A Data Augmentation Approach using WGAN with Grey Wolf Optimizer (GWO) to Improve Deep CNN Weak Supervised Classification of Hyperspectral Images

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ABSTRACT

- This paper proposes a new approach to improve weak supervised classification of deep CNN architectures based on data augmentation by integrating Grey Wolf Optimizer (GWO) with Wasserstein Generative Adversarial Network (WGAN).
- WGAN is used to generate virtual pixels which would be incorporated in the training set of the deep CNN.
- The architecture of WGAN model is optimized using GWO in order to generate high quality samples.

ABSTRACT

- The proposed GWO-WGAN-CNN classifier is evaluated on three hyperspectral datasets:
  - *Indian Pines;*
  - *Pavia University;*
  - *Salinas.*
- The experiments have lead to better accuracy for the proposed model compared to the standalone CNN classifier.

OVERVIEW

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1. Introduction

a) Hyperspectral Image Classification

- The classification of HSI is a fundamental area of research in remote sensing, primarily due to the vast amount of spectral and spatial information that these images provide [1].
- HSI classification involves assigning a specific label to each hyperspectral pixel which is a difficult task due to the high-dimensional feature spaces and significant pixel redundancy and correlation [2].
- Numerous machine learning techniques have been applied to solve it, such as classic algorithms (e.g., SVM [3], multinomial logistic regression [4]) or Deep Learning methods (particularly deep-CNNs [5]).

1. Introduction

b) Deep-CNN

- Deep-CNN models are suitable for capturing the detailed information present in HSI.
- However, the very high complexity of the feature hyperspace coupled with the relatively low number of labelled data make the classification process still a difficult task.
- This paper proposes a novel approach in improving the classification results by augmenting the training set.

1. Introduction

Wasserstein Generative Adversarial Network (WGAN)

- These deep learning models try to approximate an unknown data distribution based on training samples.
- The concept is based on generating new virtual samples by using two distinct networks:
  - The generator which maps random noise from the latent space to the desired distribution. Its role is to generate new samples.
  - The discriminator whose role is to distinguish between authentic samples from the training set and fake samples created by the generator.
- Through iterative training, the discriminator improves its ability to identify real samples, while the generator is optimized to create samples that are indistinguishable from real ones [6]

1. Introduction

c) Grey Wolf Optimizer (GWO)

- GWO is part of the Swarm Intelligence class of algorithms and it has employed in solving various optimization problems [7].
- This optimization method is based on the hunting behavior of the grey wolves.
- A mathematical model is constructed to mimic the social hierarchy, tracking and attacking of the prey.
- Each wolf can be considered a candidate solution, where the α wolf provides the best current solution, the β wolf the second-best solution and so on.
- The hunt is guided by the three best solutions while the ω wolves follow the best solutions.

1. Introduction

c) Grey Wolf Optimizer (GWO)

- The encircling behavior is modeled the following equations:

$$\vec{D} = \left|\vec{C} \,.\, \vec{X}_p(t) - \vec{X}(t)\right| \qquad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \qquad (2)$$

Where t is the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors which are calculated based on (3) and (4), $\vec{X}_p$ is the position of the prey and $\vec{X}$ is the wolf's position.

$$\vec{A} = 2\vec{a}.\vec{i} - \vec{a} \qquad (3)$$

$$\vec{C} = 2.\vec{j} \qquad (4)$$

1. Introduction

c) Grey Wolf Optimizer (GWO)

- There are two random vectors in the interval [0, 1], $\vec{i}$ and $\vec{j}$.
- $\vec{a}$ is a vector linearly decreased from 2 to 0.
- The algorithm continues with the hunting phase which is modelled by (5) and (6).

$$\vec{D}_\alpha = |\vec{C}_1.\overrightarrow{X_\alpha} - \vec{X}|, \quad \vec{D}_\beta = |\vec{C}_2.\overrightarrow{X_\beta} - \vec{X}|, \vec{D}_\delta = |\vec{C}_3.\overrightarrow{X_\delta} - \vec{X}| \qquad (5)$$

$$\vec{X}_1 = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}, \vec{X}_2 = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}, \quad \vec{X}_3 = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \qquad (6)$$

- The top three solutions then guide the search in the next iterations as described in (7). Fig. 1 presents the GWO pseudocode which was implemented.

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \qquad (7)$$

1. Introduction

c) Grey Wolf Optimizer (GWO)

GWO

1. Initialise wolves population. Each wolf has an associated position vector.
2. While t < defined no. of iterations
    3. For each wolf:
        4. Update the position of the current wolf based on (7)
    5. Update the parameters based on (3) and (4)
    6. Compute the objective function of all the agents
    7. Re-evaluate the social hierarchy by selecting the alpha, beta and delta wolf.
    8. t = t + 1
9. Return the alpha wolf solution.

1. Introduction

d) Contributions

- In this paper, we propose a novel optimization approach for deep CNN used for HSI classification by integrating WGAN with GWO.

- This hybrid approach of integrating a deep learning model (WGAN) with the Swarm Intelligence algorithm (GWO) is designed to enhance WGAN's data augmentation capabilities by optimizing the architecture of the WGAN using GWO.

- Combining these techniques addresses two main limitations:
  1. It significantly improves the quality of the artificially generated samples.
  2. By providing the artificial samples, the training set of the deep CNN is extended and thus, it can provide better generalization to achieve better accuracy on the original test set.

2. Proposed GWO-GAN-CNN Classifier

- The model proposed in this paper is a deep-CNN classifier, where the training set has been augmented using an optimized WGAN with GWO.

- The initial architecture which acted as the starting point for the BA can be seen in the fig. 2 [8].

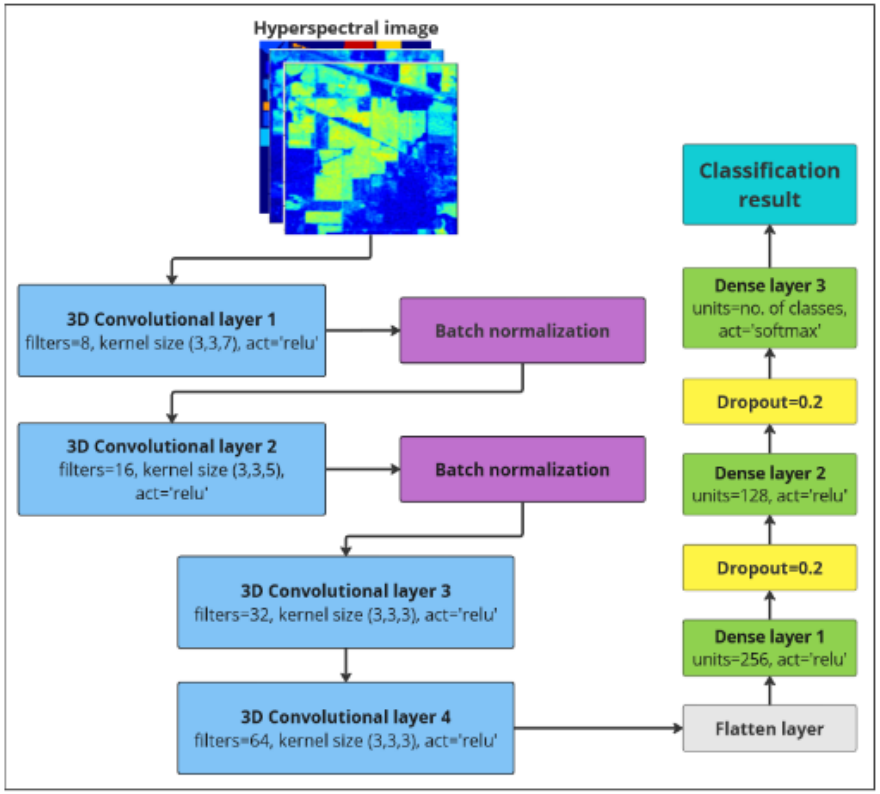


Fig. 2. Initial CNN architecture

2. Proposed GWO-GAN-CNN Classifier

- The algorithm begins with a pre-processing step. It is a common approach in HSI classification to split the image into m x n x k parallelepipeds, where the first two are spatial dimensions and k is the spectral dimension.
- The goal is to classify each parallelepiped and assign the classified label to the central pixel of the parallelepiped. This approach takes into account both spectral and spatial information [9].
- In order to increase the performance of the deep CNN, a WGAN model is implemented. The goal of the WGAN is to generate virtual pixels which would afterwards be incorporated in the training set of the deep CNN.

2. Proposed GWO-GAN-CNN Classifier

- The architectures of the used WGAN can be seen in fig. 3 [10].

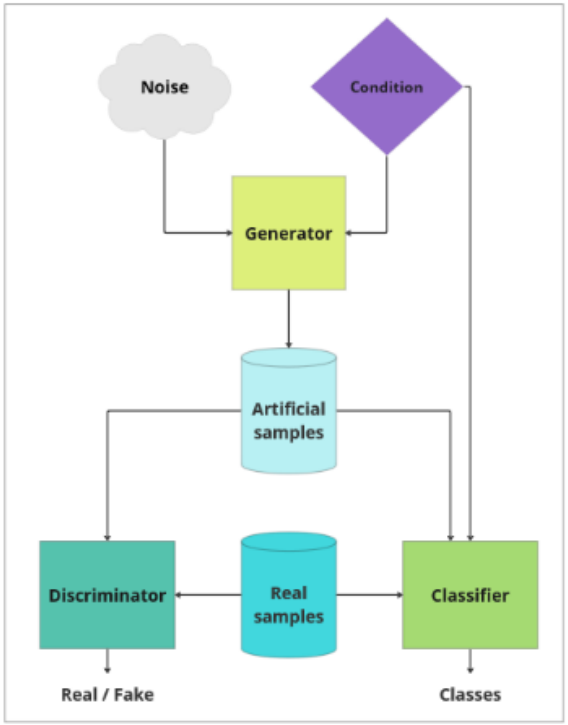


Fig. 3. Architecture of the WGAN

2. Proposed GWO-GAN-CNN Classifier

- Conceptually, this paper uses an adapted version of the WGAN which is composed of three distinct networks working together towards the same goal, i.e., creating virtual samples that closely resemble the authentic samples.
  - The generator has the goal of generating the virtual samples.
  - The discriminator receives as input both real samples from the training set and fake samples generated by the generator, and outputs the probability that each given sample is real or fake.
  - Lastly, the classifier network of the WGAN outputs the probability of each class.
- The used activation function in all the networks is Leaky ReLU with the input parameter set to 0.01 (i.e., the parameter which controls the angle of the negative slope) and the training is done using Gradient Penalty.

2. Proposed GWO-GAN-CNN Classifier

- The proposed model is then optimized using GWO.
- The objective function which has to be minimized is the loss function of the WGAN, which was specifically chosen as an overall loss being the weighted sum of the generator loss and the classifier loss of the WGAN model.
- GWO tries to optimize three main parameters of the WGAN:
  - **Learning rate**
  - **Number of neurons in the hidden layers**
  - **Batch size.**

2. Proposed GWO-GAN-CNN Classifier

- Firstly, the wolves population is initialized by associating to each wolf a position vector defined as $\overrightarrow{X_p}$ = [learning rate, number of neurons in the hidden layers, batch size].
- GWO works by updating iteratively the position of each wolf based on the objective function and evaluating the objective function.
- After the defined number of iterations has elapsed, the best solution found is returned, i.e., the best architecture of the GAN model.
- After the best architectures has been found, it is used to generate the artificial samples which would then be used for the training of the deep CNN model.

3. Experimental Results

a) Experimental Configuration

- Three distinct classifiers have been evaluated using the metric **overall accuracy**:

1. The standalone Deep-CNN using 5% of the original dataset as training set and the rest for testing (Deep-CNN)
2. Deep-CNN augmented model with standard WGAN is tested, using a varying number virtual pixels for the training (WGAN-CNN)
3. The proposed model is tested using the same principles as described in the regular WGAN-CNN model, but the augmented sets were generated with an optimized WGAN with GWO (GWO-WGAN-CNN).

3. Experimental Results

b) Indian Pines dataset

- The Indian Pines dataset was acquired using the AVIRIS sensor.
- It is a hyperspectral image of 145x145 pixels, with 200 spectral bands. The ground truth is categorized into sixteen classes.

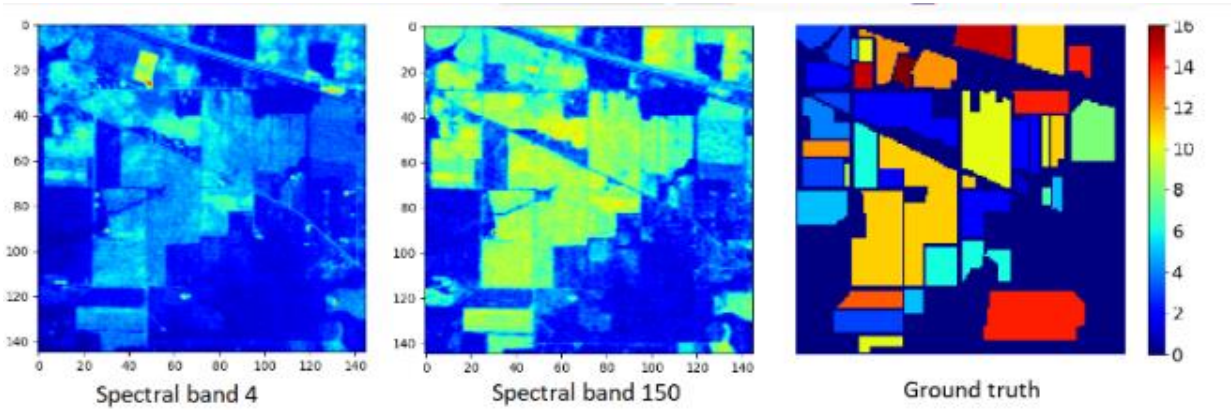


Fig. 4. Visualization of two spectral bands and the ground truth of the Indian Pines dataset.

3. Experimental Results
b) Indian Pines dataset

Table I. Accuracy results for Indian Pines Dataset

Classifier type with 5% authentic samples in the training set (461 original pixels in the training set)	**Overall Accuracy [%]**
CNN	77.08
WGAN-CNN augmented with 4380 virtual pixels	79.20
WGAN-CNN augmented with 8759 virtual pixels	80.13
GWO-WGAN-CNN augmented with 4380 virtual pixels	81.34
GWO-WGAN-CNN augmented with 8759 virtual pixels	83.19

3. Experimental Results
b) Indian Pines dataset

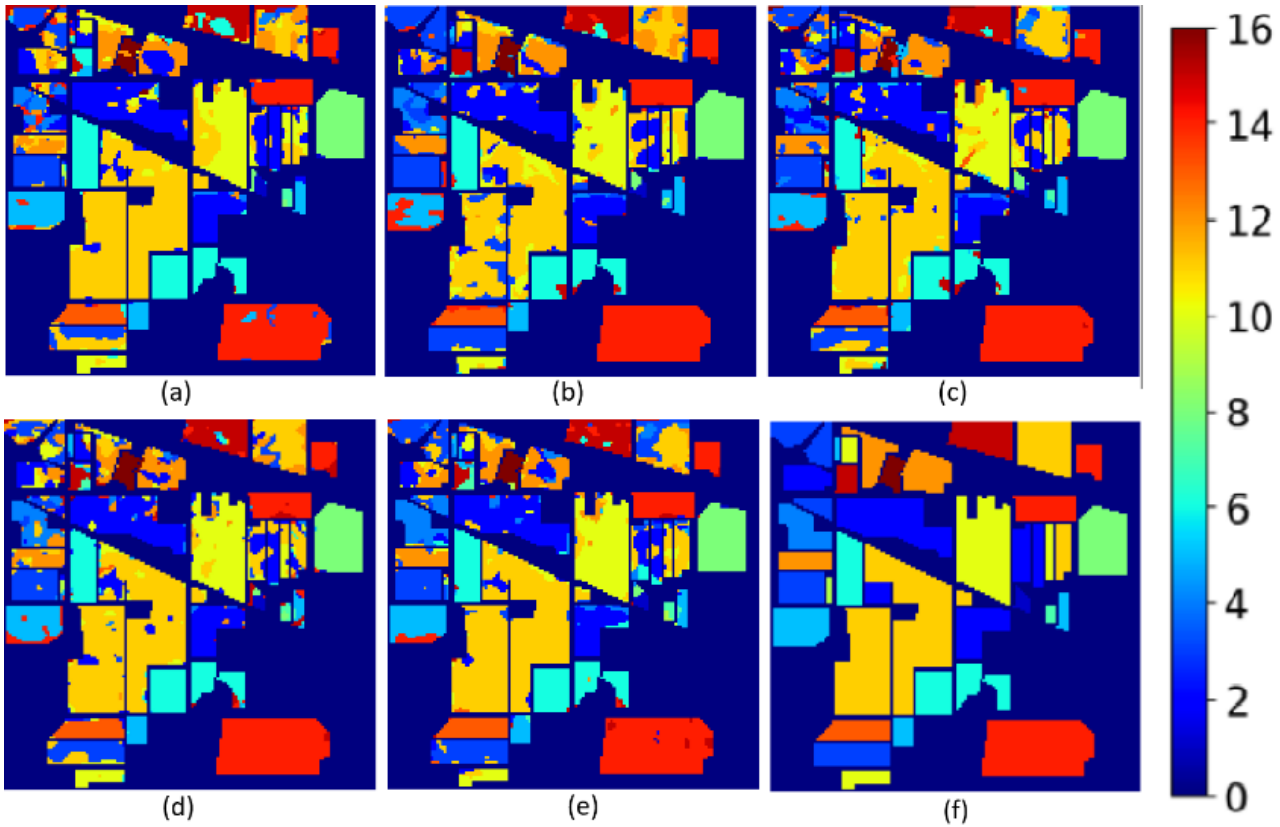


Fig. 5. Indian Pines: (a) CNN, (b) WGAN-CNN with initial virtual pixels, (c) WGAN-CNN with extended number of virtual pixels, (d) GWO-WGAN-CNN with initial virtual pixels, (e) GWO-WGAN-CNN with extended number of virtual pixels, (f) ground truth

3. Experimental Results

c) Pavia University dataset

- The Pavia University dataset was captured using the ROSIS sensor.
- An image has the size of 610x340 pixels and it has 103 spectral bands.
- The dataset is labeled in 9 distinct classes, as referenced in.

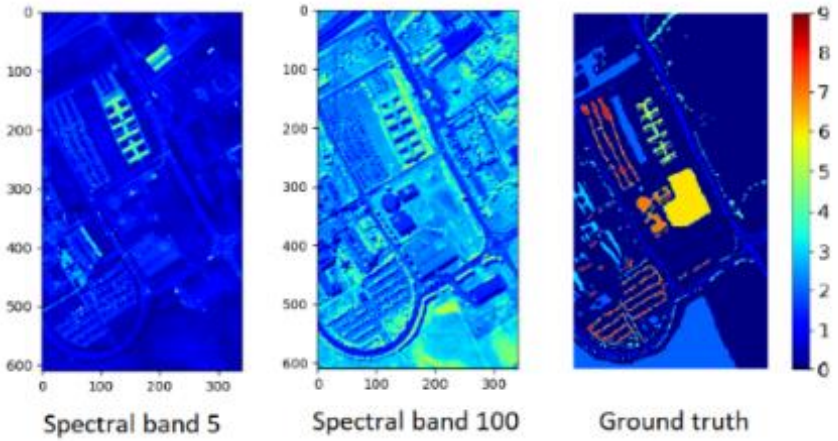


Fig. 6. Visualization of two spectral bands and the ground truth of the Pavia University dataset.

3. Experimental Results
c) Pavia University dataset

Table II. Accuracy results for Pavia University Dataset

Classifier type with 5% authentic samples in the training set (1925 original pixels in the training set)	**Overall accuracy [%]**
CNN	88.85
WGAN-CNN augmented with 18288 virtual pixels	93.84
WGAN-CNN augmented with 36576 virtual pixels	93.06
WGO-WGAN-CNN augmented with 18288 virtual pixels	94.13
WGO-WGAN-CNN augmented with 36576 virtual pixels	96.37

3. Experimental Results

c) Pavia University dataset

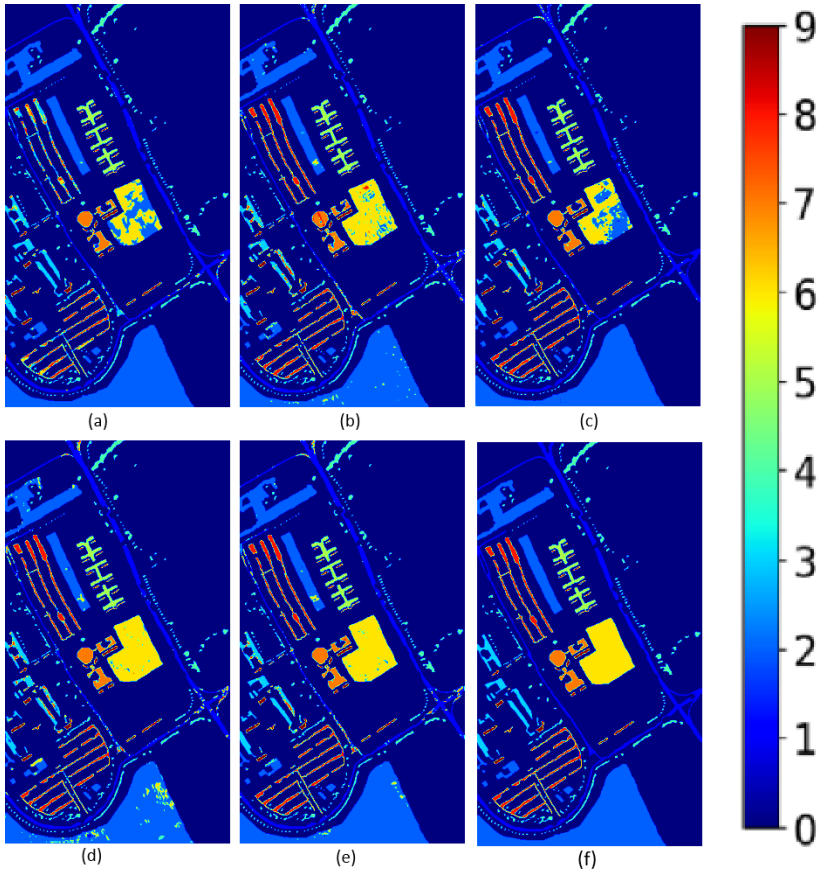


Fig. 7. Pavia University: (a) CNN, (b) WGAN-CNN with initial virtual pixels, (c) WGAN-CNN with extended number of virtual pixels, (d) GWO-WGAN-CNN with initial virtual pixels, (e) GWO-WGAN-CNN with extended number of virtual pixels, (f) ground truth

3. Experimental Results

d) Salinas dataset

- Salinas dataset was collected using the AVIRIS sensor.
- It consists of 512x217 spectral samples.
- There are 204 spectral bands in this dataset.

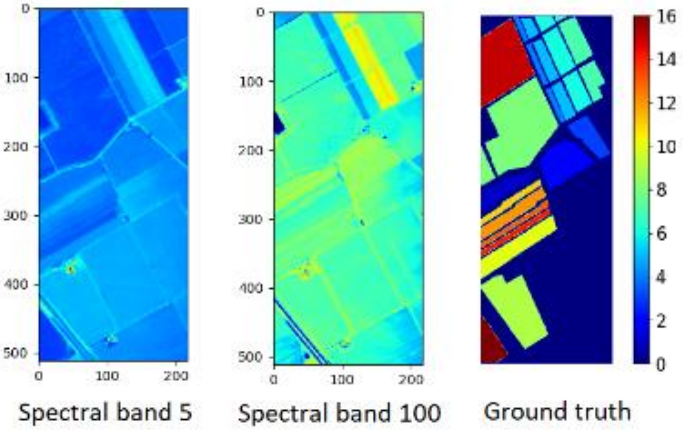


Fig. 8. Visualization of two spectral bands and the ground truth of the Salinas dataset.

3. Experimental Results
d) Salinas dataset

Table III. Accuracy results for Salinas Dataset

Classifier type with 5% authentic samples in the training set (2435 original pixels in training set)	**Overall Accuracy [%]**
CNN	91.17
WGAN-CNN augmented with 23132 virtual pixels	90.87
WGAN-CNN augmented with 46264 virtual pixels	91.19
WGO-WGAN-CNN augmented with 23132 virtual pixels	93.33
WGO-WGAN-CNN augmented with 46264 virtual pixels	93.39

3. Experimental Results

d) Salinas dataset

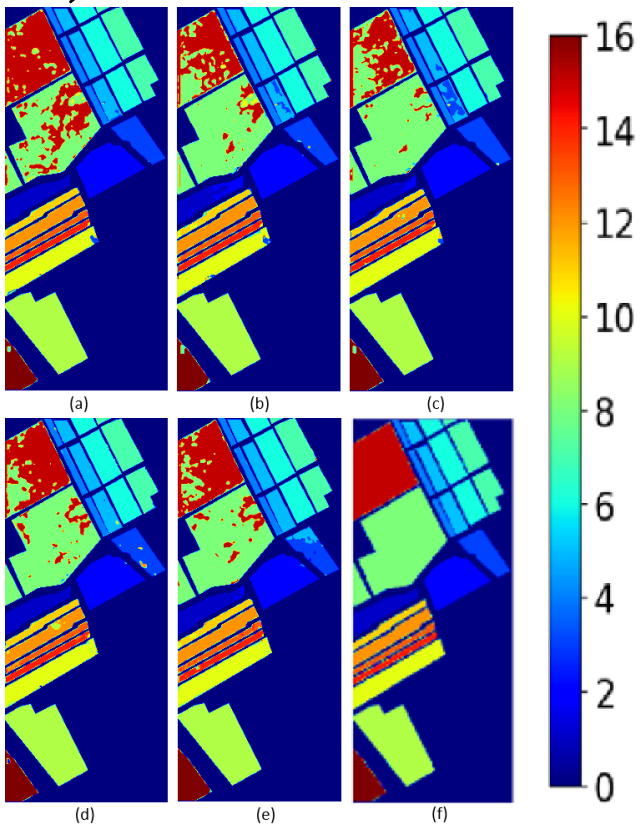


Fig. 9. Salinas: (a) CNN, (b) WGAN-CNN with initial virtual pixels, (c) WGAN-CNN with extended number of virtual pixels, (d) GWO-WGAN-CNN with initial virtual pixels, (e) GWO-WGAN-CNN with extended number of virtual pixels, (f) ground truth

4. Conclusions

- This paper proposes a novel method of generating artificial samples for improving the training of a deep CNN by optimizing a WGAN with GWO.
- The conducted experiments have shown a significant improvement in the accuracy of the classifiers by adding the artificial samples generated by the optimized WGAN to the original training set.
- The presented approach proves two main points in dealing with HSI and deep learning models.
    1. Data augmentation is clearly a suitable approach for improving the performances of the models.
    2. It proves the capabilities of GWO in solving optimization problems aimed at refining deep-learning models.

4. Conclusions

- The time complexity represents a limitation of this approach.
- WGAN models have rather complex architecture and the handling of such models would require in most of the cases specialized hardware, such as graphical processing units designed for deep learning models.
- Future work could focus on optimizing even more of parameters of the WGAN and exploring ways to apply the proposed algorithm to other classification problems.

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THANK YOU!