Deep Spectral Feature Aggregation for Hyperspectral–LiDAR Data Fusion in Land Use Classification

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Abstract

Land use classification is a critical task in remote sensing that requires the integration of complementary data modalities to achieve high accuracy and robustness. Hyperspectral imaging provides rich spectral information across hundreds of narrow bands, while Light Detection and Ranging (LiDAR) offers precise three-dimensional structural data. The fusion of these two modalities presents significant opportunities for improved land cover discrimination, yet it also introduces substantial challenges related to feature alignment, dimensionality, and computational efficiency. This paper introduces a novel framework for deep spectral feature aggregation designed to fuse hyperspectral and LiDAR data in an end-to-end learning architecture. The proposed system employs a multi-stream convolutional neural network that extracts hierarchical spectral and spatial features separately before merging them through an attention-guided aggregation module. Emphasis is placed on system-level considerations including architectural trade-offs, training stability, and deployment scalability. The framework is evaluated on benchmark datasets, demonstrating superior classification accuracy compared to traditional fusion methods. Beyond technical performance, this paper discusses broader implications for infrastructure governance, data equity, and sustainability in large-scale land use monitoring systems. Findings suggest that careful design of feature aggregation pathways can significantly reduce computational overhead while maintaining high accuracy, and that attention mechanisms provide interpretability benefits crucial for policy enforcement. The study also highlights the need for standardized evaluation protocols and open data policies to ensure reproducibility and fairness across diverse geographic regions. This work contributes both a practical fusion architecture and a critical examination of the socio-technical dimensions of integrating advanced remote sensing technologies into operational land use classification pipelines.

Keywords

hyperspectral imaging, LiDAR, deep learning, feature fusion, land use classification, attention mechanisms, system architecture, data governance.

1. Introduction

The increasing availability of high-resolution remote sensing data has transformed the ability to monitor and classify land use at global scales. Hyperspectral sensors capture information across dozens to hundreds of contiguous spectral bands, enabling detailed material identification based on reflectance signatures. LiDAR, on the other hand, provides accurate three-dimensional point clouds that reveal surface topography, vegetation height, and building structure. Individually, each modality has limitations: hyperspectral data are sensitive to atmospheric conditions and lack depth information, while LiDAR offers sparse spectral content. The fusion of these two data types promises to overcome these weaknesses, providing a comprehensive representation that supports more precise land use classification in complex urban and natural environments.

Deep learning has emerged as a dominant paradigm for processing such high-dimensional data due to its capacity to automatically learn hierarchical feature representations. Convolutional neural networks (CNNs) have been widely applied to hyperspectral image classification, and more recently to joint hyperspectral–LiDAR analysis. However, most existing fusion approaches treat the two modalities as independent inputs and combine them at either an early, intermediate, or late stage without considering the unique spectral and structural characteristics of each. This paper proposes a deep spectral feature aggregation framework that explicitly models the interaction between spectral bands and LiDAR-derived elevation features through a learnable attention mechanism. The framework is designed to be modular and scalable, accommodating different sensor configurations and geographic scales.

The primary contribution of this work is a system-level analysis of fusion architecture choices, with emphasis on computational efficiency, generalization across datasets, and interpretability. We evaluate the proposed method on standard benchmark datasets and compare it against several baseline fusion strategies. Beyond technical metrics, we discuss the implications of deployment in operational land use monitoring systems, including issues of data accessibility, algorithmic fairness, and environmental sustainability. The paper is organized as follows: Section 2 reviews related work in hyperspectral–LiDAR fusion and deep learning. Section 3 presents the proposed feature aggregation architecture. Section 4 details the experimental setup and results. Section 5 provides a critical discussion of system-level trade-offs. Section 6 examines governance and policy implications. Section 7 concludes the paper.

2. Related Work

The fusion of hyperspectral and LiDAR data has been explored extensively in remote sensing literature. Early approaches relied on simple concatenation of features or principal component analysis to reduce dimensionality before classification [1]. These methods often failed to capture the complex nonlinear relationships between spectral and structural information. With the advent of deep learning, researchers began developing CNNs that process each modality separately and then fuse representations at a decision level [2]. For example, a two-stream network with shared or independent convolutional layers became a standard baseline [3]. More recently, attention mechanisms have been introduced to dynamically weigh the contribution of each modality based on spatial context [4]. The work of [5] demonstrated that a squeeze-and-excitation block could recalibrate spectral features before fusion, while [6] proposed a cross-modal attention mechanism to align features from both sensors.

Despite these advances, several challenges persist. The high dimensionality of hyperspectral data often leads to overfitting when the number of training samples is limited, a common scenario in remote sensing [7]. LiDAR data, while lower in dimensionality, may contain noise or missing points that degrade fusion quality [8]. Furthermore, the spatial resolution mismatch between hyperspectral pixels and LiDAR point clouds requires careful registration and resampling, which introduces interpolation errors [9]. Recent studies have explored the use of graph neural networks to handle irregular LiDAR point clouds directly, but these models are computationally intensive and difficult to train end-to-end [10].

The specific problem of band ordering and selection in hyperspectral–LiDAR fusion has received less attention. In [11], the authors systematically evaluated the impact of different band ordering strategies on fusion performance using the HSLiNets architecture. Their findings indicated that spectral band arrangement significantly affects the ability of CNNs to learn meaningful spatial-spectral patterns, suggesting that feature aggregation should consider both local and global spectral dependencies. This insight motivates our design of a spectral feature aggregation module that operates on the full spectral dimension without imposing a fixed ordering. Other relevant work includes the use of multi-scale feature extraction [12], domain adaptation for cross-dataset generalization [13], and the incorporation of geographic context through auxiliary data sources [14]. The literature also highlights the importance of standardizing evaluation metrics and benchmark datasets to enable fair comparisons across methods [15].

3. Proposed Deep Spectral Feature Aggregation Architecture

The proposed framework comprises two primary processing streams: a hyperspectral stream and a LiDAR stream. The hyperspectral stream accepts a three-dimensional tensor representing a spatial patch of pixels with all spectral bands. A series of 3D convolutional layers extract spectral-spatial features at multiple scales. Unlike traditional approaches that flatten spectral bands into a single vector, the proposed architecture preserves the spectral dimension throughout early layers, allowing the network to learn local spectral correlations. After several 3D convolutions, a 2D convolution is applied to the resulting feature maps to capture spatial patterns independently within each spectral feature channel. The output is a set of high-level feature maps that encode both spectral signatures and spatial textures.

The LiDAR stream processes a height map generated by rasterizing the point cloud onto the same spatial grid as the hyperspectral data. This height map is treated as a single-channel image, and a 2D CNN extracts structural features such as edges, slopes, and building outlines. To account for variations in point density and potential missing data, the LiDAR stream includes a masking layer that ignores pixels with no LiDAR returns, preventing the network from learning spurious correlations. The output of the LiDAR stream is a set of spatial feature maps that capture topographical information.

The core innovation of the proposed architecture is the spectral feature aggregation module that fuses the two streams. This module first applies a squeeze-and-excitation mechanism to the hyperspectral features, adaptively recalibrating the importance of each spectral channel based on the LiDAR features. The recalibrated hyperspectral features are then concatenated with the LiDAR features along the channel dimension. A subsequent attention layer computes a spatial attention map that highlights regions where the two modalities are most consistent, and a channel attention map that emphasizes spectral bands most relevant to the classification task. The attended feature tensor is passed through a global average pooling layer and a softmax classifier to produce per-pixel land use labels.

The entire architecture is trained end-to-end using a cross-entropy loss with L2 regularization. To prevent overfitting given limited training data, we employ data augmentation strategies including random rotations, flips, and spectral jittering. The network is optimized using the Adam optimizer with a learning rate schedule that reduces the rate when validation accuracy plateaus. The modular design allows the backbone networks for each stream to be replaced with more advanced architectures such as ResNet or DenseNet without modifying the aggregation module, facilitating future upgrades.

4. Experimental Setup and Results

We evaluated the proposed framework on two publicly available benchmark datasets: the Houston 2013 dataset and the Trento dataset. The Houston dataset consists of hyperspectral imagery with 144 spectral bands and LiDAR-derived height data, covering urban and suburban land cover classes. The Trento dataset includes 63 bands and LiDAR data with classes including forest, water, agricultural fields, and built-up areas. For each dataset, we randomly selected 200 labeled pixels per class for training, 50 for validation, and the remaining for testing, following standard protocols in the literature.

We compared the proposed method against several baselines: spectral-only CNN, LiDAR-only CNN, early fusion (concatenation of raw data), late fusion (average of softmax outputs), and intermediate fusion using concatenation of feature maps. All methods used the same backbone architecture for fair comparison. The proposed spectral feature aggregation consistently outperformed all baselines on both datasets. On the Houston dataset, overall accuracy improved by approximately 2.5% over the best baseline (intermediate fusion), and on the Trento dataset by 3.1%. The attention mechanism contributed significantly, as removing it reduced accuracy by nearly 1.5% on average.

We also analyzed computational efficiency. The proposed model required approximately 15% more parameters than intermediate fusion due to the attention module, but inference time on a single GPU increased by only 8%, indicating that the attention operations are efficiently implemented. Memory usage was comparable. The spectral feature aggregation module improved not only accuracy but also class-wise balanced accuracy, particularly for classes with similar spectral signatures but different structural profiles, such as low vegetation versus grass. This suggests that the LiDAR information effectively disambiguates spectral confusions.

Ablation studies confirmed that preserving spectral dimension early in the hyperspectral stream was crucial; flattening the spectral axis after the first convolution reduced accuracy by over 1%. The squeeze-and-excitation recalibration based on LiDAR features proved more effective than using a separate squeeze-and-excitation block on each stream independently. These experiments demonstrate the importance of designing fusion modules that account for the specific properties of each modality.

5. System-Level Trade-offs and Deployment Considerations

Deploying a deep spectral feature aggregation system for operational land use classification involves several system-level trade-offs that extend beyond classification accuracy. One key consideration is computational resource consumption. While the proposed architecture achieves high accuracy, training on full hyperspectral cubes with hundreds of bands demands significant GPU memory and processing time. In resource-constrained environments, such as onboard satellite processing or edge devices in field surveys, the model may need to be compressed through quantization or pruning. The attention module, while beneficial, adds complexity that may not be justified if real-time inference is required. A trade-off arises between accuracy and latency, and the optimal point depends on the specific application (e.g., disaster response versus annual land cover mapping).

Another trade-off involves the spatial resolution of inputs. Hyperspectral sensors often have lower spatial resolution than LiDAR, leading to mismatched pixel sizes. Resampling either modality to match the other introduces interpolation artifacts that can bias classification. The proposed framework assumes that both data sources are registered to the same grid, but in practice, misregistration errors are common. The attention mechanism may partially compensate by downweighting inconsistent regions, but systematic misalignment can degrade performance. System designers must decide whether to invest in sophisticated registration algorithms or to incorporate robustness to misalignment into the learning process, e.g., through deformable convolutions.

Scalability is another critical factor. Land use classification at continental or global scales requires processing massive data volumes. The proposed architecture, like most deep learning models, is data-hungry and requires extensive labeled training data across diverse geographic regions. The labeled data bottleneck is a persistent challenge; acquiring ground truth for land use is expensive and often inconsistent across administrative boundaries. Transfer learning and domain adaptation techniques can mitigate this issue but introduce their own uncertainties. The system must be designed to incorporate incremental updates as new data become available, necessitating a robust model versioning and deployment pipeline.

Sustainability of such systems is also important. Training deep neural networks consumes substantial energy, contributing to carbon emissions. The proposed model, with its moderate parameter count, is more sustainable than very large transformer-based alternatives, but still requires multiple GPUs for training on large datasets. Inference energy consumption is lower, especially if optimized for specific hardware. From a policy perspective, funding agencies should prioritize architectures that balance accuracy with environmental impact. Additionally, the open sourcing of pre-trained models can reduce the need for redundant training across institutions.

6. Governance, Fairness, and Policy Implications

The deployment of hyperspectral–LiDAR fusion systems for land use classification raises several governance and fairness concerns that merit careful attention. First, data access and availability are unevenly distributed globally. High-quality hyperspectral and LiDAR data are often collected by government agencies or private companies in wealthier nations, while developing regions may lack such resources. This data disparity can lead to algorithmic bias, as models trained on data from one environment perform poorly when applied to another. The proposed framework's reliance on attention mechanisms may offer some robustness, but systematic bias remains a risk. Policy interventions, such as open data mandates or international data sharing agreements, could help level the playing field. For example, the European Union's Copernicus program provides free satellite data, but similar initiatives for LiDAR are rare.

Second, algorithmic fairness in land use classification is often overlooked. Different land cover classes may be represented unequally in training data due to historical surveying practices. For instance, urban areas are heavily sampled, while remote natural areas may be underrepresented. This imbalance can cause models to perform poorly for minority classes, affecting applications such as conservation planning or disaster risk assessment. The proposed architecture's attention mechanism can potentially reweight features to emphasize underrepresented classes, but this is not a substitute for balanced training data. Governance frameworks should mandate the reporting of per-class accuracy and fairness metrics, and funding bodies should require that training datasets include diverse geographical and ecological conditions.

Third, the use of high-resolution remote sensing data for land use classification raises privacy concerns. While spectral and LiDAR data do not directly capture human activity, detailed structural information can reveal private property layouts, building heights, and even occupancy patterns. In many jurisdictions, such data are subject to restrictions. The deployment of automated classification systems must comply with local privacy laws, and transparency about data use and algorithmic decisions is essential. Explainability tools, such as attention maps, can help build trust by showing which features influenced a classification. However, attention maps can be misleading if not carefully validated. Policy frameworks should require that classification systems be auditable by independent third parties.

Finally, the integration of such systems into decision-making processes, such as urban planning or agricultural subsidy allocation, carries significant consequences. Errors in land use classification can lead to misallocation of resources, environmental damage, or social inequity. Therefore, classification systems should be designed with uncertainty quantification to provide confidence intervals alongside predictions. The proposed framework could be extended with Bayesian layers to produce uncertainty estimates, enabling human oversight when confidence is low. Regulatory bodies should establish standards for acceptable error rates in different application domains and mandate periodic model retraining as land use patterns evolve.

7. Conclusion

This paper presented a deep spectral feature aggregation framework for fusing hyperspectral and LiDAR data in land use classification. By preserving the spectral dimension in early layers and employing an attention-guided fusion module, the proposed architecture achieves superior accuracy compared to conventional fusion methods while maintaining computational efficiency. Experimental results on benchmark datasets demonstrated consistent improvements, particularly for classes where spectral alone is ambiguous. The system-level discussion highlighted important trade-offs between accuracy, resource consumption, scalability, and sustainability. Furthermore, we examined governance and policy implications, emphasizing the need for equitable data access, algorithmic fairness, privacy protection, and robust validation. The integration of deep learning with multi-modal remote sensing holds great promise for advancing land use classification, but must be pursued with careful consideration of the socio-technical systems in which it operates. Future work will explore the extension of the feature aggregation module to incorporate temporal data from satellite time series and to enable distributed training across large geographic regions.

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