Potato Plant Disease Detection using Hyperspectral Images

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Introduction

- Manual plant health assessment is time-consuming, subjective, and error-prone [1].
- Visual symptoms of potato virus diseases often appear late and are difficult to distinguish [2].
- This research investigates hyperspectral image segmentation of potato plants under real field conditions using transformer-based spectral–spatial learning, with a focus on analysing pixel-level behaviour.

Abstract

This work studies hyperspectral image segmentation for analysing potato virus diseases under real field conditions. Hyperspectral cubes acquired with a Specim FX-17 camera are processed using spectral normalisation and patch-based training. A transformer-based model is trained using patch-based, center-pixel supervision to segment background and plant tissue, and to analyse PVY and PLRV-affected regions at pixel level. Experimental results show robust plant–background separation and more consistent segmentation of healthy tissue, while discrimination between PVY and PLRV remains challenging due to limited spectral separability.



Figure 1. Example preview image of a potato plant from the hyperspectral field dataset. The image is visualized using three selected NIR bands mapped to RGB for display purposes.

Materials and Methods

- **Dataset:** Field-acquired hyperspectral images using Specim FX-17
- **Spectral range:** 900–1700 nm (224 bands)
- **Annotations:** Plant-level manual labeling (Background, Healthy, PVY, PLRV).
- **Data Split:** Plant-wise split to prevent data leakage (Train / Validation / Test on different plants).
- **Preprocessing:** Spectral normalization and patch extraction.
- **Model:** Masked Spectral–Spatial Transformer (MaskedSST).
- **Training:** Patch-based learning with center-pixel supervision.

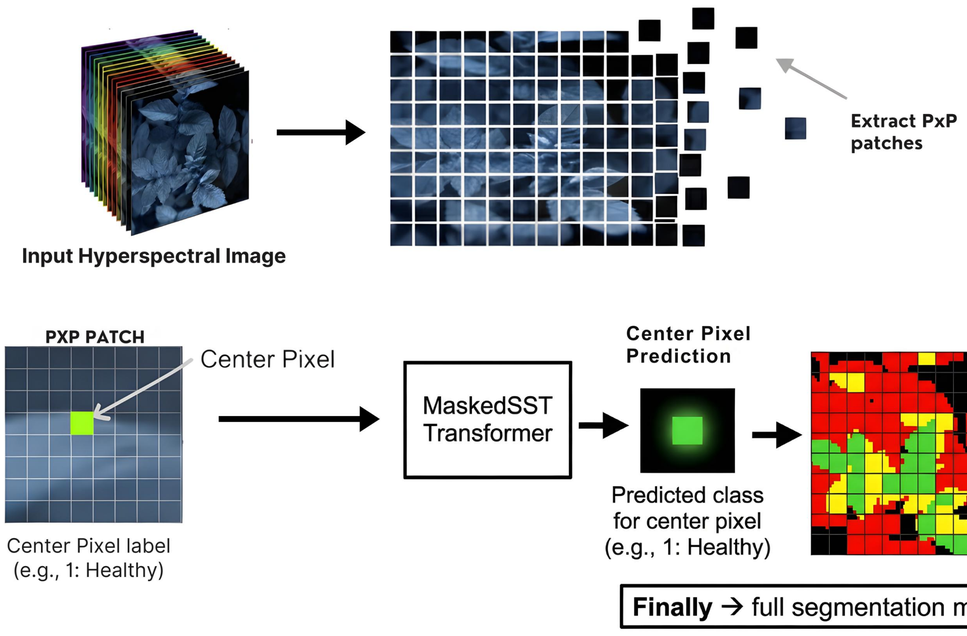


Figure 2. Reference Image-Guided Workflow: A workflow Illustrating the process from data Input to the final prediction using a reference image. (a) Original Image used for segmentation. (b) Full hyperspectral image are divided into small spectral–spatial patches. (c) Each patch is assigned the class of its center pixel. (d) MaskedSST predicts the class for the center pixel. (e) Sliding-window inference reconstructs the full segmentation mask.

Experiments

- Multiple training configurations were evaluated to analyse the impact of spectral normalisation, patch size, and data splitting strategy.
- Nine experimental configurations were explored in total. Model selection was performed on a validation set.
- All quantitative and qualitative results are reported on the held-out test set.

Configuration	Mean IoU	Pixel Acc.	Precision	Recall	F1 score
Z-score baseline	0.223	50.1 %	0.422	0.346	0.380
Spectral ℓ2 normalization	0.288	54.3 %	0.447	0.382	0.411
Spectral ℓ2 + larger patch	0.269	51.8 %	0.407	0.364	0.384
Plant-wise split	**0.289**	**57.2 %**	**0.4848**	**0.4695**	**0.4767**
Data augmentation	0.286	55.1 %	0.4585	0.4321	0.4445

Table 1. Quantitative segmentation results on the test set for the five core experimental configurations.

Results

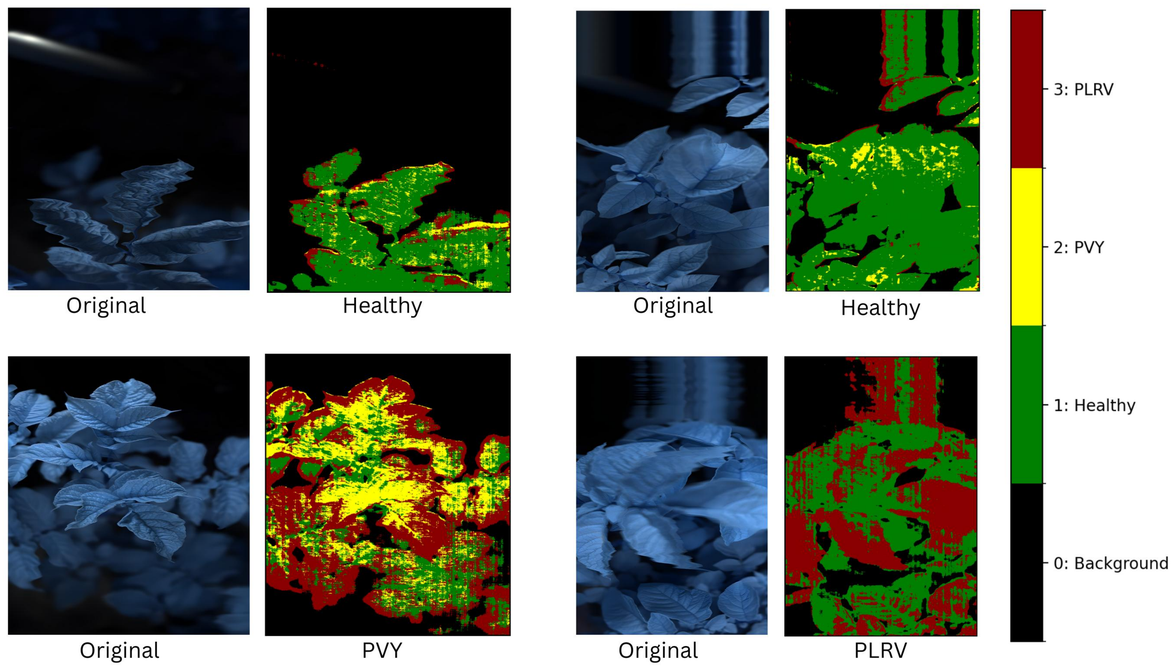


Figure 3. Qualitative segmentation results on unseen test plants. Left: grayscale NIR visualisation. Right: predicted segmentation mask. Healthy tissue is segmented more consistently, while PVY and PLRV show frequent confusion due to spectral similarity.

Conclusions

- Transformer-based hyperspectral segmentation enables robust localisation of plant tissue in field-acquired data.
- Spectral normalisation significantly improves training stability and overall segmentation performance.
- Background and plant tissue are separated reliably, while segmentation of healthy tissue is more consistent than virus-infected regions.
- Discrimination between PVY and PLRV remains limited due to strong spectral overlap within the available wavelength range.
- Under the studied conditions, the approach is not suitable for reliable automated disease diagnosis and primarily serves to analyse the limitations of pixel-wise hyperspectral segmentation in real field settings.

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- [2] Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2010). Plant Disease Severity Estimated Visually, by Digital Photography and Image Analysis, and by Hyperspectral Imaging. *Critical Reviews in Plant Sciences*, 29(2), 59–107. https://doi.org/10.1080/07352681003617285