Abstract

Hyperspectral image (HSI) classification has gained increasing attention owing to its applications in agriculture, environmental monitoring, and urban planning. Despite remarkable progress with deep learning (DL), challenges such as high dimensionality, scarcity of labeled data, computational complexity, and class imbalance hinder deployment. This thesis addresses these challenges through DL models that progressively enhance performance, efficiency, and robustness.

The motivation behind this research stems from the growing need for automated, accurate, and scalable HSI classification methods that can handle the complexities of real-world remote sensing data. Traditional machine learning (ML) approaches, while effective in certain scenarios, struggle to deal with the high dimensionality of HSI data and the imbalanced class distributions common in such datasets. Recent advances in DL have shown promise in improving feature extraction and classification performance. However, these methods are often computationally expensive, and many fail to adequately address class imbalance, which can significantly affect the accuracy.

Chapter 1 introduces the fundamentals of HSI, its diverse applications, and the key challenges in HSI classification. It outlines the research motivation, states the problem formulation, and provides a structured overview of the contributions. Chapter 2 provides a comprehensive survey of HSI classification methods, from traditional ML to advanced DL approaches. Methods are categorized by feature type (spectral, spatial, spectral–spatial) and contextual modeling (local, global, hybrid), which offers a taxonomy for methodological developments in later chapters.

In Chapter 3, a morphologically dilated convolutional neural network (MDCNN) is developed, integrating spectral–spatial features with morphological filtering. Using 30% of the data for training, the model achieves state-of-the-art (SOTA) performance, with Overall Accuracy (OA) of 99.99% on Pavia University (PU) and 100% on Salinas (SA), surpassing all CNN models by approximately 2.3% OA. Despite this high accuracy, MDCNN primarily focuses on local features and also demands high computation.

To resolve these challenges, we proposed LogGroupFormer in Chapter 4. It is a lightweight hybrid model that integrates CNN and Transformer to capture local-global spectral–spatial features. On the Indian Pine (IP) dataset, it achieves OA of 96.95%, outperforming SOTA model SSFTT by 1.76%, IFormer by 0.59%, and LGSA-ViT by 2.99%. Furthermore, it reduces parameters (P_M) by ~35% and computational overheads (C_{FLOPs}) in Floating Point Operations (FLOPs) by ~40% compared to SSFTT, confirming both accuracy and efficiency gains. Despite these improvements, LogGroupFormer still faces quadratic time complexity.

Building further, in Chapter 5, we proposed the Convolution-Kaiming-Gaussian Focused Linear Network (CKGFLNet), which employs linear attention for reduced complexity along with Gaussian–Kaiming initialization for stable optimization. Compared to the closest SOTA model, LGSA-ViT, CKGFLNet achieves accuracy improvements of about 0.08% on the IP dataset and 0.12% on PU. Moreover, CKGFLNet demonstrates notable efficiency, reducing training time (Tr) by approximately 10–15% across all datasets. These results highlight both the effectiveness and scalability of the proposed model for hyperspectral image classification.

In Chapter 6, we proposed the Hierarchical Clustering-Based Convolution with Flattened Kaiming-Gaussian Transformer Network (HieraKGTNet), which integrates clustering-based convolution, linear attention–based transformer modules, Gaussian–Kaiming initialization, and a Multiclass Poly Focal Loss (MPF-Loss) to enhance recognition of hard-to-classify classes in HSI data. On IP and PU, HieraKGTNet boosts per-class accuracy for challenging categories such as *Alfalfa*, *Oats*, and *Gravel* by up to 12.5% compared to SOTA methods. Additionally, HieraKGTNet reduces P_M count by ~28% and C_{FLOPs} by ~32% relative to closest SOTA models in terms of computational performance, confirming its robustness and efficiency.

Chapter 7 concludes the thesis by summarizing the key contributions and findings. It also outlines future research directions, including semi-supervised learning, domain adaptation, and efficient HSI analysis on edge devices.

Keywords: *Class Imbalance, Convolutional Neural Networks, Deep Learning, Dilation, Focal Loss, Global Context Modeling, Hybrid Architecture, Hyperspectral Image Classification, Kaiming–Gaussian Linear Attention, Logarithmic Convolution, Morphology, Remote Sensing, Spatial Features, Semantic Tokenization, Spectral Features, Superpixel Segmentation, Transformer Networks.*