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Band Selection using Reinforcement Learning for Hyperspectral Images followed by CNN-based Classification

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***Abstract*—Hyperspectral imaging (HSI) is a hot topic in the analysis of remote sensing data due to the large quantity of information included in these kinds of images, which enables a better characterization and utilization of the Earth's surface by integrating rich spectral and spatial information. The basic goal of hyperspectral imaging involves band selection, and feature extraction, followed by classification. The choice of bands is a crucial step in the effective processing of hyperspectral pictures. It describes the method of picking the bands in a hyperspectral image that are most important. By selecting a limited number of optimal bands, we aim at speeding up model training, improving accuracy, or both. In this research, we compare all the discussed methodologies in-depth by first providing quantitative findings utilizing well-known and often used HSI situations. In order to determine which paradigms and methodologies are most appropriate, we will evaluate and review the ones that are now in use. Second, we will use reinforcement learning to train an intelligent agent that, given a hyperspectral image, can automatically learn a policy to choose the best band subset.**

***Index Terms*— deep learning, hyperspectral image classification, band selection, deep reinforcement learning, Q-network, dimensionality reduction, CNN, neural networks.**

I. INTRODUCTION

Hyperspectral imaging is a spectroscopy-based analytical technique. It entails collecting and evaluating information for each pixel in an image of a scene over a variety of electromagnetic spectrum bands, including those outside the range visible to the human eye.

In hyperspectral imaging, hundreds of images from the same spatial area taken at various wavelengths are gathered to create a so-called hyperspectral cube, in which the scene's spatial extent is represented by two dimensions and its spectral content by a third. For each pixel in the hyperspectral image, a vector of reflections in each electromagnetic band exists. This vector represents the distinct spectral characteristic of each pixel in the hypercube. Any pixel's spectral signature contains a piece of characteristic information about the pixel's content. Finding items, recognizing materials, and detecting processes are just a few of the numerous fields where HSI is useful. The atmosphere, environment, urban, agriculture, geological and mineral exploration, coastal zone, marine, forestry (i.e. tracking forest health), water quality and surface contamination, inland waters and wetlands, snow and ice, biology, medical contexts, and food processing are just a few of the real-world applications it has been used in. Additionally, HSI has been employed in air, water, and spacecraft to collect

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thorough spectrum data for a number of applications.

Hyperspectral data contains redundancy, with data from one band to the next generally changing very little. Since processing such a massive amount of data is challenging due to an image's hundreds of sub - bands in the electromagnetic visible band, we must turn these infinite details into limited ones by choosing the right spectral bands without losing any information features. We can speed up processing times and increase target detection accuracy by removing duplicated data. Dimensionality reduction and band selection are two techniques that can be used for this.

In general, the term "dimensionality reduction" refers to the application of a mathematical transformation on an input dataset to produce an output dataset whose bands are a linear combination of each input band. The early bands of the converted data frequently contain the unique information of the image, but the later bands typically contain noise and redundant data. In order to excel in a number of tasks, such as classification and anomaly detection, band selection is a feature selection strategy that selects a collection of bands that are the most representative. To solve the problem of dimensionality and reduce the amount of hyperspectral data, band selection is a useful technique.

The following are the novel contributions made by this work:

- To use several deep learning approaches for classifying hyperspectral images and find one that offers excellent accuracy while attempting to speed up computation.
- To include several feature extraction methods into the classification framework for the purposes of spatial feature modelling, dimensionality reduction, improving dis- criminative information, and redundancy reduction.
- In order to remove duplicate information and lighten the computational load for possible real-time applications of hyperspectral imaging, reinforcement learning should be used for band selection in hyperspectral image classification.

II. METHODOLOGY

A. Hyperspectral Band Selection using Deep Reinforcement Learning

1) The dataset contains the HSIs with pixel data for 103 bands where we have to select k optimal bands.

2) Framing problem as MDP Define a 5-tuple (A, S, P, R,) A = set of all actions

S = set of all states

P : S × A → P(S) (Markov transition function)

R : S × A → P(R) (Distribution of immediate rewards of state-action pairs)

(0, 1) (Discount factor)

P(.—s, a) represents the probability distribution of the next state after performing an action an A at a states S, and R(—s, a) represents the distribution of the immediate reward for the selected action.

Action: The complete set of all actions C is identical to the set of bands, i.e., C = 1, 2,..., L where L = 103(in this case). Let B be a set consisting of actions that have been taken before. Then, the actual set of actions for the current time step is

$$A = C \setminus B$$

State: The state is represented as the action history of the agent and is denoted as an L-dimensional vector with multihot encoding that records which actions have been taken (i.e., which spectral bands have been chosen) in the past. For example, si = 1 means that the ith band has been picked in previous time steps, while si = 0 represents that it is still selectable.

Transition: The transition function P represents the next state as a possible outcome of taking action at a state. The state is updated by changing the action history as follows:

B' = B a

where B' represents the set of selected bands associated with the next state s'

Reward: Here is the way to instantiate the reward scheme

Information Entropy: Information entropy is capable of measuring the information amount of a random variable quantitatively. Hence, we use it to evaluate the richness of spectral information of bands. the reward R(s, s') can be calculated as follows:

R(s, s') = MIE(s') - MIE(s)

3) Band Selection Policy using Deep Reinforcement Learning The policy we seek is an action-value function, denoted by Q(s, a), which specifies the action to be taken when the current state is s. Based on this function, the agent selects the action with the highest reward value. Bands with a high information entropy or low correlation are likely to be selected.

B. Proposed Spectral CNN models for HSI data analysis

Regarding the existing spectral models, they have considered the spectral pixels $xi\ n^{channels}$ as the input data, where $n_{channels}$ can either be the number of original bands n_{bands} or a reasonable number of spectral channels n_{new},

extracted using PCA, to which 1D kernels are applied on each CONV layer, $k^{(l)}$ x $q^{(l)}$, obtaining, as a result, an output $X^{(l)}$ composed by $k^{(l)}$ feature vectors. After step 3 in 4.1.1 the optimal bands are selected for classification using the Spectral CNN model.

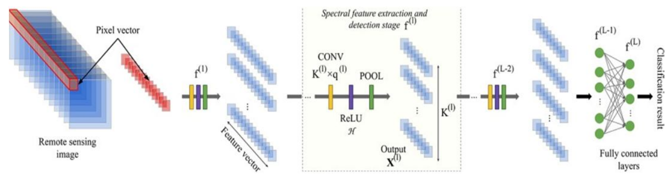

Fig. 1. The CNN1D architecture is commonly employed for spectral analysis, applying a hierarchical stack of L FE and detection stages, where each CONV layer exhibits kernels of $k^{(l)}$ x $q^{(l)}$.Adapted from *"Deep learning classifiers for hyperspectral imaging: A review"* by Mercedes Eugenia Paoletti, J. M. Haut, J. Plaza, A. Plaza, published on 1 December 2019, Isprs Journal of Photogrammetry and Remote Sensing

C. Proposed Spatial CNN for HSI data analysis

With regards to the existing spatial models, they only consider the spatial information or data obtained from the HSI data cube. Pertaining to that, in order to process the spatial information, we usually employ CNN2D architectures , where each CONV layer applies $k^{(l)}$ x $k^{(l)}$ x $k^{(l)}$ kernels over the input data, obtaining as a result $k^{(l)}$ feature maps.

The spatial information can be extracted from the original HSI data cube by reducing the spectral dimension by using some dimensionality reduction-method, such as PCA, and cropping spatial patches of d x d pixel-centered neighbors. After step 3 in 4.1.1 the optimal bands are selected for classification using the Spatial CNN model.

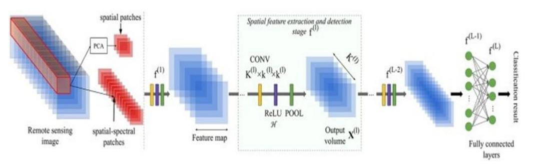

Fig. 2. The CNN2D model can perform both spatial and spectral-spatial analysis by accepting spatial patches with few principal components or spectral-spatial patches with all (or most) available spectral bands, to which each CONV layer applies a kernel of K(l) x k (l) x k (l) .Adapted from "Deep learning classifiers for hyperspectral imaging: A review" by Mercedes Eugenia Paoletti, J. M. Haut, J. Plaza, A. Plaza, published on 1 December 2019, Isprs Journal of Photogrammetry and Remote Sensing

D. Proposed Spectral-spatial CNN for HSI data analysis

With regards to the existing spectral-spatial models, they consider both spectral and spatial properties from the HSI data cube. Because CNN models are so flexible, a variety of approaches and architectures may be created to carry out the spectral-spatial processing.

These models perform spectral-spatial processing in different ways. The most direct one adopted is to feed the model with 3-D neighboring regions of size d x d x n channels, where n channels can be certain number of PCs or the original n bands. In this regard, some methods perform an initial dimensionality reduction in order to reduce the spectral correlation and redundancy. After step 3 in 4.1.1 the optimal bands are selected for classification using the Spectral-spatial CNN model.

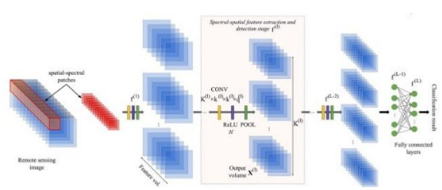

Fig. 3. The CNN3D model is employed for spectral-spatial analysis, taking full advantage of the spectral signatures contained in the input data by applying CONV layers with K(l) x k(l) x q(l) kernels. Adapted from "Deep learning classifiers for hyperspectral imaging: A review" by Mercedes Eugenia Paoletti, J. M. Haut, J. Plaza, A. Plaza, published on 1 December 2019, Isprs Journal of Photogrammetry and Remote Sensing

E. Implementation Details

The parameters of CNN1D, CNN1D Proposed, CNN2D, CNN2D Proposed, CNN3D & CNN3D Proposed models have been adjusted using 10 epochs. Furthermore, the topology details of each model are reported on Table 1. It should be emphasized that we adhere to the standard that shallow models are made up of single-hidden layer designs and deep architectures contain at least two hidden layers. In addition, the inclusion of batch normalization (BN) in some layers of the convolutional models intends to, on the one hand, avoid vanishing/exploding gradients and, on the other hand, maintain the distribution of the layer's inputs. We have empirically shown that BN speeds up and stabilizes the training phase on some (but not all) CNN models. We observed that certain setups benefited these specific convolutional models in this way.

III. EXPERIMENTS AND ANALYSIS

A. Hyperspectral Data Set Description

The UP scene: It was acquired by the ROSIS sensor (Kunkel et al., 1988) over the campus of the University of Pavia, in the north of Italy. The dataset(Fig. 9) contains nine different classes that belong to an urban environment with multiple solid structures, natural objects and shadows. After discarding the noisy bands, the considered scene contains 103 spectral bands, with a size of 610 x 340 pixels with spatial resolution of 1.3 mpp and covering the spectral range from 0.43 to 0.86 μm. Finally, about 20% of the pixels (42776 of 207400) contain ground-truth information.

B. Experiment Setting

Evaluation: As to evaluation measurements, we make use of the following ones.

i. The overall accuracy (OA): It computes the number of correctly classified HSI pixels divided by the number of samples
ii. The average accuracy (AA): It computes the mean of the classification accuracies of all classes
iii. The Kappa coefficient: It measures the agreement between the resulting classification map and the original ground truth map.

Dimensionality Reduction Techniques used for Comparison:

i. Feature Extraction: Principal Component Analysis (PCA)
ii. Band Selection: Deep Reinforcement Learning (DRL) model for unsupervised hyperspectral band selection.

Classification Setting:

i. CNN1D: The CNN1D architecture is commonly employed for spectral analysis, applying a hierarchical stack of L FE and detection stages, where each CONV layer exhibits kernels of $K^{(l)}xq^{(l)}$.
ii. CNN2D: The CNN2D model can perform both spa- tial and spectral-spatial analysis by accepting spatial patches with few principal components or spectral- spatial patches with all (or most) available spectral.
bands, to which each CONV layer applies a kernel of $K(l)_{x}k(l)_{x}K(l)$.
iii. CNN3D: The CNN3D model is employed for spectral-spatial analysis, taking full advantage of the spectral signatures contained in the input data by applying CONV layers with $K^{(l)}xk^{(l)}xK^{(l)}xq^{(l)}$ kernels.

IV. RESULTS AND DISCUSSION

As observed in Table II, the proposed model generates the highest accuracy for CNN3D with 50 bands which is the spatial-spectral model. The Kappa Coefficient is found to be 99.89%, Average Accuracy is 99.92% and Over Accuracy is 99.82%. However, CNN3D takes the highest amount of time among the other classifiers. For CNN2D with 50 optimal bands, which is the spatial model, the accuracy and the time taken are dropped to some extent. For CNN1D the accuracy and time are further reduced, considering 60 as the optimal bands.

We performed the classification on hyperspectral images using a different number of bands like 30, 40, 50, 60,...so on. Through this experiment, we observed that CNN1D produces good results for 60 bands and the other two classifiers CNN2D and CNN3D produce good results when 50 bands are chosen as the optimal bands as shown in fig. 6. Hence, we consider 60 bands as the optimal number of bands for CNN1D and 50 bands for CNN2D and CNN3D.

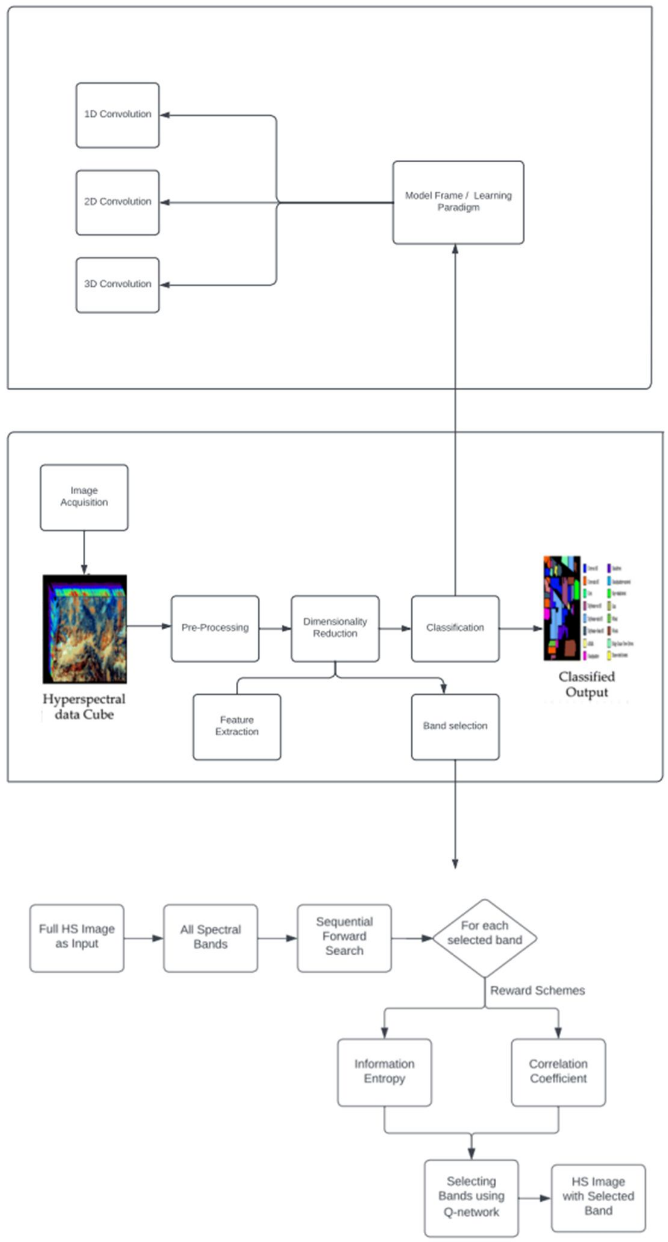

Fig. 4. Proposed System

V. Conclusions and Further Work

Through our project, we were able to run and implement a band selection algorithm and then run classification models on the same. This helped in reducing the computation time by a significant amount and improved accuracy to a certain extent. Identifying better dimension reduction methods using feature extraction technique and taking the intersection of the bands selected using feature extraction and Band Selection using Deep Reinforcement Learning to obtain better results. Combining Deep Reinforcement Learning and some heuristic band selection framework like the Clustering-based method is probable to result in better band selection solutions. Further, better reward functions or models can be used in order to improve band selection to an even better extent.

TABLE I. NEURAL NETWORK BASE MODEL TOPOLOGIES, EMPHASIZING THE INPUT, HIDDEN AND OUTPUT LAYERS IN ORDER TO DEMONSTRATE THE DEPTH OF EACH ARCHITECTURE. IN THIS SENSE, THE TERM "LINEAR INPUT" REFERS TO THE INPUT LAYER OF EACH MODEL, WHILE THE LAST DENSELY-CONNECTED LAYER WITH SOFMAX FUNCTION IS THE OUTPUT LAYER

Model	Main layer	Normalization	Activation Function	Downsampling
CNN1D	Linear input(n_{bands})	-	-	-
	CONV(20 X 24)	-	ReLU	POOL(5)
	FC(100)	BN	ReLU	-
	FC(n_{class})	-	Softmax	-
CNN2D	Linear input(19 x 19 × $n_{channels}$)	-	-	-
	CONV(50 x 5 x 5)	-	ReLU	-
	CONV(100 x 5 x 5)	-	ReLU	POOL(2 x 2)
CNN3D	Linear input(19 x 19 × $n_{channels}$)	-	-	-
	CONV(32 x 5 x 5 x 24)	BN	ReLU	-
	CONV(64 x 5 x 5 x 16)	BN	ReLU	POOL(2 x 2 x 1)
	FC(300)	BN	ReLU	-
	FC(n_{class})	-	softmax	-
				-

TABLE II. CLASSIFICATION RESULTS FOR THE UP DATASET FOR 30, 40, 50, 60, 70 AND 80 BANDS

Bands	CNN1D Proposed				CNN2D Proposed				CNN3D Proposed			
	Kappa	**AA**	**AO**	**Time**	**Kappa**	**AA**	**AO**	**Time**	**Kappa**	**A**	**AO**	**me**
30	88.90%	88.85%	91.68%	6.61s	.50%	99.19%	99.56%	129.47s	98.21%	.72%	.10%	0.32s
40	89.35%	89.65%	92.01%	6.85s	.12%	.65%	99.34%	95.22s	99.42%	.65%	.34%	0.59s
50	92.34%	92.66%	94.25%	6.81s	.51%	99.36%	99.63%	73.73s	99.89%	.92%	.82%	7.73s
60	93.04%	92.63%	94.76%	7.18s	.36%	99.18%	99.52%	80.03s	99.64%	.18%	.52%	9.99s
70	90.97%	91.04%	93.24%	7.11s	.37%	.27%	99.52%	87.65s	99.66%	.27%	.52%	2.78s
80	91.89%	92.35%	.86%	6.78s	98.87%	97.92%	.15%	3.48s	99.11%	98.78%	99.29%	889.17s

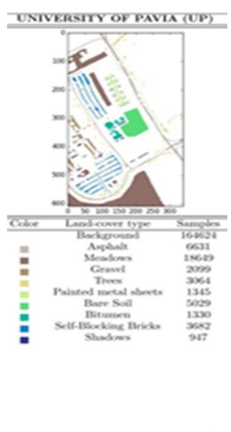

Fig. 5. Number of available samples University of Pavia (UP) dataset. The samples for the latter scene are divided into two categories: training (top) and testing (bottom). Adapted from "*Deep learning classifiers for hyperspectral imaging: A review*" by Mercedes Eugenia Paoletti, J. M. Haut, J. Plaza, A. Plaza, published on 1 December 2019, Isprs Journal of Photogrammetry and Remote Sensing

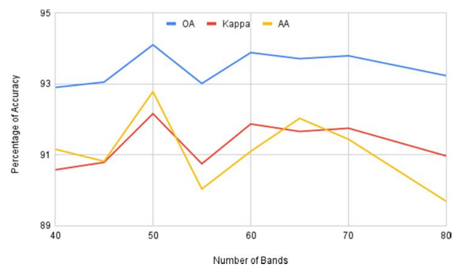

Fig. 6. Accuracy curve for different number of bands for CNN2D

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