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Sub-Pixel Semantic Segmentation for Precision Agriculture: Identifying Micro-Defects in Crop Foliage

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Abstract: Early detection of micro-defects in crop foliage—including sub-millimetre chlorotic lesions, fungal hyphae boundaries, and early-stage necrotic patches—remains one of the most challenging problems in computational precision agriculture. Conventional semantic segmentation models operate at the native pixel resolution of remotely-sensed or macro-lens imagery and consistently fail to recover boundary-level structural detail at scales below one pixel. This paper presents Sub-Pixel Segmentation Network (SPSNet), a novel deep-learning architecture that incorporates learned sub-pixel convolution layers, spectral-channel attention, and a multi-scale hierarchical decoder to segment foliage defects at resolutions exceeding the sensor's native sampling grid. Our model is trained and evaluated on FoliageDefect-22K, a purpose-built annotated dataset comprising 22,400 high-resolution images across six crop species and nine defect categories collected under controlled and field conditions. SPSNet achieves a mean Intersection-over-Union (mIoU) of 91.7%, surpassing the nearest competing method by 8.5 percentage points, while maintaining near-real-time inference at 18.3 frames per second on a single NVIDIA A100 GPU. Ablation studies confirm the individual contribution of each architectural component. These results establish sub-pixel segmentation as a viable and practical tool for deployment in precision agricultural monitoring systems.

Keywords: precision agriculture, semantic segmentation, sub-pixel convolution, foliage micro-defects, deep learning, crop health monitoring, spectral attention

I. INTRODUCTION

Global food security is increasingly pressured by the twin challenges of a rising human population and climate-driven disruption of agricultural ecosystems. The Food and Agriculture Organisation (FAO) estimates that plant diseases and pest infestations account for losses of up to 40% of annual food production worldwide, with a disproportionate burden falling on smallholder farmers in the developing world [1]. The capacity to identify the earliest morphological signatures of plant disease—before visible chlorosis or necrosis spreads across the canopy—is therefore of profound agronomic and economic significance.

Traditional plant pathology relies on trained agronomists conducting in-field visual inspection, a process that is labour-intensive, temporally sparse, and highly subjective. The integration of high-resolution digital imaging with computer vision methods has substantially advanced automated disease detection over the past decade. Convolutional neural networks (CNNs) trained on image classification benchmarks, such as PlantVillage [2], can now match expert-level accuracy for identifying broad disease categories from leaf photographs. However, classification-level outputs—a single label per image—provide insufficient spatial resolution for localised disease management strategies that target affected sub-regions of individual plants.

Semantic segmentation bridges this gap by assigning a class label to every pixel in an image, enabling spatial delineation of diseased tissue. Fully convolutional networks (FCNs) [3], encoder-decoder architectures such as U-Net [4], and recent transformer-based models including SegFormer [5] and Mask2Former [6] have achieved impressive segmentation benchmarks on natural image datasets. Nevertheless, their application to foliage micro-defect identification faces three fundamental barriers:

(i) Resolution ceiling: early-stage defect lesions often span areas smaller than a single pixel in wide-area drone or satellite imagery, making pixel-level labels inadequate.

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(ii) Spectral ambiguity: subtle chromatic differences between early chlorosis, water stress, and healthy tissue are often below the perceptual threshold of standard RGB sensors but detectable in near-infrared (NIR) or hyperspectral bands.
(iii) Temporal variability: pathogen progression exhibits non-linear dynamics across growth stages, complicating the construction of generalised models from static snapshots.

This paper directly addresses these barriers with SPSNet, a segmentation architecture purpose-built for sub-pixel foliage defect identification. Our principal contributions are:
1. A sub-pixel convolution decoder that reconstructs segmentation maps at 4× the sensor's native resolution using learned pixel-shuffle upsampling, recovering structural detail below the Nyquist limit.
2. A spectral-channel attention module (SCAM) that selectively amplifies disease-relevant spectral bands in multi-spectral and RGB+NIR inputs.
3. FoliageDefect-22K, a publicly released annotated benchmark for foliage micro-defect segmentation spanning six crop species under diverse field and controlled-environment conditions.
4. A comprehensive empirical evaluation demonstrating state-of-the-art performance and computational efficiency suitable for edge deployment on agricultural UAV platforms.

II. RELATED WORK

2.1 Semantic Segmentation in Agriculture

The application of semantic segmentation to agricultural imaging has matured considerably since the introduction of FCN-based architectures. Mohanty et al. [2] demonstrated that CNNs could classify 26 leaf diseases with over 99% accuracy under controlled imaging conditions, establishing a critical proof of concept. Subsequent work by Ferentinos [7] and Brahimi et al. [8] extended classification to field conditions using transfer learning from ImageNet-pretrained models. Segmentation-specific pipelines for plant phenotyping—including leaf-level instance segmentation for plant architecture analysis—have been developed using Mask R-CNN variants [9].

More recently, attention mechanisms and transformer backbones have been integrated into agricultural segmentation pipelines. SA-UNet [10] augments the standard U-Net skip connections with spatial self-attention to improve boundary localisation in high-density canopy imagery. However, none of these approaches explicitly model the sub-pixel structure of early-stage micro-lesions, which motivates the present work.

2.2 Sub-Pixel and Super-Resolution Methods

Sub-pixel convolution, first introduced for image super-resolution by Shi et al. [11], rearranges feature maps of depth r^2C into an output of depth C at spatial resolution r× the input, using a periodic shuffling operation. This approach has since been adopted in video super-resolution [12], medical image reconstruction [13], and satellite image sharpening [14]. Coupling sub-pixel upsampling with a segmentation objective requires careful design of the loss function to handle the jointly-learned super-resolution and classification tasks.

In the medical imaging domain, sub-pixel techniques have been applied to histopathological slide segmentation where cellular structures exhibit fine boundary detail [15]. Our work is the first, to our knowledge, to apply learned sub-pixel upsampling specifically to semantic segmentation of crop foliage under field conditions.

2.3 Spectral Attention in Remote Sensing

Channel attention mechanisms, popularised by the Squeeze-and-Excitation (SE) network [16], adaptively recalibrate feature responses along the channel dimension. Their application to multi-spectral remote sensing imagery has shown that selectively weighting vegetation-index-responsive channels significantly improves land cover classification [17]. Our SCAM builds on this principle, extending channel attention with explicit spectral prior knowledge derived from the normalised difference vegetation index (NDVI) and the chlorophyll red-edge index (CRE).

III. METHODOLOGY

3.1 Network Architecture: SPSNet

SPSNet adopts a hierarchical encoder-decoder topology with three specialised components: a multi-scale convolutional encoder, a spectral-channel attention module, and a sub-pixel convolution decoder. The overall pipeline accepts an image of dimensions $H \times W \times C$ (where $C \in \{3, 4\}$ for RGB or RGB+NIR input) and produces a segmentation map of dimensions $4H \times 4W \times K$, where K is the number of defect classes.

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The encoder is based on a modified ResNet-50 backbone with dilated convolutions at stages 3 and 4 (dilation rates 2 and 4, respectively) to preserve spatial resolution while expanding the effective receptive field. Feature pyramids are constructed at four scales (strides 4, 8, 16, and 32) using a Feature Pyramid Network (FPN) neck, yielding aggregated multi-scale feature tensors F_1 through F_4.

The SCAM is inserted between the encoder and decoder. For an input feature tensor $F \in \mathbb{R}^{BxcxHxW}$, global average pooling is applied along spatial dimensions to obtain a descriptor vector $d \in \mathbb{R}^{Bxc}$. Two fully connected layers with ReLU and sigmoid activations produce channel weights $w \in \mathbb{R}^{Bxc}$. Crucially, weights are initialised with a spectral prior vector constructed from the known absorptance spectra of chlorophyll a and b across the sensor's spectral bands, enabling faster convergence on disease-relevant features.

The sub-pixel decoder receives the SCAM-modulated features and progressively upsamples from stride 32 to the target 4× super-resolved output using four stages of sub-pixel convolution. At each stage, a 3×3 convolution expands the channel count by a factor of $r^2 = 4$, followed by a PixelShuffle operation that rearranges the depth-wise expanded feature map into a spatially upsampled tensor. Skip connections from the FPN are fused at each decoder stage via element-wise addition after channel alignment with 1×1 convolutions.

3.2 Loss Function

Training SPSNet requires a composite loss function that jointly supervises segmentation quality at multiple scales and enforces temporal consistency across sequential frames:

$$L\_total = \lambda_1 \cdot L\_CE + \lambda_2 \cdot L\_Dice + \lambda_3 \cdot L\_boundary + \lambda_4 \cdot L\_temporal$$

The cross-entropy term L_CE provides per-pixel classification supervision with inverse-frequency class weighting to address severe class imbalance (healthy tissue constitutes over 85% of pixels in most images). The Dice loss L_Dice penalises volumetric overlap discrepancy and is particularly effective for small-object segmentation. The boundary loss L_Boundary, formulated as a distance-transform-weighted cross-entropy on the predicted boundary map, explicitly supervises the sub-pixel boundary localisation. The temporal consistency loss L_temporal penalises label disagreement between predicted segmentation maps for overlapping regions in consecutive video frames, reducing flickering artefacts during deployment on continuous video streams. Hyperparameters (λ_1=1.0, λ_2=0.5, λ_3=0.3, λ_4=0.2) were determined via grid search on the validation split.

3.3 FoliageDefect-22K Dataset

No existing public benchmark provided the combination of high spatial resolution, multi-spectral channels, and pixel-accurate sub-pixel defect annotations required to validate SPSNet. We therefore constructed FoliageDefect-22K, comprising 22,400 images across six economically significant crop species: rice (Oryza sativa), wheat (Triticum aestivum), tomato (Solanum lycopersicum), maize (Zea mays), soybean (Glycine max), and grape (Vitis vinifera).

Images were captured at 5,472 × 3,648 pixel resolution using a multispectral Micasense RedEdge-MX camera mounted on a DJI Matrice 300 RTK UAV at altitudes of 5–15 m above the canopy. Macro-lens ground-level imaging was additionally performed for a subset of 4,200 images to capture sub-millimetre lesion structure. Nine defect categories were annotated: (1) early chlorosis, (2) late chlorosis, (3) fungal lesion boundary, (4) bacterial spot, (5) viral mosaic, (6) rust pustule, (7) blight margin, (8) insect feeding trace, and (9) mechanical damage. Annotation was performed by three certified plant pathologists using a custom polygon-labelling tool at 2× optical zoom, with inter-annotator agreement verified using Cohen's kappa ($\kappa = 0.87$). The dataset is partitioned into 16,000 training, 3,200 validation, and 3,200 test images.

IV. EXPERIMENTAL RESULTS

4.1 Implementation Details

All models were implemented in PyTorch 2.1.0 and trained on 4× NVIDIA A100 (80 GB) GPUs using distributed data-parallel training. The AdamW optimiser with an initial learning rate of 1×10^{-4}, weight decay of 0.01, and a cosine annealing scheduler was used for 120 training epochs with a batch size of 16. Standard data augmentation included random horizontal and vertical flipping, random cropping at 512×512, colour jitter (±10% brightness, contrast, saturation), and mixup augmentation (α=0.2). Input images were normalised per channel using dataset statistics. Training convergence was reached at approximately epoch 95 based on validation mIoU.

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4.2 Comparison with State-of-the-Art

Table 1 reports performance on the FoliageDefect-22K test set for SPSNet against three established segmentation baselines: FCN-8s, DeepLab v3, and SegFormer-B2, all retrained from scratch on our dataset under identical data splits and augmentation protocols to ensure fair comparison.

Table 1. Segmentation performance on the FoliageDefect-22K test set (best results in bold).

Method	mIoU (%)	F1-Score	Precision (%)	Recall (%)
FCN-8s	71.4	0.738	74.2	73.6
DeepLab v3	78.9	0.801	80.5	79.3
SegFormer-B2	83.2	0.847	85.1	84.3
SPSNet (Proposed)	**91.7**	**0.923**	**92.8**	**91.1**

SPSNet achieves an mIoU of 91.7%, representing an absolute improvement of 8.5 pp over SegFormer-B2 (83.2%), the nearest competitor. Performance gains are most pronounced for small-area defect categories: for fungal lesion boundary (category 3) and rust pustule (category 6), SPSNet achieves per-class IoU values of 89.3% and 86.7% respectively, compared to 71.2% and 68.9% for SegFormer-B2. This differential confirms that sub-pixel upsampling provides the greatest benefit precisely where conventional models fail—at fine-grained, boundary-dominated defect classes.

4.3 Ablation Study

To isolate the contribution of each architectural component, we conducted a structured ablation study, progressively adding each module to a baseline ResNet-50 encoder with bilinear upsampling. Results are reported in Table 2.

Table 2. Ablation study on FoliageDefect-22K validation split. Δ mIoU is relative to the preceding row.

Configuration	mIoU (%)	Δ mIoU	Params (M)
Baseline encoder only	79.1	—	24.3
+ Sub-pixel conv decoder	84.6	+5.5	26.8
+ Spectral attention module	88.3	+3.7	28.1
+ Temporal consistency loss	91.7	**+3.4**	28.1

The sub-pixel convolution decoder contributes the largest single increment (+5.5 pp), confirming that the core resolution recovery mechanism is the primary driver of performance. The spectral attention module adds +3.7 pp, demonstrating that disease-specific spectral weighting provides meaningful discriminative signal beyond what the encoder learns in an unguided fashion. The temporal consistency loss adds a further +3.4 pp, with the gain primarily observed in the video-stream evaluation subset, where it reduces per-frame label flickering by 62% as measured by the temporal consistency metric of Voigtlaender et al. [18].

4.4 Computational Efficiency

SPSNet processes 512×512 RGB inputs at 18.3 FPS on a single NVIDIA A100, and 6.1 FPS on an NVIDIA Jetson AGX Orin (the target edge platform for UAV deployment), with INT8 quantisation applied via TensorRT. The model contains 28.1 million parameters, comparable to SegFormer-B2 (27.4 M) and well within the memory budget of contemporary embedded GPUs. These characteristics make SPSNet suitable for real-time onboard inference during UAV survey flights.

V. DISCUSSION

The results of this study confirm that segmentation at sub-pixel resolution is not merely a theoretical refinement but a practically consequential capability in precision agricultural diagnostics. The performance gap between SPSNet and pixel-aligned baselines widens sharply for defect categories with compact spatial extent, consistent with the hypothesis that these categories are most severely affected by the resolution ceiling of conventional upsampling methods.

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The spectral attention module's contribution is particularly instructive. In standard RGB imaging, early-stage chlorotic lesions appear as subtle yellowing that overlaps visually with natural variation in leaf coloration due to developmental gradients or shadows. The SCAM's spectral prior effectively down-weights spectrally uninformative channels while amplifying NIR reflectance differentials—a well-established chlorophyll-content proxy—resulting in a sharper discriminative boundary. This mechanism generalises across crop species despite differences in baseline leaf reflectance, as evidenced by consistent per-species improvements.

Several limitations merit acknowledgement. First, FoliageDefect-22K was collected across a geographically constrained set of locations (India, Mexico, Taiwan, and California), and model generalisation to crops grown under substantially different soil, humidity, or solar irradiance conditions has not been validated. Second, the temporal consistency module requires sequential frame inputs, which are unavailable in single-shot still imaging pipelines. Extending the architecture to handle single-frame inputs without degrading boundary accuracy remains an open problem. Third, although SPSNet is optimised for six crop species, pathogens can differ substantially in their macroscopic and microscopic presentation across botanic families, and periodic retraining or domain adaptation will be necessary for deployment across broader taxonomic ranges.

Future work will investigate: (i) the extension of SCAM to hyperspectral inputs with 30+ bands, exploiting the full spectral richness of emerging high-altitude sensors; (ii) few-shot adaptation protocols for novel pathogen detection with minimal annotation cost; and (iii) integration with agronomic decision-support systems that translate segmentation outputs into variable-rate treatment maps for precision pesticide or fertiliser application.

VI. CONCLUSION

This paper has presented SPSNet, a semantic segmentation architecture engineered to identify micro-defects in crop foliage at sub-pixel resolution. Through the combination of a sub-pixel convolution decoder, a spectrally-informed channel attention module, and a temporal consistency regularisation loss, SPSNet achieves an mIoU of 91.7% on the FoliageDefect-22K benchmark—outperforming all evaluated baselines by a substantial margin while maintaining computationally feasible inference speeds. The FoliageDefect-22K dataset, released publicly alongside this publication, provides a rigorous evaluation standard for future research in fine-grained plant disease segmentation.

By enabling the detection of disease signatures at spatial scales below the native sensor resolution, this work directly supports the precision agriculture paradigm: earlier, more localised intervention decisions that reduce chemical inputs, limit crop yield loss, and ultimately contribute to more sustainable food production systems. We anticipate that the architectural principles developed here—particularly the combination of sub-pixel upsampling with domain-specific spectral attention—will prove transferable to other high-stakes remote sensing segmentation tasks where fine spatial detail carries disproportionate diagnostic value.

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