In Situ Root Segmentation: Paper Summary (2020-2025)

Chen et al. (2024)

Method: DeepLabv3+ with enhanced decoder architecture for root segmentation in situ.

They tailored the decoder with upsampling and refinement modules to preserve spatial detail in soil-root images.

Accuracy: F1 ~ 0.98, Recall ~ 0.985, Precision ~ 0.970.

Strengths: High accuracy and computational efficiency, simple architecture, ideal for high-throughput rhizotron image analysis.

Limitations: Still requires labeled data for new conditions or species.

Source: https://onlinelibrary.wiley.com/doi/full/10.1111/pbi.70040

Yu et al. (2024)

Method: Combined U-Net with EnlightenGAN to enhance in situ segmentation with occlusion recovery.

The GAN model was trained to reconstruct root segments hidden under soil or noise artifacts, improving continuity and measurement accuracy.

Accuracy: Enhanced over baseline U-Net; better trait measurement fidelity reported.

Strengths: Non-destructive imaging pipeline; excellent for trait estimation and visualization in noisy/occluded images.

Limitations: More complex training pipeline; GANs can be unstable or hard to interpret.

Source: https://www.sciencedirect.com/science/article/pii/S2643651524001638

Li et al. (2023)

Method: Modified U-Net with ResNet encoder, PSA attention module, and class-weighted focal loss.

Designed for imbalanced pixel distributions and fine root detail recovery in peanut/corn datasets.

Accuracy: F1 ~ 95.1%, IoU ~ 0.9548, Pixel Accuracy ~ 0.9917.

Strengths: High precision on thin roots, robust performance across datasets, attention improves feature localization.

Limitations: High training time; overfitting risk if data diversity is low.

Source: https://www.frontiersin.org/articles/10.3389/fpls.2023.1115713/full

Baykalov et al. (2023)

Method: Benchmarking study of 6 DL models (U-Net, FCN, PSPNet, etc.) across 8 species, 6 soils, 4 minirhizotron setups.

Focused on generalization with/without augmentation.

Accuracy: Model-dependent; U-Net with stronger encoders performed best.

Strengths: Comprehensive generalization analysis; showed augmentation reduces false positives.

Limitations: No new model proposed; insights limited to current architectures.

Source: https://plantmethods.biomedcentral.com/articles/10.1186/s13007-023-01101-2

Seidenthal et al. (2022)

Method: ITErRoot iterative U-Net that refines segmentation progressively.

Designed to maintain spatial continuity in thin, branching root structures.

Accuracy: High F1 and boundary preservation; superior continuity vs. plain U-Net.

Strengths: Strong generalization across species; excels at segmenting complex root systems.

Limitations: Slower inference due to multi-stage prediction; higher GPU memory use.

Source: https://www.nature.com/articles/s41598-022-19754-9

Shukla et al. (2025)

Method: GTUNet / TransUNet with super-resolution module as preprocessing.

Targeted blurry or low-resolution soil images to upscale them before segmentation.

Accuracy: Better precision on thin-root features vs. baseline U-Net.

Strengths: Solves a key challenge in blurred image recovery; modular pipeline.

Limitations: SR step can cause artifacts; more complex model management.

Source: https://link.springer.com/chapter/10.1007/978-981-97-5212-6_2

Yu et al. (2023)

Method: EnlightenGAN-based reconstruction pipeline after U-Net segmentation.

Used GANs to recover root structures in areas with occlusions and poor visibility.

Accuracy: Improves root coverage, trait estimation, and spatial structure recovery.

Strengths: Ideal for messy field images; helps recover underrepresented root parts.

Limitations: GANs can be sensitive to training noise; requires tuning.

Source: https://phys.org/news/2023-12-harnessing-ai-non-destructive-situ-root.html

Comparative Insights and Recommendations

Best for Accuracy & Trait Estimation

Li et al. (2023) and Chen et al. (2024): both reach >95% F1, with Chen using DeepLabv3+ for speed and Li using a more accurate (but heavier) U-Net variant.

Shukla (2025) stands out when fine detail in blurry imagery is a problem.

Yu (2024) is excellent for trait-level recovery when occlusions or soil noise affect root visibility.

Best for Generalization

Baykalov (2023): U-Net with data augmentation was most robust across species and soil conditions.

Seidenthal (2022): ITErRoot has exceptional generalizability, especially in thin, branching systems.

Best for Speed and Simplicity

Chen (2024): DeepLabv3+ offers accurate, fast segmentation with a practical decoder design.

Li (2023) is more accurate but has higher resource requirements.

Best for Occlusion Recovery or Incomplete Roots

Yu (2023) with GAN enhancement is ideal when root segments are missing, e.g., due to overlapping or noisy soil.

Yu (2024) builds on this with segmentation + reconstruction to better handle fragmented root phenotypes.

Overall Recommendation

Goal	Best Option
Best all-around balance (speed + accuracy)	Chen et al. (2024)
Highest raw accuracy	Li et al. (2023)
Best for difficult conditions (noise, occlusions)	Yu et al. (2024)
Most generalizable	Seidenthal et al. (2022) or Baykalov et al. (2023)
Recovery from blurry data	Shukla et al. (2025)
Root gap reconstruction	Yu et al. (2023)