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## DEVELOPMENT OF VISION-GUIDED AUTONOMOUS ROBOT FOR PHENOTYPIC MONITORING IN TOMATO BREEDING

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### ABSTRACT

Phenotypic monitoring in crop breeding requires continuous data collection throughout growth cycles, yet traditional manual methods are both labor-intensive and time-consuming. Individual plant tracking over extended periods poses particular challenges due to field scale and measurement frequency requirements across diverse agricultural environments. This study presents an autonomous robotic platform integrating computer vision and precision positioning technologies for automated phenotypic data collection in open-field tomato breeding programs. The system addresses two critical technical requirements: autonomous navigation along crop rows and accurate individual plant localization for temporal tracking across growing seasons. The navigation subsystem employs Fast Segmentation Convolutional Neural Network (Fast-SCNN) for real-time furrow segmentation, generating reference trajectories for path following control. For plant-level localization, the system detects plant support stakes positions using dense optical flow combined with Gaussian mixture background subtraction, subsequently correlating visual landmarks with Real-Time Kinematic (RTK) coordinates to enable persistent plant identification across multiple visits. Experimental validation demonstrated navigation precision with mean lateral deviation of 1.86 cm and angular deviation of 2.65° during autonomous operation. Plant detection achieved 98.4% accuracy, while RTK-based localization maintained mean absolute error of 0.083 m. These performance metrics enable reliable phenotypic data association at the individual plant level throughout the growing season. The integrated robotic platform significantly reduces manual labor requirements compared to conventional monitoring approaches while providing standardized, repeatable measurements critical for genetic evaluation. This automation framework demonstrates substantial potential for scaling precision agriculture applications in breeding programs.

**Keywords:** autonomous navigation, phenotypic monitoring, semantic segmentation, plant localization, agricultural robotics.

## INTRODUCTION

Phenotypic monitoring requires precise data collection for quantitative evaluation of genetic improvements in crop breeding programs. Traditional manual methods are labor-intensive and time-consuming, particularly for individual plant tracking across extended growth cycles. Advances in artificial intelligence and autonomous technologies have enabled agricultural robots to support farming tasks with greater efficiency and precision (Gill et al., 2022; Tripodi et al., 2018). However, existing agricultural robots face significant challenges in the narrow-row, high-density cropping environments where conventional navigation methods often fail due to canopy occlusion and heterogeneous field conditions. This study presents an autonomous robotic platform integrating vision-based navigation with RTK positioning for automated phenotypic monitoring in open-field tomato breeding. The system combines semantic segmentation for trajectory correction with a novel stake-based plant localization algorithm using Gaussian mixture background subtraction and dense optical flow, enabling centimeter-level precision for individual plant tracking throughout growing seasons.

## MATERIALS AND METHODS

### PLATFORM DESIGN

A six-wheel-drive robotic platform was equipped with a forward-facing webcam for navigation, dual 120° wide-angle Pi cameras for plant imaging and an RTK module for centimeter-level localization. A Jetson Orin NX serves as the on-board computing unit operating under ROS2 framework for real-time sensor fusion and autonomous control.

### NAVIGATION SYSTEM

The navigation subsystem employs Fast-SCNN (Poudel et al., 2019) for semantic segmentation of crop rows from RGB images. The network outputs binary masks separating crop rows from background regions, followed by using Canny edge detection and Hough transform for boundary line extraction. The guidance trajectory is computed as the median of detected boundary lines, providing reference coordinates for path following control using a PID controller with lateral offset and angular deviation as error signals (Fig. 1).

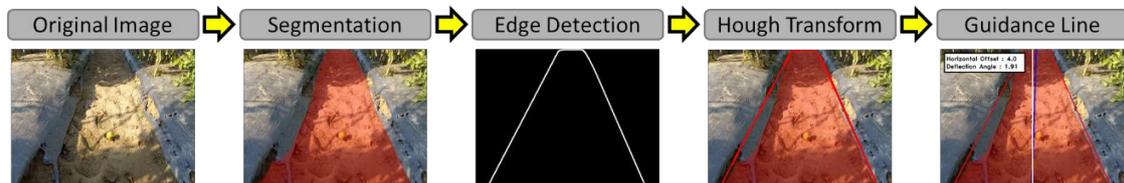


Fig.1 Vision-based navigation system for autonomous crop row following.

### SUPPORT STAKE LOCALIZATION ALGORITHM

Individual tomato plants are localized using support stakes placed during early growth stages. The localization algorithm integrates Gaussian Mixture Model (GMM) for background subtraction with dense optical flow to track stake movement during vehicle

traversal (Fig. 2). The GMM adapts to varying light conditions by modeling background pixels with a probabilistic model, enabling extraction of foreground stakes. Dense optical flow (Farneback, 2003) is applied to foreground contours to compute motion vectors. The algorithm filters out motion vectors from distant objects before analyzing cumulative optical flow distribution, identifying peaks corresponding to stake positions. When motion peaks occur within the image center zone, corresponding RTK coordinates are recorded as reference plant positions. This approach minimizes false detections from moving vegetation while ensuring accurate spatial registration between visual landmarks and geographic coordinates.

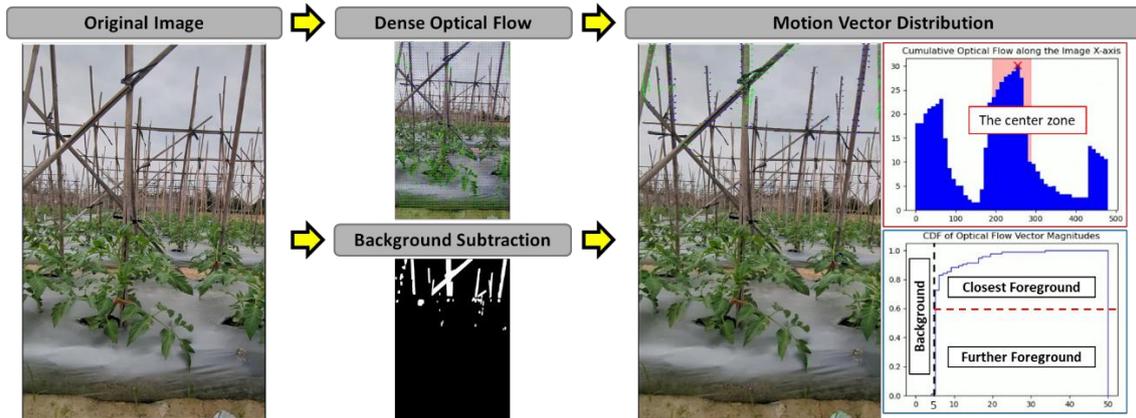


Fig.2 GMM-optical flow integration for plant stake detection and localization.

## RESULTS & DISCUSSION

### NAVIGATION PERFORMANCE

Fast-SCNN achieved robust segmentation performance across varying environmental conditions, with an average mIoU of 0.9267. Training with AdamW optimizer yielded superior performance compared to SGD, particularly in challenging scenarios with weed occlusion (Table 1). AdamW optimizer’s adaptive learning rate was effective for complex lane contours, improving weed-scenario performance. During field testing at 0.15 m/s travel speed, the autonomous navigation system achieved mean lateral deviation of 1.86 cm and angular deviation of 2.65°, demonstrating centimeter-level precision appropriate for precision agriculture.

Table 1 Lane identification model performance with different optimizer (mIoU).

Optimizer	Training	Validation	Testing			
			Normal	Weeds	Lodging	Moss
SGD	0.9356	0.9389	0.9054	0.8725	0.9494	0.9886
AdamW	0.9332	0.9430	0.9073	0.9093	0.9418	0.9846

### PLANT LOCALIZATION PERFORMANCE

The integrated GMM-optical approach significantly improved stakes detection accuracy. Under adequate lighting conditions, stake detection accuracy reached 98.4% compared to 92.9% with the conventional optical flow method. The GMM background modeling effectively suppressed noise caused by swaying vegetation and varying illumination.

However, performance degraded under backlit conditions, where foreground stakes and background exhibited similar intensity values. For individual tomato plant localization during monitoring tasks involving 17 plants, the RTK system demonstrated high positional accuracy and repeatability, with mean nearest-neighbor distance of 0.114 m and mean positional error of 0.083 m. These performance metrics indicate the system's capability for reliable individual plant identification and tracking across multiple field visits.

## CONCLUSIONS

The study developed a vision-guided autonomous robot integrating Fast-SCNN, GMM, dense optical flow, and RTK positioning for tomato phenotypic monitoring. The system achieved centimeter-level navigation accuracy (1.86 cm lateral, 2.65° angular), 98.4% stake detection accuracy, 0.083 m mean positional error, enabling reliable individual plant tracking. The platform significantly reduces manual labor while providing standardized measurements essential for genetic evaluation, demonstrating substantial potential for scaling precision agriculture applications in breeding programs.

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