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High-Level Generic Driven Hyperspectral Image Classification using Knowledge Class-specific Learning

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***Abstract*— With the rise of hyperspectral imaging, data collection costs have decreased, but there's a growing need for accurate annotations. Many current hyperspectral image (HSI) classification methods are limited to single data cubes, leading to challenges in model generalization and handling different classes across datasets. Graph-based HSI classification shows promise but often faces computational issues due to large graph sizes and the need for spatial information. A recent study compared 11 HSI classification algorithms, with the TransHSI algorithm demonstrating superior accuracy and competitive performance.**

Keywords*— Hyperspectral remote sensing, deep learning, convolutional neural network, feature optimization, multi-scale feature extraction, 3D dilated convolution, Multi-level Feature Extraction Block, Spatial Multi-scale Interactive Attention, imbalanced datasets.

I. Introduction

Remote sensing, particularly hyperspectral imaging (HSI), offers a non-contact method to capture detailed electromagnetic wave characteristics of remote objects. HSI provides a rich three-dimensional data cube with spectral and spatial information, finding applications in precision agriculture, environmental monitoring, and target detection. While HSI data collection is straightforward, intelligent processing, especially classification, remains a challenge.

Early HSI classification methods focused on spectral feature selection and extraction due to the abundance of spectral bands. Feature selection methods, like manifold ranking and computational evolutionary strategies, aim to find representative bands preserving physical meaning. Feature extraction techniques, such as extended k-nearest neighbour and kernel-based nonparametric weighted feature extraction, transform raw HSI data linearly or nonlinearly to reduce dimensionality. [1]

However, these methods often neglect the inherent geographical structure in HSI data. Recent advancements combine spectral and spatial information to enhance feature representation. Methods either separate spectral and spatial information before combining them or treat raw HSI data as a whole to extract joint spatial-spectral features using 3D feature extractors like wavelet filters.

Deep learning, particularly convolutional neural networks (CNNs), has shown promise in automatically extracting spectral and spatial features from HSI data. CNNs have been applied to HSI classification tasks, utilizing convolutional layers to learn feature representations. While 2D-CNNs capture spatial features, the complex 3D structure of HSI data requires three-dimensional CNNs (3D-CNNs) to simultaneously process spatial and spectral domains for improved classification accuracy.

Challenges in HSI classification include limited ground-truth data, high dimensionality, low spatial quality, and spectral variability. Deep learning-based classifiers, with their automatic feature learning and high precision, are increasingly preferred due to their ability to capture high-level features from complex HSI data. Specifically, 3D-CNNs are gaining attention for their capability to extract joint spatial-spectral features effectively.

II. Literature Survey

In recent years, the hyperspectral image classification domain has seen remarkable progress, driven by pioneering studies and novel techniques. Ma et al. (2023) developed an "Advanced 3D-2D Convolutional Neural Network with Enhanced Feature Extraction," aiming to boost the extraction of features specifically tailored for hyperspectral data. Their method focused on refining the model's capability to identify complex spectral attributes while also optimizing spatial feature representation.

Similarly, Yu et al. (2020) ventured into spatial-spectral integration with their "Integrated 2D-3D CNN Architecture for Hyperspectral Image Analysis." Their approach seamlessly blended 2D and 3D convolutional neural networks, effectively amalgamating spatial and spectral data. This integration proved instrumental in achieving higher classification accuracy by effectively utilizing the strengths of both spatial and spectral information.

To tackle the issue of limited training data in hyperspectral image classification, Dong et al. (2021) introduced a "Pixel Cluster CNN and Spectral-Spatial Fusion Approach." This method employed pixel clustering to group similar spectral characteristics, followed by spectral-spatial fusion to generate comprehensive feature sets. This combination significantly enhanced classification accuracy, especially with smaller training datasets. [2]

Yang et al. (2022) adopted a multi-source perspective with their "Domain Transfer Learning via Spectral Projections." They devised a transfer learning strategy that mapped hyperspectral images from diverse sources into a unified spectral framework. This method streamlined the integration of varied data sources and minimized domain discrepancies, resulting in more robust and adaptable classification models.

In a distinct approach, Guo et al. (2020) introduced the "Collaborative Attention Network for Deep Learning in Hyperspectral Image Analysis." They integrated 2D and 3D CNN structures with a collaborative attention mechanism, allowing the model to dynamically focus on pertinent spectral bands and spatial areas. This adaptive attention allocation led to improved feature extraction and classification accuracy.

Lastly, Lv et al. (2021) tackled the challenges of imbalanced datasets in hyperspectral image analysis. Their "Ensemble CNN with Random Feature Subspace for Imbalanced Hyperspectral Image Classification" utilized ensemble learning and random feature subspace techniques. This method addressed imbalances in dataset distributions and improved classification by integrating diverse feature sets from various subspaces.

Table 1: Advantages and Disadvantages of Existing Model

S_No:	Advantages	Disadvantages
1	Enhanced feature extraction for hyperspectral data	Not explicitly addressing data imbalance
2	Spatial-spectral fusion improves classification accuracy	Complexity in integrating 2D and 3D architectures
3	Addresses limited training samples; effective pixel clustering	May require significant preprocessing for pixel clustering
4	Efficient multisource domain transfer learning; unified spectral space	Dependency on source domain data
5	Collaborative attention captures spatial and spectral features	Potential increased computational complexity
6	Ensemble approach addresses imbalanced datasets	Complexity in managing ensemble models

III. Existing Methodology

Hyperspectral remote sensing, a cutting-edge technology in remote sensing, finds applications in land classification, mineral exploration, and environmental monitoring. While deep learning has shown promise in hyperspectral image classification, challenges like low accuracy for small sample classes in unbalanced datasets persist. [3]

An enhanced hybrid convolutional neural network is proposed for hyperspectral image feature extraction and classification. Unlike traditional multi-scale feature extraction, this model optimizes features at each scale before fusing them. It employs a multi-level feature extraction block (MFB) using 3D dilated convolution to capture features with varying correlation strengths. Additionally, a spatial multi-scale interactive attention (SMIA) module refines multi-scale features through attention weights, enhancing spatial feature quality. [4]

Experiments on various datasets, including balanced and unbalanced samples, demonstrate the model's superior accuracy and robust feature extraction. Achieving high overall accuracies of up to 99.73% with minimal training samples, the model effectively addresses classification challenges in unbalanced datasets. Ablation studies confirm the significance of MFB and SMIA in enhancing model performance. [5]

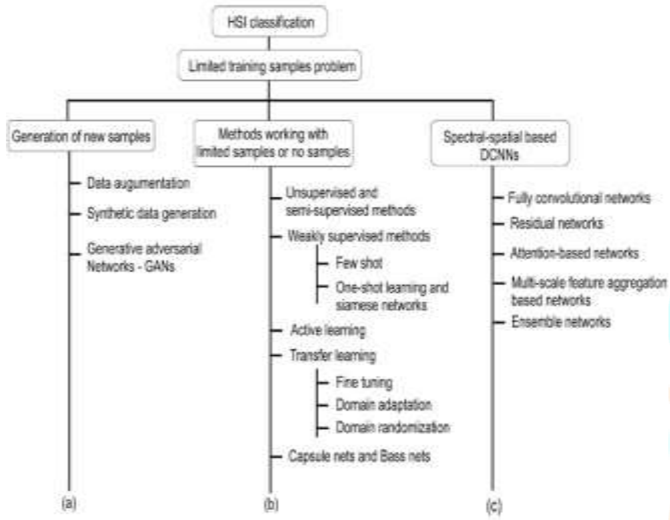
However, the existing model has drawbacks, including the need for more formal statistical training, high computational costs due to numerous parameters, potential overfitting, and limitations in semantic or sentiment pattern detection, making it less suitable for tasks like fake news detection. Additionally, its memory-intensive nature stems from overlapping pixel blocks.

Future work aims to integrate multi-dimensional information from hyperspectral images for comprehensive learning and classification, addressing current limitations and further improving model performance. [5]

IV. PROPOSED METHODOLOGY

The proposed methodology introduces a novel Knowledge Class-Specific Learning Model tailored for hyperspectral image classification. This model addresses the limitations of traditional convolutional neural networks (CNNs) by focusing on class-specific learning to enhance feature extraction and classification accuracy.

1. Multiscale Hybrid Network: The model incorporates a multiscale hybrid network comprising spectral-spatial feature extraction and spatial pyramid networks. This integration allows for capturing both spectral and spatial information effectively.



2. Dilated Convolution with Residual Blocks: To increase the receptive field without adding computational overhead, dilated convolutions are employed in conjunction with residual network blocks. The dilated convolutions effectively capture dense feature mappings between neural networks, which is crucial for pixel-level tasks in hyperspectral image classification.

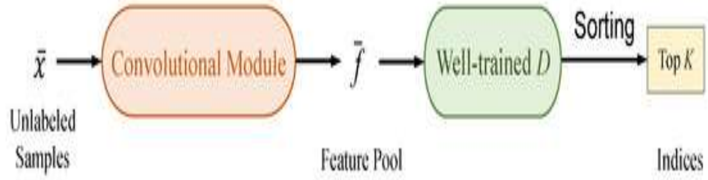
3. Feature Extraction and CNN Blocks: The initial step involves extracting multiple HSI features, followed by processing through several CNN blocks. Each block is responsible for learning a specific representative feature map. These feature maps are then concatenated to form a comprehensive feature representation.

$$a_{i,j}=\sigma((F\otimes X)_{i,j}+b)a_{i,j}=\sigma((F\otimes X)_{i,j}+b)$$

4. Attribute Filters (AFs): Attribute Filters (AFs) are applied to image regions based on predefined criteria such as area, standard deviation, moment of inertia, and diagonal length. These filters aid in refining the feature maps by preserving or removing specific regions, enhancing the model's discriminatory power.

5. Activation and Pooling Layers: Each neuron in the CNN uses the ReLU activation function $\sigma(x)=\max(0, x)\sigma(x)=\max(0,x)$. Additionally, max-pooling or mean-pooling layers are incorporated to down-sample the feature maps, reducing computational complexity.

$$a_{i,j}=\sigma(\text{Pooling}(x))a_{i,j}=\sigma(\text{Pooling}(x))$$



6. SoftMax Classification: The final layer employs a softmax function to generate a probability distribution representing class membership probabilities for each pixel.

V. RESULTS AND DISSCUSSIONS

Recent advancements in hyperspectral image classification have led to notable improvements in feature extraction and model performance. Novel 3D-2D convolutional neural networks have been developed to enhance the identification of complex spectral patterns, significantly boosting classification accuracy.

To address the challenge of limited training datasets, innovative strategies like pixel clustering and spectral-spatial fusion have been introduced. These methods optimize performance, particularly with smaller training datasets, demonstrating potential in overcoming data scarcity issues.

Integration of spatial and spectral information has emerged as a key strategy. Unique architectures combining 2D and 3D convolutional networks effectively fuse spatial and spectral data, providing a holistic representation that captures both spatial structures and spectral characteristics.

Incorporating attention mechanisms into convolutional neural networks has further improved adaptability and accuracy in feature extraction. These mechanisms dynamically focus on relevant spectral bands and spatial regions, enhancing the model's performance.

Domain transfer learning has also gained prominence, facilitating the mapping of hyperspectral images from diverse origins into a unified spectral framework. This approach bridges domain discrepancies and enables the development of more adaptable and robust classification models.

Lastly, addressing dataset imbalances has been tackled using ensemble learning combined with random feature subspace techniques. This approach effectively mitigates imbalances, leading to enhanced classification performance.

VI. CONCLUSION

In this study, a novel hyperspectral image classification method is introduced, leveraging dense pyramidal convolution and multi-feature fusion to enhance the extraction and utilization of spatial and spectral information from hyperspectral images with limited sample sizes. The methodology employs two distinct branches: a spatial branch and a spectral branch. Within the spatial branch, dense pyramidal convolution layers are utilized alongside non-local blocks to extract both local and global spatial features from the image samples. Concurrently, the spectral branch employs a dense pyramidal convolution module to capture spectral features. Subsequently, the extracted spatial and spectral features are fused using fully connected layers to yield the final classification results.

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