Enhancing U-Net for PCB Segmentation Using Hyperspectral Imaging in E-waste Recycling

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1. Introduction

1.1 Problem Statement

Printed Circuit Boards(PCBs) contains valuable metals.
Efficient segmentation of components is critical for automated recycling.
Traditional segmentation used **RGB imaging,** which cannot differentiate visually similar parts.
Recent research leverages **hyperspectral imaging** to capture rich spectral signatures, enabling material discrimination in E-waste recycling

1.2 HSI(Hyperspectral Imaging)

Hyperspectral Camera captures images at **individual spectral bands(400~1000nm)**, and by extracting the distinctive features of each band, it enables more fine-grained material analysis.

1.3 Proposed Approach

Integration of a Spectrum Channel Reduction Block into existing CNN models to enhance segmentation performance.

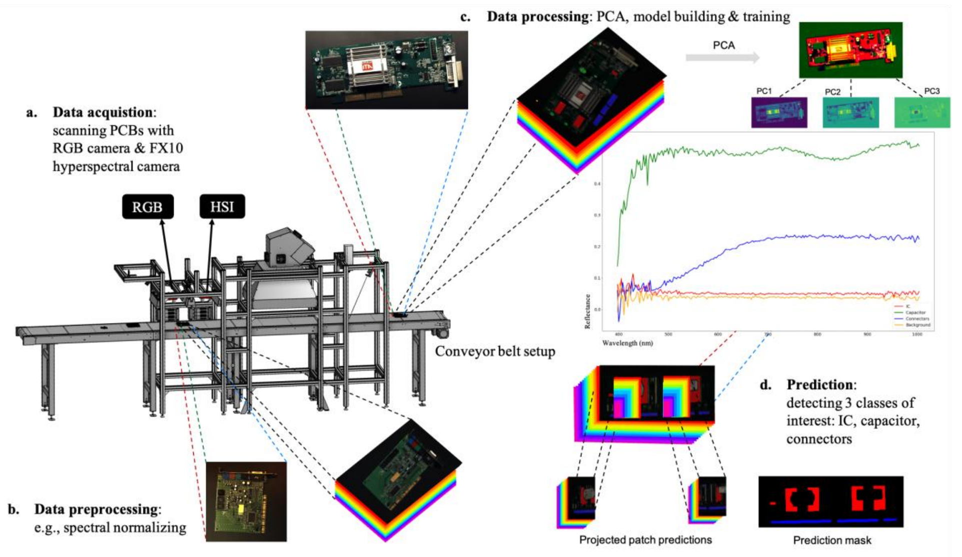


Figure 1. Data Collection Environment

2. HSI Dataset

2.1 PCB-Vision dataset

- 53 PCB samples 224-band HSI
  - Train(126), Validation(3), Test(30)
- 3 labeled classes : IC, Capacitor, Connector

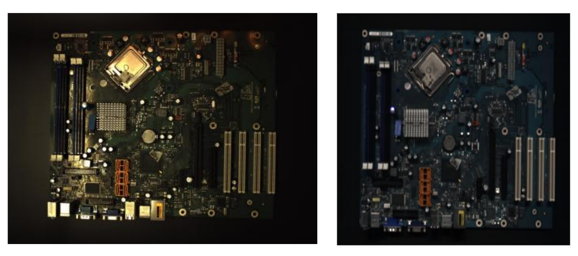


Figure 2. Original vs Background-Removed, Normalized Image

2.2 Preprocessing

- Slicing 10 noisy bands
- Background masking using PCB masks
- Spectral normalization (white/dark reference)

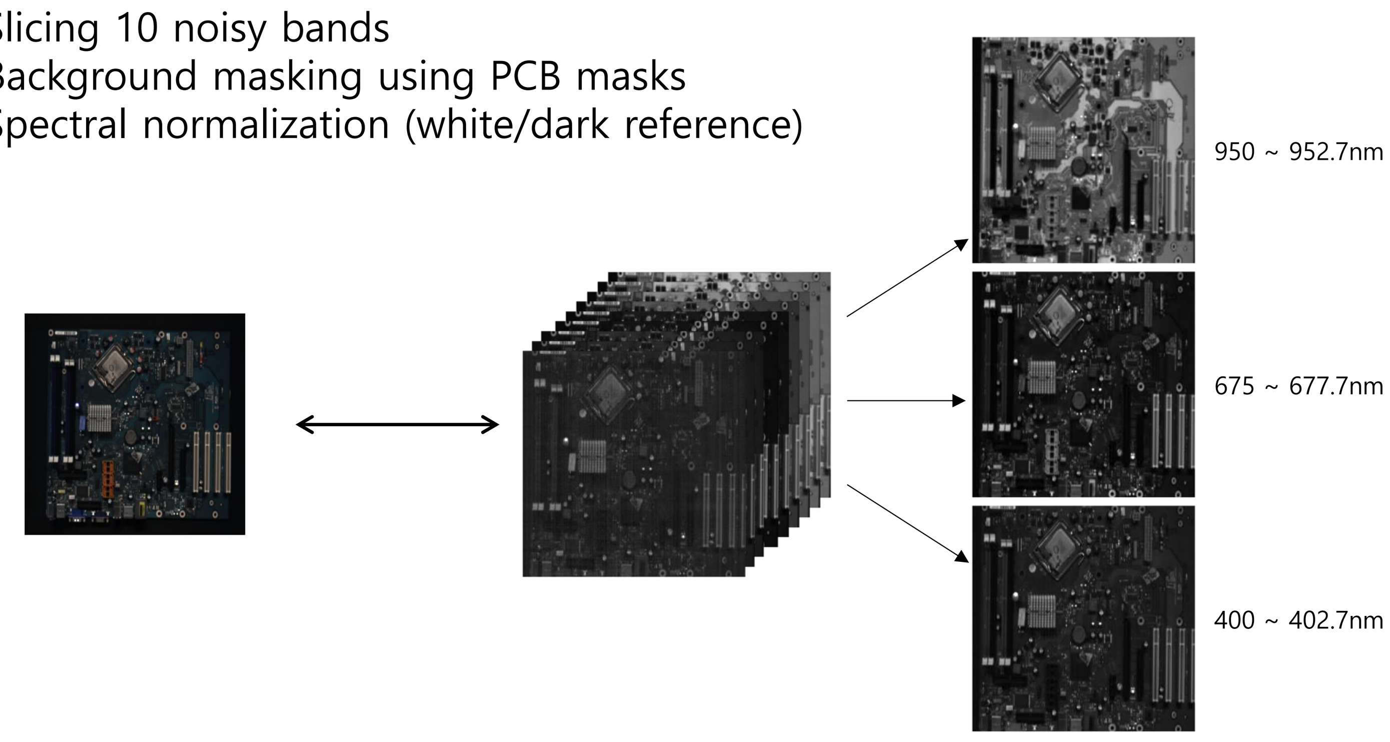


Figure 3. Visualized PCB-Vision dataset

3. PCB Segmentation Model

In this project, we compare model outputs by applying three different input strategies to the same dataset.
The base architecture used in prior studies include **U-Net**, **ResU-Net**, and **Attention U-Net**.

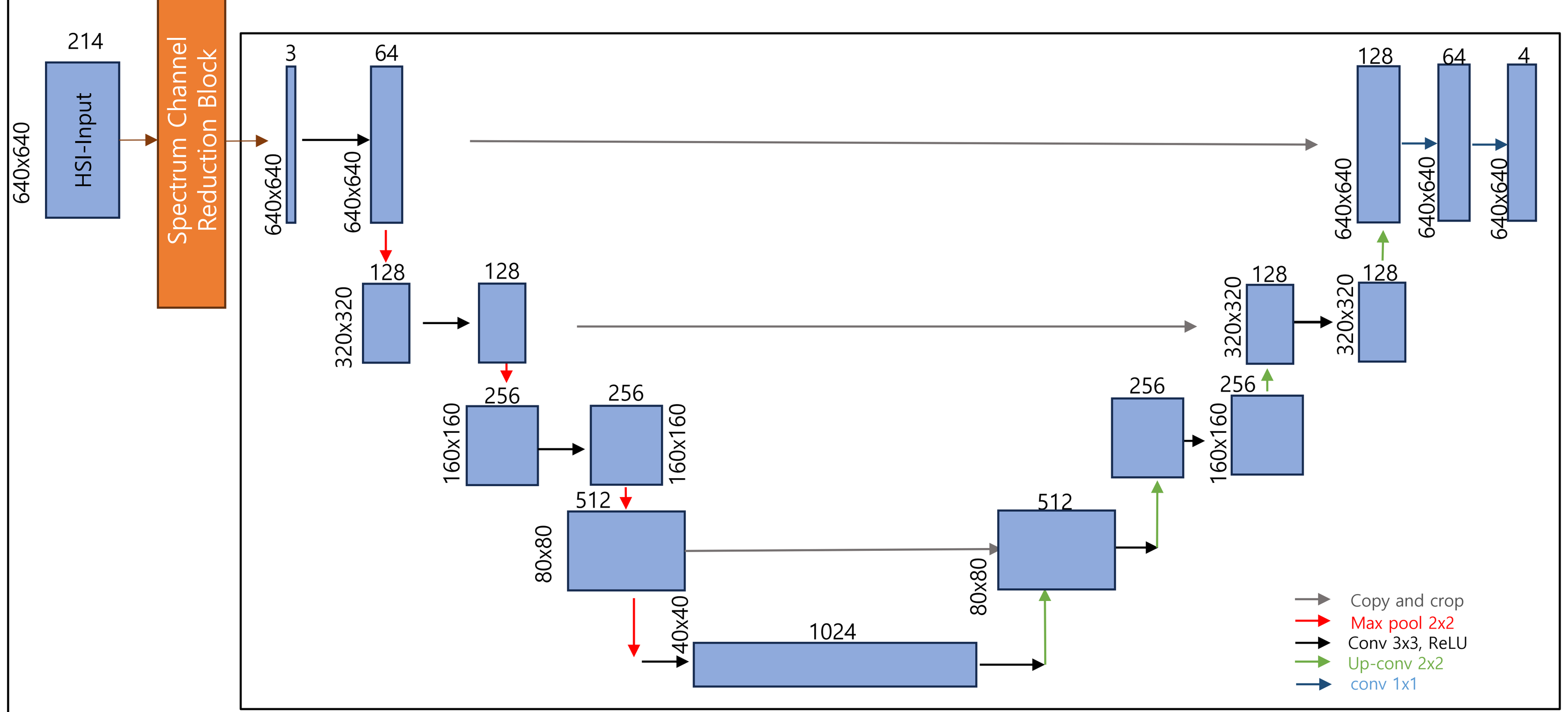


Figure 4. Structure of U-net with Channel Reduction Block

(Baseline model #1) CNN with Full Spectrum Input

The hyperspectral input (640x640x214) is directly applied to U-Net

(Baseline model #2) PCA + CNN

The hyperspectral input 224 is reduced to 3 channels using PCA

(Proposed Model) Spectrum channel reduction block + CNN

The hyperspectral input 224 is reduced to 128 channels then to 3 using 1x1 CONV layers

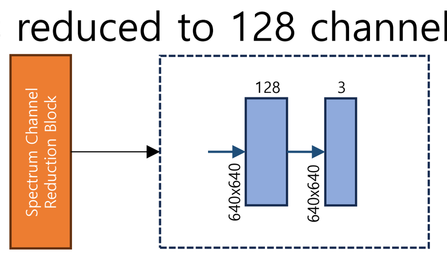


Figure 5. Spectrum Channel Reduction Block of Proposed Model

4. Model Experiment

4.1 Model Metrics and PCB segmentation result

- **IoU(Intersection over Union)** : Measures pixel-level overlap between predictions and ground truth
- **F1 Score** : Harmonic mean of precision and recall, balances false positives and false negatives under class imbalance

Both metrics applied to models trained on HSI images to **evaluate segmentation quality**

Table 1. F1 Score Comparison across PCB Component Classes

Metric	Base Architecture	Spectrum Channel Reduction Block	Others	IC	Capacitor	Connectors
F1 Score	U-net	Baseline #1	0.95	**0.75**	0.57	0.31
		Baseline #2	0.95	0.27	0.23	0.05
		Proposed	**0.96**	0.67	**0.58**	**0.46**
	Attention U-net	Baseline #1	**0.97**	**0.71**	**0.65**	**0.66**
		Baseline #2	0.94	0.25	0.23	0.10
		Proposed	0.96	0.70	0.36	0.54
	ResU-net	Baseline #1	0.96	**0.74**	0.53	0.51
		Baseline #2	0.94	0.14	0.16	0.02
		Proposed	**0.97**	0.72	**0.56**	**0.71**

Table 2. IoU Comparison across PCB Component Classes

Metric	Base Architecture	Spectrum Channel Reduction Block	Others	IC	Capacitor	Connectors
IoU	U-net	Baseline #1	**0.95**	0.27	0.23	0.05
		Baseline #2	0.91	**0.60**	0.40	0.18
		Proposed	0.93	0.51	**0.41**	**0.30**
	Attention U-net	Baseline #1	**0.95**	**0.56**	**0.49**	**0.49**
		Baseline #2	0.90	0.14	0.13	0.05
		Proposed	0.93	0.54	0.22	0.37
	ResU-net	Baseline #1	0.94	**0.59**	0.36	0.34
		Baseline #2	0.90	0.07	0.08	0.01
		Proposed	**0.94**	0.56	**0.39**	**0.55**

5. Discussion

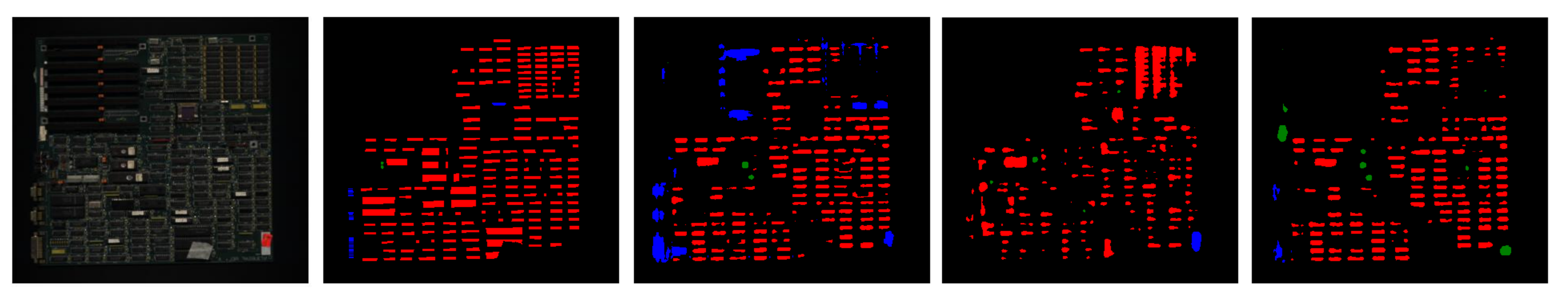
5.1. Effect of Random Seed in Deep Learning

- IoU / F1 score variation between reference paper : $\pm 0.01, 0.13$
- Cause : Random data order, weight initialization, seed sensitivity

5.2. Performance Comparison

Table 3. Model Performance Comparison

Comparison	Key Insight
Baseline #1 vs Proposed	Input channel size significantly impacted speed and maintain accuracy
Baseline #2 vs Proposed	Proposed > Baseline #2 in accuracy (non-linear mapping preserves spectrum data)



Original Image | Ground Truth Mask | Baseline #1 | Baseline #2 | Proposed

Figure 6. Visualized Segmentation Result

Model	Pre Process layer	Flops(G)	Params(M)
U-net	Baseline #1	**342.34**	**31.04**
	Baseline #2	392.12	31.16
	Proposed	353.93	31.07
Attention U-net	Baseline #1	**416.97**	**34.88**
	Baseline #2	466.76	35.0
	Proposed	428.57	34.91
ResU-net	Baseline #1	**506.47**	**13.04**
	Baseline #2	606.03	13.29
	Proposed	518.06	13.07

Table 4. Gflops and Params Comparison across Models

6. Conclusion

6.1 Improvements over Prior Work

- Achieved at **least 2× higher per-class accuracy** compared to Baseline 1.
- Reduced FLOPs by up to **16%** vs Baseline 2 while keeping overall performance within a **±15%** margin—and even outperforming on some classes

6.2 Further Work

Trained on three base architectures;
observed less-than-expected reductions in FLOPs and parameters after channel reduction.
Plan to evaluate smaller base architectures to better match input dimensions and validate accuracy trade-offs.