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Explainable AI for Remote Sensing Image Processing: Advanced Interpretation Techniques for Agriculture Monitoring

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INTRODUCTION & AIM

Deep learning and remote sensing have revolutionized agricultural monitoring, delivering unprecedented precision. Yet their black-box nature limits interpretability and trust. This work advances Explainable AI (XAI) techniques to make remote sensing models more transparent, interpretable and actionable.

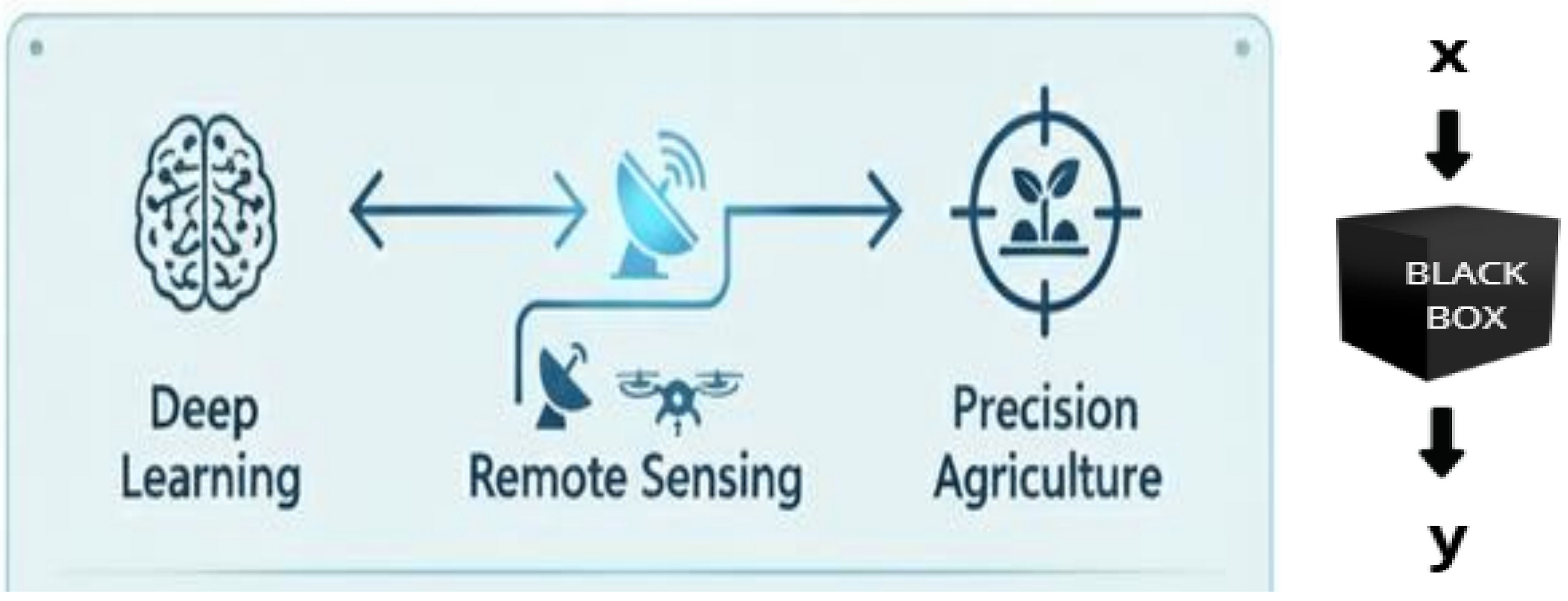

Figure 1: Conceptual Framework for Explainable AI in Remote Sensing for Precision Agriculture

METHOD

This study introduces two novel explainable AI frameworks for crop-type segmentation using multispectral Sentinel-2 imagery. A lightweight U-Net processes 32×32 spectral patches for precise pixel-level mapping. SpectroXAI-LLaMA is a post-hoc pipeline combining multiple XAI methods with a rule-based Chain-of-Thought (CoT) and LLaMA reasoning to generate human-readable explanations, while IMPACTX-GC-RS is a self-explaining U-Net that learns and generates its own Grad-CAM explanations during training, embedding interpretability directly into the model.

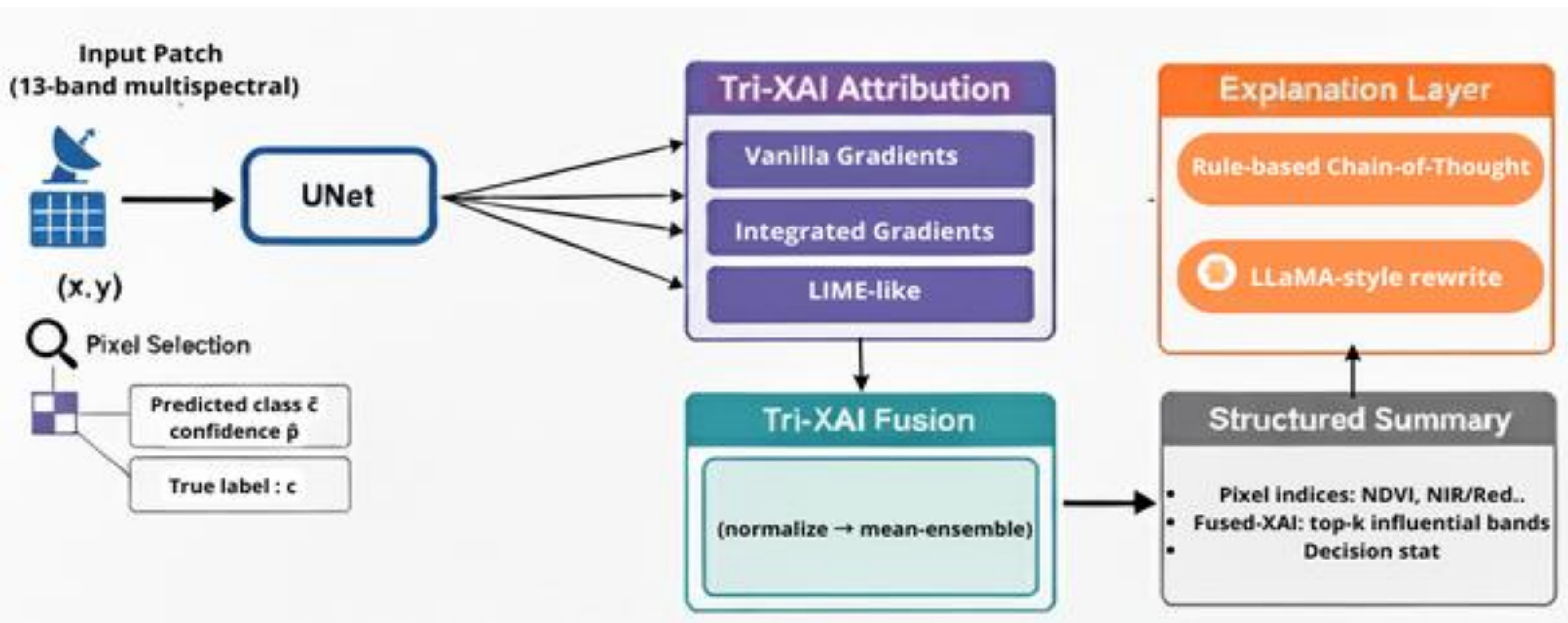

Figure 2: SpectroXAI-LLaMA Framework

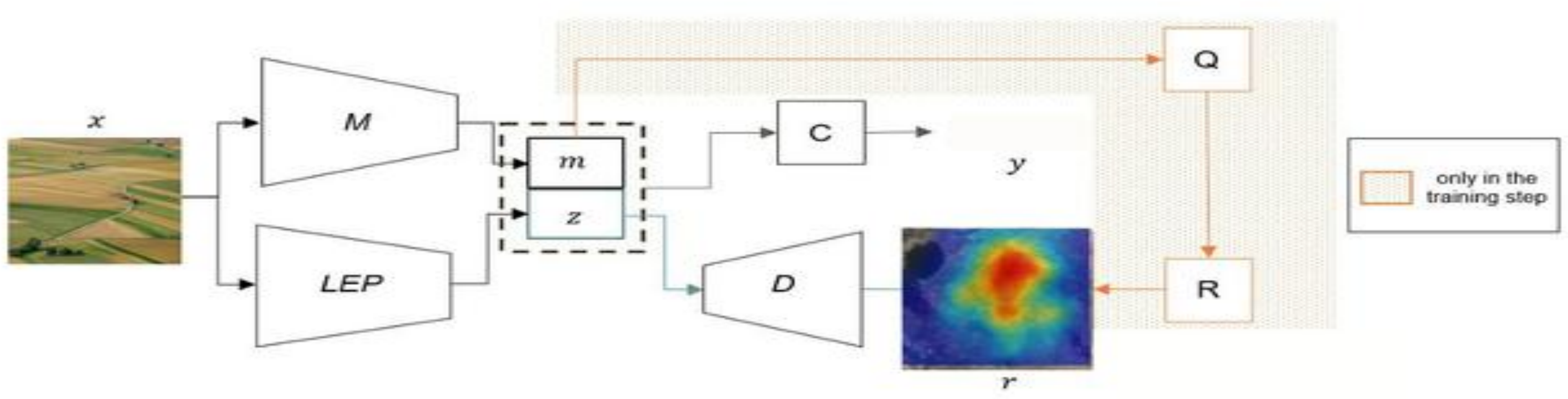

Figure 3: IMPACTX-GC-RS Framework

RESULTS & DISCUSSION

Integrating XAI methods enhanced both model performance and transparency. The IMPACTX-GC-RS framework improved segmentation accuracy, notably increasing the mean IoU over the baseline U-Net and resolving all confusion between Cereals and Potatoes. Its explanations were structurally sound, with Grad-CAM heatmaps aligning with agronomic features. Concurrently, SpectroXAI-LLaMA provided spectral-level insights by identifying key bands for vegetation, which its LLaMA module reformulated into actionable, human-readable text. This demonstrates that explainability is not just for transparency but can also lead to more robust, field-ready segmentation models

Table 1: Performance comparison between baseline U-Net and IMPACTX-GC-RS

Metrics	U-Net Baseline	IMPACTX_UNet
Mean IoU	0.9625	**0.975**
IoU (Cereals)	0.9689	**0.984**
IoU (Potatoes)	0.9467	**0.975**
Cereals→Potatoes	Errors 18 pixels	**0 pixels**

(a) Ground Truth (b) Predicted Mask (c) Predicted Explanation

Figure 4: IMPACTX-GC-RS segmentation and explanation

CONCLUSION

This study demonstrates that explainability and accuracy in agricultural AI are not mutually exclusive but mutually reinforcing. By introducing SpectroXAI-LLaMA and IMPACTX-GC-RS, we show that integrating interpretability through both post hoc reasoning and self-explaining architectures can elevate model performance while providing transparency that aligns with agronomic logic. These frameworks offer a blueprint for building accountable, insight-driven models that enhance user trust and operational reliability in precision agriculture.

REFERENCES

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