Label Semantics for Robust Hyperspectral Image Classification

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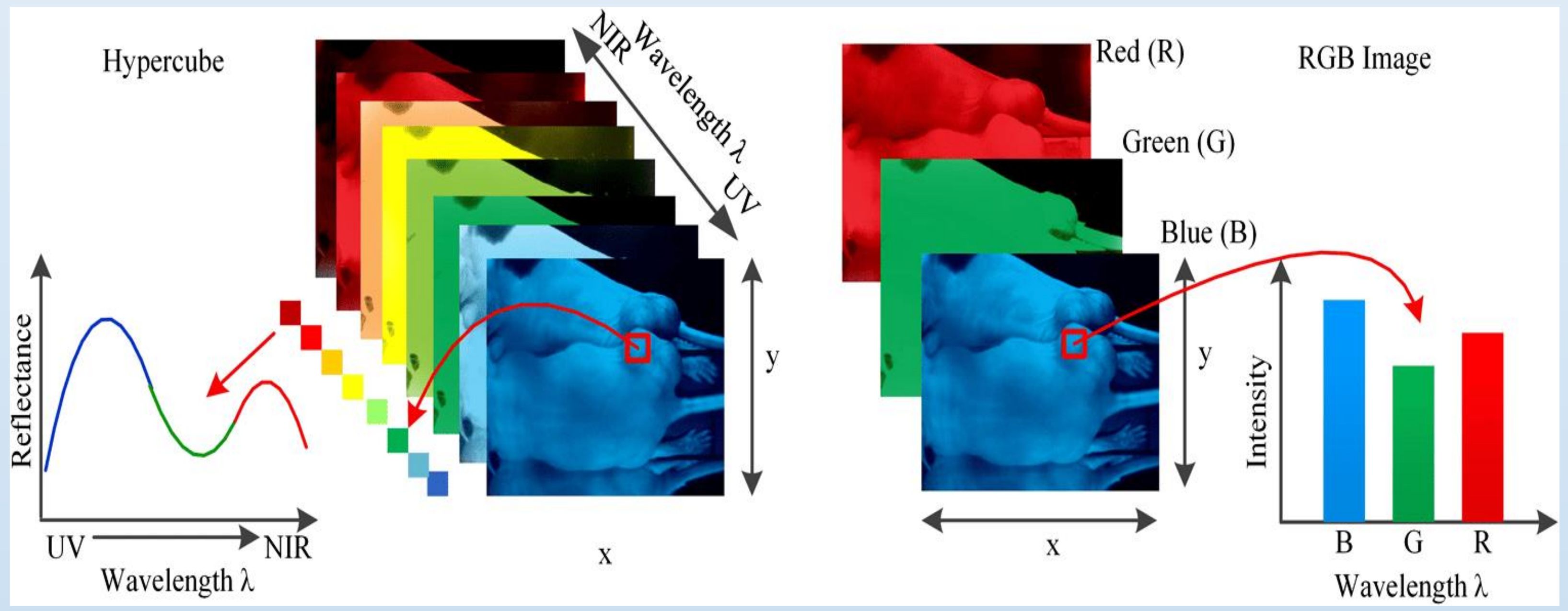
What is HSI?

Hyperspectral images (HSI) capture detailed **spectral information across numerous contiguous bands** of the electromagnetic spectrum for each pixel in an image.

RGB vs Hyperspectral Image (HSI)

Hyperspectral images capture information across **hundreds of narrow spectral bands**, providing detailed **spectral data** for each pixel. RGB images only contain data in **three broad bands**: red, green, and blue—what the human eye naturally perceives.

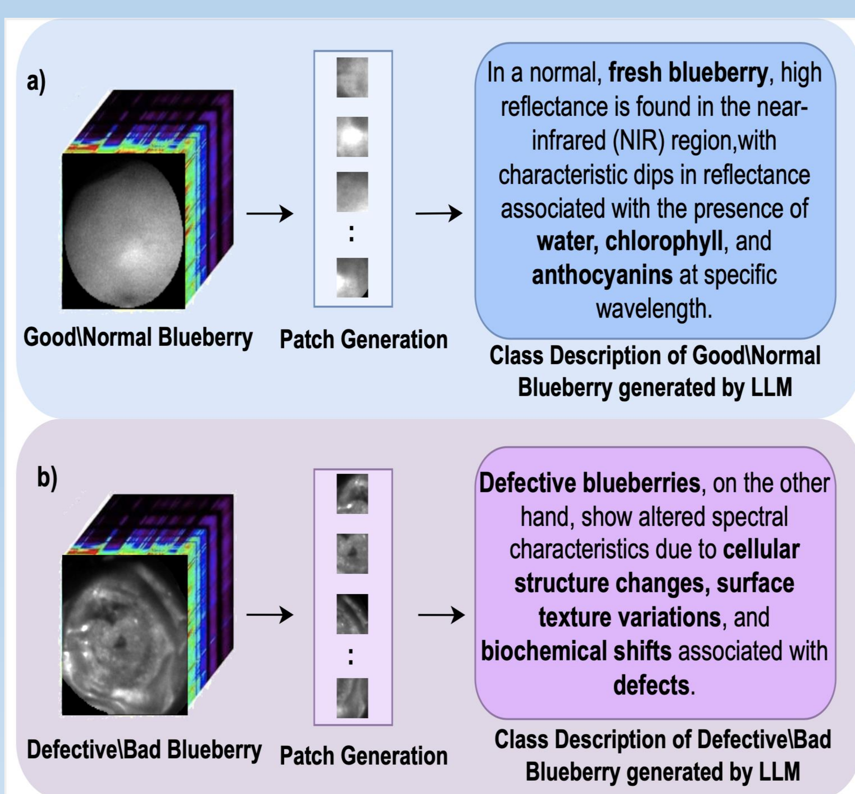


Motivation

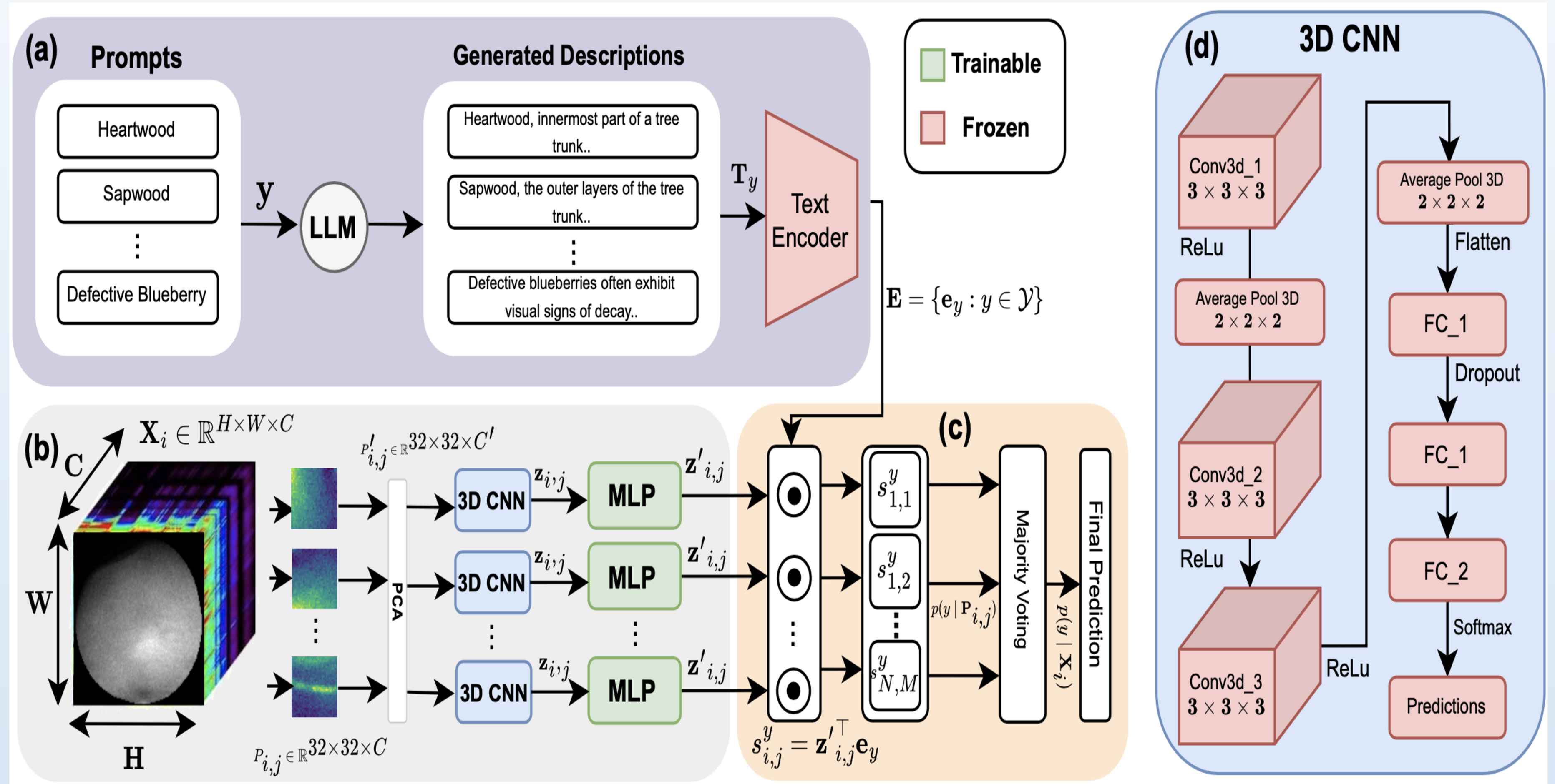
- **Deep learning models** often face challenges in **generalization** due to limited labeled samples and the **high dimensionality** of spectral data.
- Enhancing **model robustness** is essential for effective **real-world deployment** despite these constraints.

Problem Statement

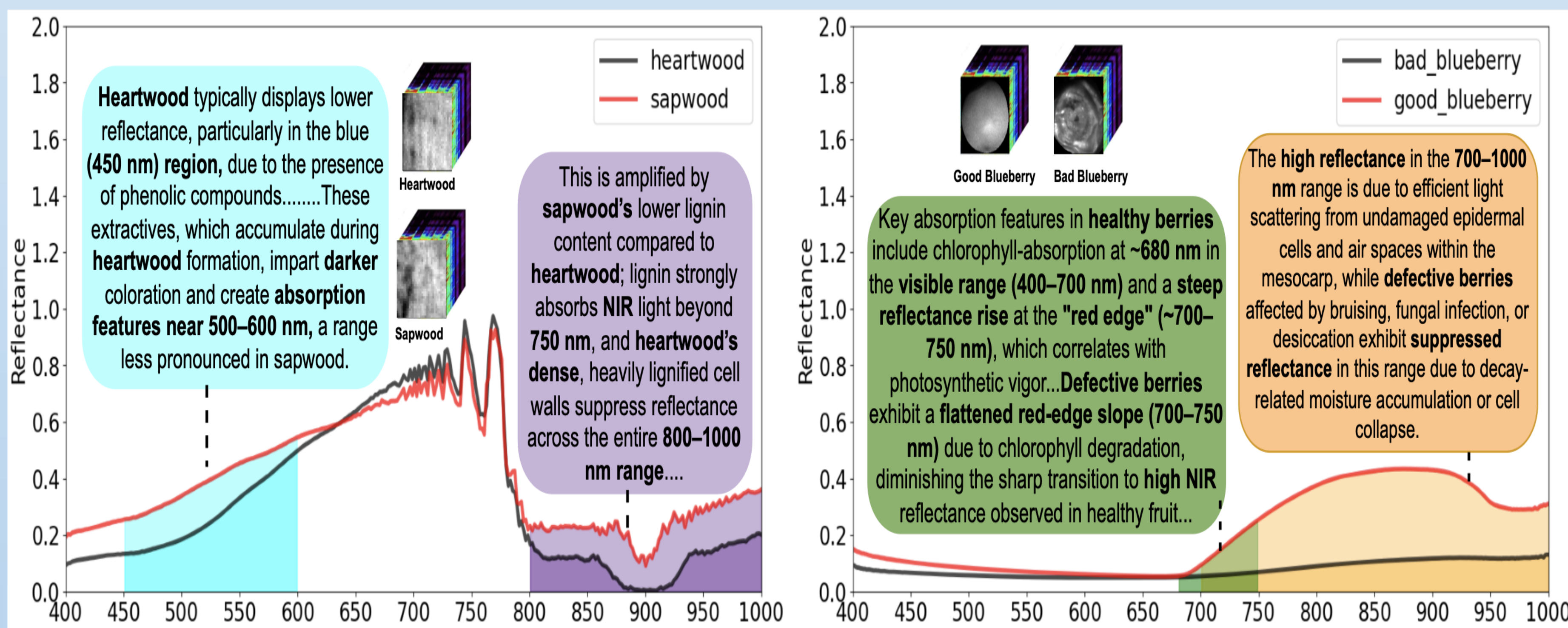
- Existing **HSI classification models** often **ignore semantic information** embedded in class labels.
- This work focuses on improving **model robustness** and **generalization** by utilizing **label semantics**.
- It leverages **comprehensive semantic information** from detailed class descriptions generated by an **LLM (Large Language Model)**.



Proposed Model - S3FN Architecture



Why This Works?



- **Mean spectral reflectance** curves for **wood** *(heartwood & sapwood)* and **blueberries** *(healthy/good & bad/defective)* illustrate key **absorption** and **reflectance** features.
- Spectral mean reflectance curves were computed as per **Section III-C**, by **averaging reflectance values** across all pixels for each **spectral band**.
- **LLM-generated semantic descriptions** capture **class-specific spectral characteristics**, highlighted in **color-coded regions**.
- These descriptions help in **enhancing label embeddings** for robust **hyperspectral image classification**.
- For example, **Heartwood** shows **lower reflectance** in the **blue (450 nm)** region due to the presence of **phenolic compounds**.

Results

Performance Comparison of different HSI datasets. **RoBERTa** is used as a text encoder for all experiments

Hyperspectral Wood

Model	PR	Recall	F1	ACC
SVM	89.0	89.0	89.0	88.6
KNN	84.0	84.0	84.0	84.0
Random Forest	82.0	82.0	82.0	81.1
Neural Network	88.0	87.0	87.0	87.1
Decision Tree	59.0	58.0	58.0	58.3
Cifar10Net	-	-	-	93.9
S3FN (Ours)	**95.0**	**95.0**	**95.0**	**94.7**

HyperspectralBlueberries

Model	PR	Recall	F1	ACC
SVM	92.0	92.0	92.0	91.7
KNN	76.0	75.0	75.0	75.2
Random forest	77.0	76.0	77.0	76.4
Neural Network	86.0	86.0	86.0	85.8
Decision Tree	81.0	80.0	80.0	80.0
LDA	90.8	78.6	-	85.3
RLDA	**97.7**	93.7	-	95.7
RLDA&LDA	96.5	**96.7**	-	**96.6**
S3FN (Ours)	86.0	86.0	86.0	86.4

DeepHS-Fruit

Model	Ripeness (C1)		Ripeness (C2)	
	Avocado	Kiwi	Avocado	Kiwi
SVM	57.1	55.5	80.0	56.5
KNN	57.1	33.3	86.6	65.2
Random Forest	53.3	57.8	87.0	61.7
Neural Network	80.0	78.9	93.5	76.5
Decision Tree	80.0	42.1	70.9	53.1
ResNet-18	44.4	60.0	66.7	33.3
AlexNet	33.3	33.3	33.3	33.3
HS-CNN	44.4	66.7	33.3	33.3
S3FN (Ours)	**66.7**	**70.4**	**47.1**	**44.8**

Conclusion

This project uniquely integrates **LLM-generated textual descriptions** as **semantic guidance** for **hyperspectral image classification**. Unlike methods relying on **spectral-spatial features** or **static embeddings**, **S3FN** dynamically enhances **feature-label alignment** using **rich contextual embeddings**, surpassing **predefined labels** and **simpler representations** for improved classification performance.