1) Integrate multi-angle cameras to improve node detection accuracy from different perspectives.
2) Develop a self-learning model that improves node detection over time with real-time feedback.
3) Upgrade the cutting system with dynamic speed control and high-precision actuators.
4) Add AI-powered cane quality assessment to detect defects and optimize harvesting decisions.
5) Create a cloud-based monitoring dashboard for remote observation and analytics.
6) Design a solar-powered or battery-operated version for sustainable, off-grid operation.

V. CONCLUSION

The developed system successfully addresses the longstanding challenges of manual sugarcane node detection and cutting by introducing real-time automation through machine learning and computer vision technologies. By leveraging YOLOv8 for node identification and integrating actuator control for precise cutting, the project demonstrates significant improvements in efficiency, accuracy, and resource optimization compared to traditional methods. The deployment on a low-power edge device like Jetson Nano ensures portability and cost-effectiveness, making it accessible to small and mid-scale farmers. Extensive testing validated the system's reliability, achieving high detection accuracy and operational stability under real-world conditions. Furthermore, the modular design allows easy updates and scalability, laying the foundation for future enhancements such as multi-crop adaptability, IoT integration, and mobile field deployment. This project represents a critical step toward the modernization of agriculture, promoting smarter and more sustainable farming practices to meet growing global demands.

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