

HSI-LightNet: A Reliability-Oriented Lightweight Network for Hyperspectral Image Classification

HSI-LightNet: Rangkaian Ringan Berorientasikan Kebolehpercayaan untuk Pengelasan Imej Hiperspektral

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ABSTRACT

Hyperspectral image classification (HSIC) plays an important role in land-cover mapping, agricultural monitoring, urban analysis, and environmental observation because hyperspectral sensors capture rich spectral information across many narrow bands. Despite this, it is still difficult to apply HSIC in practice because of high spectral dimensionality, limited labelled samples, class imbalance, and the high computational complexity of deep learning algorithms. In this extended abstract, we propose the reliability-oriented lightweight spectral-spatial network HSI-LightNet that aims at jointly optimizing the classification accuracy with class-balanced reliability and model efficiency. The proposed framework is training-only standardization and PCA, local patch-based learning, grouped 1×1 spectral mixing, optional spectral gating, depthwise separable convolution, global average pooling and a compact classifier. The overall accuracy of the selected configurations for Indian Pines, Pavia University, Salinas, and WHU-Hi LongKou is 96.92%, 99.86%, 99.93%, and 99.90%, respectively, with only 15.66K–16.62K parameters and 1.814M–1.987M MACs per patch. These results suggest that compact spectral-spatial networks can offer a favourable accuracy-efficiency compromise when considering HSIC models as a function of classification reliability and also computational complexity.

Keywords: Hyperspectral image classification; lightweight deep learning; spectral-spatial learning; model efficiency; remote sensing

ABSTRAK

Pengelasan imej hiperspektral (HSIC) memainkan peranan penting dalam pemetaan tutupan bumi, pemantauan pertanian, analisis bandar, dan pemerhatian alam sekitar kerana penerima hiperspektral mampu menangkap maklumat spektral yang kaya merentasi pelbagai jalur sempit. Walau bagaimanapun, pengaplikasian HSIC secara praktikal masih sukar disebabkan oleh kedimensian spektral yang tinggi, sampel berlabel yang terhad, ketidakseimbangan kelas, serta kerumitan pengiraan yang tinggi dalam algoritma pembelajaran mendalam. Dalam abstrak lanjutan ini, kami mencadangkan rangkaian spektral-ruang ringan berorientasikan kebolehpercayaan, iaitu HSI-LightNet, yang bertujuan untuk mengoptimumkan ketepatan pengelasan secara bersama dengan kebolehpercayaan keseimbangan kelas dan kecekapan model. Kerangka yang dicadangkan ini merangkumi pemiawaian khusus latihan dan PCA, pembelajaran berasaskan tampalan tempatan, pencampuran spektral 1×1 berkumpulan, penggetan spektral pilihan, konvolusi boleh pisah mengikut kedalaman (depthwise separable convolution), pengumpulan purata global, dan pengelas yang padat. Ketepatan keseluruhan bagi konfigurasi yang dipilih untuk Indian Pines, Pavia University, Salinas, dan WHU-Hi LongKou masing-masing ialah 96.92%, 99.86%, 99.93%, dan 99.90%, dengan hanya 15.66K–16.62K parameter dan 1.814M–1.987M MAC untuk setiap tampalan. Keputusan ini menunjukkan bahawa rangkaian

spektral-reruang yang padat mampu menawarkan tolak ansur ketepatan-kecekan yang memberangsangkan apabila mempertimbangkan model HSIC sebagai fungsi kepada kebolehpercayaan pengelasan dan juga kerumitan pengiraan.

Kata kunci: Pengelasan imej hiperspektral; pembelajaran mendalam ringan; pembelajaran spektral-spatial; kecekapan model; penderiaan jauh

INTRODUCTION

Hyperspectral image classification (HSIC) is an important remote-sensing task since hyperspectral sensors capture hundreds of narrow and contiguous spectral bands. This allows the materials that comprise the land cover to be discriminated, even when they look the same or similar in RGB or multispectral data. In spite of their good performances with a few training samples, traditional HSIC approaches including support vector machines and kernel-based classifiers rely on handcrafted spectral or spectral-spatial features (Melgani and Bruzzone, 2004).

To enhance HSIC, deep learning techniques have been adopted that learn the discriminative features directly from the image patches. CNN-based methods (Hu et al., 2015), hybrid 3-D-2-D CNNs (e.g., HybridSN (Roy et al., 2020)), Transformer-style models (e.g., SpectralFormer (Hong et al., 2022) and SSFTT (Sun et al., 2022)), and recent Mamba-based HSIC models (Yao et al., 2024; He et al., 2024; Li et al., 2025) have attained robust benchmark performance. Yet, there are many highly effective models that need greater parameter space or more complicated sequence modeling. Also, overall accuracy (OA) can mask poor performance on the minority classes. Thus, this work introduces a lightweight spectral-spatial network named HSI-LightNet that focuses on achieving accuracy, class-balanced reliability, and computational efficiency.

RELATED WORK

The previous studies conducted in the field of HSIC were based on spectral classifiers, support vector machines, and handcrafted spectral-spatial features (Melgani and Bruzzone, 2004). Later, CNNs gained popularity due to their ability to capture the local spatial pattern in hyperspectral patches (Hu et al., 2015). To capture spectral-spatial information more effectively, HybridSN fused the 3-D and 2-D convolution (Roy et al., 2020). Attention mechanisms were incorporated into transformer-based approaches like SpectralFormer and SSFTT to capture spectral or spectral-spatial relationships (Hong et al., 2022; Sun et al., 2022). To address the quadratic self-attention (SA) complexity and enhance long-range spectral-spatial modeling, Mamba-based models like SpectralMamba, 3DSS-Mamba, and MambaHSI are recently proposed (Yao et al., 2024; He et al., 2024; Li et al., 2025). Few-shot and cross-domain HSI classification have also been investigated using lightweight CNN-Transformer (Yang et al., 2026). A summary of the positioning of representative families of HSIC models is provided in Table 1. While the recent models show some progress in spectral-spatial representation learning, the reporting of efficiency is still sometimes incomplete. To bridge this gap, the HSI-LightNet is built on a combination of a compact spectral-spatial feature extraction and reliability-oriented evaluation including OA, AA, W5AA, parameter count, and MACs per patch.

TABLE 1. Summary of representative HSIC model families.

Method family	Examples	Main strength	Main limitation / gap
Classical spectral methods	SVM-based HSIC (Melgani and Bruzzone, 2004)	Effective with limited samples	Depend on handcrafted features and may not fully exploit spatial context
CNN and hybrid CNN	Deep CNN, HybridSN (Hu et al., 2015; Roy et al., 2020)	Strong local spectral-spatial feature learning	3-D/hybrid designs can increase parameters and MACs
Transformer-based HSIC	SpectralFormer, SSFTT (Hong et al., 2022; Sun et	Models long-range spectral-spatial dependencies	Self-attention may increase memory and computation

	al., 2022)		
Recent Mamba-based HSIC	SpectralMamba, 3DSS-Mamba, MambaHSI (Yao et al., 2024; He et al., 2024; Li et al., 2025)	Efficient long-range sequence modeling	Practical comparison still depends on protocol, datasets, and efficiency reporting
Lightweight CNN–Transformer	LGDAF-Net (Yang et al., 2026)	Lightweight design for few-shot/cross-domain settings	Focus differs from controlled lightweight benchmark evaluation
HSI-LightNet	Proposed work	Compact grouped spectral mixing and depthwise separable spatial learning	Evaluated as an accuracy–efficiency trade-off, not as a universal highest-accuracy model

METHODOLOGY

The proposed HSI-LightNet framework starts by training-only standardization and PCA-based spectral reduction. Only the training pixels are used for fitting the standardization and PCA to prevent information leakage. Following the PCA, every labelled centre pixel is represented by a local 11×11 spectral–spatial patch. The overall processing flow of HSI-LightNet is illustrated in Figure 1.



FIGURE 1. Compact processing flow of the proposed HSI-LightNet architecture.

Here, grouped 1×1 convolution is used for compact spectral mixing and depthwise separable convolution is used for low cost computation, which is based on the lightweight design of MobileNet (Howard et al., 2017) separating spatial filtering and channel mixing. The optional Spectral Gating Module (SGM) introduces group-level gates that are inspired by channel-attention mechanisms (Hu et al., 2018), to recalibrate feature responses. The model was evaluated on Indian Pines, Pavia University, Salinas, and WHU-Hi LongKou, including the UAV-borne WHU-Hi benchmark family (Zhong et al., 2018).

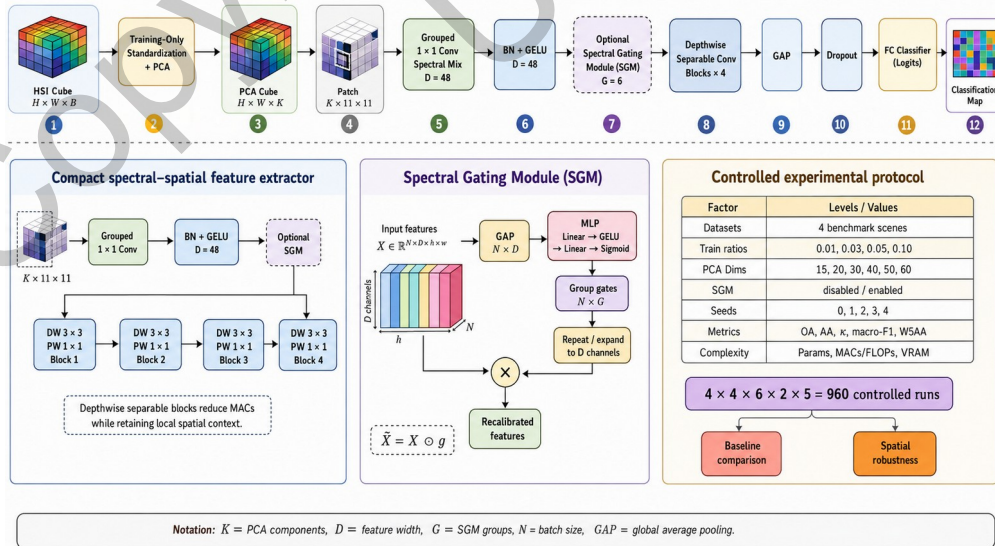


FIGURE 2. Overview of the proposed HSI-LightNet framework, including training-only preprocessing, compact spectral–spatial feature extraction, optional spectral gating, and the controlled evaluation protocol.

Figure 2 illustrates the overall workflow of HSI-LightNet. The input hyperspectral cube is initially normalized and dimensionally reduced by PCA trained on the training data, and then local spectral–

spatial patches are collected around the labeled pixels. Then, a grouped 1×1 convolution is used for compact spectral mixing, which is followed by BN and gelu activation by the feature extractor. The depthwise separable blocks lower the amount of computation in spatial feature extraction, and the optional Spectral Gating Module (SGM) recalibrates the spectral-spatial feature responses when it would be beneficial. Finally the class prediction is obtained by global average pooling and a compact classifier. All datasets report OA, AA, W5AA, and the number of parameters and MACs per patch using the same controlled protocol.

RESULTS AND DISCUSSION

Table 2 summarizes the selected HSI-LightNet configurations. The configurations were selected by considering classification performance and computational efficiency rather than OA alone.

TABLE 2. Selected HSI-LightNet results on four benchmark hyperspectral datasets. Results are reported as mean $\pm$ standard deviation over five seeds.

Dataset	PCA	SGM	OA (%)	AA (%)	W5AA (%)	Params/MACs
Indian Pines	60	Enabled	96.92 $\pm$ 0.54	98.22 $\pm$ 0.27	95.15 $\pm$ 0.78	16.19K / 1.814M
Pavia University	20	Disabled	99.86 $\pm$ 0.05	99.76 $\pm$ 0.08	99.56 $\pm$ 0.14	15.66K / 1.871M
Salinas	60	Disabled	99.93 $\pm$ 0.03	99.93 $\pm$ 0.02	99.76 $\pm$ 0.07	15.86K / 1.814M
WHU-Hi LongKou	40	Disabled	99.90 $\pm$ 0.02	99.75 $\pm$ 0.05	99.57 $\pm$ 0.08	16.62K / 1.987M

The configurations selected for the experiments achieved high OA with only 15.66K–16.62K parameters and 1.814M–1.987M MACs/patch. Indian Pines is the most difficult dataset owing to high class imbalance, and the accuracy for HSI-LightNet on tails (W5AA) was 95.15%. These results indicate that to test the lightweight HSIC models, accuracy and reliability should be used in conjunction with computational complexity, and not accuracy measures alone.

CONCLUSION

HSI-LightNet, a reliability-oriented lightweight spectral-spatial network for hyperspectral image classification is presented in this extended abstract. The proposed model consists of training only preprocessing, PCA based spectral reduction, grouped 1×1 spectral mixing, optional spectral gating and depthwise separable convolution. Experimental results on four benchmark datasets demonstrate that HSI-LightNet classifies with high accuracy with good class-balanced reliability, while keeping a small number of parameters and low MACs per patch. In the future, HSI-LightNet will be expanded towards compression aware optimization and hardware aware deployment on edge devices.

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