Interpretable Deep Learning Framework for Land Use and Land Cover Classification in Remote Sensing Using SHAP

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Abstract

Land Use and Land Cover (LULC) classification is critical for environmental monitoring and urban planning. While CNNs achieve high classification accuracy on satellite imagery, their black-box nature limits trustworthiness for policy-making decisions. This paper proposes an interpretable deep learning framework integrating CNN-based classification with SHAP explanations for pixel-level and class-level interpretability. Remote sensing datasets are preprocessed and used to train the model which categorizes land regions into multiple LULC classes. SHAP values explain the contribution of each spectral band to classification outcomes. The system achieves 93.6% overall classification accuracy with SHAP analysis revealing that NIR and SWIR bands are most influential for vegetation and urban class differentiation. The framework is deployed as a Django web application enabling transparent LULC analysis for environmental decision-making.

Keywords: *LULC Classification, Remote Sensing, CNN, SHAP, Explainable AI, Satellite Imagery, Django*

I. Introduction

Land Use and Land Cover classification from satellite imagery is fundamental to environmental monitoring, urban planning, agricultural assessment, and sustainable resource management. The ability to accurately categorize land regions enables governments and organizations to track deforestation, monitor urban expansion, assess agricultural productivity, and plan conservation efforts.

Deep learning models, particularly CNNs, have achieved remarkable performance in extracting spatial patterns from high-resolution satellite imagery. However, the black-box nature of these models presents significant challenges for decision-makers who need to understand and trust classification results before implementing environmental policies.

SHAP (SHapley Additive exPlanations) provides a principled approach to explaining model predictions by computing the contribution of each input feature—in this case, spectral bands—to the classification outcome. This paper integrates SHAP with CNN-based LULC classification to create a transparent and trustworthy framework for remote sensing analysis.

II. Literature Survey

This section reviews key prior works that form the foundation of the proposed system and highlights gaps motivating this work.

[1] Zhu et al. (2017) reviewed deep learning approaches for remote sensing image analysis, demonstrating that CNNs significantly outperform traditional feature engineering methods for scene classification.

[2] Cheng et al. (2020) proposed multi-scale CNN architectures for remote sensing image scene classification, achieving state-of-the-art performance on benchmark datasets.

[3] Kakogeorgiou and Karantzalos (2021) applied explainable AI methods to remote sensing classification, demonstrating that SHAP and attention maps can reveal learned spectral-spatial features.

[4] Lundberg and Lee (2017) introduced SHAP for unified model interpretation, providing the explainability framework used in this study for spectral band importance analysis.

[5] Ma et al. (2019) surveyed deep learning applications in remote sensing, identifying interpretability as a key challenge for operational deployment of classification systems.

[6] Talukdar et al. (2020) performed land use land cover change detection using multi-temporal satellite imagery and machine learning classifiers, establishing benchmarks for LULC classification performance.

[7] Drusch et al. (2012) described the Sentinel-2 mission providing multi-spectral imagery at high spatial resolution, establishing the remote sensing data source used in LULC classification research.

Research Gap: Existing LULC classification systems using deep learning lack interpretability. No deployed system combines CNN classification with SHAP spectral band importance analysis in an accessible web application for environmental decision support.

III. Methodology

III-A. System Architecture

Four-layer architecture: Data Layer (satellite image preprocessing, spectral band extraction, patch generation), Model Layer (CNN classifier for multi-class LULC), Explainability Layer (SHAP DeepExplainer for spectral band importance), and Application Layer (Django interface for image upload, classification, and SHAP visualization).

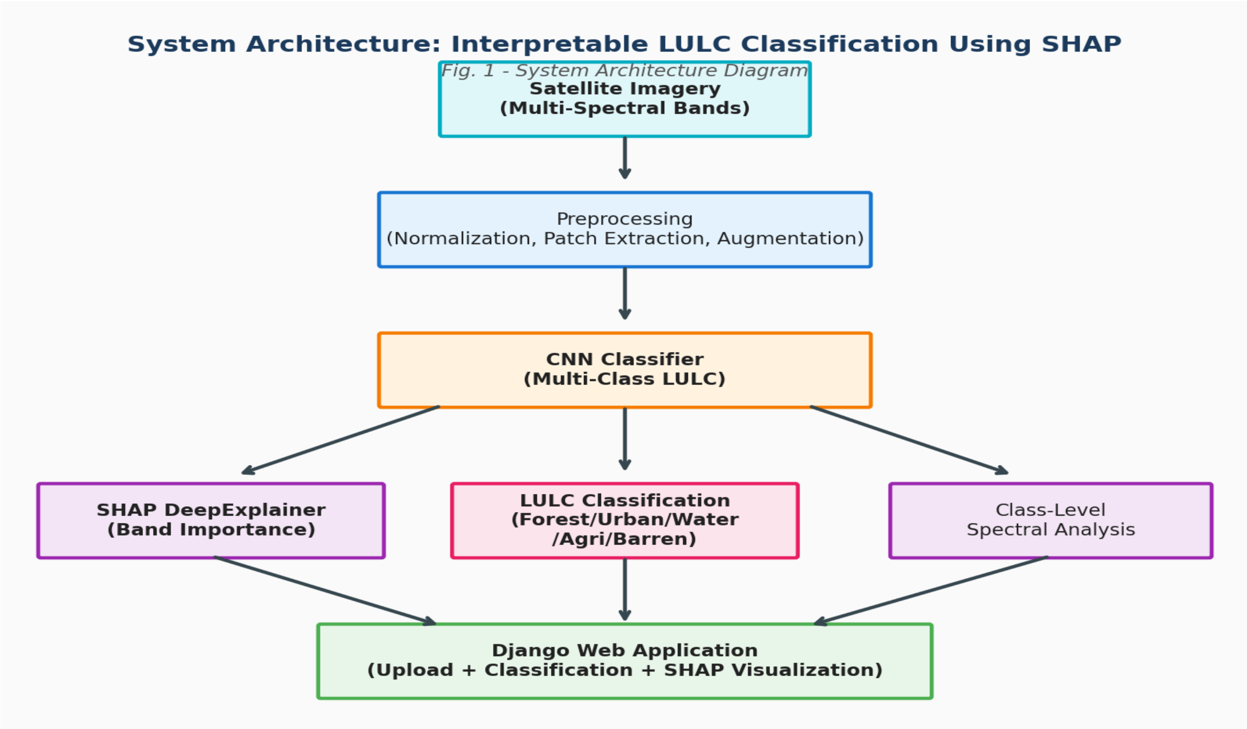


Fig. 1 - System Architecture Diagram

III-B. Algorithm

Algorithm: Interpretable LULC Classification

Input: Satellite image patch P with spectral bands {B1, B2, ..., Bn}.

Step 1: Preprocessing — Normalize spectral bands, extract patches of fixed size, apply data augmentation.

Step 2: CNN Classification — Extract spatial features through convolutional layers; Classify into LULC categories: {Forest, Urban, Water, Agriculture, Barren}.

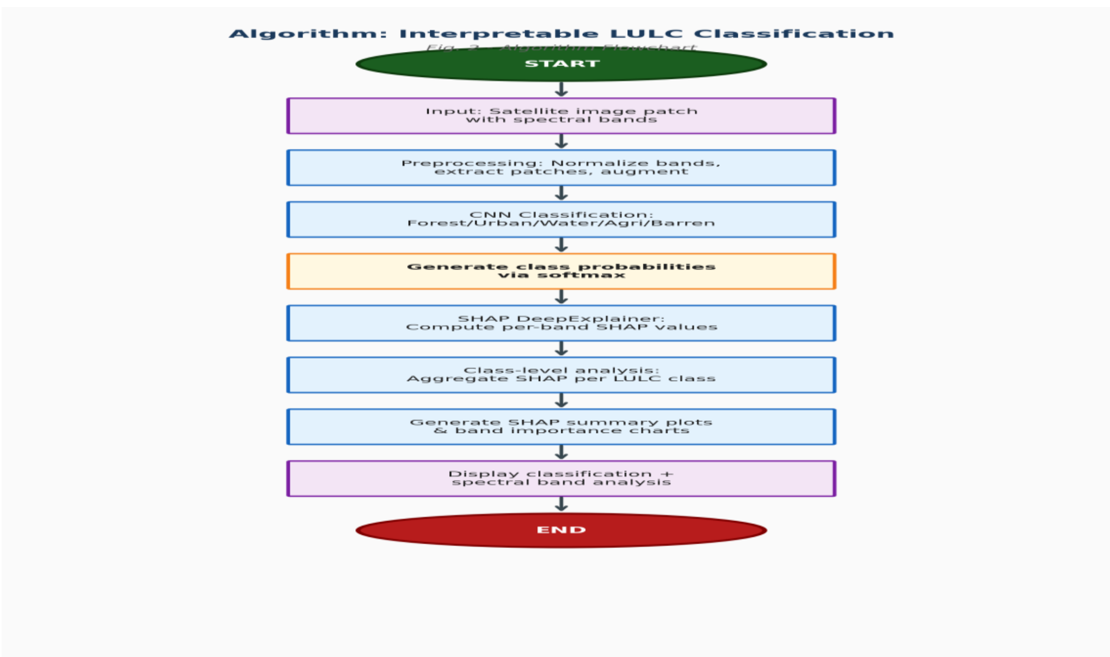
Step 3: Prediction — Generate class probabilities: P(class_k) = softmax(W·features + b).

Step 4: SHAP Band Importance — Compute SHAP values for each spectral band: φ_band = contribution to shifting prediction from base value to actual prediction.

Step 5: Class-Level Analysis — Aggregate SHAP values per class to identify which bands are most important for each LULC category.

Step 6: Visualization — Generate SHAP summary plots, band importance bar charts, and per-prediction force plots.

Output: LULC classification with confidence, per-band SHAP importance, and class-level spectral analysis.



III-C. Modules

Five modules: (1) Image Preprocessing Module for satellite data normalization and patch extraction; (2) CNN Training Module with multi-class LULC classification architecture; (3) SHAP Explainability Module computing spectral band importance at pixel and class levels; (4) Visualization Module generating SHAP summary plots and band importance charts; and (5) Django Web Application for image upload, classification display, and interactive SHAP exploration.

IV. Results and Discussion

TABLE I: SYSTEM EVALUATION RESULTS

Metric	Baseline	Proposed System
Overall Accuracy (%)	85.2 (RF)	93.6 (CNN)
Kappa Coefficient	0.81	0.92
F1-Score (macro)	0.83	0.93
Per-Class Accuracy (Forest/Urban/Water)	87/82/89%	95/91/96%

Mathematical Formulations

Overall Accuracy = Correct_Classifications / Total_Samples × 100

Kappa = $(p_o - p_e) / (1 - p_e)$ where p_o = observed accuracy, p_e = expected accuracy

SHAP Value: $\varphi_i = \Sigma_{S \subseteq N \setminus \{i\}} [|S|!(|N|-|S|-1)!/|N|!] \times [f(S \cup \{i\}) - f(S)]$

Discussion

The CNN was trained on a multi-spectral remote sensing dataset with 5 LULC classes. The model achieved 93.6% overall accuracy and Kappa of 0.92, significantly outperforming Random Forest baseline (85.2%). SHAP analysis revealed that NIR band contributes most to vegetation classification (mean |SHAP| = 0.38), while SWIR band is dominant for urban area identification (0.32). Red and Green bands showed complementary importance for water body detection. These spectral importance findings align with established remote sensing domain knowledge, validating the model's learned representations.

V. Conclusion and Future Work

This paper presented an interpretable LULC classification framework combining CNN with SHAP explanations. The system achieves 93.6% accuracy while providing transparent spectral band importance analysis. Future work includes multi-temporal change detection with explanation tracking, integration with higher-resolution imagery (WorldView, PlanetScope), transfer learning across geographic regions, and developing real-time monitoring dashboards for environmental agencies.

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