Band Selection in Hyperspectral Images

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Abstract*—Hyperspectral imaging (HSI) captures extensive spectral information across multiple wavelengths, enhancing the analysis of materials and objects. However, the high dimensionality of hyperspectral data presents challenges, including increased computational complexity and potential overfitting in classification tasks. This study investigates two deep learning methods for hyperspectral band selection and classification: the attention-based convolutional neural network (CNN) by Lorenzo et al. [2]and the Ternary Weight CNN (TWCNN) by Feng et al.[3] The attention-based CNN leverages attention mechanisms to prioritize informative spectral bands, effectively reducing the number of selected bands. In contrast, TWCNN integrates band selection, feature extraction, and classification into a unified framework utilizing a ternary weight system (-1, 0, 1) to discern important bands efficiently. Additionally, we explore the framework proposed by Feng et al.[1], which formulates hyperspectral band selection as a reinforcement learning (RL) problem through a semisupervised CNN called EvaluateNet. This approach assesses candidate band subsets using both labeled and unlabeled samples while incorporating an intraclass compactness constraint to enhance evaluation performance and minimize redundancy. We implemented both models, constructing multiple variants of the attention-based CNN and experimenting with hyperparameters and loss functions. While the attention-based CNN showed strong performance on select datasets, it struggled with the Indian Pines dataset due to inadequate incorporation of spatial information. Conversely, TWCNN successfully merges spectral and spatial features, improving its effectiveness in complex datasets. This research underscores the significance of integrating spatial features in hyperspectral image classification. Furthermore, it highlights that selecting an appropriate modeling approach should consider the dataset's specific characteristics. Overall, the study demonstrates the potential of advanced deep learning methodologies, including reinforcement learning strategies, in enhancing hyperspectral band selection processes and improving classification accuracies. These findings are expected to contribute to real-world applications in fields such as agriculture, environmental monitoring, and remote sensing.

***Index Terms*—Hyperspectral Imaging (HSI), Band Selection, Deep Learning, Attention-Based Convolutional Neural Network (CNN), Ternary Weight CNN (TWCNN), Reinforcement Learning (RL), Spectral Features, Spatial Features, Classification, Dimensionality Reduction, Anomaly Detection**

I. INTRODUCTION

Hyperspectral imaging (HSI) is an advanced remote sensing technology that captures detailed spectral information across a broad range of wavelengths, from visible to short-wave infrared (400 to 2500 nanometers). Unlike traditional imaging systems, which use a few broad spectral bands (e.g., RGB), hyperspectral sensors capture hundreds of narrow and contiguous bands. This results in a rich, multidimensional dataset where each pixel contains a unique spectral fingerprint, providing comprehensive insights into material composition and environmental conditions. The extensive spectral coverage of hyperspectral imaging enables precise material identification, object detection, and change detection across various fields, including agriculture, environmental monitoring, and urban planning. However, the high dimensionality of hyperspectral data poses significant challenges, such as increased computational demands, data storage issues, and potential overfitting during classification tasks [1] . Addressing these challenges is crucial for efficient HSI data processing. Band selection is a key step in hyperspectral image analysis that involves identifying and retaining the most informative spectral bands while discarding redundant or irrelevant ones. This process is vital for reducing data dimensionality, enhancing computational efficiency, and improving classification performance. Traditional deep learning-based methods for band selection often face difficulties due to their complex optimization problems and the need for extensive training [1]. Recent advancements offer innovative solutions to these challenges. For instance, a significant advancement is presented by Ribalta Lorenzo et al. (2020),[2] who introduce an attention-based CNN method for hyperspectral band selection. Their approach employs attention mechanisms to weight the importance of spectral bands, facilitating the identification of the most informative regions of the spectrum. The attention-based method is modular, easy to implement, and has demonstrated competitive performance with state-of-the-art techniques, achieving high-quality classification while maintaining computational efficiency. Additionally, Feng et al. (2019) [3] present the Ternary Weight Convolutional Neural Network (TWCNN), which integrates band selection, feature extraction, and classification into a unified framework. By using ternary weights to indicate selected bands, TWCNN simplifies and accelerates the band selection process while optimizing performance through end-to-end training. Their experimental results highlight the model's effectiveness in selecting bands and improving classification accuracy. These papers build upon those advancements by exploring and evaluating novel band selection algorithms for hyperspectral imaging. By addressing the challenges associated with hyperspectral data processing and leveraging innovative techniques from recent research, this study aims to advance the efficiency and effectiveness of hyperspectral image analysis.

II. LITERATURE SURVEY

Hyperspectral imaging (HSI) has attracted much interest because it can record delicate spectral information in several bands, which is incredibly useful for remote sensing applications. However, processing and analyzing hyperspectral data can be difficult due to its high dimensionality. Many approaches have been put out to deal with these issues, especially regarding band selection.

Lorenzo et al. [2] introduce a novel method that integrates attention-based convolutional neural networks (CNNs) with anomaly detection for improved band selection in hyperspectral imaging. Their approach adds attention modules to CNNs, which help identify and prioritize the most informative spectral bands, specifically focusing on areas important for classification and segmentation. Subsequently, an anomaly detection algorithm selects bands considered ”anomalous” due to their significant informational value while minimizing redundancy. This method is data-driven and modular, making it adaptable to various CNN architectures. It shows impressive performance by reducing the number of spectral bands by 14-19% for the Salinas Valley dataset and by 9-27% for the Pavia University dataset, all while maintaining classification accuracy. The approach is efficient for real-time applications and demonstrates strong generalization and scalability, making it suitable for large-scale tasks. Moreover, it improves interpretability through heatmaps that illustrate the importance of selected bands and enhances classification for minority classes in imbalanced datasets. The research also discusses the potential to extend the method to spatial-spectral CNNs and the role of hyperparameter tuning in band selection.

Feng et al. [3] present the Ternary Weight Convolutional Neural Network (TWCNN), which integrates band selection, feature extraction, and classification into a unified framework for hyperspectral data analysis. The TWCNN achieves a high overall accuracy of 95.9% using only 10 selected bands, demonstrating its effectiveness even with a limited subset of spectral data. It employs a ternary weight system (-1, 0, 1) for efficient band selection during the initial layer, allowing the model to quickly identify discriminative bands while eliminating redundancies. This end-to-end approach optimizes the classification process compared to traditional methods that separate these tasks. Although TWCNN has higher time complexity than some filter-based methods, it is faster than other deep learning models since it avoids extensive random search techniques. Furthermore, TWCNN effectively extracts both spectral and spatial features, enhancing its performance, and notably achieves strong classification results with only 5% of the Indian Pines dataset used for training. Overall, TWCNN demonstrates superior results compared to existing band selection methods, positioning it as a state-of-the-art solution in hyperspectral imaging.

Feng et al. [1] propose a novel framework that formalizes hyperspectral band selection as a reinforcement learning (RL) problem, aiming to enhance the efficiency and effectiveness of this critical process in hyperspectral image analysis. The authors introduce a semisupervised convolutional neural network (CNN) known as EvaluateNet, which evaluates candidate band subsets by utilizing both labeled and unlabeled samples. This network incorporates an intraclass compactness constraint to improve evaluation performance without the need for fine-tuning. New reward functions are designed to guide the RL process, taking into account the performance of EvaluateNet while penalizing redundant band selections. This design encourages the exploration of diverse band subsets. The study implements two algorithms: one for fixed band selection and another for adaptive band selection, both leveraging advantage actor-critic (A2C) techniques to optimize the band selection process. Experimental results demonstrate that the proposed methods significantly outperform several state-of-the-art algorithms. Specifically, the overall accuracy achieved is approximately 96.5% on the Indian Pines dataset, around 98.2% and 98.5% on the Pavia University dataset for the fixed and adaptive selection algorithms, respectively, and an overall accuracy of 97.8% on the University of Houston dataset. These findings highlight the effectiveness of deep reinforcement learning in hyperspectral band selection, showcasing its potential to improve classification performance and reduce noise in selected bands.

III. Implementation and Experimental Details

In this section, we describe the implementation details of the hyperspectral band selection methods that we adopted from recent research: the attention-based convolutional neural network (CNN) method by Lorenzo et al. [2] and the Ternary Weight CNN (TWCNN) method by Feng et al. [3]. Both methods aim to improve the efficiency of hyperspectral band selection and classification tasks by reducing the dimensionality of hyperspectral data while maintaining or enhancing classification accuracy.

A. Attention-based CNN for Band Selection (Lorenzo et al.)

The method introduced by Lorenzo et al. [2] integrates attention mechanisms with CNNs to improve band selection in hyperspectral imaging. Their approach adds attention modules to the convolutional layers of the CNN, enabling the model to prioritize spectral bands that are most informative for classification and segmentation tasks. These attention modules assign a weight to each band, allowing the model to focus on the most relevant parts of the spectrum while discarding less important bands.

To implement this method, we first constructed a standard CNN architecture with multiple convolutional and pooling layers for feature extraction. Attention modules were then added after the convolutional layers to assign weights to each spectral band. These weights allow the model to highlight the most discriminative bands in hyperspectral data. In addition, we have used (as mentioned in the paper[2]) an Elliptical Envelope (EE) alagorithm that identifies bands with significant information, which are considered ”anomalous” and crucial for classification tasks. The inclusion of anomaly detection helps to minimize redundancy in the selected bands, ensuring that only the most informative bands are used.

The performance of the attention-based CNN was evaluated on the Salinas Valley and Pavia University datasets. We achieved a reduction in the number of selected bands by 80-90% for the Salinas Valley dataset and 70-80% for the Pavia University dataset, all while maintaining high classification accuracy. The method demonstrated strong generalization, making it suitable for real-time hyperspectral image processing and large-scale applications. Furthermore, the attention mechanism improved the interpretability of the model, as it provided heatmaps that visually indicated which spectral bands were most important for the classification process.

B. Ternary Weight Convolutional Neural Network (TWCNN) for Band Selection (Feng et al.)

The Ternary Weight CNN (TWCNN) method proposed by Feng et al. [3] an end-to-end approach for band selection, feature extraction, and classification. Unlike traditional methods that rely on separate steps for band selection and classification, TWCNN integrates these tasks into a unified framework, significantly reducing computational complexity. The key innovation of TWCNN is the use of ternary weights (-1, 0, 1) for band selection, which allows the model to efficiently identify important spectral bands while eliminating redundant ones.

To implement the TWCNN model, we first constructed a CNN architecture with multiple layers, where the first layer uses ternary weights to select bands. The ternary weight system allows the model to assign a weight of -1 to unimportant bands, 0 to unused bands, and 1 to selected bands. This weight assignment process occurs during the initial layers of the CNN, making the band selection process more efficient than traditional methods that require complex optimization techniques. The model is then trained end-to-end, where the ternary weights are updated during backpropagation.

We evaluated the TWCNN method using the Indian Pines dataset, which is widely used for hyperspectral image classification. Despite using only 10 selected bands, the model achieved an overall accuracy of 95.9%, demonstrating the effectiveness of the ternary weight system for band selection. The method also outperformed other deep learning models in terms of both computational efficiency and classification accuracy. Additionally, TWCNN effectively extracts both spectral and spatial features, further enhancing its performance. Notably, the model achieved strong classification results using only 5% of the dataset for training, highlighting the method's ability to work with limited training data.

Both methods implemented in this work showcase the potential of deep learning techniques to improve hyperspectral band selection, reduce dimensionality, and enhance classification accuracy. By integrating novel architectures and optimization techniques, these methods offer promising solutions for hyperspectral data analysis in real-time applications.

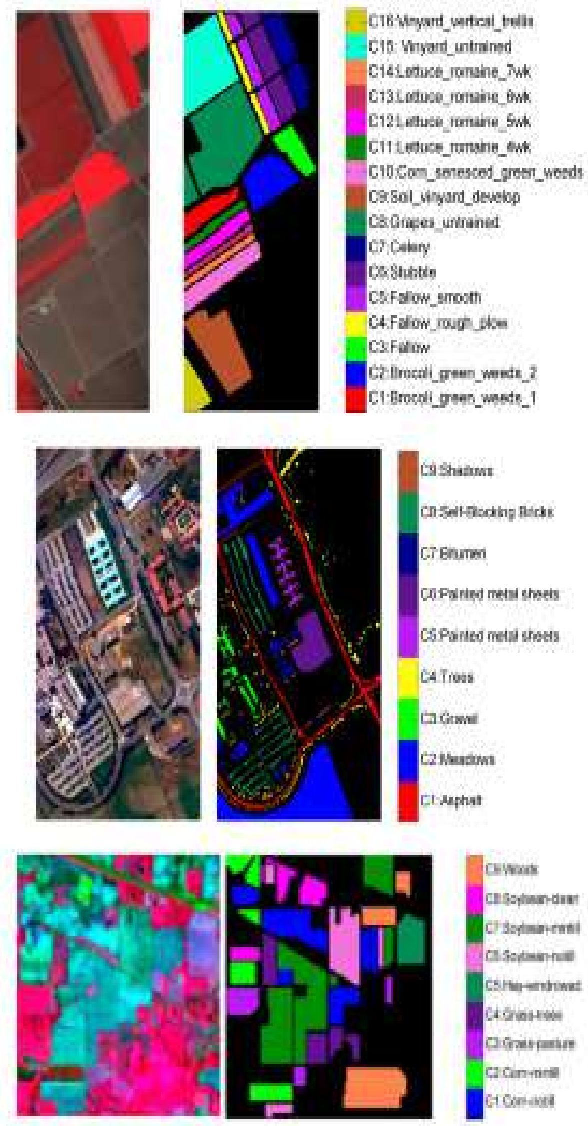

Fig. 1. Original Hyperspectral Image, Ground Truth and Label Category, (top)Salinas valley, (middle)Pavia University, (bottom) Indian Pines.

C. Dataset

1) Salinas Valley: This set (217 x 512 pixels) was captured over Salinas Valley in California, USA, with a spatial resolution of 3.7 m. The image shows different sorts of vegetation, corresponding to 16 classes (Figure 1(top)). The original data contains 224 bands, however 20 bands were removed by the authors of this set due to either atmospheric absorption or noise contamination [93] (204 bands remained).

2) Pavia University: This set (340 x 610 pixels)was captured over Pavia University in Lombardy, Italy, with a spatial resolution of 1.3 m. It shows an urban scenery with nine classes (Figure 1(middle)). The set contains 103 bands, as 12 most noisy bands (out of 115) were removed by its authors.

3) Indian Pines: The Indian Pines dataset (145 x 145 pixels) was captured over the Indian Pines area in the state of Indiana, USA, using the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensor. The dataset has a spatial resolution of 20 meters per pixel and includes 204 spectral bands, after removing 20 bands due to atmospheric absorption and sensor noise. It represents a variety of land cover types, including agricultural fields, forests, and other natural and man-made features, with a total of 16 different classes (Figure 1(bottom)). The dataset is widely used for hyperspectral image analysis, offering rich spectral information across the visible to infrared spectrum, making it suitable for a range of remote sensing applications.

IV. Results

The accuracy and band selection that we were able to attain through experimentation with varying contamination rate and attention module counts were covered in this part. Accuracy is not greatly reduced even if the model is trained on both the original and chosen numbers of bands.

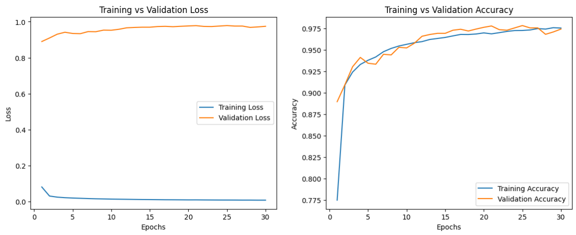

Fig. 2. Training and Validation on Salina Valley before band selection

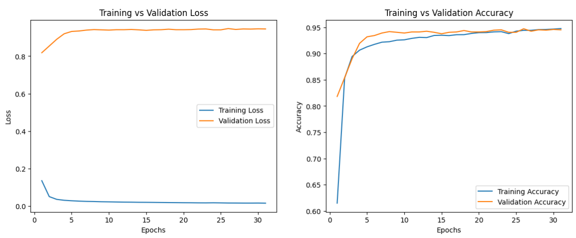

Fig. 3. Training and Validation on Salina Valley after band selection

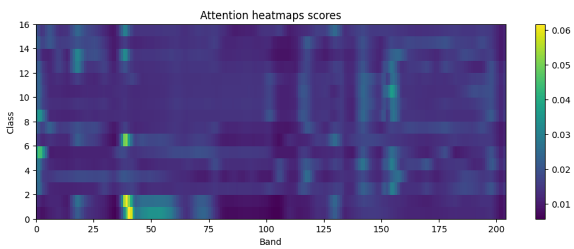

Fig. 4. Attention Heatmap on Salina Valley

The number of selected bands are 19 out of 204 (i.e, 0, 1, 2, 3, 28, 38, 39, 40, 41, 42, 43, 85, 86, 131, 132, 133, 134, 135, 136). Accuracy drops from 96.71% (Figure 2) to 95.33% (Figure 3).

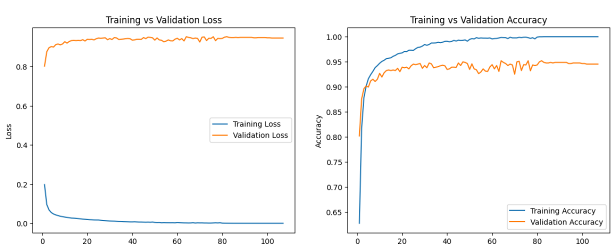

Fig. 5. Training and Validation on Pavia University before band selection

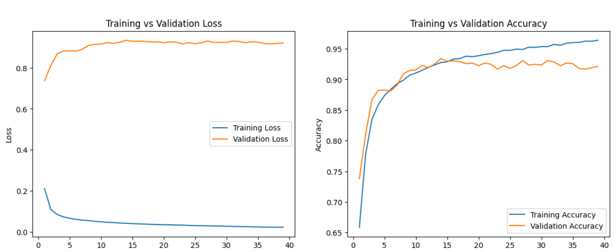

Fig. 6. Training and Validation on Pavia University after band selection

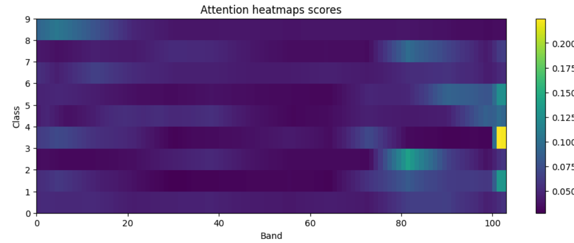

Fig. 7. Attention Heatmap on Pavia University

The number of selected bands are 51 out of 103 (i.e, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 100, 101, 102). Accuracy drops from 93.41% (Figure 5) to 89.38% (Figure 6).

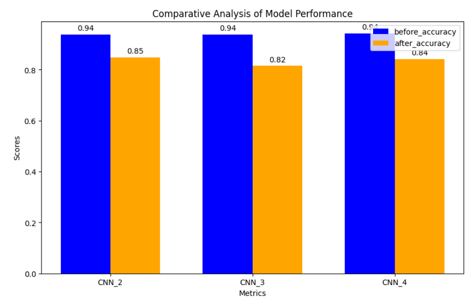

Fig. 8. Accuracy comparison of Attention Module CNNs before and after band selection on Pavia

To compare the accuracy of band selection on the Pavia University dataset, varying numbers of attention modules are utilized. There are anything between two and four modules. In three situations, there is no discernible change in accuracy. Therefore, there are just a few significant bands that aid in classification.

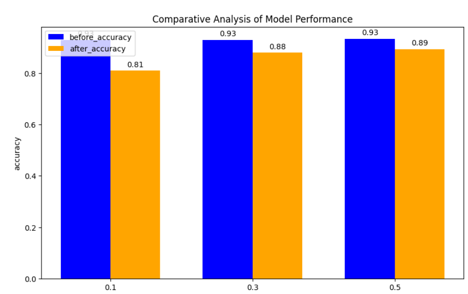

Fig. 9. Accuracy Comparison of different contamination rate before and after band selection on Pavia

Experiments with different contamination rates are performed to compare the accuracy of band selection on the Pavia University dataset. They're 0.1, 0.3, and 0.5. There is a decline in the accuracy difference in three cases.

V. Conclusion

In this study, we implemented two models: the attention-based CNN and the Ternary Weight Convolutional Neural Network (TWCNN). For the attention-based CNN, we constructed multiple models varying the number of building blocks and contamination rates. We trained these models using different batch sizes, learning rates, and loss functions, including binary cross-entropy and sparse categorical cross-entropy.

In the TWCNN, we aimed to achieve optimal accuracy by applying the proposed methods and loss functions. However, we found that the loss remained constant despite extensive parameter tuning and experimentation with various loss functions. Our practical implementation indicated that the attention-based CNN performed well on the Salinas Valley and Pavia University datasets, demonstrating its capability to handle those scenarios effectively.

Nevertheless, its performance on the Indian Pines dataset was not as expected, which may be attributed to its lack of utilization of spatial information. Conversely, the TWCNN leverages both spectral and spatial information, which contributed to its superior performance on the Indian Pines dataset. This highlights the importance of integrating spatial features in hyperspectral image classification tasks, particularly in complex datasets. Overall, our results suggest that while both models have their strengths, the choice of model may depend on the specific characteristics of the dataset being analyzed.

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