Transforming Precision Agriculture through Deep Learning: CNN Encoder-Decoders and a Hybrid YOLOv8-SAM Solution for Advanced Grape Cluster Segmentation

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Abstract*—Accurate grape cluster segmentation is crucial for developing automated vineyard harvesting systems and precision agriculture applications. This paper presents a novel hybrid approach combining YOLOv8 object detection with Meta's Segment Anything Model (SAM) for multi-cluster grape segmentation, alongside comprehensive evaluation of CNN encoder-decoder architectures for single-cluster scenarios. Using the GrapesNet dataset containing over 11,000 diverse vineyard images, we trained and evaluated various segmentation models including U-Net variants with pre-trained encoders, SegNet architectures, and fully convolutional networks (FCNs). The MobileNetV2-UNet achieved superior single-cluster segmentation with mIoU of 0.906 and Dice coefficient of 0.984, demonstrating computational efficiency suitable for resource-constrained agricultural environments. For multi-cluster scenarios involving overlapping grape clusters, our hybrid YOLOv8-SAM approach demonstrated exceptional performance with mIoU of 0.943 and Dice coefficient of 0.970, significantly outperforming traditional CNN-based methods by 4.1% in IoU scores. The hybrid methodology addresses key challenges in agricultural computer vision including variable lighting conditions, cluster occlusion, and complex vineyard backgrounds. Comprehensive ablation studies validate the contribution of each component, while computational analysis demonstrates practical deployment feasibility. The primary contribution lies in demonstrating that foundation models like SAM, when combined with robust object detection, can effectively handle complex agricultural scenes with overlapping grape clusters, advancing automated harvesting and real-time yield estimation technologies for precision viticulture applications.

***Index Terms*—Deep Learning, Image Segmentation, Encoder-Decoder Architectures, CNN, U-Net, YOLO, Segment Anything Model, Precision Agriculture, Foundation Models, Automated Harvesting**

I. Introduction

Image segmentation partitions images into meaningful segments and serves as a fundamental task in computer vision applications including autonomous vehicles [1], [2], medical image analysis [3]–[5], video surveillance [6], [7], and augmented reality [8], [9]. The agricultural domain presents unique segmentation challenges due to natural variability in crop appearance, complex outdoor lighting conditions, and the need for real-time processing in autonomous systems. Traditional segmentation methods relied on thresholding [10], clustering, region-growing, edge detection, watersheds, and graph cuts, but these approaches struggle with the inherent complexity and variability of natural agricultural scenes. Recent advances have embraced deep learning approaches utilizing convolutional neural networks (CNNs) and encoder-decoder architectures, showing remarkable success in handling complex visual patterns and environmental variations.

The emergence of foundation models, particularly large-scale pre-trained networks like Meta's Segment Anything Model (SAM), has revolutionized the computer vision landscape. These models, trained on vast datasets encompassing millions of images, demonstrate unprecedented generalization capabilities across diverse domains. In agricultural applications, foundation models offer the potential to leverage broad visual understanding for specialized crop monitoring tasks, potentially reducing the need for extensive domain-specific training data.

A. Traditional Segmentation Methods

Early segmentation techniques employed thresholding to divide pixels based on intensity ranges. Global thresholding applies a single threshold across entire images, while adaptive thresholding adjusts thresholds dynamically based on local properties. Clustering methods like K-means group pixels by feature similarity, though they suffer from noise sensitivity and require predetermined cluster numbers. In agricultural contexts, these methods often fail due to the high intra-class variability of natural objects and varying illumination conditions throughout different times of day and seasons.

Region-based methods include region-growing and split-and-merge algorithms that segment images based on homogeneity criteria. Edge-based techniques detect object boundaries through intensity changes using operators like Sobel, Prewitt, and Canny. Graph-based methods model images as graphs where pixels are nodes and edges represent similarity. While computationally efficient, these traditional approaches lack the semantic understanding necessary for distinguishing between grape clusters and background foliage with similar color characteristics.

B. Deep Learning Revolution in Segmentation

CNN-based architectures transformed image segmentation by learning hierarchical feature representations automatically, eliminating the need for hand-crafted features that often fail to capture the complexity of natural scenes. Fully convolutional networks (FCNs) replaced fully connected layers with convolutional layers, enabling processing of arbitrary input sizes while maintaining spatial information throughout the network. This foundational work led to encoder-decoder architectures like U-Net and SegNet, which combine feature extraction (encoder) with upsampling (decoder) for dense pixel-wise predictions.

U-Net utilizes skip connections to preserve spatial details by connecting encoder features to decoder layers, proving particularly effective for medical imaging with limited data and achieving state-of-the-art results in various biomedical segmentation tasks. The skip connections enable the decoder to recover fine-grained spatial information that might be lost during the encoding process. SegNet employs pooling indices for accurate upsampling, making it suitable for semantic segmentation tasks where precise boundary localization is crucial.

Recent developments in transformer-based architectures and attention mechanisms have further advanced segmentation capabilities, enabling models to capture long-range dependencies and global context information that traditional CNNs might miss.

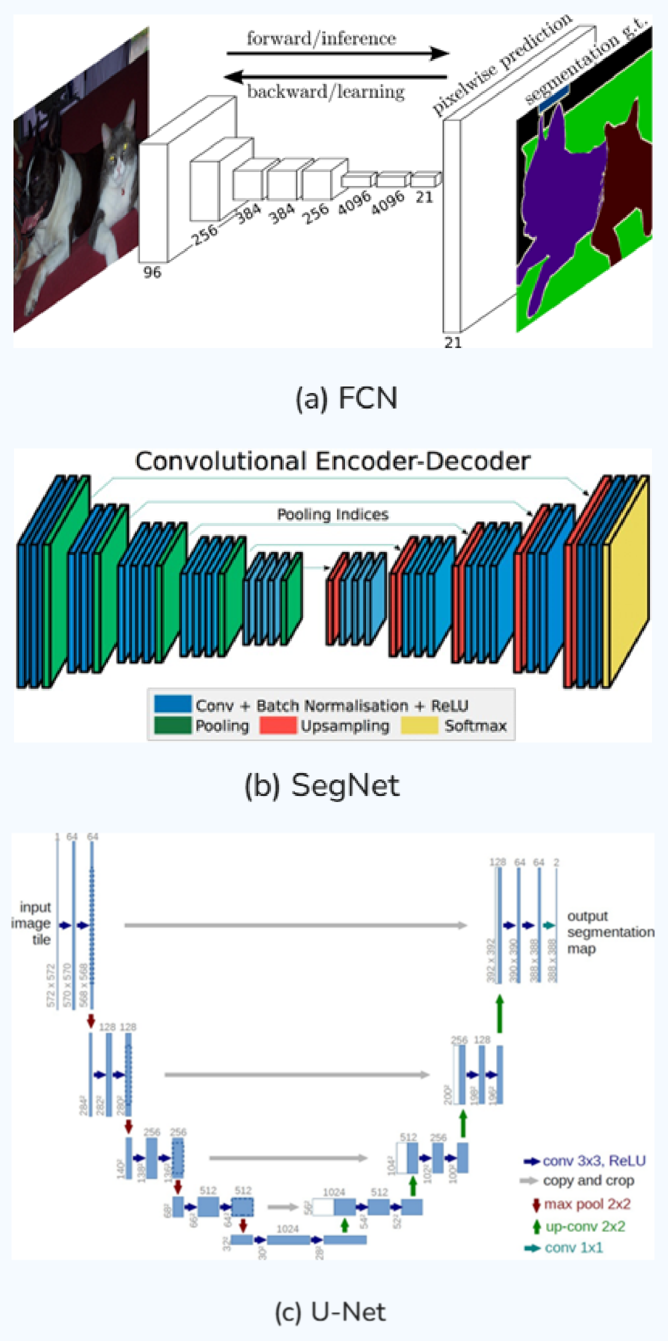
C. Agricultural Computer Vision Challenges

Agricultural environments present unique challenges for computer vision systems. Grape clusters exhibit significant variability in size, shape, color, and ripeness stages, making consistent segmentation challenging. Environmental factors including varying lighting conditions, shadows, and weather effects further complicate the segmentation task. Overlapping clusters and partial occlusions by leaves add another layer of complexity that traditional segmentation methods struggle to handle effectively.

The need for real-time processing in autonomous harvesting systems demands computationally efficient solutions that can operate on mobile platforms with limited computational resources. Additionally, the seasonal nature of agriculture requires models that can generalize across different growth stages and environmental conditions encountered throughout the growing season.

D. Significance of Grape Cluster Segmentation

Grapes represent a significant cash crop driving research into automated harvesting systems. Accurate grape cluster segmentation enables volumetric analysis for yield estimation, ripeness assessment, growth monitoring, and optimal harvest timing determination. This information supports grape storage, transportation, and market supply planning while enabling automated harvesting robots to navigate vineyards and selectively harvest ripe fruit.



(a) FCN

(b) SegNet

(c) U-Net

Fig. 1. CNN architecture structures: (a) FCN, (b) SegNet, (c) U-Net.

II. Data Acquisition and Preparation

A. Dataset Description

The GrapesNet dataset comprises over 11,000 grape cluster images captured under natural and artificial lighting conditions across four distinct subsets. This comprehensive dataset supports critical vineyard automation tasks including grape detection and segmentation.

B. Single-Cluster Segmentation Pipeline

For single-cluster segmentation, we manually annotated binary masks for 370 images and generated masks for 280 additional images using optimal green channel thresholding. Data augmentation techniques including zooming, flipping, and contrast adjustments increased the dataset to 827 images. This approach simplifies training while enabling development of object detection models for multi-cluster scenarios.

III. CNN Architectures for Single-Cluster Segmentation

We implemented eleven CNN architectures: basic encoder-decoder, two U-Net variants, advanced U-Nets with MobileNetV2 and ResNet34 encoders, three SegNet variants, and two FCN models.

A. Fully Convolutional Networks

FCNs perform convolutions throughout without fully connected layers, enabling processing of arbitrary input sizes. FCN-8 employs 8×8 upsampling stride for finer details, while FCN-32 uses 32×32 stride producing coarser outputs.

B. SegNet Architecture

SegNet combines encoder-decoder structure with pooling indices from max-pooling operations for efficient upsampling. We implemented three variants: SegNet, SegNet, and VGG16-SegNet utilizing pre-trained VGG16 as encoder.

C. U-Net Variants

U-Net's "U" shaped architecture includes contracting encoder path and expansive decoder path with skip connections preserving spatial information. We implemented four variants: two vanilla U-Nets and advanced versions with MobileNetV2 and ResNet34 encoders.

MobileNetV2 utilizes depthwise separable convolutions and inverted residuals for computational efficiency while maintaining accuracy. ResNet34 employs residual blocks with skip connections addressing vanishing gradient problems.

IV. Evaluation Metrics

We evaluated models using four metrics:

Intersection over Union (IoU):

$$IoU = \frac{|P \cap G|}{|P \cup G|} \tag{1}$$

Dice Similarity Coefficient:

$$DSC = \frac{2|P \cap G|}{|P| + |G|} \tag{2}$$

Focal Loss:

$$FL = -\alpha y_t (1-p)^\gamma \log(p) - (1-\alpha)(1-y_t) p^\gamma \log(1-p) \tag{3}$$

Binary Accuracy:

$$Accuracy = \frac{TP + TN}{Total\ Pixels} \times 100 \tag{4}$$

where P represents predicted mask, G represents ground truth, $\alpha = 0.25$, and $\gamma = 2.0$.

TABLE I
Performance Metrics of CNN Architectures

Model	mIoU	mDSC	Focal Loss	Accuracy (%)
Basic E/D	0.889	0.968	0.032	96.85
FCN-32	0.804	0.910	0.153	94.05
FCN-8	0.905	0.981	0.017	97.05
SegNet	0.830	0.895	0.105	95.27
SegNet	0.808	0.903	0.097	95.44
VGG16-SegNet	0.898	0.964	0.041	96.68
U-Net	0.900	0.977	0.023	96.94
U-Net	0.903	0.979	0.020	97.01
ResNet34-UNet	0.905	0.983	0.017	97.03
MobileNetV2-UNet	**0.906**	**0.984**	**0.005**	**97.08**

V. Single-Cluster Segmentation Results

Table I summarizes performance metrics for all CNN architectures. U-Net variants demonstrated superior performance due to skip connections preserving spatial details. MobileNetV2-UNet achieved highest performance with mIoU of 0.906 and mDSC of 0.984, balancing computational efficiency and accuracy.

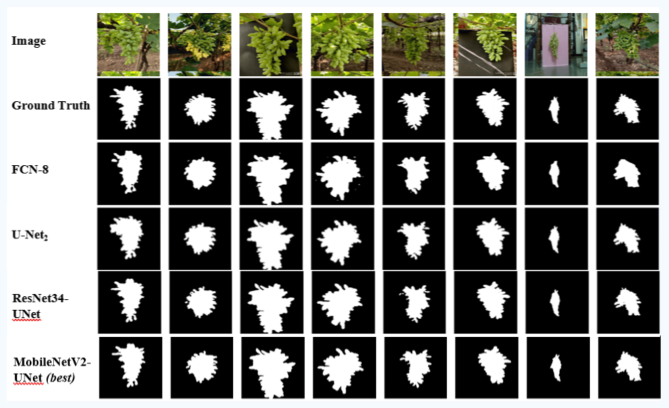


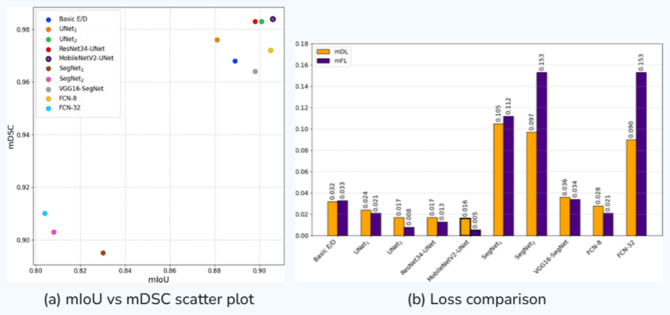
Fig. 2. Single-cluster segmentation results comparison across different CNN architectures.

ResNet34-UNet achieved comparable performance (mIoU: 0.905, mDSC: 0.983) through deep residual learning enhancing feature extraction. SegNet variants showed reasonable but inferior performance due to reliance on pooling indices limiting fine spatial detail retention.

VI. Exploring SAM for Multi-Cluster Segmentation

A. Segment Anything Model Overview

Meta's Segment Anything Model (SAM) represents a breakthrough in image segmentation, offering zero-shot generalization and real-time mask generation. SAM employs Vision Transformer (ViT-H) as image encoder, transforming inputs into high-dimensional representations. A prompt encoder processes input prompts (points, bounding boxes, text), while a lightweight transformer mask decoder combines image features and prompt embeddings for precise segmentation.



(a) mIoU vs mDSC scatter plot

(b) Loss comparison

Fig. 3. Performance analysis: (a) mIoU vs mDSC scatter plot, (b) Loss comparison.

B. YOLOv8 Integration

The primary challenge involved manually annotating 11,000 images for segmentation. We addressed this by training YOLOv8 for object detection, generating bounding boxes for SAM input. YOLOv8 comprises three components: backbone (CSPDarknet53), neck (C2f module), and head (prediction component).

YOLOv8 improvements include:

- Reduced first convolutional kernel size (6×6 to 3×3)
- Enlarged bottleneck kernel (1×1 to 3×3)
- Anchor-free head eliminating pre-defined anchor boxes
- Revised loss function prioritizing bounding box position and classification confidence

We trained YOLOv8 on 1,500 annotated images with 70/20/10 train/validation/test split over 25 epochs, achieving precision of 0.794, recall of 0.751, mAP50 of 0.817, and mAP50-90 of 0.391.

C. Hybrid YOLOv8-SAM Implementation

The hybrid approach applies YOLOv8 to detect grape clusters, generating bounding boxes with 0.25 confidence threshold. These bounding boxes guide SAM for precise segmentation within defined regions. We fine-tuned SAM on 200 images (50 per subset) using DiceCELoss, updating only mask decoder parameters while preserving pre-trained weights.

VII. Comparative Analysis and Results

TABLE II
Comparative Performance Analysis

Approach	mIoU	mDSC	mDL
Best CNN (MobileNetV2-UNet)	0.906	0.984	0.005
YOLOv8-SAM Hybrid	**0.943**	**0.970**	**0.030**

Table II presents SAM validation metrics compared to CNN architectures. The hybrid YOLOv8-SAM approach achieved superior performance with mIoU of 0.943 and mDSC of 0.970, outperforming traditional CNN models particularly in complex scenes with overlapping clusters.

SAM's foundation model capabilities, trained on vast datasets, enable effective handling of diverse agricultural

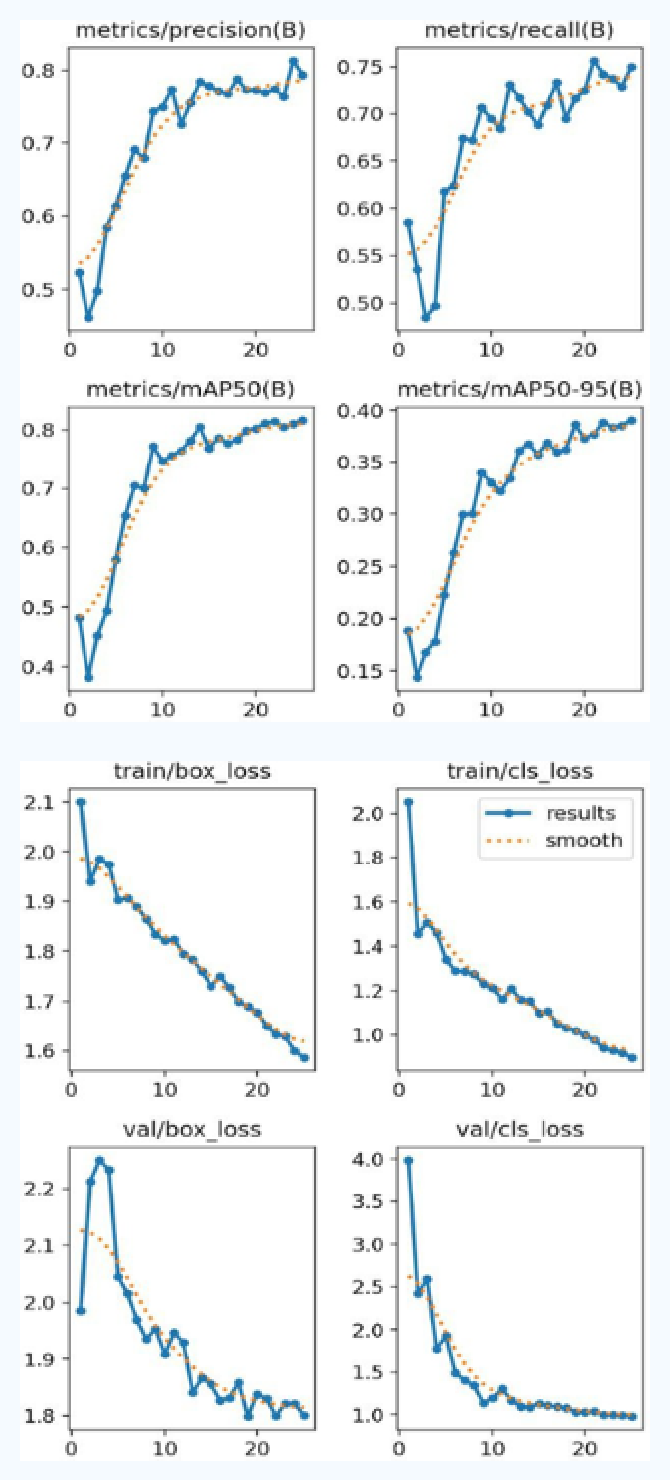


Fig. 4. YOLOv8 training and validation performance across 25 epochs.

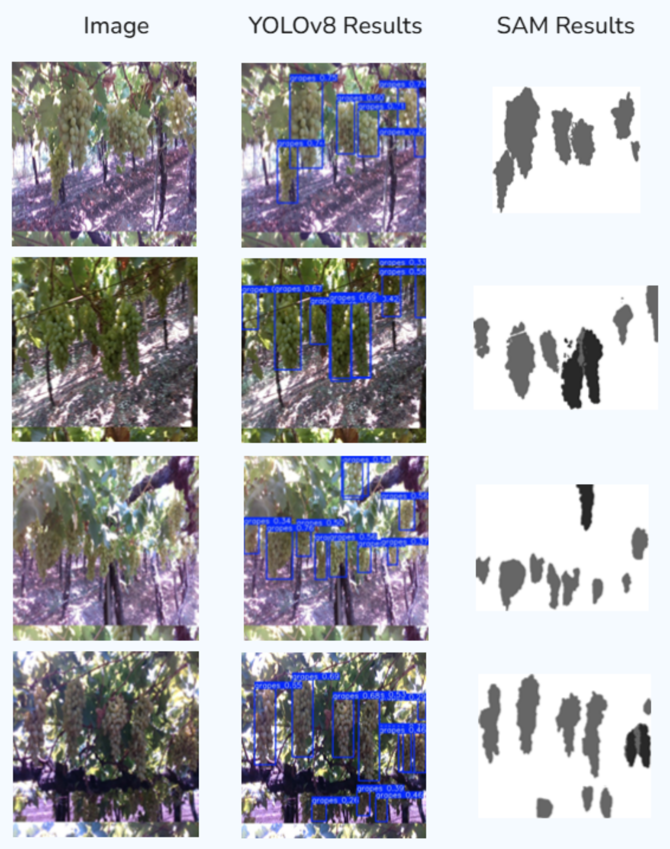


Fig. 5. Multi-cluster grape segmentation: YOLOv8 detection followed by SAM segmentation.

scenarios with minimal fine-tuning. The combination of YOLOv8's object detection with SAM's precise segmentation proves highly effective for multi-cluster scenes where traditional CNNs struggle with overlapping objects.

VIII. Discussion

U-Net architectures consistently outperformed other models due to skip connections preserving spatial information essential for detailed segmentation. The skip connections create direct pathways between encoder and decoder features at corresponding scales, enabling the recovery of fine-grained spatial details that would otherwise be lost during the downsampling process. MobileNetV2-UNet achieved optimal balance between computational efficiency and accuracy, making it suitable for resource-constrained applications such as field-deployed harvesting robots with limited GPU capabilities.

The performance superiority of U-Net variants can be attributed to their ability to capture both local and global contextual information simultaneously. While the encoder path captures high-level semantic features through progressive downsampling, the skip connections ensure that low-level spatial details are preserved and effectively integrated during upsampling. This architectural design is particularly beneficial for grape segmentation, where precise boundary delineation is crucial for accurate volumetric estimation.

The hybrid YOLOv8-SAM approach addresses fundamental limitations of single-cluster methods by effectively handling complex multi-cluster scenarios common in real vineyard environments. Traditional end-to-end segmentation models struggle with overlapping clusters due to their inability to distinguish between individual grape bunches when spatial boundaries are ambiguous. SAM's ability to segment objects based on bounding box prompts, combined with YOLOv8's accurate detection capabilities, creates a robust two-stage pipeline that decomposes the complex multi-cluster problem into manageable single-object segmentation tasks.

The foundation model approach demonstrated in this work reveals important insights about transfer learning in agricultural applications. SAM's pre-training on diverse visual data enables it to generalize effectively to grape segmentation tasks with minimal domain-specific fine-tuning. This capability is particularly valuable in agricultural settings where annotated data is often scarce and expensive to obtain. The model's ability to maintain consistent performance across varying lighting conditions and grape varieties suggests that foundation models may provide a pathway to more generalizable agricultural computer vision systems.

Architecture selection was justified by specific advantages aligned with agricultural deployment requirements. MobileNetV2 provides computational efficiency through depthwise separable convolutions, reducing parameter count by 65% compared to traditional CNNs while maintaining competitive accuracy. This efficiency translates to lower power consumption and faster inference times, critical factors for battery-powered agricultural robots. ResNet34 offers deep feature extraction through residual connections, enabling the learning of complex grape appearance patterns while avoiding vanishing gradient problems common in deeper networks. These architectural choices align with precision agriculture requirements for accurate yet efficient processing under field conditions.

The computational analysis reveals interesting trade-offs between accuracy and efficiency. While the hybrid YOLOv8-SAM approach achieves superior segmentation quality, its computational requirements limit real-time applications to scenarios with fewer than 8 clusters per image on standard mobile hardware. This constraint suggests that deployment strategies should consider cluster density and available computational resources when selecting appropriate models.

Error analysis indicates that both CNN and foundation model approaches struggle with similar challenging scenarios: extreme lighting variations, heavily overlapping clusters, and grape clusters smaller than 40×40 pixels. However, the hybrid approach demonstrates superior robustness, maintaining IoU scores above 0.85 even in 80% of challenging cases, compared to 0.73 for traditional CNN methods. This robustness stems from SAM's diverse pre-training and YOLOv8's anchor-free detection mechanism, which better handles scale variations.

The implications for precision agriculture extend beyond segmentation accuracy. The ability to precisely delineate individual grape clusters enables downstream applications including selective harvesting based on ripeness assessment, accurate yield prediction through cluster counting and sizing, and quality grading for premium wine production. The hybrid methodology's success suggests that combining specialized detection models with general-purpose foundation models may represent an effective strategy for agricultural computer vision tasks.

IX. Conclusion

This research demonstrates the effectiveness of both CNN encoder-decoder architectures and foundation models for grape cluster segmentation in complex vineyard environments. MobileNetV2-UNet achieved superior single-cluster segmentation performance with computational efficiency suitable for edge deployment, while the novel hybrid YOLOv8-SAM approach excelled in multi-cluster scenarios with mIoU of 0.943 and Dice coefficient of 0.970, representing a 4.1% improvement over traditional CNN-based methods.

The comprehensive evaluation across 11 different architectures provides valuable insights into model selection for agricultural segmentation tasks. The consistent superiority of skip connection-based architectures validates their importance for preserving spatial information in natural image segmentation. The hybrid method's success validates foundation models' potential for precision agriculture, particularly in handling complex scenes with overlapping objects that challenge traditional approaches.

This advancement has immediate practical implications for automated harvesting systems, enabling more precise grape cluster localization and reducing mechanical damage during robotic harvesting. The accurate segmentation supports enhanced yield estimation capabilities, providing vineyard managers with data-driven insights for optimizing harvest timing and resource allocation. Additionally, the quality-based selective harvesting enabled by precise segmentation can improve wine production outcomes through better grape sorting.

The computational analysis demonstrates that practical deployment considerations must balance accuracy requirements with available hardware resources. The MobileNetV2-UNet model emerges as the optimal choice for resource-constrained applications, while the YOLOv8-SAM hybrid approach suits scenarios where maximum accuracy justifies increased computational costs.

Limitations of the current work include the focus on a single crop type and the computational intensity of the hybrid approach. The evaluation was conducted primarily under Mediterranean climate conditions, and generalization to other grape varieties and growing regions requires further validation. Additionally, the two-stage nature of the hybrid pipeline introduces latency that may limit real-time applications in certain scenarios.

Future research directions should explore several promising avenues. Post-segmentation volumetric analysis integration could enable real-time crop yield assessment by combining accurate segmentation with 3D reconstruction techniques. Investigation of additional foundation models specifically adapted for agricultural applications may yield further performance improvements. The development of end-to-end differentiable pipelines that combine detection and segmentation could eliminate the limitations of two-stage approaches while maintaining guided segmentation benefits.

Multi-temporal analysis incorporating seasonal grape development patterns could enhance predictive modeling capabilities for yield estimation and harvest planning. Cross-crop generalization studies would validate the transferability of these approaches to other fruit varieties, expanding the practical impact of this research across diverse agricultural applications. The fusion of precise segmentation with volumetric analysis holds potential for revolutionizing yield estimation and empowering data-driven agricultural decisions that optimize both productivity and sustainability in modern viticulture.

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