Open Set Domain Adaptation for Hyperspectral Image Classification using Generative Adversarial Network

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Abstract Hyperspectral image (HSI) classification attracted lots of attention due to its complexity in dealing with large dimensions. In recent years, the techniques for dealing with the HSI have been evolved, ensuring the increase in efficiency to some extent in classification and other perspectives. Domain adaptation is a well-established technique for using any trained classification model, when the feature space from target domain are a subset of feature space from source domain.The objective of this paper is to create an efficient and effective model for HSI classification by implementing Open set (OS) domain adaptation and Generative Adversarial Network (GAN). This have advantages in quite few ways, such as creating a single training model that deals with various HSI dataset with common classes, classifying the features in any data to specific trained classes and unknown (to be labelled) making it easy to annotate. The proposed open set domain adaptation for HSI clasification is evaluated using Salinas and Pavia. The proposed method resulted in the classification accuracy for unknown classes as 99.07% for Salinas and 81.65% for Pavia.

1 Introduction

In the recent years, machine learning and deep learning techniques depicts a remarkable performance in different fields like speech processing, forecasting, computer vision, machine translation, prediction and health care [8], [19]. Hyperspectral remote sensing is one of the area, where deep learning is applied due to its inexplicable efficacy [1]-[3], [9]. Hyperspectral remote sensing uses electromagnetic spectrum to identify and classify the objects, based on spectral response. Hyperspectral images (HSI) consist of spatial and spectral information. Spectral information are given in

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form of bands and number of bands varies depending on the sensor.

Generative adversarial network (GAN) [10]-[12] is a classification technique, which comprise of two portion as follows: a Generator and a Classifier. Generator in the network, considers a random data and continuously tries to imitate the input data. the Classifier in the network is trained to classify the original data from the generated data. Because of this continuous training between the generator and classifier in GAN network, high accuracy rates can be obtained with less data samples.

Now there is a high chance that various dataset may or may not contain common classes. In such case, a model trained for one dataset can be used in other dataset with necessary modifications. This technique is represented as Transfer Learning (TL) [15]-[17]. Domain adaptation is a part of TL, where a features of a target dataset are a subset of features of source dataset [14], [18]. There are two types of domain adaptation namely: Closed set (CS) and Open set(OS) domain adaptation. CS domain adaptation is used when the number of classes in both source and target domain are exactly the same. Whereas, OS domain adaptation is used when target domain contains unknown classes that are not presented in source domain [4], [5].

In the proposed work, we present a novell approach for dealing with HSI classification using OS domain adaptation and GAN [6]. In practical, the unknown class is unlimited, which makes it difficult to address with high precision, when training source domain. To overcome this issue, we make use of OS domain adaptation by backpropogation [6], [7], for training unknown class samples, as well as increasing the individual class accuracy. Each pixel in the HSI represents the spectral signature of the specific class. This also means that the class labelling has to be done for every pixel, which is very difficult in real life scenario. Also, pre-processing is done to extract 1D pixel data with class information from 3D HSI image, to train the model.

The methodology is described in detail in section 2. The experiment is carried out on two set of HSI data after pre-processing, as mentioned in section 3. Experimental results and conclusion are discussed in section 4 and section 5.

2 Methodology

In this paper, we have considered the architecture used in [6] to implement OS domain adaptation for HSI. The data x_s and label y_s from source (X_s, Y_s) and data x_t for target (X_t) are considered. The general architecture used in the work is described in Fig 1.

The class dimension for source data is K (known class) and for target data is K+1 (known + unknown class). Generally, the number of input and output classes in a model must be same. Unlike other open set domain adaptation models [5], we do not provide any data to separately train for unknown classes. To make up for the missing class data, the generated data from generator, which fails to pass through the classifier will be used to train the unknown class in source domain. Hence, there is no need to provide data separately for unknown class during training.

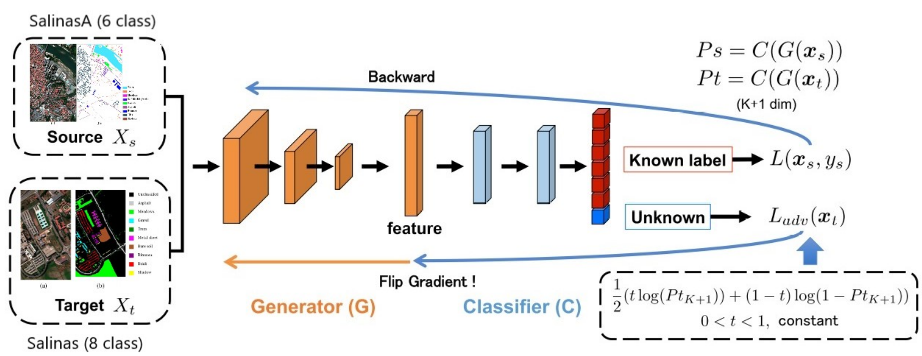

Fig 1: Open set model architecture [6] mapped for Hyperspectral image classification.

When input data(x) is passed into the network, the generator will try to increase the error rate by generating images. This generated images G(x) is then passed as input to the classifier. The Classifier will try to get a boundary between known and unknown target class. There the common class data (x_s, y_s) present in the target will be classified as known and remaining data as unknown class.

The output of classifier C(G(x)) will have K+1 logits. The softmax function is used to convert the logits into probabilities [6]. Thus, we get K+1 dimensional output for K dimensional input. The classifier is trained to give output of p$(y = K+1|x_t)$ = t, where $0 < t < 1$. In our experiment, the value of t=0.5 is set as a boundary between known and unknown class [1].

3 Dataset and Model Description

This section provides the intuitive understanding of HSI dataset and Convolution Neural Network model used in the experiment.

Salinas is HSI datset collected over Salinas Valley, California using AVIRIS sensor [13]. The spatial resolution for this dataset is 3.7-meter pixels. The dimension of the data is $512 \times 217 \times 224$ with total of 16 classes.

Class	Features	Source dataset (SalinasA)	Target dataset (Salinas)
0	Brocoli_green_weeds_1	391	2008
1	Corn_senesced_green_weeds	1343	3278
2	Lettuce_romaine_4wk	616	1068
3	Lettuce_romaine_5wk	1524	1927
4	Lettuce_romaine_6wk	675	916
5	Lettuce_romaine_7wk	799	1070
6	Unkown (Brocoli_green_weeds_2 and Fallows)	0	5702
Total samples		5348	15969

Table 1: Dataset Description for SalinasA(source) and Salinas(target).

SalinasA is one of the extracted subscene of Salinas image, which comprise $86 \times 83 \times 224$ pixels with 6 classes [13]. For one of our experiment, we consider, salinasA dataset with 6 classes (Source) and Salinas dataset with 8 classes (Target) is used. The class and sample for each class is mentioned in Table 1.

PaviaU is one of the two datsaset obtained from Pavia, Northern Italy using ROSIS sensor [13]. Pavia University is comprised $610 \times 610 \times 102$ pixels representing 9 classes, after discarding few samples with no information.

Class	Features	PaviaU (Source Domain- 5 class)	PaviaU (Target Domain- 9 class)
0	Asphalt	1000	6631
1	Bare Soil	1000	5029
2	Gravel	1000	2099
3	Trees	1000	3064
4	Painted metal sheets	1000	1345
5	Unknown (Meadows, Self-Blocking Bricks and Shadows)	0	24607
Total samples		5000	42775

Table 2: Dataset Description for PaviaU with 5 classes(Source) and PaviaU with 9 classes(Target).

For next part of the experiment, 5 classes were selected from PaviaU dataset with 1000 samples in each class, which is used for source training. Then the complete PaviaU dataset with around 42,775 samples with 9 classes is used as target. The dataset details are mentioned in Table 2.

The Convolutional neural network (CNN) is used for training the model in the architecture. The details regarding layers of CNN used in the experiment is shown in Fig 2. 1D-batch normalization is used with convolution and fully connected layer.

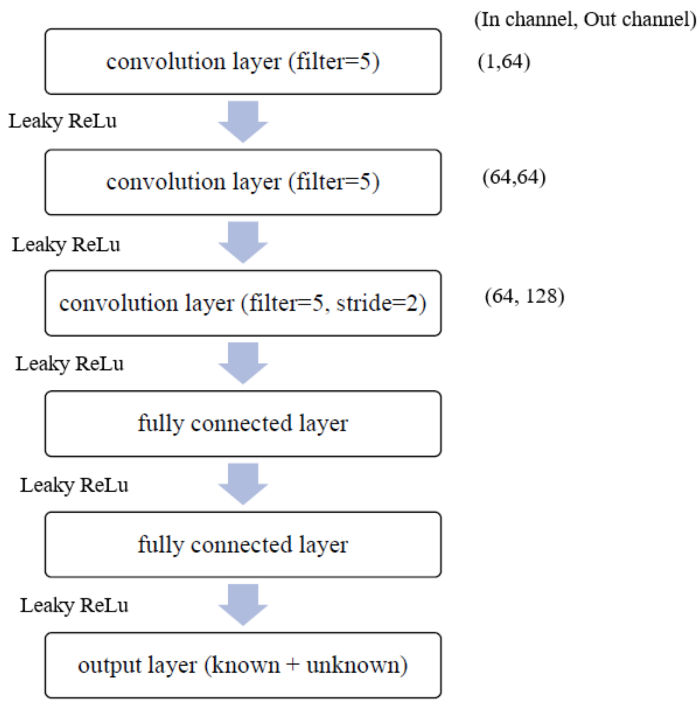

Fig 2: Convolution Neural Network used in the proposed open-set domain adaptation for hyperspectral image classification.

4 Experimental results

The parameters which gives the best results for our model during the experiment are mentioned below. In the proposed work, the network is trained for 2000 epochs and batch size of 128. Adam optimization method with learning rate of (0.001) and cosine-rampdown is used for training the network [6].

4.1 Slainas Dataset

The main purpose of the work is to identify the model effectiveness in classifying the unknown class. So precision, recall (classwise accuracy) and f1-score are calculated with contingency values obtained using CM and are used to evaluate the model. Table 3 shows the results for 1st experimental setup using SalinasA (source-6 class) and Salinas (target-8 class). The receiver operating characteristics (ROC) curve is a plot between true positive rate and false positive rate, in which the area under the curve (AUC) represents the accuracy of various classifier. The average accuracy of the known class is 95.10% and AUC is 98%. By using confusion matrix (CM) in Fig 3, we can interpret that from unknown class with 5702 samples collected from multiple classes, 53 samples are misclassified into other classes and classification accuracy of 99.07% and AUC of 0.98%is obtained. We can interpret from above results that our classifer model works well in both known and unknown classes.

Class	Features	Precsision	Recall	F1-Score
0	Brocoli_green_weeds_1	1.00	0.93	0.96
1	Corn_senesced_green_weeds	1.00	0.93	0.96
2	Lettuce_romaine_4wk	0.96	0.93	0.95
3	Lettuce_romaine_5wk	0.94	1.00	0.97
4	Lettuce_romaine_6wk	0.97	0.97	0.97
5	Lettuce_romaine_7wk	0.96	0.94	0.95
6	Unknown (Brocoli_green_weeds_2 and Fallows)	0.95	0.99	0.97
Average		0.97	0.96	0.96

Table 3: Classwise Accuracy for SalinasA (source) and Salinas (target) obtained using the proposed method.

4.2 PaviaU Dataset

For the second experiment, PavaiU dataset is considered to check the authenticity of OS domain adaptation for HSI in classifying unknown class data. Table 4 shows the precision, recall and f1-score results for PaviaU (source -5 class -5,000 samples) and PaviaU (target -9 class -42,775 samples). The average accuracy rate of known class is 85.97%. On further study using CM in Fig 4, around 4400 samples out of 24,607 unknown samples are misclassified into other classes and the classification accuracy rate of 81.65% is obtained unknown class. when the proportion between known and unknown class sample is taken into consideration, this further proves that the model works well in classifying unknown class samples. We got an average

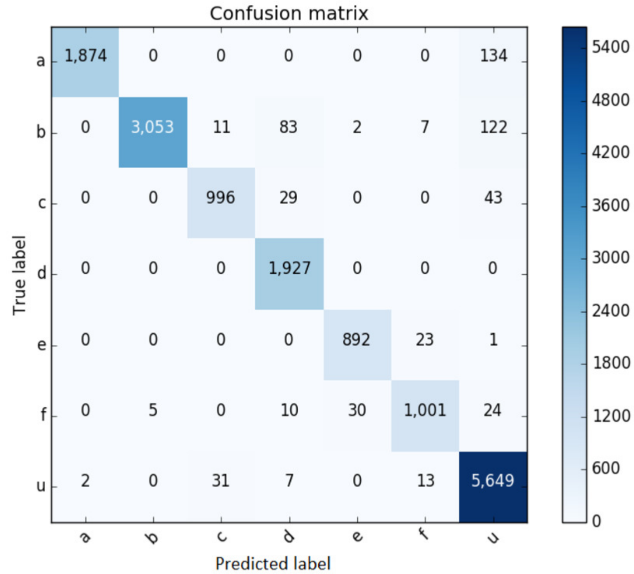

Fig 3: Confusion Matrix obtained for the proposed method for SalinasA (source) and Salinas (target) dataset.

rate of above 80% in both precision and recall (sensitivity) and overall average AUC of 84%. which further proves that open set domain adaptation can implemented in HSI classification.

Class	Features	Precision	Recall	F1-Score
0	Asphalt	0.78	0.98	0.93
1	Gravel	0.91	0.59	0.72
2	Trees	0.61	0.87	0.72
3	Self-Blocking Bricks	0.69	0.87	0.71
4	Bare Soil	1.00	0.99	0.99
5	Unknown (Meadows, Painted metal sheets and Shadows)	0.88	0.83	0.85
Average		0.81	0.86	0.83

Table 4: Classwise Accuracy for PaviaU with 5 classes (source) and PaviaU with 9 classes (target) obtained using the proposed method.

The Table 5 gives the overall accuracy rates for the experiments discussed above. We evaluated the performance of the model using classification accuracy for known and unknown classes. we also calculated precision, recall, f1-score for further stud-

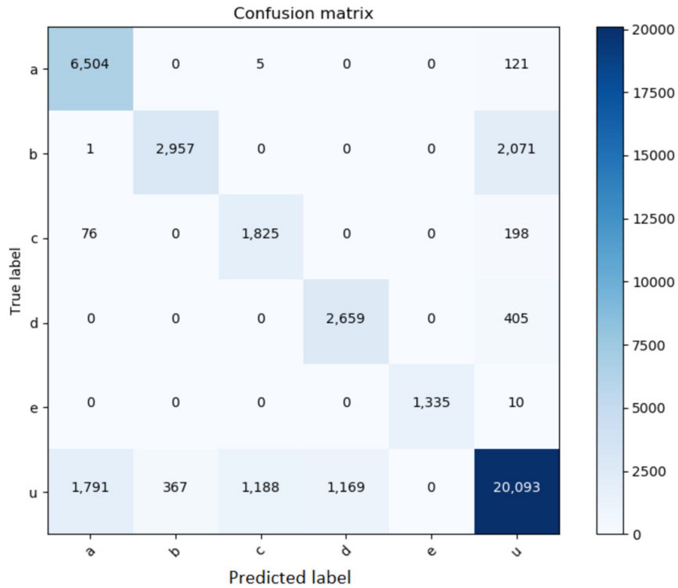

Fig 4: Confusion Matrix obtained for the proposed method for PaviaU dataset with 5 classes (source with 1000 samples in each class) and 8 classes (target).

ies. It is observed from the results, that the model could accurately distinguish the unknown class from known classes in Hyperspectral dataset. Since the number of training samples chosen in both cases is low, it can be said that GAN plays an important role in obtaining the desired results.

Dataset	known Class Accuracy (%)	Unknown Class Accuracy (%)	Overall Accuracy (%)
SalinasA and Salinas	95.10	99.07	96.38
PaviaU with 5 and 9 classes	85.97	81.65	82.69

Table 5: Performance of the proposed open set domain adaptation method for hyperspectral image datasets.

5 Conclusion

In this work, we applied open set domain adaptation to hyperspectral dataset using GAN. The obtained results shows that, open set domain adaptaion works well with

HSI and it will increase the efficiency of HSI classification models. It is clear from the experimental analysis that, various HSI dataset can share a common training model irrespective of the number of classes (excluding common classes) and samples with the use of GAN network.

As the future scope of the present work, the hyperparamter tuning can be performed to increase the efficiency of the proposed model and also it can be extended to other HSI dataset with different spectral ranges.

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