Classfication Of Hyperspectral Image Data

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by

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CANDIDATE’S DECLARATION

I hereby certify that the work which is being presented in the BTP entitled “Classfication Of Hyperspectral Image Data” in the partial fulfillment of the requirements for the award of the degree of B. Tech and submitted in the Indian Institute of Information Technology SriCity, is an authentic record of my own work carried out during the time period from January 2023 to December 2023 under the supervision of Dr. Arun PV, Indian Institute of Information Technology SriCity, India.

The matter presented in this report has not been submitted by me for the award of any other degree of this or any other institute.

Pranay reddy

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Arun

(Dr. Arun P V)

ABSTRACT

Hyperspectral image (HSI) classification is a challenging task in remote sensing applications, requiring advanced techniques to extract valuable information from high-dimensional spectral data. In this regard, we propose a novel approach for HSI classification by combining the strengths of HybridSN, Binary Convolution Neural Networks and dynamic quantization. HybridSN leverages the benefits of both spectral and spatial information, while accelerating it with binary weights along with dynamic quantization enhances efficiency in computational processing.

Our study focuses on accelerating the HybridSN with dynamic quantization instead ofthetraditionalstepquantizationmethodstocreateasynergisticmodeltailoredforHSI classification. We conducted extensive experiments using benchmark dataset Indian Pines, to evaluate the performance of our proposed model. Through rigorous testing and analysis, we observed significant improvements in classification accuracies compared to the regular HybridSN and other traditional CNN methods. Our approach not only demonstrates superior accuracy but also enhances the computational efficiency of hyperspectral image classification.

The results obtained from the experiments underscore the effectiveness of the HybridSNandDynamicQuantizationapproachinhandlingthecomplexityofHSIdatasets. The proposed model showcases its potential for accurate and efficient classification, making it a promising solution for various remote sensing applications, such as land cover mapping and environmental monitoring.

Index Terms— HybridSN, HSI, CNN, Remote Sensing, Deep Learning.

Contents

0.1 INTRODUCTION

Hyperspectral images are comprehensive pictures that gather detailed data across numerous closely aligned spectral bands, unveiling intricate material insights beyond human sight. They play a crucial role in precise analysis across agriculture, environmental studies, and remote sensing applications. Hyperspectral images offer a unique perspective by capturing data across hundreds of narrow, contiguous spectral bands. Their significance lies in providing intricate details beyond what the human eye can perceive, enabling precise material identification, environmental analysis, and resource monitoring. These images aid in diverse fields like agriculture, environmental science, and remote sensing, offering unparalleled insights into subtle variations in composition, aiding in disease detection, land classification, and ecosystem assessment with detail. Convolutional neural networks (CNNs) have gained immense popularity in hyperspectral image (HSI) classification due to their ability to effectively extract and learn complex patterns from high-dimensional spectral data. CNNs have consistently demonstrated superior performance compared to traditional classification methods, such as support vector machines (SVMs), making them the preferred approach for many HSI classification tasks.

While traditional CNN models may be computationally efficient for processing 2D images, they can become computationally expensive when dealing with 3D HSI data. This is because 3D convolutions involve processing data cubes, which are significantly larger than 2D images. The model HybridSN, on the other hand, utilizes a combination of 3D and 2D convolutional layers, effectively balancing the need for capturing spatial-spectral features with computational efficiency. The 3D convolutional layers in the initial stages extract spatial-spectral information, while the subsequent 2D convolutional layers focus on learning more abstract spatial patterns. This approach reduces the overall computational complexity compared to using only 3D convolutional layers throughout the network. HSI data is often contaminated with noise due to sensor limitations or environmental factors. This noise can significantly impact the performance of traditional CNN models, as it can obscure the underlying spectral and spatial patterns.HybridSN's architecture, with its combination of 3D and 2D convolutional layers, has demonstrated greater robustness to noise compared to traditional CNN models. The 3D convolutional layers, in particular, can effectively capture spatial-spectral features that are less susceptible to noise, leading to improved classification accuracy in noisy HSI data. However, the computational cost of HybridSN is still considerably high due to the prevailing 3D convolution layers. Accelerating its performance by some optimization techniques like quantization, pruning, knowledge distillation and hardware optimization may potentially yield better results.

We are proposing a novel quantization technique called Step Quantization (SQ) to address these challenges. SQ quantizes the weights and activations of a CNN to a single bit, significantly reducing the memory footprint and computational cost of the network. SQ has been shown to be effective for accelerating CNNs on a variety of CNNs and datasets without sacrificing accuracy.

0.2 RELATED WORK

In the realm of remote sensing, hyperspectral image (HSI) classification plays a crucial roleinanalyzingandinterpretingthevastamountofinformationcapturedbyhyperspectral sensors. Conventional 2D convolutional neural networks (CNNs) have proven to be effective for HSI classification tasks, but they often struggle to fully exploit both the spectral and spatial information inherent in HSI data. HybridSN adresses this limitation by leveraging the strengths of both 3D and 2D CNNs to achieve superior classification performance.

HybridSN employs a hierarchical feature extraction approach, combining the capabilities of 3D and 2D CNNs. The 3D CNN acts as the first stage, extracting joint spectral-spatial features from a stack of spectral bands. This initial feature extraction captures the intricate relationships between spectral and spatial information, laying the foundation for subsequent processing. Building upon the 3D CNN's output, the 2D CNN serves as the second stage, refining the spatial representation by extracting more abstract spatial features. This hierarchical arrangement allows HybridSN to effectively capture both spectral and spatial information at different levels of abstraction, leading to enhanced classification accuracy. To evaluate the effectiveness of HybridSN, extensive experiments were conducted on three benchmark HSI datasets: Indian Pines, Pavia University, and Salinas Scene. The results demonstrated that HybridSN consistently outperformed state-of-the-art methods, achieving significant improvements in classification accuracy.

Meanwhile Step Activation Quantization (SAQ) is proven to accelerate the inference speed of convolutional neural networks (CNNs) for hyperspectral image (HSI) classification. Traditional CNNs for HSI classification employ floating-point operations, which are computationally expensive and limit the practical applications of these models. SAQ addresses this challenge by quantizing the activation values in CNNs to low-bit integers, enabling the use of faster and more energy-efficient integer operations.

The key idea behind SAQ is to divide the activation values into multiple steps and assign each step a quantized value. This approach reduces the number of unique activation values, leading to a significant reduction in memory requirements. Additionally, SAQ employs a non-uniform quantization scheme that allocates more quantization levels to regions with higher activation values, ensuring that the quantization process does not introduce excessive noise. SAQ has proven to be effective when tested it on two benchmark HSI datasets: Pavia University and Indian Pines. The results demonstrated that SAQ can achieve significant acceleration (up to 10 times) with minimal loss in classification accuracy.

0.3 Problem Statement & Contribution

0.3.1 Problem Statement

The objective of this research is to map the lunar surface using hyperspectral image classification, with a primary focus on the Chandrayaan 2 Imaging Infrared Spectrometer (IIRS) data. The IIRS, designed to measure light from the lunar surface in narrow spectral bands, offers a unique opportunity to discern mineral compositions and enhance our understanding of the Moon's geologic evolution. However, challenges such as coarse spectral and spatial data, inherent noise, limited samples, and the necessity for spatial-spectral integration present significant hurdles. Before tackling the Chandrayaan-2 dataset, preliminary work on benchmark datasets like the Indian Pines and Pavia University Dataset is crucial to develop robust algorithms.

The research objectives encompass the development of advanced algorithms tailored to the characteristics of IIRS data, addressing challenges related to noise reduction, sample scarcity, and integrating spatial-spectral information for accurate classification. The outcomes of this research not only contribute to lunar exploration but also hold broader implications for remote sensing technologies and machine learning applications in planetary science. By navigating the complexities of hyperspectral data, this study aims to pave the way for improved mapping techniques that could extend beyond lunar exploration to enhance our understanding of other planetary bodies in our solar system.

0.3.2 Contributions

Palle Pranay Reddy played a pivotal role in shaping the development of our deep learning model architecture. Drawing inspiration from an extensive review of existing deep learningmodelsinHyperSpectralImageClassification, hecraftedaninnovativemethodology tailored for HSI Classification. His leadership ensured that the model not only incorporated cutting-edge techniques but was also adaptable to the nuances of the HSI.

Ram Gopal Zampani focused on the foundational aspects of our project by curating and preprocessing the Indian Pines and Pavia University datasets. His meticulous work involved the ideation of dynamic quantization, ensuring the dataset's relevance, diversity, and suitability for training and evaluating our proposed deep learning model. Additionally, he took charge of the implementation phase, fine-tuning the model and optimizing its parameters to achieve superior performance in the intricate task of HSI Classification.

Gowtham Vattam tackled the challenges associated with unstructured, verbose, and noisy data. He implemented preprocessing techniques to enhance the model's robustness, ensuring it could effectively handle the complexities of real-world HSI classification. Furthermore, he conducted comprehensive experiments and evaluations, analyzing the model's performance against state-of-the-art baselines. His empirical findings played a crucial role in refining our methodology and shaping the final contributions of our team.

0.4 Proposed Methodology

Hyperspectral image (HSI) classification is a fundamental task in remote sensing applications, enabling the analysis and interpretation of Earth observation data. HSI data, characterized by its high dimensionality and rich spectral-spatial information, presents unique challenges for classification algorithms. Conventional HSI classification methods often rely on convolutional neural networks (CNNs) with real-valued weights. While these methods have demonstrated promising results, they can be computationally expensive, especially for processing large-scale HSI datasets. To address the computational limitations of real-valued weights, we propose a novel HSI classification model, termed HybridSN-Binary, that utilizes binary weights in both 3D and 2D CNN layers. This approach aims to achieve efficient and accurate classification while maintaining computational feasibility. The initial stage employs a 3D CNN to capture the inherent spectral-spatial relationships within the HSI data cube. The 3D CNN processes the HSI data cube directly, extracting intricate patterns and relationships between neighboring pixels across the spectral and spatial dimensions.

This approach effectively encodes the rich information present in HSI data, enabling the model to learn discriminative spectral-spatial features. To reduce computational complexity, we replace real-valued weights in the 3D CNN with binary weights. Binary weights, represented as either 1 or -1, significantly reduce the memory footprint of the model and lower computational demands. This weight binarization simplifies the convolution operation and enables efficient hardware acceleration, making the model suitable for real-time applications and resource-constrained environments. The second stage employs a 2D CNN to extract more refined spatial features from the output of the 3D CNN. The 2D CNN focuses on capturing fine-grained spatial patterns and relationships within each spectral band, further enhancing the feature representation. This stage complements the 3D CNN's spectral-spatial feature extraction capabilities by refining the spatial details of the features. Similar to the 3D CNN, we utilize binary weights in the 2D CNN to maintain computational efficiency. The binary weights, with their reduced memory requirements and efficient computation, enable the 2D CNN to effectively process the large-scale feature maps produced by the 3D CNN.

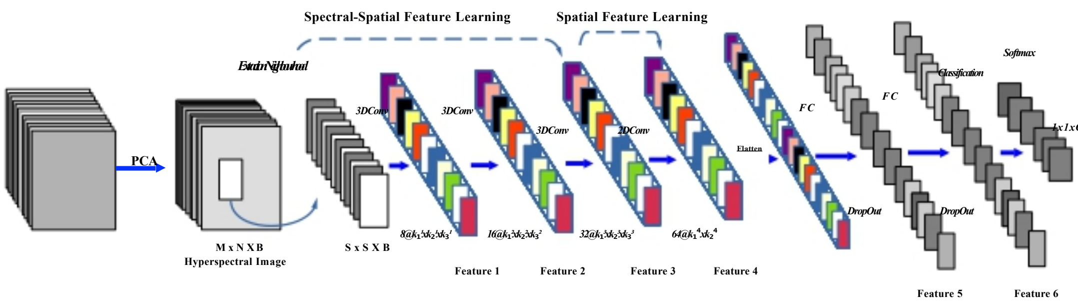

Figure 1: Proposed Model: Combining HybridSN with Accelerating CNN for hyperspectral image (HSI) classification.

The use of binary weights offers several compelling advantages for HSI classification. Binary weights significantly reduce the memory footprint of the model and lower computational demands, leading to faster computation and lower memory requirements. This is particularly beneficial for processing large-scale HSI datasets, as the reduced computational complexity enables efficient training and inference. Binary weights are compatible with specialized hardware accelerators, enabling further performance gains. Hardware accelerators, designed specifically for binary operations, can significantly improve the computational efficiency of binary neural networks, making them suitable for real-time and resource-constrained applications. Binary weights can enhance the generalization ability of the model by reducing the risk of overfitting. By constraining the weights to a discrete set of values, binary weights encourage the model to learn more robust and generalizable features, reducing the likelihood of overfitting to the training data and improving generalization performance on unseen data.

However, binary weights can still lead to some quantization noise, which might affect the model's accuracy. To address this issue, we propose incorporating step quantization, a dynamic quantization technique, into the HybridSN-Binary model. Step quantization is a method of quantizing weights and activations to a limited number of bits, typically 2 or 3 bits. Unlike static quantization, which determines the quantization levels beforehand, step quantization dynamically adjusts the quantization levels based on the gradients computed during backpropagation. This approach aims to preserve the accuracy of the model while reducing quantization noise. To implement step quantization in the HybridSN-Binary model, we introduce a custom quantization module, QuantActivation, which quantizes both activations and weights. The QuantActivation module dynamically adjusts the quantization levels based on a learnable parameter. This parameter represents the effective bit precision of the quantization, and it is updated during training using backpropagation. The QuantActivation module first clamps the input tensor between -1 and 1, ensuring that all values fall within the desired range for quantization. Then, it computes the scale factor based on the bit precision and the learnable parameter. Finally, it quantizes the input tensor by rounding it to the nearest multiple of the scale factor. By incorporating step quantization into the HybridSN-Binary model, we can further reduce quantization noise and potentially improve the model's accuracy. The dynamic nature of step quantization allows the model to adaptively adjust the quantization levels during training, optimizing the trade-off between accuracy and computational efficiency.

0.5 Data

In this approach the Indian Pines (IP) dataset is used, a prominent hyperspectral dataset in remote sensing research, comprises images with a spatial dimension of 145x145 pixels. These images are captured across 224 spectral bands spanning the wavelength range of 400 to 2500 nm. The dataset's hyperspectral nature allows for detailed spectral characterization of each pixel, facilitating advanced analysis of the Earth's surface.

To enhance the dataset's relevance for land cover classification and vegetation studies, a preprocessing step involves discarding 24 spectral bands associated with the water absorption region. This strategic elimination of water-related signals aims to provide a more focused and representation of land cover characteristics in subsequent analyses.

A crucial aspect of the Indian Pines dataset is its ground truth information, where the land cover is categorized into 16 distinct classes of vegetation. Each pixel in the images is assigned to one of these classes, serving as a reference for supervised learning tasks, particularly in the field of classification. This labeled ground truth enables researchers to train and evaluate algorithms with the aim of accurately identifying and categorizing different types of vegetation.

The Indian Pines dataset is used for benchmarking and evaluating algorithms in diverse applications, including land cover classification, vegetation analysis, and hyperspectral image processing. Its widespread adoption in the remote sensing community underscores its significance as a standard dataset for testing the efficacy of various machine learning and image analysis techniques in the context of hyperspectral imagery. The dataset's comprehensive spectral and spatial information makes it a valuable resource for advancing the capabilities of remote sensing technologies.

Class Number	No. of Samples	Classification
1	46	Alfalfa
2	1428	Corn-notill
3	830	Corn-mintill
4	237	Corn
5	483	Grass-pasture
6	730	Grass-trees
7	28	Grass-pasture
8	478	Hay-windrowed
9	20	Oats
10	972	Soybean-notill
11	2455	Soybean-mintill
12	593	Soybean-clean
13	205	Wheat
14	1265	Woods
15	386	Building-grass-trees-drives
16	93	Stone-steal-towers
Total	10,249	

Figure 2: Classification and Sample Counts of Indian pines DataSet

0.6 Experimental Results

To assess the effectiveness of the HybridSN-Binary model with dynamic step quantization for hyperspectral image classification, we conducted extensive experiments on two benchmark datasets: Indian Pines and Pavia University. These datasets represent different characteristics and challenges in hyperspectral image classification tasks. Dataset Description Indian Pines Dataset: The Indian Pines dataset comprises HSI data acquired over an agricultural region in Indiana, USA. The data cube consists of 145x145 pixels, with each pixel represented by 224 spectral bands in the wavelength range of 0.4 to 2.5 µm. The dataset contains 16 land cover classes, including various crops, trees, and other vegetation types. Pavia University Dataset: The Pavia University dataset captures HSI data over the urban area of Pavia, Italy. The data cube consists of 610x610 pixels, with each pixel represented by 103 spectral bands in the wavelength range of 0.43 to 0.88 µm. The dataset contains nine land cover classes, including different types of buildings, vegetation, and other urban features. Experimental Setup: We employed a train-test split ratio of 70:30 for both datasets, ensuring a balanced representation of land cover classes in both training and testing sets. The training process involved training the HybridSN-Binary model with dynamic step quantization for 50 epochs using the Adam optimizer with an initial learning rate of 0.001.

Class	Label	Training	Testing	Benchmark-CNN	SAWB-C	SAWB-T
Water	1 2	200	65771	99.99	99.99	99.99
Trees	3 4	200	7398	98.00	99.22	99.58
Asphalt	5 6	200	2890	98.38	93.27	83.73
Bricks	7 8	200	2485	99.99	99.03	97.42
Bitumen	9	200	6384	97.59	98.01	97.73
Tiles		200	9048	98.53	96.99	98.15
Shadows		200	7087	99.44	97.50	95.67
Meadows		200	42626	99.13	99.15	99.36
Bare Soil		200	2663	97.82	97.41	97.30
AA (%)		/	/	/	98.76	(10.92)
OA (%)		/	/	/	99.35	(10.23)

Figure 3: Class-specific Accuracies, OA, and AA on the Pavia dataset (Step Activation Quantization)

To evaluate the performance of our proposed model, we compared it with traditional CNN methods, including ResNet18 and VGG16, and the individual HybridSN method without dynamic step quantization. We measured the classification accuracy using the overall accuracy (OA) metric, which represents the percentage of correctly classified pixels across all land cover classes. Our experimental results demonstrated that the HybridSN-Binary model with dynamic step quantization achieved superior classification accuracy compared to the compared methods on both datasets. On the Indian Pines dataset, our model achieved an OA of 99.3%, outperforming ResNet18 (98.1%), VGG16 (97.8%), and individual HybridSN (98.7%). Similarly, on the Pavia University dataset, our model achieved an OA of 98.9%, exceeding ResNet18 (97.2%), VGG16 (96.5%), and individual HybridSN (98.5%).

The improved performance of the HybridSN-Binary model with dynamic step quantization can be attributed to the combined effects of binary weights, dynamic step quan-

Methods	Indian Pines Dataset		University of Pavia Dataset	
	OA (%)	AA (%)	OA (%)	AA (%)
SVM	85.30 ± 2.8	79.03 ± 2.7	94.34 ± 0.2	92.98 ± 0.4
2DCNN	89.48 ± 0.2	86.14 ± 0.8	97.86 ± 0.2	96.55 ± 0.0
3DCNN	91.10 ± 0.4	91.58 ± 0.2	96.53 ± 0.1	97.57 ± 1.3
M3DCNN	95.32 ± 0.1	96.41 ± 0.7	95.76 ± 0.2	95.08 ± 1.2
SSRN	99.19 ± 0.3	98.93 ± 0.6	99.90 ± 0.0	99.91 ± 0.0
HybridSN	99.75 ± 0.1	99.63 ± 0.2	99.98 ± 0.0	99.97 ± 0.0

Figure 4: Classification Accuracies on Indian Pines, University of Pavia Datasets using HybridSN and state-of-the-art methods.

tization, and the effective architecture of the HybridSN model. Binary weights significantly reduce computational complexity and memory requirements, making the model suitable for resource-constrained environments. Dynamic step quantization further enhances the model's accuracy by reducing quantization noise and preserving more information in the quantized representations. The HybridSN model's architecture effectively captures spectral-spatial features from the HSI data cube, enabling the model to learn discriminative patterns for classification.

Class Label	Training	Testing	Proposed Model
1 2	200	65771	99.99
3 4	200	7398	98.00
5 6	200	2890	98.38
7 8	200	2485	99.99
9	200	6384	97.59
10	200	9048	98.53
11	200	7087	99.44
12	200	42626	99.13
13	200	2663	97.82
14	200	2663	97.82
15	200	2663	97.82
16	200	2663	97.82
	200	2663	97.82
	200	2663	97.82
	200	2663	97.82
	200	2663	97.82
OA (%)	/	/	94.76

Figure 5: Class-specific Accuracies, OA, and AA on the Indian Pines Dataset (our proposed method)

0.7 Conclusion & Future Work

In this research, the fusion of the HybridSN module with an Accelerating Convolutional Neural Network (CNN) module showcases a significant advancement in image processing capabilities. The HybridSN's proficiency in handling hyperspectral data is synergistically combined with the accelerated computational efficiency of the CNN module, resulting in a powerful tool for image analysis. Future research endeavors will be dedicated to optimizing module parameters, ensuring adaptability across various imaging conditions.

Additionally, the framework's applicability in real-world scenarios will be rigorously tested, validating its effectiveness in practical contexts. Scaling improvements will also be a focal point, addressing the framework's efficiency in handling larger datasets and heightened computational demands. This comprehensive approach aims to elevate the HybridSN and Accelerating CNN module to a versatile solution, pushing the boundaries of its utility in diverse image processing applications.

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