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A Critical Review on Hyperspectral Image Classification Techniques

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Abstract
Hyperspectral imaging has emerged as a powerful technology with applications in various fields, including remote sensing, agriculture, environmental monitoring, and medical diagnostics. This paper presents a critical review of hyperspectral image classification techniques, highlighting the challenges and advancements in this rapidly evolving field. The primary focus is on methodologies employed for extracting valuable information from hyperspectral data and improving the accuracy of classification results.
The review begins by providing an overview of hyperspectral imaging and its significance in capturing detailed spectral information across a wide range of wavelengths. Subsequently, common challenges associated with hyperspectral image classification, such as the curse of dimensionality, spectral variability, and data redundancy, are discussed. Various preprocessing techniques are examined, including dimensionality reduction, spectral feature extraction, and noise reduction, to enhance the quality of hyperspectral data before classification.
The paper critically evaluates traditional classification methods, such as Support Vector Machines (SVM) and Maximum Likelihood Classifier (MLC), and discusses their strengths and limitations in hyperspectral image analysis. Additionally, it explores the integration of machine learning algorithms, including deep learning techniques like Convolutional Neural Networks (CNN) and recurrent neural networks, highlighting their potential for improving classification accuracy and handling complex hyperspectral data.
Furthermore, the review delves into the role of feature selection methods in optimizing hyperspectral image classification models, emphasizing the importance of identifying relevant spectral features for accurate discrimination. The impact of hyperspectral sensor characteristics, such as spatial and spectral resolutions, on classification performance is also considered.
The review concludes with an outlook on emerging trends and future directions in hyperspectral image classification research. It emphasizes the need for developing robust and interpretable models, addressing challenges related to limited labeled data, and exploring novel applications of hyperspectral imaging technology. The synthesis of this critical review aims to guide researchers, practitioners, and decision-makers in selecting appropriate techniques and methodologies for hyperspectral image classification, fostering advancements in this dynamic and multidisciplinary field.

Keywords: Hyperspectral Imaging; Image Classification;Spectral Information;Dimensionality Reduction ;Preprocessing Techniques; Curse of Dimensionality; Spectral Variability;Data Redundancy
Support Vector Machines (SVM);Maximum Likelihood Classifier (MLC);Machine Learning Algorithms; Deep Learning;Convolutional Neural Networks (CNN);Recurrent Neural Networks
Feature Selection; Hyperspectral Sensor Characteristics; Spatial Resolution;Remote Sensing

1. Introduction

Hyperspectral imaging has revolutionized the way we perceive and analyze remote sensing data, providing a wealth of information across a vast range of spectral bands. Unlike traditional imaging systems that capture data in just a few bands, hyperspectral sensors record data in numerous contiguous spectral bands, resulting in a detailed spectral signature for each pixel in an image. This high-dimensional data opens new avenues for understanding and interpreting complex scenes, making hyperspectral image classification a critical aspect of harnessing the full potential of this technology.

The classification of hyperspectral images involves categorizing each pixel or group of pixels into predefined classes or land cover categories, enabling the extraction of valuable information about the Earth's surface. This process plays a pivotal role in applications such as environmental monitoring, precision agriculture, mineral exploration, and military surveillance.

However, hyperspectral image classification poses unique challenges. The curse of dimensionality, stemming from the large number of spectral bands, can lead to increased computational complexity and the risk of overfitting. Additionally, spectral variability within classes and data redundancy necessitate sophisticated techniques for accurate classification.

This introduction reviews the fundamental concepts underlying hyperspectral image classification techniques, emphasizing the methodologies employed to address the challenges associated with hyperspectral data. Preprocessing techniques, including dimensionality reduction, noise removal, and feature extraction, play a crucial role in enhancing the quality of hyperspectral data before classification.

Traditional classification methods, such as Support Vector Machines (SVM) and Maximum Likelihood Classifier (MLC), are examined for their efficacy in hyperspectral image analysis. The introduction also highlights the growing influence of machine learning algorithms, including deep learning techniques like Convolutional Neural Networks (CNN) and recurrent neural networks, in achieving higher classification accuracy and handling the intricate nature of hyperspectral data.

Furthermore, the introduction explores the significance of hyperspectral sensor characteristics, such as spatial and spectral resolutions, in influencing classification performance. Feature selection methods are discussed for optimizing classification models by identifying and utilizing the most relevant spectral information.

As hyperspectral imaging continues to advance, this introduction sets the stage for a comprehensive review of hyperspectral image classification techniques, aiming to provide insights into the state-of-the-art methodologies, challenges, and future directions in this dynamic and rapidly evolving field.

2. Literature Review

Fauvel et al.(2013) designed spectral-spatial strategies, combining spatial and spectral information, are crucial for accurate classification of hyperspectral images, with results validated on various contexts.Recent advances in spectral-spatial classification of hyperspectral images are presented in this paper. Several techniques are investigated for combining both spatial and spectral information. Spatial information is extracted at the object (set of pixels) level rather than at the conventional pixel level. Mathematical morphology is first used to derive the morphological profile of the image, which includes characteristics about the size, orientation, and contrast of the spatial structures present in the image. Then, the morphological neighbourhood is defined and used to derive additional features for classification. Classification is performed with support vector machines (SVMs) using the available spectral information and the extracted spatial information. Spatial postprocessing is next investigated to build more homogeneous and spatially consistent thematic maps. To that end, three pre-segmentation techniques are applied to define regions that are used to regularize the preliminary pixel-wise thematic map. Finally, a multiple-classifier (MC) system is defined to produce relevant markers that are exploited to segment the hyperspectral image with the minimum spanning forest algorithm. Experimental results conducted on three real hyperspectral images with different spatial and spectral resolutions and corresponding to various contexts are presented. They highlight the importance of spectral-spatial strategies for the accurate classification of hyperspectral images and validate the proposed methods.

Usó et al.(2007) presented a clustering-based technique for hyperspectral band selection using information measures, reducing data redundancy and improving accuracy in pixel image classification tasks.

Hyperspectral imaging involves large amounts of information. This paper presents a technique for dimensionality reduction to deal with hyperspectral images. The proposed method is based on a hierarchical clustering structure to group bands to minimize the intracluster variance and maximize the intercluster variance. This aim is pursued using information measures, such as distances based on mutual information or Kullback-Leibler divergence, in order to reduce data redundancy and non useful information among image bands. Experimental results include a comparison among some relevant and recent methods for hyperspectral band selection using no labeled information, showing their performance with regard to pixel image classification tasks. The technique that is presented has a stable behavior for different image data sets and a noticeable accuracy, mainly when selecting small sets of bands

Prabhakar et al.(2017) reviewed the state-of-the-art in hyperspectral image classification using Deep Learning techniques, highlighting the potential for improved accuracy in remote sensing applications.Hyperspectral Image (HSI) processing is the new advancement in image / signal processing field. The growth over the years is appreciable. The main reason behind the successful growth of the Hyperspectral imaging field is due to the enormous amount of spectral and spatial information that the imagery contains. The spectral band that the HSI which contains is also more in number. When an image is captured through the HSI cameras, it contains around 200-250 images of the same scene. Nowadays HSI is used extensively in the fields of environmental monitoring, Crop-Field monitoring, Classification, Identification, Remote sensing applications, Surveillance etc. The spectral and spatial information content present in Hyperspectral images are with high resolutions.Hyperspectral imaging has shown significant growth and widely used in most of the remote sensing applications due to its presence of information of a scene over hundreds of contiguous bands In. Hyperspectral Image Classification of materials is the critical application of HSI using Hyperspectral sensors. It collects hundreds of spectrum channels, where each channel consists of a sharp point of Electromagnetic Spectrum. The paper mainly focuses on Deep Learning techniques such as Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Support Vector machines (SVM), K-Nearest Neighbour (KNN) for the accuracy in classification. Finally in the summary the current state-of-the-art scheme, a critical discussion after reviewing the research work by other professionals and organizing it into review-based paper, also implying about the present status on classification accuracy using neural networks is carried out.

The proposed two-dimensional Empirical Wavelet Transform (2D-EWT) based hyperspectral image classification method outperforms other methods and reduces computational time, offering improved performance in classification evaluation measures.

Hyperspectral image classification is one of the major field of application for hyperspectral imaging systems. Though hyperspectral data gives accurate results than their multispectral counterparts, they are computationally more complex due to their high dimensionality. One of the classical problem while dealing with supervised hyperspectral classification is the class imbalance problem that arises due to the limited availability of samples for training. In order to deal with high dimensionality, many feature mining techniques has been proposed in literature for hyperspectral images. In this paper, we propose a hyperspectral image classification method based on two-dimensional Empirical Wavelet Transform (2D-EWT) feature extraction and compare it with that of Image Empirical Mode Decomposition (IEMD) based extracted features and raw features. Here, the focus is upon the fact that the number of features trained should be less than what is to be tested. Since the computational time for classification is also of prime importance, only some of the fast and best of the classifiers are selected. Sparse-based classifiers are one of the fast and efficient method for supervised classification of hyperspectral images. Subspace Pursuit (SP) and Orthogonal Matching Pursuit (OMP) algorithms are used in our experiments for sparse-based classification. Other classifiers used are Support Vector Machine (SVM) and Hybrid Support Vector Selection and Adaptation (HSVSA). The proposed methodology gives improved performance in terms of classification evaluation measures for hyperspectral image classification task.

Shetty et al.(2021) reviewed existing hyperspectral data processing and analysis approaches, providing a generalized framework for future potential and challenges in developing robust algorithms for hyperspectral data processing and analysis.

Kale et. Al(2017) Recent advances in the sensors technology for imaging spectroscopy coupled with high computing power, raise the demand to develop the algorithms for processing and analysis of hyperspectral data for various applications. Well known techniques and algorithms are available for processing multispectral data in the literature. Researchers tried to use similar approaches for hyperspectral data analysis and succeeded up to some extent. Several techniques for atmospheric correction, dimensionality reduction, endmember extraction and classification has been developed and reported accordingly. To process and evaluate the hyperspectral data for domain applications require generalized framework. This article critically reviews most of the existing hyperspectral data processing and analysis approaches and gives generalized framework. Which offers considerate view for future potential and focuses emerging challenges in the development of robust algorithms for hyperspectral data processing and analysis.

Dahiya et al. (2022) Deep learning classifiers are more preferable for hyperspectral imaging classification due to advantages like shorter training time, handling complex data, and lesser user intervention requirements.

Table1: Comparison of Unsupervised Classification Algorithm

Classifier	Characteristics	Example	Study area	References
PCA[a]	(1) Reduces dimensionality (2) Helpful in covariance calculation	(1) Landsat-8 (2) Sentinel-2	(1) Land use (2) Crop detection	23 24
K-means	(1) Pixel with a smaller spectrum (2) It constructs tight clusters	(1) MODIS[e] (2) MODIS	(1) Paddy cropping (2) Forest detection	25 26
ICA[b]	(1) It separates unmixed pixels (2) It focuses on independent components	(1) Landsat-8 (2) Landsat-ETM+[f]	(1) Crop classification (2) Geological mapping	27 28
GMM[c]	(1) It is a fuzzy method (2) Describes statistical behavior of data	(1) MODIS (2) Landsat-5,7,8	(1) Winter crop mapping (2) Crop mapping	29 30
AE[d]	(1) It provides filter for data (2) Follows unsupervised approach	(1) Sentinel-2 (2) Landsat-8	(1) Urban Land cover (2) Forest monitoring	31 32

Table 2: Comparison of supervised Classification Algorithm

Classifier	Characteristics	Example	Study area	References
K-NN[a]	(1) Lazy algorithm (2) Based on Euclidean distance	(1) Sentinel-2 (2) Landsat-8	(1) Land cover (2) Cloud detection	13 14
SVM[b]	(1) Hyperplane required to classify classes (2) Used for binary classification problems	(1) Sentinel-1 (2) Sentinel-1, Sentinel-2	(1) Wetland (2) LULC	15 16
RF[c]	(1) Builds multiple decision trees (2) Helpful in relevant feature selection	(1) HyMap (2) Lansat-7	(1) Object detection (2) Crop classification	12 17
ANN[d]	(1) Consists of neurons to store information (2) Input is stored in its network	(1) AVIRIS[f] (2) Landsat-8, MODIS and Sentinel-1 A	(1) Land use and Land cover (2) Soil salinity estimation	18 19
DT[e]	(1) Flexible algorithm (2) Requires less data preparation as compared to other algorithms	(1) Landsat-8 (2) Landsat-8, MODIS[g]	(1) Vegetation (2) Cropland mapping	20 21

3. Problem Identification of Hyperspectral Image Classification Techniques:

A. Curse of Dimensionality:

Issue: The hyperspectral data is characterized by a high-dimensional feature space due to the large number of spectral bands, leading to computational challenges and increased susceptibility to overfitting.

Impact: Traditional classification algorithms may struggle with the curse of dimensionality, affecting their efficiency and generalization to new data.

B. Spectral Variability:

Issue: Intra-class spectral variability arises from the diverse nature of materials within the same land cover class, making it challenging to accurately classify pixels based solely on their spectral signatures.

Impact: Classification accuracy can be compromised, especially when dealing with heterogeneous landscapes or dynamic environmental conditions.

C. Data Redundancy:

Issue: Hyperspectral data often contains redundant information, where certain bands may convey similar spectral characteristics, diminishing the discriminative power of the data.

Impact: Redundancy can contribute to increased computational complexity and may not necessarily enhance classification performance, making efficient data representation crucial.

D. Limited Labeled Data:

Issue: Annotated hyperspectral datasets for training classification models are often scarce and expensive to acquire, hindering the development of robust and accurate classifiers.

Impact: The scarcity of labeled data can result in models that are sensitive to variations in the training set, limiting their applicability to diverse real-world scenarios.

E. Complexity of Hyperspectral Sensors:

Issue: Variability in sensor characteristics, including differences in spatial and spectral resolutions, can introduce challenges in standardizing classification methodologies across different hyperspectral sensors.

Impact: Models may need to be adapted or fine-tuned for specific sensor configurations, limiting the transferability of classification techniques.

F. Interpretability of Models:

Issue: Complex machine learning and deep learning models may lack interpretability, making it challenging to understand the decision-making process and trust the reliability of classification results.

Impact: In applications where interpretability is crucial, such as environmental monitoring or resource management, the black-box nature of models can be a significant drawback.

G. Robustness to Environmental Conditions:

Issue: Hyperspectral image classification techniques may struggle to maintain robust performance under varying environmental conditions, such as changes in illumination, atmospheric interference, or seasonal variations.

Impact: Inaccuracies in classification results under different conditions may limit the reliability of hyperspectral data for long-term monitoring and decision-making.

Identifying and addressing these challenges is crucial for advancing hyperspectral image classification techniques, enabling their broader application across diverse domains and improving the reliability of extracted information from hyperspectral data.

Hyperspectral image classification is a powerful technique that involves analyzing and interpreting data from a large number of narrow and contiguous spectral bands. Each pixel in a hyperspectral image represents a spectrum, providing detailed information about the surface properties of the imaged scene.

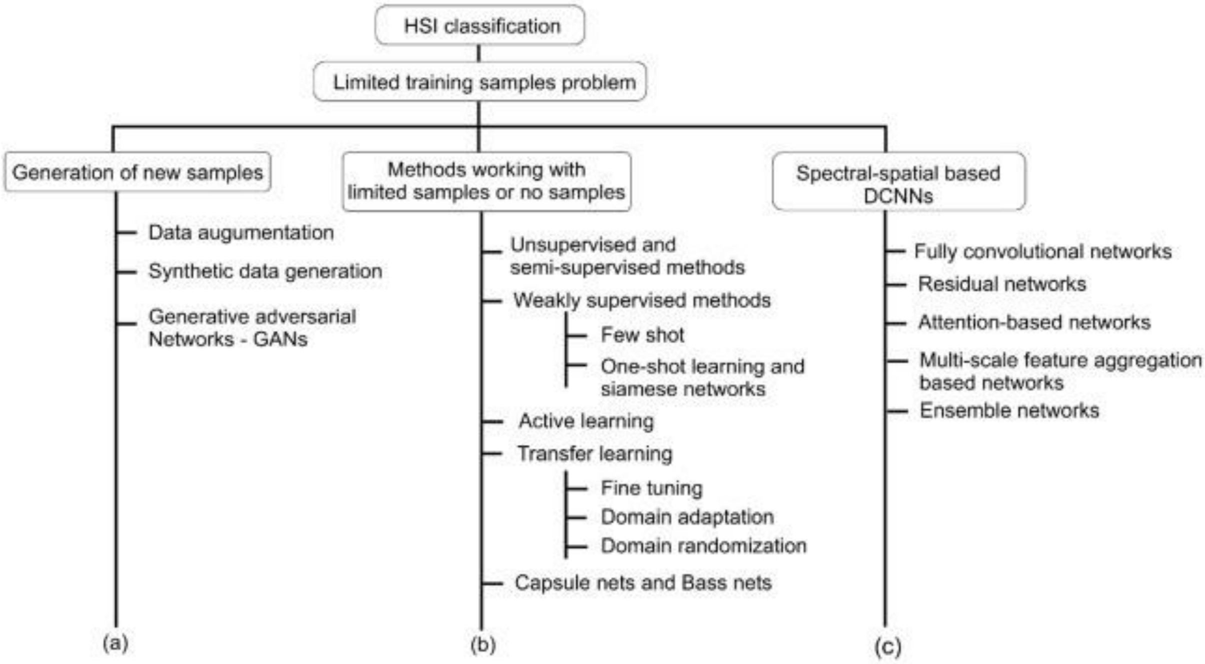

Figure 1(a) Generation of new Sample (b) Generation of no Sample (c) DCNNs

4. Summary Key Idea of Hyperspectral Image Classification

The key idea behind hyperspectral image classification is to leverage detailed spectral information captured across numerous narrow and contiguous bands to accurately categorize and interpret the content of an image. By analyzing the unique spectral signatures associated with different materials or features, hyperspectral image classification enables the identification and mapping of specific objects, land cover types, or conditions within a scene. This technique finds application across diverse fields, including remote sensing, agriculture, defense, medicine, and urban planning, providing valuable insights for tasks such as environmental monitoring, precision agriculture, target detection, disease diagnosis, and land cover classification. Ongoing research aims to enhance hyperspectral image classification through advanced deep learning architectures, semantic segmentation, data augmentation, active learning, explainability, multi-modal fusion, and real-time processing, contributing to improved accuracy, efficiency, and applicability in various domains.

Here are some highlights of the applications of hyperspectral image classification:

Remote Sensing:

Vegetation Monitoring: Hyperspectral imagery is extensively used for monitoring vegetation health, identifying plant species, and detecting diseases or stress conditions in crops. Different plants have unique spectral signatures, making it possible to discriminate between them.

Environmental Monitoring: Hyperspectral data is valuable for monitoring environmental changes, such as identifying pollutants, monitoring water quality, and assessing land cover changes.

Mineral Exploration: Hyperspectral sensors can detect subtle variations in the spectral signatures of minerals, aiding in mineral exploration and geological mapping.

Military and Defense:

Target Detection: Hyperspectral imaging is used for target detection and identification. The unique spectral signatures of objects allow for the discrimination between different materials, making it useful for military reconnaissance and surveillance.

Camouflage Detection: Hyperspectral sensors can reveal hidden objects or camouflaged targets by detecting variations in their spectral signatures against the background.

Medical Imaging:
Disease Detection: Hyperspectral imaging has applications in medical diagnostics, particularly in detecting diseases such as cancer. Different tissues and cells exhibit distinct spectral characteristics, enabling the identification of abnormal conditions.

Tissue Classification: Hyperspectral imaging can assist in distinguishing between different tissue types during medical procedures, providing surgeons with real-time information for better decision-making.

Precision Agriculture:
Crop Monitoring: Hyperspectral data can be used for precision agriculture by providing information about crop health, nutrient levels, and water content. This allows for targeted interventions, optimizing resource use and increasing crop yield.

Pest and Disease Identification: Hyperspectral imaging helps in early detection of pests and diseases in crops, enabling timely and precise pest management strategies.

Forestry:
Tree Species Identification: Hyperspectral data aids in identifying tree species and assessing forest health. This is crucial for sustainable forest management and monitoring.

Deforestation Monitoring: Hyperspectral imagery can be used to monitor deforestation and land-use changes over time.

Urban Planning:
Land Cover Classification: Hyperspectral data is useful for detailed land cover classification in urban areas, assisting in urban planning, infrastructure development, and environmental impact assessments.

Change Detection: Hyperspectral imagery helps monitor changes in urban landscapes over time, facilitating informed decision-making for urban development.

5. Feature direction of further Research of Hyperspectral Image Classification

The field of hyperspectral image classification continues to evolve, and there are several directions for further research to enhance its capabilities and applications. Here are some key areas for future research:

Deep Learning Architectures:
End-to-End Learning: Investigate and develop end-to-end deep learning architectures for hyperspectral image classification, allowing the model to automatically learn hierarchical features and representations directly from the raw data.
Transfer Learning: Explore transfer learning techniques to leverage pre-trained models on large datasets, potentially from different domains, to improve the performance of hyperspectral image classification on smaller datasets.

Semantic Segmentation:
Pixel-Level Classification: Move beyond traditional pixel-wise classification and focus on semantic segmentation techniques for hyperspectral images. This involves assigning a class label to each pixel, providing more detailed and fine-grained information about the scene.

Spatial-Spectral Fusion: Investigate methods for effective fusion of spatial and spectral information, considering both contextual and spectral characteristics for accurate segmentation.

Data Augmentation and Synthesis:
Generation of Synthetic Data: Develop techniques for generating synthetic hyperspectral data to augment limited labeled datasets. This can help improve the robustness and generalization of models.

Domain Adaptation: Explore methods for adapting models trained on one hyperspectral dataset to perform well on different datasets with varying sensor characteristics, resolutions, and atmospheric conditions.

Active Learning:
Efficient Labeling Strategies: Investigate active learning strategies to optimize the process of labeling hyperspectral data, focusing on selecting the most informative samples for annotation to improve model performance with limited labeled data.

Incremental Learning: Explore incremental learning approaches to adapt the model to new classes or environmental conditions over time, without retraining the entire model from scratch.

Explain ability and Interpretability:
Interpretable Models: Develop interpretable models and techniques for explaining the decisions made by hyperspectral image classification models, enhancing the trust and adoption of these models in real-world applications.
Feature Attribution Methods: Investigate methods for attributing model decisions to specific spectral bands or spatial regions, providing insights into which features contribute most to classification outcomes.

Multi-Modal Fusion:
Integration with Other Modalities: Explore the integration of hyperspectral data with other imaging modalities, such as LiDAR or radar, to improve classification accuracy and provide a more comprehensive understanding of the scene.
Temporal Analysis: Investigate hyperspectral time series analysis to capture dynamic changes in land cover, vegetation health, and other features over time.

Real-Time Processing:
Efficient Inference: Develop efficient algorithms and architectures for real-time hyperspectral image classification, enabling applications in dynamic and time-sensitive environments, such as disaster response or autonomous systems.
On-Board Processing: Explore on-board processing capabilities for sensors to perform initial data processing and classification tasks, reducing the need for extensive data transmission and processing at centralized locations.

Continued research in these areas can contribute to advancing the capabilities of hyperspectral image classification, making it more robust, interpretable, and applicable to a wider range of domains and real-world scenarios.

6. Conclusion

hyperspectral image classification techniques represent a powerful and evolving field with significant potential across various domains. The critical review of these techniques highlights both strengths and areas for improvement. Hyperspectral imagery captures a wealth of spectral information, allowing for detailed discrimination between materials and features. This richness is advantageous in applications requiring precise identification and characterization. Hyperspectral image classification has demonstrated versatility, finding applications in fields such as remote sensing, agriculture, defense, medicine, and urban planning. This adaptability underscores its value in addressing a wide range of real-world challenges. The integration of advanced machine learning, especially deep learning, has shown promise in improving classification accuracy. These techniques leverage complex relationships within the data, enabling more robust and automated feature extraction. In remote sensing, hyperspectral imaging contributes to comprehensive environmental monitoring, resource management, and land cover mapping. Its ability to provide detailed information about the Earth's surface enhances decision-making processes. Limited labeled hyperspectral datasets pose a challenge for training robust models. Further efforts are needed to address data scarcity through techniques like data augmentation, synthesis, and effective active learning strategies.
The computational demands of hyperspectral image processing, especially with deep learning models, can be intensive. Research should focus on developing more efficient algorithms for real-time applications and resource-constrained environments. Enhancing the interpretability and explain ability of hyperspectral image classification models remains an ongoing concern. Transparent models and effective feature attribution methods are essential for building trust and understanding model decisions. Achieving robust performance

across diverse hyperspectral datasets with varying sensor characteristics and environmental conditions remains a challenge. Research should explore domain adaptation techniques to enhance model generalization. While hyperspectral imaging offers detailed spectral information, integrating it with other modalities such as LiDAR or radar could provide a more comprehensive understanding of the scene. Research should focus on effective fusion strategies.

In conclusion, hyperspectral image classification techniques hold great promise but require continued research and development to overcome challenges and fully realize their potential. Advancements in data availability, interpretability, and computational efficiency will contribute to making hyperspectral imaging an even more impactful tool for a broad range of applications.

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