IRX-1D: A Simple Deep Learning Architecture for Remote Sensing Classifications

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Abstract: This study proposes a simple deep learning architecture combining elements of Inception, ResNet and Xception networks. Four new datasets were used for classification with both small and large training samples. Results in terms of classification accuracy suggests improved performance by proposed architecture in comparison to Bayesian optimised 2D-CNN. Comparison of results using small training sample with Indiana Pines hyperspectral dataset suggests comparable or better performance by proposed architecture than the reported works. In spite of achieving high classification accuracy with limited training samples, comparison of classified image suggests different land cover class is assigned to same area when compared with the classified image provided by the model trained with large training samples with all datasets.

1. Introduction

Image classification is one of the important techniques to extract information from remote sensing data. Through image classification process, each pixel or a patch of pixels is assigned to a land cover class on the basis of their spectral, spatial and spatial-spectral characteristics (Benediktsson and Ghamisi, 2015). With the availability of remote sensing data at different resolution having fewer to hundreds of wavebands through a constellation of satellites, demand of rapid and accurate classification is increasing. Developments in machine learning tools have led to development of techniques to efficiently classify remote sensing images almost in real time. Since 2000, classifiers like support vector machines ((SVM; Vapnik, 1995) and random forest ((Breiman, 2002) becomes popular for remote sensing classifications due to increased classification accuracy and requiring smaller computational cost and fewer hyper-parameters in comparison to extensively used neural network. In spite of their extensive use, these classifiers were using the spectral information without giving any consideration to spatial information surrounding the individual pixels. Research in the area of spatial-spectral classification of remote sensing data (Ghamisi et al, 2018) suggest the usefulness of spatial/contextual information in terms of reduced uncertainty in pixel labeling leading to a reduced salt and pepper noise in the classified image. However, use of spatial-spectral classifiers have shortcomings due to the reason that the derived features were mainly based on prior knowledge and may not be correctly describing complex changes in land cover (Song et al., 2019).

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With the introduction of deep learning (DL) algorithms during last decade, remote sensing community started using these algorithms for land cover classification studies due to their capabilities to derive higher level of spatial information through feature extraction from image patches (Zhu et al., 2017; Li et al., 2018; Song et al., 2019; Gu et al., 2019; Ma et al., 2019). Out of different DL algorithms proposed in literature, CNN based network architectures are found to be most powerful due to their computational efficiency and ability to recognize the patterns in the images (Krizhevsky et al., 2012). The use of 2D and 3D-CNN has extensively been used with remotely sensed images because of their ability to extract spatial-spectral features thus achieving improved classification accuracy within last few years (Chen et al., 2014, Hu et al. 2015; Cheng et al., 2016; Nataliia et al., 2017; Weng et al., 2017; Ying, Zhang and Shen, 2017; Paoletti et al., 2018; Cheng et al., 2018; Shunping et al., 2018; Zhong et al., 2019; Gu, Wang, and Li, 2019; Roy et al., 2019; Paoletti et al., 2019; Audebert, Le Saux and Lefèvre, 2019; Guandong et al., 2020; Qin et al, 2020; Li, Liang, and Wang, 2020; Li et al., 2020; Cao et al., 2020; Zhang, Yue and Qin, 2020; Huang and Chen, 2020; Cao and Guo, 2020; Ahmad, 2020; Hu et al., 2020). Most of the research work on the use of CNN based classifiers for land cover classification reported so far deals in proposing algorithms that improves classification accuracy using standard datasets. Comparison of results of CNN based DL classifiers especially with standard hyperspectral datasets suggests wide variation in classification accuracy by different deep learning architectures (Paoletti et al., 2019).

Keeping in view of extensive use of deep learning algorithms in classification of hyperspectral data, this study proposes a new architecture by combining components of some of the popular existing architectures. The other objectives of this study includes: (1) using four new remote sensing datasets (2 multi and two hyperspectral) for classification with proposed DL architecture (2) using large and small training samples so as to compare the performance and suitability of proposed architectures for remote sensing classifications (3) comparing performance of proposed architectures in terms of classification accuracy and trainable parameters with all four datasets and (4) classifying standard Indian Pines hyperspectral dataset using proposed architecture with limited training samples and comparing its performance with reported work so far.

2. Convolution neural network (CNN)

CNN based deep learning algorithms are most widely used classification algorithms using remote sensing data within last decade (Song et. al., 2019). CNN consists of convolutional layers, pooling and fully connected layers as well as an output layer respectively (Michelucci, 2019). Convolution
layers uses convolution kernels on image patches of predefined size derived from remote sensing image. After convolution operation, the output of the convolution kernel is passed through an activation function to obtain convolved feature map. The feature map obtained from first convolution layer is inputted to subsequent convolutional layers after passing it to a pooling layer. A pooling layer is normally used to reduce the spatial dimensionality of feature maps leading to a reduction in computation cost during network training. After passing through convolution and pooling layers, output of last pooling or convolution layer is flattened so as to pass it to fully connected layer. A fully connected layer may consist of several hidden layers each having a large number of neurons. Fully connected layer maps the input received by it into linearly separable space followed by the output layer which output the classification results using a function (e.g. softmax; Goodfellow, Bengio and Courville, 2016).

In this study, we propose a simple architecture combining components of three well known deep learning algorithms including Inception (Szegedy et al. 2015), ResNet (He et al. 2015) and Xception (Chollet, 2017) to classify remote sensing images especially with limited training samples.

2.1 Inception Network

Inception network was proposed to avoid the problem of overfitting in popular CNN based architectures and to achieve better performance using deep stacked convolution layers (Szegedy et al. 2015). This architecture uses filters of varying sizes working with same convolution layer to extract the information and then concatenate these features to be fed to further layers. This way network becomes wider in place of deeper. Original inception network, used for ImageNet dataset was very deep. Keeping in view of the limited number of land cover classes and the computational resources, size of this network was modified in present study. The Inception Module of the modified network consists of four parallel paths as described below:

- 1*1 convolution on input (say f1 filters)
- 1*1 convolution followed by 3*3 convolution on input (say f2 and f3 filters)
- 1*1 convolution followed by 5*5 convolution on input (say f4 and f5 filters)
- Maxpool followed by 1*1 convolution (say f6 filters)

An inception module is described as = \{(f1), (f2, f3), (f4, f5), (f6)\} (Figure 1).
2.2 Residual Network (ResNet)

To improve the performance of deep neural networks, several studies suggested using large number of layers (Simonyan and Zisserman, 2015; Szegedy et al., 2015) considering depth of network as of crucial importance. On the other hand, studies by He and Sun (2015) and Srivastava, Greff, and Schmidhuber (2015) suggested that increasing depth of the network forces classification accuracy to saturate followed by degradation. To overcome the problem of accuracy degradation using very deep neural networks, He et al. (2016) proposed a deep residual learning framework called as ResNet. This network used skip connections in a network, whereas skip connection is additional connection between two layers, skipping two or more layers in-between. Residual blocks are the building blocks of ResNet and are of two types, I) convolution block and II) Identity block. An identity block is used to keep output shape same as input whereas a convolution block is used to change the output shape. Figure 2 provide details of residual blocks used in ResNet architecture.

2.3 Xception

Normally a convolution layer works by learning filter in 3D space, with 2 spatial and 1 channel (i.e. band) dimension. This process forces a convolution kernel to work simultaneously for mapping cross-channel and spatial correlations. Xception (Chollet, 2017) is a convolution neural network architecture working on depthwise separable convolution layers. In this architecture, mapping of cross-channels and spatial correlations in the feature maps of convolution neural networks is completely disassociated. Xception uses depthwise convolutions followed by pointwise convolutions, thus reducing the size of the network (in terms of numbers of parameters). An Xception block consists of two parallel paths as described below:

- Separable block of $f_1$ filters followed by separable block of $f_2$ filters
• 1*1 convolutions (pointwise convolution) of f2 filters followed by batch normalization

An Xception block is described by (f1, f2). Architecture of Xception block used in this study is provided in Figure 3.

Figure 2. Residual Blocks used with ResNet (a) Identity Block and (b) Convolutional Block

Figure 3. Structure of (a) Conv Block (b) Separable Block (c) Middle Flow Block and (d) Xception Block used in this study.

2.4 Proposed Architecture

Deep learning architectures discussed in sections 2.1-2.3 are large in size and requires high computational resources during training. To overcome the problem of computational resources and the availability of limited training samples for remote sensing classifications, we propose an
architecture expected to perform well with remote sensing data using limited training samples and have few parameters during training. Following strategy was adopted to choose the proposed architecture:

- Fundamental building blocks of three architectures including Inception, ResNet and Xception are used only once with all datasets and named as I, R, X (IRX model).
- Different combinations of kernel sizes were tried to fine-tune IRX model for different datasets used for classification in this study.
- A kernel size of 1 was used throughout with Inception, ResNet and Xception blocks and used with IRX model after different trials.
- Kernel size of 1 (1×1 filter) will have a single weight for each band and does not use any neighboring pixels of the input image and results in a single output value. Keeping this in view, it may be considered as a linear weighting of the input. A convolutional layer with a 1×1 filter can effectively be used to control the number of feature maps and helps in reducing no of parameters in the model. Throughout this study, this model is referred as IRX-1D. Further details of this model are provided in figure 4 and table 1.

![Fig 4. Structure of IRX-1D architecture](image)

| Parameters                           | Details                      |
|---------------------------------------|------------------------------|
| Convolution Filters in Inception Module | {(64), (64, 64), (64, 64, 64)} |
| Convolution Filters in Identity Block  | 64, 64, 256                  |
| Convolution Filters in Xception Block | 64, 64, 64                   |
| Convolution Filters in Separable Block| 64                           |
| Convolution kernel size used throughout | 1                            |
| Fully connected units with output layer | 128, 64, No of Classes       |
3. Dataset and Methodology

To study the performance of proposed deep learning architectures for remote sensing classifications four remote sensing datasets (two multispectral: ETM+ & Sentinel 2 and two hyperspectral: DAIS & AVIRIS-NG) covering different regions were used in this study.

1. AVIRIS-NG hyperspectral data used in this study was acquired on 8 February, 2016 through an aerial campaign over Anand district in Gujarat, Ahmedabad (India). The area covers the research farms of Anand Agricultural University with wheat, maize, sorghum, amaranthus, mustard, chickpeas, lucerne, brinjal, fennel, bare soil, built-up-area, tobacco, and plantation as main land cover types. For AVIRIS-NG sensor, data was collected in 425 wavebands covering 0.35 to 2.5 μm range. A total of 13 classes were used to classify the AVIRIS-NG data. Out of total 425 bands, bands: 1-5,196-207, 285-320 was removed due to stripping problem in reflectance data. Thus, a total of 372 bands covering a study area of size 1101 rows and 566 columns were used for classification (Figure 5(a)). Field visit was carried out on the same day image was acquired and used to prepare reference image (Figure 6(a)).

2. Second hypersepcetral data was acquired using DAIS 7915 instrument through an airborne campaign on 29th June 2000 covering La Mancha Alta region south of Madrid, Spain (Figure 5(a)). The area in Spain is Mediterranean semi-arid wetland, which supports rain-fed cultivation of wheat and barley and other crops such as vines and olives. This instrument has a spatial resolution of 5 m and operates in the wavelength range 0.4 μm to 12.5 μm. Bands 1 – 72, covering the optical region of the spectrum were used in this study. The data in these bands show moderate to severe striping problems, especially in the near-infrared region (bands 41 – 72). Bands that were most severely affected by striping were identified by visual inspection. As a result, seven bands with severe striping problems (bands 41, 42 and 68 to 72) were removed from the data set. Striping in the remaining 65 bands was reduced using a Fourier-based filtering technique. It was not possible to collect information on land cover types at the time of DAIS overflights. Field observations were undertaken in late June 2001, exactly one year after the image data were acquired, to generate a reference data set. Only those land cover types that were most likely to have remained unaltered since the previous year was used. The use of ground reference data collected one year after the date of image acquisition was justified on the grounds that, in an area of Mediterranean climate, the weather patterns and soil conditions tend to be very similar from one year to the next (Figure 6(b)).
3. ETM+ multispectral data was acquired over an agricultural area near Littleport in Cambridgeshire, UK. Land cover classification includes seven land cover types, namely, wheat, sugar beet, potato, onion, peas, lettuce and beans. The dataset was acquired on 19 June 2000 and image of the size of 330 rows and 307 columns at 30m spatial resolution was used for final classification (Figure 5(c)). A field visit was carried out to generate reference image of the study area (Figure 6(c)).

4. Another multispectral dataset covering Central State farm in Hissar, Haryana (India) and acquired using Sentinel 2 satellite was used. It comprises of agricultural farmland in which various seasonal crops (winter and summer) are grown (Figure 5(d)). The dataset was acquired on 8th March 2020 and a filed visit was carried out on 13 March 2020. The image of the size of 722 columns and 1014 rows at 10 m spatial resolution were used for final classification in eight land cover classes namely: wheat, barley, lentil, gram, mustard, Oat, peas and non-agricultural area (Figure 6(d)).

For all classifications with IRX-1D using above four datasets, ReLU activation function, Adamgrad optimizer with learning rate of 0.01 and 100 epochs were used. All the experiments were performed on Google Colab. Google Colab is an online platform that provides the facility to run the Jupyter notebook codes with Graphical Processing Unit (GPU), 25 GB of Random Access Memory (RAM) (Carneiro et al., 2018). Computational cost of running this architecture on Google Colab was found to vary for same image patch and training sample size, a reason training time of the architecture is not provided. For all training and testing, entire samples were divided randomly in training and testing datasets of varying sizes in a way that same samples are selected for each trial, if more than one trial is carried out.

4. Results
Different classifications were carried out using the proposed deep learning architecture. Classifications includes six randomly selected training sample sizes (i.e. 5%, 10%, 15%, 25%, 50% and 75%) with all datasets. Further, three different image patch sizes (3, 5 and 7) were also used during classification with different percentage of training samples. Choice of smaller patch size is necessitated by the fact that a large patch size is found to deteriorate the quality of classified images, which is a major output required for different research areas and administrative decisions for correct area calculations of different land cover classes. Table 2 provide classification accuracies and kappa values obtained by proposed deep learning architecture with varying percentage of training samples using different image path sizes. Results from Table 2 suggest encouraging performance by the proposed architecture in terms of classification accuracy. Comparison of classification accuracies
achieved with different datasets using image patch size of 3, 5 and 7 suggests an increase in classification accuracy with increasing patch size. Further, results with increasing training sample size also suggest a continuous increase in classification accuracy will all four remote sensing datasets. To compare the performance of proposed architecture in terms of number of parameters and size, an image patch size of 7 was used (Table 3). Results from Table 3 indicates requirement of smaller number of parameters with small model size by the proposed architecture.

Figure 5: Image of different study areas using (a) AVIRIS-NG, (b) DAIS (c) ETM+ and (d) Sentinel 2 sensors
4.1. Comparison with 2D-CNN

To compare the performance of IRX-1D architecture using limited training samples, an optimized 2D-CNN based deep learning architectures was used. For all datasets, Bayesian approach was used to tune the hyper parameters of 2D-CNN based deep learning architectures using 10% training samples only. The Bayesian optimization approach use Bayes’ rule to find the minimum or
maximum of an objective function within a bounded set of solutions (Snoek, Larochelle and Adams, 2012).

Table 2. Overall classification accuracy with IRX-1D architecture with all datasets using different training samples. (a) image patch size=3, (b) image patch size =5, and (c) image path size=7. Values in bracket represents kappa value.

### Table 2(a)

| Data     | 5%            | 10%            | Training samples | 15%            | 25%            | 50%            | 75%            |
|----------|----------------|----------------|------------------|----------------|----------------|----------------|----------------|
| AVIRIS-NG| 96.37(0.959)   | 97.49(0.972)   | 97.68(0.974)     | 99.20(0.991)   | 99.24(0.991)   | 99.80(0.998)   |
| DAIS     | 96.33(0.956)   | 97.91(0.972)   | 98.65(0.984)     | 98.9(0.987)    | 99.71 (0.997)  | 99.87 (0.998)  |
| ETM+     | 93.59(0.913)   | 95.71(0.942)   | 96.37(0.951)     | 96.99(0.959)   | 98.50(0.980)   | 98.52 (0.980)  |
| Sentinel 2| 87.94(0.844)   | 89.75(0.869)   | 92.99(0.909)     | 94.23 (0.925)  | 95.93(0.947)   | 96.02 (0.949)  |

### Table 2(b)

| Data     | 5%            | 10%            | Training samples | 15%            | 25%            | 50%            | 75%            |
|----------|----------------|----------------|------------------|----------------|----------------|----------------|----------------|
| AVIRIS-NG| 97.51(0.972)   | 98.58(0.984)   | 98.74(0.986)     | 99.44(0.994)   | 99.95(0.999)   | 100 (1.00)     |
| DAIS     | 97.30 (0.967)  | 98.61 (0.983)  | 99.22(0.991)     | 99.72(0.997)   | 99.92 (0.999)  | 99.96 (0.999)  |
| ETM+     | 94.78(0.929)   | 96.95(0.959)   | 97.74(0.969)     | 98.58(0.981)   | 99.45(0.993)   | 99.79 (0.997)  |
| Sentinel 2| 92.96(0.909)   | 94.21(0.925)   | 95.81(0.946)     | 97.19(0.964)   | 98.59 (0.982)  | 99.53 (0.994)  |

### Table 2(c)

| Data     | 5%            | 10%            | Training samples | 15%            | 25%            | 50%            | 75%            |
|----------|----------------|----------------|------------------|----------------|----------------|----------------|----------------|
| AVIRIS-NG| 98.16 (0.979)  | 99.49 (0.994)  | 99.53 (0.995)    | 99.81 (0.998)  | 100 (1.0)      | 100 (1.0)      |
| DAIS     | 98.45 (0.981)  | 99.30 (0.992)  | 99.63 (0.996)    | 99.82 (0.998)  | 99.97 (0.999)  | 99.99 (0.999)  |
| ETM+     | 95.99 (0.946)  | 97.20 (0.961)  | 98.19 (0.975)    | 99.00 (0.987)  | 99.64 (0.996)  | 99.77 (0.997)  |
| Sentinel 2| 94.17 (0.925)  | 96.83 (0.959)  | 97.67 (0.969)    | 99.10 (0.988)  | 99.30(0.991)   | 99.91 (0.999)  |
Table 3. Comparison of number of parameters and size of IRX-1D model with different dataset (image patch size of 7).

| Dataset     | No of Parameters (x1000) | Size of model weight file (MB) |
|-------------|--------------------------|-------------------------------|
| AVIRIS-NG   | 202.400                  | 1.825                         |
| DAIS        | 123.464                  | 1.190                         |
| ETM+        | 108.295                  | 1.070                         |
| Sentinel 2  | 107.848                  | 1.070                         |

In comparison to grid search method, the Bayesian algorithm obtains an optimal set of solutions with less iteration and computational resources (Lu et al., 2019). In order to restrict the computational cost, limited range of different hyper-parameters were considered (Table 4) during Bayesian optimization of CNN based DL architecture. Only 50 trials of combinations of different hyper-parameters and 100 epochs were used to obtain their optimal values (Table 5).

Table 4. Hyper parameters values used during Bayesian optimization of CNN based DL architecture

| Hyperparameter          | Minimum number | Maximum number | Minimum value | Maximum value | step |
|-------------------------|----------------|----------------|--------------|--------------|------|
| Convolution layer number| 2              | 5              | 100 channels | 600 channels | 100  |
| Kernel size             | 3              | 5              | -            | -            | 2    |
| Pooling kernel size     | 2              | 3              | -            | -            | 1    |
| Pooling type            | Max pooling and Average pooling | 1 throughout | 0.01 and 0.001 |          |      |
| Learning rate           | 2              | 3              | 50           | 200          | 50   |
| Fully connected layer   |                |                |              |              |      |

Table 5 provides results in terms of classification accuracy and the optimal values of hyper-parameters for 2D-CNN based deep learning architectures using different datasets. Results from tables 2 and 5
indicates improved performance by the proposed IRX-1D architecture in terms of both classification accuracy and number of parameters used by the network architecture.

Table 5. Results in terms of classification accuracy and number of parameters with optimized 2D-CNN using image patch size of 7.

| Data      | Optimal Parameters                                                                 | Accuracy(%) (Kappa value) | Number of parameters (x1000) |
|-----------|-------------------------------------------------------------------------------------|----------------------------|-------------------------------|
| AVIRIS-NG | 2 convolution layers: First convolution layer with 100 filters of the size 5x5, followed by average pooling with 3x3 filter, second convolution layer with 600 filters of the size 3x3 followed by max pooling with 3x3 filter, 2 fully connected layers (200, 200), learning rate = 0.01, stride=1, Epochs=1000 | 94.96(0.943)              | 2593.713                     |
| DAIS      | 3 convolution layers: First convolution layer with 600 filters of the size 3x3, followed by max pooling with 3x3 filter, second convolution layer with 300 filters of the size 5x5 followed by max pooling with 3x3 filter, third convolution layer with 100 filters of the size 3x3 followed by max pooling with 3x3 filter, 2 fully connected layers (200, 50), learning rate = 0.01, stride=1, Epochs=1000 | 98.86(0.986)              | 5212.658                     |
| ETM+      | 2 convolution layers: First convolution layer with 600 filters of the size 3x3, followed by max pooling with 2x2 filter, second convolution layer with 100 filters of the size 5x5 followed by max pooling with 3x3 filter, 3 fully connected layers (200, 200, 50), learning rate = 0.01, stride=1, Epochs=1000 | 95.21 (0.935)             | 2563.907                     |
| Sentinel 2| 2 convolution layers: First convolution layer with 600 filters of the size 3x3, followed by max pooling with 3x3 filter, second convolution layer with 600 filters of the size 5x5 followed by max pooling with 2x2 filter, 2 fully connected layers (200, 50), learning rate = 0.01, stride=1, Epochs=1000 | 92.10(0.897)              | 9513.458                     |

4.2. Effect of image patch size on IRX-1D

To study the effect of image patch size on the performance of proposed IRX-1D architecture in terms of classification accuracy, image patch size was varied from 3 to 15 with 10% training sample size using all datasets. Figure 7 provide a plot between image patch size and classification accuracy. Results from Figure 7 suggest that classification accuracy starts declining with increasing patch size when proposed architecture is used with multispectral datasets whereas the accuracy with hyperspectral datasets almost increases continuously.
4.3. Comparison of Classified images

Keeping in view of improved performance by proposed IRX-1D architecture, classified images obtained using a patch size of 7 and 10% training samples are provided in Figure 8. Results from table 2(c) indicate increased classification accuracy with increasing training sample size. In order to judge the influence of increasing samples size on the quality of classified images, classified images obtained using AVIRIS-NG and ETM+ data with 10% and 75% training samples were compared (Figure 9). Comparison of classified images suggests different areas are being classified to different classes (e.g. black boxes on all images) when different sample size was used to train the model. This kind of over/under representation of class areas in classified images obtained using different training sample sizes may lead to wrong information about acreage under different land cover classes., This may lead to providing misleading information for studies using land cover data as an input, crop damage insurance cover, the subsidies to farmers, as well as the calculation of total volume of various produces when used over large area image classifications.
Figure 8. Classified images of (a) AVIRIS-NG (b) DAIS (c) ETM+ and (d) Sentinel 2 data using proposed IRX-1D architecture and 10% training samples.
5. Performance Comparison with Standard Hyperspectral Dataset

To judge the performance of proposed architecture with an independent standard dataset, hyperspectral image acquired over Indiana pines test site was used. This data was collected by AVIRIS airborne sensor and consists of 145 x 145 pixels and 220 spectral bands covering the wavelength range of 0.4–2.5 μm. The ground truth image consists of sixteen land cover classes. For classification of this dataset using 10% of training sample size, a patch size of 9 and 250 epochs were used. Other
parameters used were same as with the datasets used is section 3. It was observed that training error was not stabilizing using 100 epochs with Indian pines dataset, a reason of using 250 epochs. Nine different architecture using 10% training sample sizes as proposed in literatures were compared with the proposed architecture (Table 5). Comparison of results in terms of classification accuracy with different architectures suggests either improved or comparable performance by proposed IRX-1D architecture.

Table 6. Classification accuracy with Indian pines dataset using different DL architectures with 10% training samples. PS mean image patch size used with CNN.

| Classification approach                                           | Accuracy with 10% training samples (%) |
|-------------------------------------------------------------------|----------------------------------------|
| LiteDenseNet (Li and Duan, 2020)                                  | 98.27 (PS=9)                           |
| HybridSN (Roy et al., 2019)                                      | 98.39 (PS=25)                          |
| R-VCANet (Pan, Shi, and Xu, 2017)                                | 97.90                                  |
| SSCL3DNN (Hu et al., 2020)                                       | 98.79 (PS=27)                          |
| SSCL2DNN (Hu et al., 2020)                                       | 97.72 (PS=27)                          |
| Sequential Joint Deeping Learning Model (Wang, Zou, and Cai,2020) | 83.29                                  |
| 2D-3D CNN (Yu et al., 2020)                                      | 98.33 (PS=19)                          |
| Hybrid 1D, 2D and 3D CNN (Li, Liang and Wang, 2020)              | 98.22 (PS=21)                          |
| Fast 3D-CNN (Ahmad, 2020)                                        | 97.75 (PS=11)                          |
| Proposed IRX-1D                                                   | **98.85 (PS=9)**                       |
| Total params: 163,664                                            |                                        |
| Model weight file=1 MB                                            |                                        |

To judge the influence of training samples size on the quality of classified images, classified images obtained using Indian pines hyperspectral datasets with 10% and 75% training samples were also compared (Figure 10). Comparison of classification accuracy (i.e. 98.85% with 10% training samples and 99.96% with 75% training samples) suggest improved performance with increasing training sample size but a comparison of classified images suggests different areas are being classified to different classes (e.g. black boxes on both classified images) when different sample size was used to train the model with this dataset also. Thus the need of a careful approach in using classified images with different training sample sizes as an input for different studies.
5. Conclusions

In this work, we propose a novel CNN based DL architecture for classification of multispectral and hyperspectral images. The major conclusion of this work are as follows. First, results in terms of classification accuracy, number of parameters and the model size suggests improved performance by proposed architecture in comparison to optimized 2D-CNN for smaller training sample size. Second, the proposed network also found to behave in a different way with increasing image patch size with multispectral and hyperspectral datasets. The classification accuracy is found to improve with increasing size of training sample with all four datasets. Third, proposed architecture perform comparably well or better than the already suggested architectures in literature with Indian pines data sets when used with 10% training samples.
In spite of improved performance by proposed architecture in terms of classification accuracy with limited training sample size, comparison of classified image obtained by using 10% and 75% training samples suggests a wide variation in the area classified under different land cover classes, indicating the need of a cautious approach while training a network with limited training samples.

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