Hyperspectral Image Classification using Machine Learning Techniques

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Abstract

The recent advancement and popularities of remote sensing technology is increasing day by day. Due to thisthe uses of hyperspectral imaging is also gaining popularity. Feature classification of ground-truthfrom HSI is also a a popular research aspect and a great challenge whichactually attractsmoreresearch attention. In our research, a brief description on image classification models using SVM, with PCA, has been described. The study has been carried upon one common hyperspectral datasets i.e., Indian Pines which comprise various landscape fields like dense vegetation, barren land, grasslands, etc. For noisy band reduction, PCA has been used

Keywords—SVM, Remote sensing;Hyper-spectral imaging; Principal Component Analysis;

I. Introduction

Imaging is a one of the techniques to work with objects, distinguish them and to characterize the attributes to concentrate on how light collaborates with the article. Spectroscopy is a review that looks at how light acts in the objective and perceives materials dependent on their

ISSN- 2394-5125 VOL 09, ISSUE 02, 2022

distinctive otherworldly Signatures. A natural eye can see electromagnetic waves with frequencies somewhere in the range of 380 and 780 nano meters. Frequencies past this reach, for example, Infrared are undetectable to people and furthermore human has 3 shading receptors red, blue and green yet Hyperspectral Imaging is another scientific procedure dependent on spectroscopy that actions the consistent range of the light for every pixel of the scene with fine frequency goal, in the noticeable as well as in the close infrared [1][2]. HSI arrangement is an innovation to break down assortment of land cover in distantly detected hyperspectral pictures. With expanding request of remote detecting innovation additionally expanded the employments of HSI tremendously [3][12]. To Exact order of ground credits from HSI is a critical and a difficult examination region. [4]A Perfect arrangement precision is accomplished through many picture handling methods for the characterization of HIS [8].

II. PURPOSE

HIS not at all like other unearthly imaging methods, gathers and cycles the data from electromagnetic range. The objective of hyperspectral imaging is to acquire the range for every pixel in the picture of a scene, fully intent on discovering objects, distinguishing materials, or recognizing measures. Hyperspectral imaging (HSI) coordinates customary imaging and spectroscopy.And to get both spectral and spatial information from a selected sample. This technique is used to analyze the chemical composition of traces and produce their spatial distribution. HSI givesproper information for the detection, visualization, identification, age estimation in different domains. The non-destructive and significant features of HSI mark its suitability as an analytical tool for most of the domains [8].The recently developed technique of HSI acquisition is referred as snapshot techniques or single shot techniques.It collects the entirety of the hyperspectral data cube within a single integration of period.Although single shot is considered to be the acceptable future of HSI implementation. This technique is currently limited by combining lower spatial resolution and also it requires further improvement [12].

III. LITERATURE REVIEW

Remote sensing technology is constantly developing, which has greatly expanded the use of hyperspectral imaging. In the field of remote sensing, the classification of hyperspectral images (HSI) has become a hot topic. The unique properties of hyperspectral data make accurate categorization difficult. Deep learning has emerged as a potent feature extraction tool for effectively addressing nonlinear problems in recent years, and it is now widely used in a variety of image processing tasks. Various research has be done on Hyperspectral Image classification some are outlined here with. The most critical and significant step in Hyperspectral Image classification is the selection of the appropriate band and obtaining the appropriate result. In [1], SAE, DBN, CNN, RNN, and GAN are just a few of the deep models that are frequently used to classify HSIs. Then, for HSIs, it is concentrated on deep learning-based classification algorithms and gave a basic and complete description of the existing methods in a single framework. Spectral-feature networks, spatial-feature networks, and other deep networks were utilized in the HSI categorization. Network of spectral-spatial features, where each category extracts the feature that goes with it. It also compared and assessed the results of four classical machine learning-based methods and six deep learning-based

ISSN- 2394-5125 VOL 09, ISSUE 02, 2022

approaches used in HSI classification. The classification accuracies achieved by various methods show that deep learning-based approaches outperform traditional ML approaches in general, and the DFFN, which combines RL and feature fusion, achieves the best results. In [2], In contrast to traditional computer vision tasks that only look at the geographic context, the authors suggested method that can improve hyperspectral image categorization by using both geographical context and spectral correlation. For hyperspectral image classification, it recommends four novel deep learning models: 2-D convolutional neural network (2-D-CNN), 3-D-CNN, recurrent 2-D CNN (R-2-D-CNN), and recurrent 3-D-CNN (R-3-D-CNN). Six publicly available data sets were used to conduct rigorous studies. The experimental results confirm the superiority of the suggested deep learning models, particularly the R-3-D-CNN and R-2-D-CNN deep learning models when compared to other state-of-the-art methods. In [3], It is grouped into six primary topics: data fusion, unmixing, classification, target identification, physical parameter retrieval, and fast computation. We summarise the current state of the art in each topic, present examples, and point to future difficulties and research areas. In [4], The VNIR imaging spectrometer's design and construction are summarised, as well as a novel absorption band modelling method that was employed for data interpretation. We have demonstrated the utility of this methodology in distinguishing between goethite-hematite combinations and identifying non-Fe-bearing minerals in this way. Although this data is only of indirect help in the hunt for life in subsurface drill cores, it can provide essential background on the mineralogical environment.

In [6] [7], proposes a new supervised segmentation technique for remotely sensed hyperspectral image data that uses a Bayesian framework to incorporate spectral and spatial information. To better describe noise and highly mixed pixels, a multinomial logistic regression (MLR) approach is utilized to learn posterior probability distributions from spectral data using a subspace projection method. It has been demonstrated that this method accurately characterizes hyperspectral data in both the spectral and spatial domains.

In [8] In [9], The effectiveness of two feature extraction approaches is compared. The results may vary depending on the data source, but overall, Folded-PCA outperforms traditional PCA when it comes to extracting essential features from hyperspectral remote sensing photos. This is because Folded-PCA takes into account both global and local structures. As a result, Folded-PCA has proven to be both efficient and successful in extracting features from remote sensing photos. In [10,12-17], it discusses about supervised, unsupervised and semi-supervised classification for hyperspectral image data. classification purpose. Although the supervised and unsupervised categorization methods mentioned here have their own set of advantages, the application of each approach has its own set of constraints.

In [11], a Modified Fisher's Linear Discriminant Analysis (MFLDA) for hyperspectral remote sensing imagery dimension reduction is provided. Fisher's Linear Discriminant Analysis (FLDA) is base of designing an optimal transform that maximises the ratio of between-class to within-class scatter matrices so that the classes can be well distinguished in low-dimensional space. The Problem faced during training phase is lack of enough training samples and unknown information for all of the classes available so, the problem was assigned as a practical challenge to the system during implementation of MFLDA to hyperspectral pictures. As a result, the original FLDA has been changed to eliminate the need for training samples and

ISSN- 2394-5125 VOL 09, ISSUE 02, 2022

entire class knowledge. Only the desired class signatures are required by the MFLDA. The desired class information is well kept in the MFLDA-transformed data, and they can be easily segregated in the low-dimensional space, according to the classification result. In [12], this study proposes a sparse representation classification technique based on overcomplete representations to address the challenges of imprecise context information use for a hyperspectral image, sampling on super-pixels is used. This referenced paper's key contribution is that collaborative sampling on spatial and spectral in super-pixels harnesses implicit context information for test pixels, and the joint sparse optimal of sampling patches effectively integrates spectral and spatial structure information of HSI data points.

In [13], proposes a new framework for hyperspectral image classification based on multi-view nuclear norm PCA feature extraction and kernel ELM in this paper. To extract spatial information, multihypnosis prediction-based ridge regression is performed first. Second, nuclear norm-based PCA from multi-view is employed to simultaneously leverage spectral and spatial information without damaging spatial information. The findings of a real-world hyperspectral data experiment show that the suggested method outperforms existing supervised approaches currently in use.

In [17], it introduces a new clustering algorithm for hyperspectral pictures. It tries to address the following three challenges at the same time: 1) estimation of the class statistical characteristics; 2) identification of the best discriminative bands without needing the user to set their number a priori; and 3) estimation of the number of data classes describing the image under consideration. Both generated and real hyperspectral pictures were subjected to a thorough experimental investigation. In general, the collected findings suggest that, despite its fully unsupervised character, the proposed methodology can generate intriguing classification results. In [18], it focuses on applying multiple machine learning techniques such as SVM, RF, LR, KNN, and DT to classify the Indian Pines hyperspectral imagery dataset. PCA and MNF were used to reduce the number of unnecessary and noisy bands in the dataset. To determine the efficacy of the models, many performance indicators such as the confusion matrix, total accuracy, and training duration are taken into account. RF has the highest accuracy and the shortest time among all the models in the referenced research.

In [19], It presents a new RNN model for hyperspectral image classification based on the observation that hyperspectral pixels can be thought of as sequential data. In particular, it proposed Parametric Rectified Tanh (PRetanh), a novel developed activation function for RNN hyperspectral data processing that allows for relatively high learning rates without the risk of being trapped in the divergence.

In our research, a brief description on among different classification models i.e., SVM, with PCA, has been described. The study has been carried upon one common hyperspectral datasets i.e., Indian Pines which comprise various landscape fields like dense vegetation, barren land, grasslands, etc. For noisy band reduction, PCA have been used.

IV. METHODOLOGY

The systematic implementation of HSItechnique is represented in a sequence chart using the Principal Component analysis with Support Vector Machine as shown in Fig. 1 [13]. For

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HIS implementation using Indian Pines data set, with 224 spectral bands of unequal wavelengths are used.

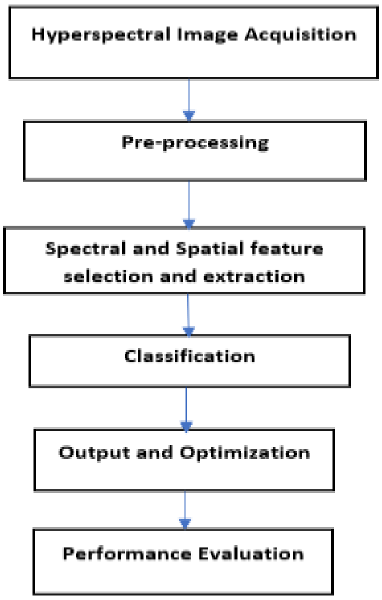

Fig. 1. Flowchart

V. EXPERIMENTAL SETUP

System design is the process or art of defining the architecture, components, modules, interfaces, and data for a system to satisfy specified requirements. One could see it as the application of systems theory to product development. There is some overlap and synergy with the disciplines of systems analysis, systems architecture, and systems engineering.This is the architecture that describes the Hyperspectral image classification process with a step by step representation.in Fig-2.

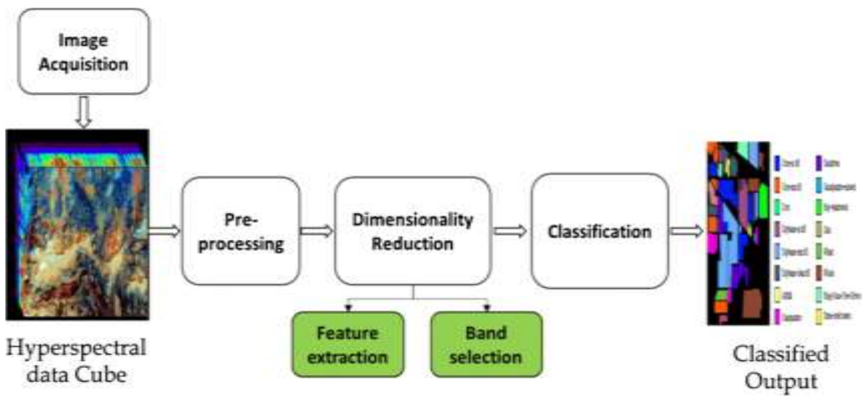

Fig. 2. Architecture

A. Dataset

We used Indian-pines dataset for the image classification. Indian Pines is the first dataset [4]. In Indian Pines dataset the data is taken by the AVIRIS spectrometer over the small area of North-Western Indiana, United States.The Image is the subset of the another image . The image consists of two-third agriculture land and one third forest, houses and roads.The dimensionality of the dataset is 145X145 pixels. It contains 145 rows, 145 columns, 16 classes, and 220 bands with the wavelength range from 400nm to 2500nm [4][8].

B. Pre-Processing

The pre-processing is one of the major part in the hyperspectral Image Classification because it shows significant impact based on the resultclassification.[4] The main aim is to select those spectral bands having the maximum variance value since the maximum variance gives more proper information, So in our work we have usedPCA to reduce the dimensionality of the used dataset by eliminating the noise in the dataset [4].

C. Feature-Selection

After completing the pre-processing phase of the dataset now it is required for the feature selection stage.In feature selection we mainly focuses on spectral signatures .In feature selection we find the reflectance values by selecting the pixel intensity values [4]. This can also be done using a simple calculation i.e by increasing the dimensions of the used dataset and we remain unchanged the ground-truth the bands because they all readily modified using PCA. The spectral information will be available as final result as 2-Dimensional or 1-Dimensional array.

VI. CLASSIFICATION

A. Support Vector Machine (SVM)

SVM are supervised learning techniques with related learning calculations fit for performing information order, relapse examination and exception discovery. It likewise performs direct arrangement, and can effectively play out a non-straight order utilizing kernel. In instance of nonlinear cases as of HIS Data is nonlinear. So, ordinary SVM technique can't fulfill the prerequisites of grouping. So to coordinate with the characterization prerequisites bit capacities are used [4][12]. In instance of bit work It changes over the given info information into a higher request and afterward select the best straight grouping surface qualities. So this new measurement esteems can be accomplished by exact internal item work. The help vector machine philosophy with direct piece is addressed in Fig. 3 [4][8].

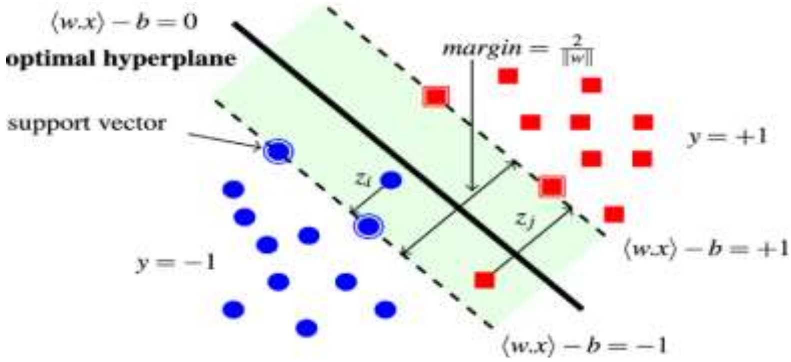

Fig 3. Support Vector machine (SVM)

VII. CLASSIFICATION RESULTS

Here we have used classification techniques for hyperspectral images. In our research the study has been carried upon one common hyperspectral datasets i.e., Indian Pines which

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comprise various landscape fields like dense vegetation, barren land, grasslands, etc.to reduce noisy band, PCA has been used [4]. Also to achieve accuracy of Classification using SVM we have used some filter techniques.Here we have used three types of areas like green grass patches from the Indian pines t and send the data to for pre processing and classification. The data was allotted to the classes 4, 5 and 6 respectively [4] [26, 27]. The detail code segments and outcomes are represented as follows.

A. Implementation of Support vector machines (SVMs)

Basiccode segment for implementation of SVM [13]

```
from sklearn import svm
from sklearn.model_selection import GridSearchCV
Create a support vector classifier
svc=svm.SVC ()
With the help of GridSearchCV and parameters_grid,
create a model
model=GridSearchCV (svc,parameters_grid)
param_grid = {'C':[0.1,1,10,100],'kernel':['rbf','poly']}
svc=svm.SVC (probability=True)
model = GridSearchCV (svc,param_grid)
```

B. Principal Component Analysis(PCA)

This is the basic algorithm for implementing the PCA

```
from sklearn.decomposition import PCA
pca = PCA (n_components = 150)
principalComponents  =  pca.fit_transform (X)
ev=pca.explained_variance_ratio_
plt.plot(np.cumsum (ev))
plt.xlabel ('Number of components')
plt.ylabel ('Cumulative explained variance')
plt.show ()
```

C. Visualizing the bands of the Hyperspectral image

- The total number of the bands in the Indianpines dataset is 200.
- The below function plots the bands of the data.
- The below is the code snippet for visualizing the bands of the hyperspectral Image:

```
import numpy as np
import matplotlib.pyplot as plt
defplot_band (dataset):
plt.figure (figsize = (8, 6))
band_no = np.random.randint (dataset.shape[2])
plt.imshow (dataset[:,:, band_no], cmap='jet')
plt.title (f'Band-{band_no}', fontsize)
plt.axis ('off')
plt.colorbar ()
plt.show ()
plot_band (dataset)
```

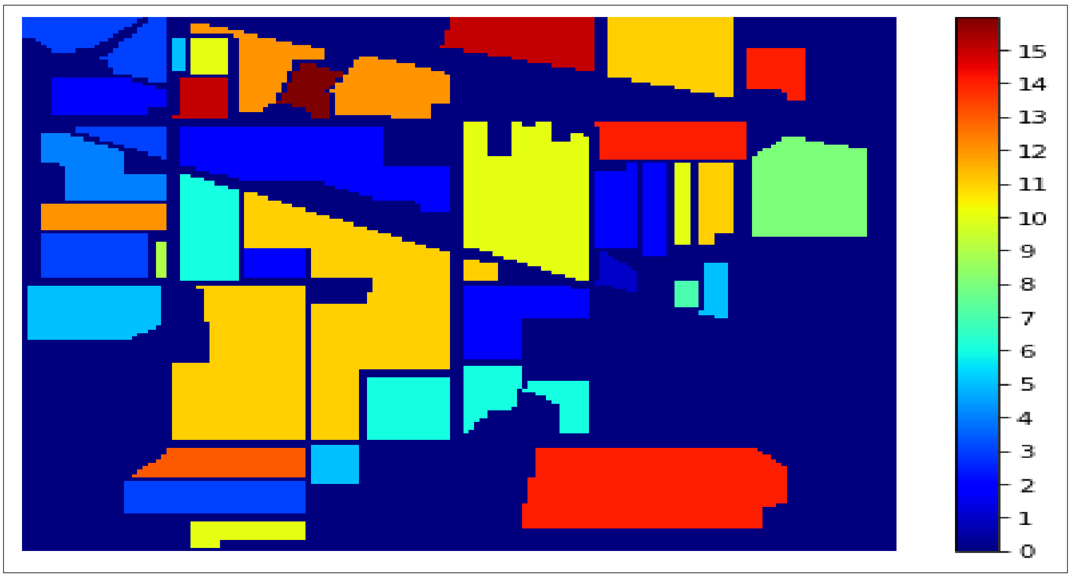

Fig 4. Bands of Indian pines images

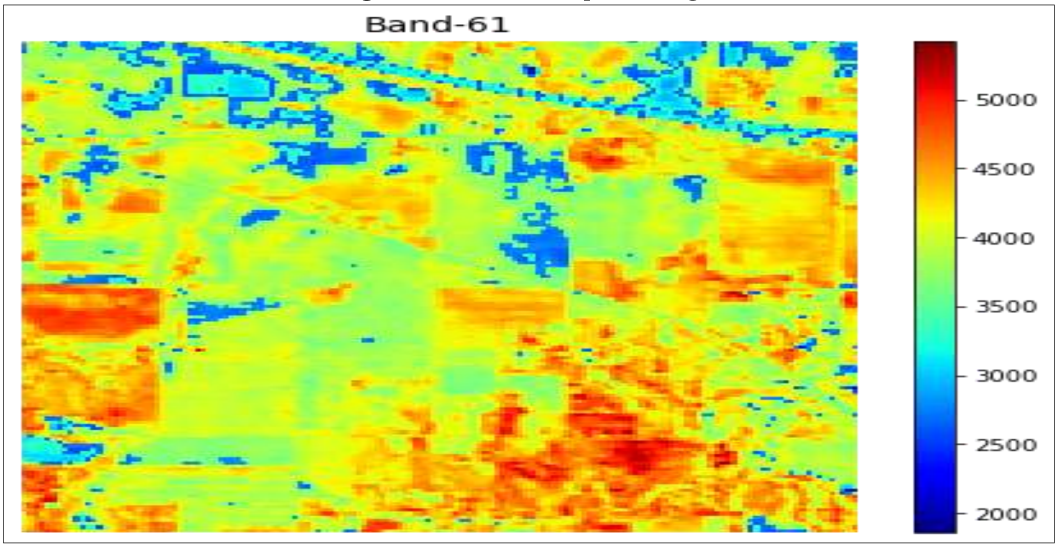

Fig 5. Ground Truth of the images

D. Visualizing ground truth of the image.

The below code snippet plots the ground truth of the indian pines dataset.

```
plt.figure (figsize = (8, 6))
plt.imshow (ground_truth, cmap='jet')
plt.axis ('off')
plt.colorbar(ticks= range (0,16))
plt.show ()
```

E. Visualizing spectral signatures

The below function plots the spectral signature.

```
defplot_signature (df):
plt.figure (figsize = (12, 6))
```

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```
pixel_no = np.random.randint (df.shape[0])
plt.plot (range (1,201),
df.iloc [pixel_no,:-1].values.tolist (),
 'b--',label = f'Class' - {df.iloc[pixel_no, -1]}')
plt.legend ()
plt.title (f'Pixel({pixel_no}) signature', fontsize = 14)
plt.xlabel ('Band Number', fontsize = 14)
plt.ylabel ('Pixel Intensity', fontsize = 14)
plt.show ()
plot_signature (df)
```

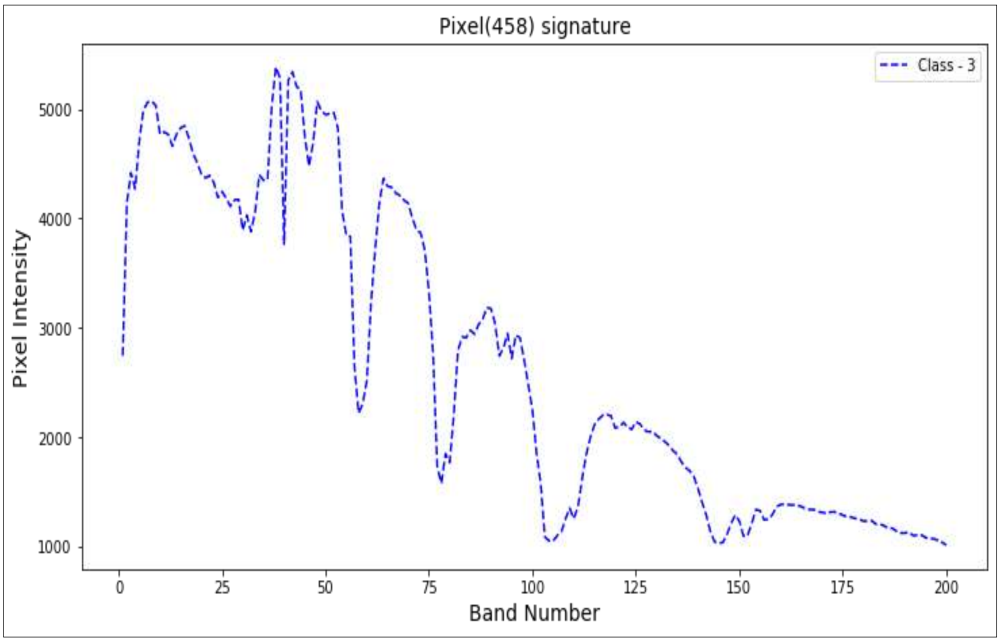

Fig 6. Spectral Signature

F. Box plot w.r.t bands of the HSI

The below is the code snippet for Box plot with respect tp bands of the HSI

```
plt.figure (figsize = (16, 6))
n = int (input ('Enter the band Number (1-200) :'))
sns.boxplot ( x=df["class"], y=df["band-1"], width = 0.3);
plt.title ('Box Plot', fontsize = 16)
plt.xlabel ('Class', fontsize = 14)
plt.ylabel (f'Band-{n}', fontsize = 14)
plt.show ()
```

G. Classification report with Data

code snippet to display the classification report.

```
from sklearn.metrics import classification_report
print('Classification report:\n',classification_report
(y_test,y_pred))
```

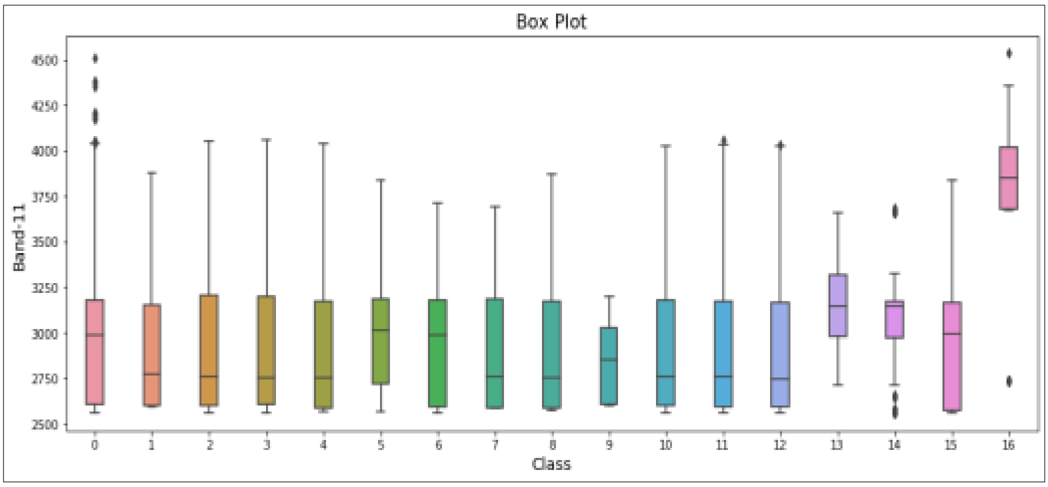

Fig7.Box plot of HSI images

SLNO	PRECISION	RECALL	F1-SCORE	SUPPORT
1	.76	.89	.72	1612
2	.01	.01	.01	7
3	.6	.52	.46	227
4	.84	.24	.28	115
5	1.01	.12	.14	44
6	.97	.57	.62	73
7	.89	.62	.64	114
8	.01	.01	.01	3
9	.78	.99	.77	69
10	.01	.01	.01	1
11	.68	.64	.56	138
12	.6	.81	.59	335
13	.72	.26	.29	100
14	.87	.85	.76	35
15	.76	.24	.28	188
16	.01	.01	.01	56
17	.82	.8	.71	20

Table-1 Classification Report

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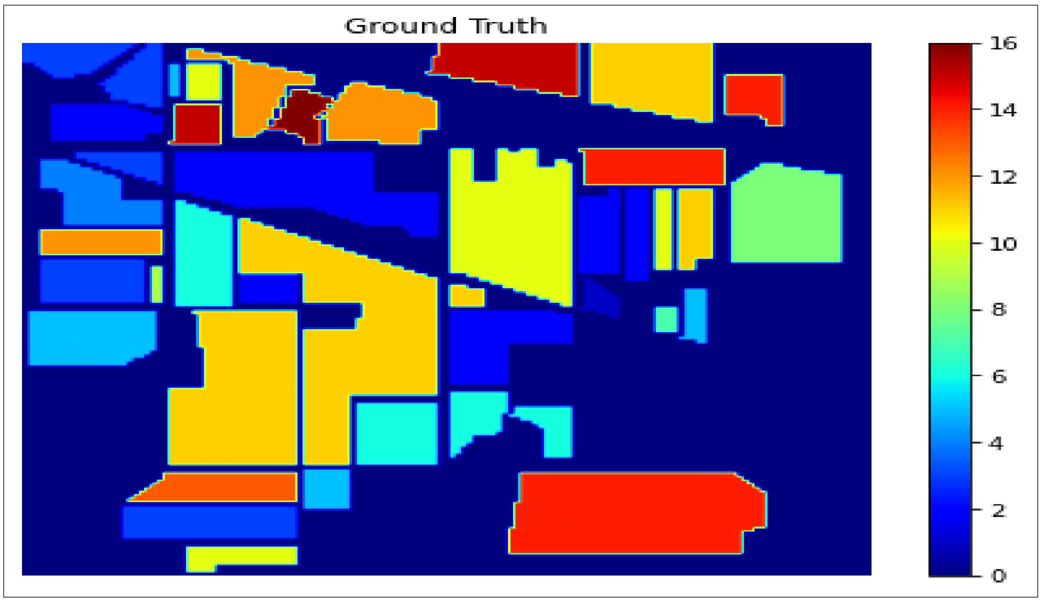

Fig-8 Classification Map using SVM

H. Classification map SVM

Below is the code snippet of Classification map

```
plt.figure (figsize = (7, 5))
plt.imshow(df.iloc[:,-1].values.reshape((144, 144)),cmap='jet')
plt.colorbar()
plt.axis('off')
plt.title('Ground Truth')
plt.savefig('ground_truth.png')
plt.show()
```

I. Classification map (PCA+SVM)

This is the code snippet to finally display the classification image using SVM+PCA

```
plt.figure(figsize = (7, 5))
plt.imshow (np.array (clmap).reshape ((144, 144)),
cmap = 'jet')
plt.colorbar ()
plt.axis ('off')
plt.title ('Classification Map (PCA + SVM)')
plt.savefig ('Classification_map.png')
plt.show ()
```

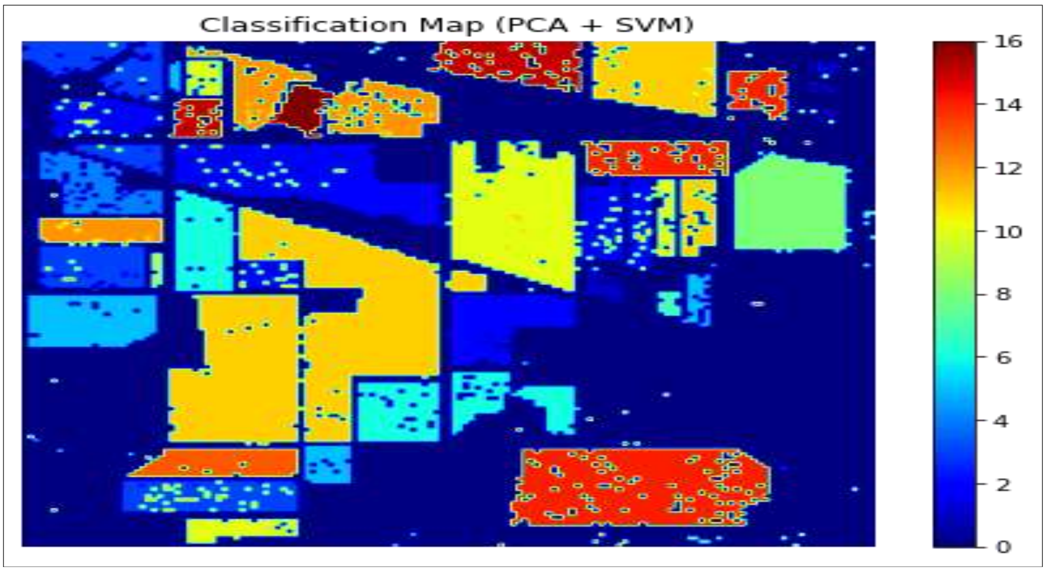

Fig 9. Classification of Map using SVM & PCA

J. Confusion Matrix

The error matrix or Confusion Matrix comparesthe ground truth with the classification result. It checks for errors in comparison. The Confusion matrix is shown in Figure-10 [4].

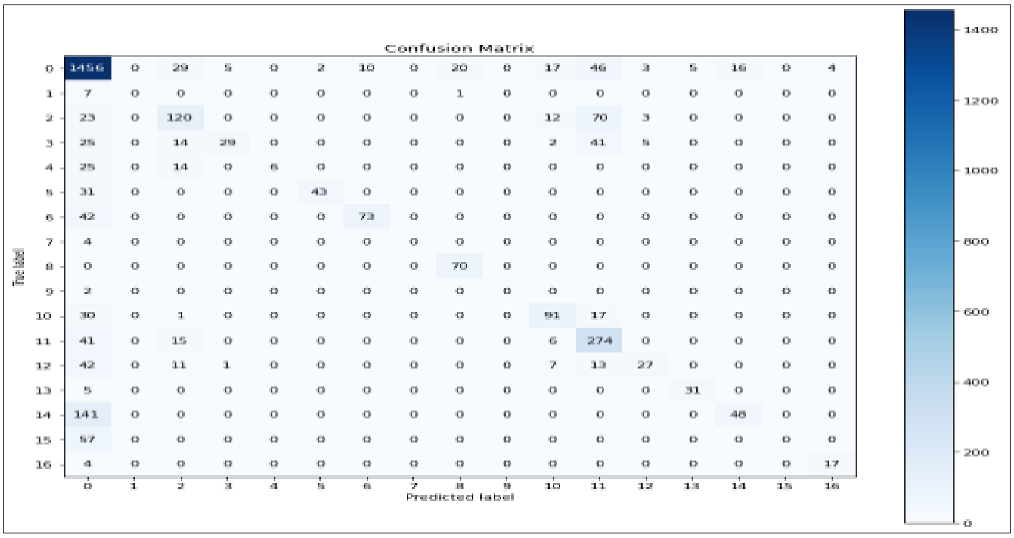

Fig. 10 Confusion matrix

K. Accuracy

The accuracy defines the difference between the samples predicted valueswith the original set of given samples.The accuracy is shown in equation 1and shown in Table 2.

$$\{ (T_P + T_N) \} / \{ (T_P + T_N + F_P + F_N) \} \qquad (1)$$

MODEL	TOTAL ACCURACY	TIME TAKEN
SVM	81.27 %	0.002
SVM+PCA	94.22%	0.001

Table-2 Accuracy

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L. Rsults Analysis

The Confusion matrix and theaccuracy values obtainedand are given infigure 10 and Table 2. From the obtained results, it is confirmed that SVM with PCA performs more accurately as compared to SVMmethods. So SVM with PCA is one of the acceptable technique for HIS [4].

VIII. CONCLUSION

In our research, a brief description on image classification models using SVM, with PCA, has been described. The study has been carried upon one common hyper spectraldatasets i.e., Indian Pines which comprise various landscape fields like dense vegetation, barren land, grasslands, etc.to reduce noisy band, PCA has been used.Alsoto achieve accuracy of Classification using SVMwe have usedsome filter techniques. It shows that the accuracy of classification results can be improved from 81.15% using SVM and accuracy is 94.22% with RBF kernels with the same set of training data.

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