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A Semi Supervised based Hyper Spectral Image (HSI) Classification Using Machine Learning Approach

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***Abstract:** In this paper, a new algorithm has been designated for classification of satellite remote sensing of hyperspectral image. The classification process is based on the three main categories: filtering, Clustering and classified, in this process to achieve a new optimal image clustering to overcome the problem of multi-label images in satellite remote processing. Finally, it gets clustered and result in classified output. The proposed research contribution is validated by classification experiments using Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) image sensors from the results the overall accuracy of single and multi-label of Salinas A dataset.*

***Keywords:** Hyperspectral Image, Clustering, Classification and Optimization.*

I. INTRODUCTION

Hyperspectral image has become a research focus in remote sensing, with endless development of the spectral resolution of remote sensing images. The SS classification is a significant research content of hyperspectral remote sensing and application. In this SS approach is to assign a unique label to each pixel in the HSIs. The HSIs consist of numerous hundreds of narrow continuous wavelength bands and it can provide high resolution sampling of the light spectrum at each pixel information for classification. At same time, the feature extraction is difficult for hyperspectral images in remote sensing. Given the complex hyperspectral dataset has limited labeled samples. The inadequate label based classification of HS remote sensing are still faces great tasks. In traditional, the HSI classification numerous method of discriminant function are applied. Such work have been followed since the early days of HSIs. Discussed the complex parameters of hyperspectral dataset, these datasets are added between the encoder layer and decoder layer in order to make the network suitable for SS based classification. A SS Convolution Neural Network (CNN) has implemented for hyperspectral image classification. In semi supervised CNN is an effective method for extracting the spatial-spectral from HSIs. In this SS-CNN method has adopted to rectify the problem of limited training class in complex hyperspectral dataset for remote sensing [1]. Suggested a new proposed algorithm, named semi-supervised rotation of forest (SSRoF). In SSRoF, one of the method of future extraction in hyperspectral dataset. The principal Component Analysis (PCA) is a tool for adopted the SS based image clustering for remote sensing. The PCA method is not reflect the discriminative information about classes and acknowledged as an unsupervised feature extraction for hyperspectral remote sensing. The proposed SSRoF has provided more advantage of both limited labeled unlabeled samples for discriminative and local structural information method. In this SSRoF has provided better class separability for subsequent in remote sensing images [2]. Presented a novel classifier of Anticipative Hybrid Extreme Rotation Forest (AHERT) classification for SS spectral-spatial correction in hyperspectral remote sensing images. In AHERT start with a model selection using small subsample of training data and ranking based performance selection of probability distribution of the classifier. In this classifier architecture has provided more frequently for train individual classifier in hyperspectral remote sensing dataset.The proposed spatial compactness removes the classification errors and the entire approach to reduce minimal sets of labelled pixels for training dataset [3]. Presented a semi-supervised HSI classification method has inspired by the generative adversarial networks (GANs). The GANs has trained on the spectral-spatial features for semi-supervised learning based on two neural networks (i.e., generator and discriminator) trained in opposition to one another. The semi-supervised learning has achieved by adding samples from the generator to the features and increasing the dimension of the classifier output [4]. Investigated on Deep Feature Extraction (DFE) for HSI classification using CNN. In this method has discussed several technique for convolution and pooling layer to extract deep features from HSIs. In this DFE is more suitable for image classification and target detection. The CNN based DFE model classification has extracted the spectral-spatial feature of HSIs [5]. Explained a concept of self-improving CNN based classification for HSIs. In this approach has reduced the lack of available training samples in HS dataset. The self-improving CNN based classification has designed for to select the most informative bands from Darwinian Particle Swarm Optimization (DPSO) [6]. The Deep Learning (DL) framework one of the tool for spectral - spatial classification of HSIs. In this DL is the process of merging the spectral and spatial feature via DL architecture. The DL based image classification has performed the two operation of stacked Auto encoders (SAEs) and deep convolutional neural networks (DCNNs) followed by a logistic regression (LR) classifier for HSIs. The DCNNs has provided to learn rich features from the training samples.

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In this DL method has introduced the technique of Spatial Pyramid Pooling (SPP) in HSI classification for the first time by pooling the spatial feature maps of the top convolutional layers into a fixed-length feature [7]. Discussed semi-supervised Discriminant Analysis and Robust Regression (DARR) based HSI classification in remote sensing. In this DARR classification is regression based semi-supervised technique. The proposed DARR method has provided better outcomes of HIS classification of labelled and unlabelled samples. In that, DARR adaptive loss function has employed to measure the representation loss also provided better enhanced classification results for HSIs [8]. Until recently, semi supervised ensembles of Extreme Learning (EL) based classification applied only for small amount of given training dataset. The classifier has provided enhanced training dataset information to entire HS datasets. In this semi supervised Ensembles of EL has performed a spatial regularization of classified labelled also provided for smoothness of most frequent selected neighbourhood pixel of HSIs [9]. A semi supervised HS image classification is mostly apply to solve the small sample size problems in spatial neighbourhood for remote sensing. In traditional, unlabelled sample information of HS dataset has typically ignored. The proposed algorithms of multinomial logistic regression (MLR) and k-nearest neighbour (KNN) has combined together to solve unlabelled information for semi supervised HS image classification [10].

II. STUDY AREA

The Salinas A hyperspectral datasets is selected for classification Experiments. The Salinas A datasets captured by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor with 224 spectral band and the dataset has a pixel value of 86 × 83, spatial resolution of 3.7m and it located within the same scene at the [samples, lines] = [591 676, 158 240] with includes six classes. The Figure 1 shows the RGB colour composition and ground truth reference map and colour code of Salinas A dataset.

(a) (b)

Figure 1. Dataset of Salinas A
(a)RGB image composite, (b) Ground- truth map

III. RELATED WORKS

1. Cellular Automata (CA)

The Cellular Automata (CA) is simple method and synchronous transition technique. The remote sensed digital image like Salinas is considered as 3×3 bidirectional array. Thus each pixel is characterized by the triplet variables as (i, j, k).Where (i, j) represent the position of the pixel and k is the associated colour. The k is assumed as to be 2^8 colour resolution. The CA follows two different rules for filtering depending on the location of the pixels in the images. The rule for the filtering pixel within the boundary involves the averaging neighbourhood pixels.

2.Image Enhancement method:

The filtered image is GWO based enhanced has been performed. The Grey Wolf Optimization (GWO) for quality improvement of the low dynamic range images and also for involves the assignment of the minimum value of the pixel intensity is considered as 0 and maximum value of the pixel intensity as 255, as the colour intensity is 2^8 bit resolution.

IV. PROPOSED METHOD

In this section has been elaborated the proposed system strategy of HSI classification of remote sensing image as shown in Figure 2.The proposed approach consist of three prevalent techniques, including image filtering, image clustering and classification. The image fusion has been performed based on pre-processing by using CA based image filtering. This provide smoothness to the image pixel and the image enhancement has been performed by using metaheuristic based Image Enhancement (MbIE). The MbIE has been provided for clear depth information of the image. The image clustering is achieved through Statistical based supervised HSI classification. Finally, it gets clustered and result in segmented output.

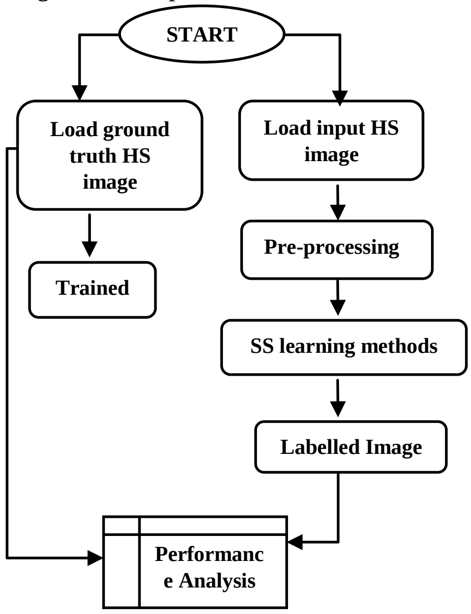

Figure 2: Block diagram of Proposed System

1. Proposed MbIE and Statistical based methods

The proposed Metaheuristic based Image Enhancement (MbIE) method is provided for image filtering and also contrast enhanced image for HSI classification in remote sensing. The MbIE in order to comport the image classification based on the technique of Grey Wolf Optimization (GWO) for quality improvement of the low dynamic range images. The proposed MbIE method is expected to provide improved enhanced output image and preserve brightness of the enhanced image very close to the input image.

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Semi supervised Learning Algorithm

Step 1 : *Find the maximum and minimum value*

Step 2 : *Calculate the PDF* of pdf_{max} *and* pdf_{min} .

Step 3 : $while\, l < max\_iter$

Step 4 : *Find the alpha value using GWO*

Step 5 : *Find the PDF value*

Step 6 : *Calculate the cumulative distribution function*

$$Cdf_{img}(k,l) = \frac{Pdf_{img}(k,l)}{sum(Pdf_{img})}$$

Step 7 : *Normalize the images*

$$Cdf_{max} = \max(Cdf_{img})$$

end m

V. RESULTS AND PERFORMANCE COMPARISON

The image in Figure 1 presents the Salinas A dataset and Figure 1 (a)-(c) shown false colour composition, reference data and colour code. The MATLAB programming is used to input the hyper spectral image as in Figure 3(a) and is filtered and enhanced as shown in Figure 3(b) and (c) respectively. The proposed algorithm is designed and developed to get the classified and segmented image as shown in Figure 3(f) and evaluates the each stage of the proposed MbIE and SAbC algorithm for the Salinas dataset.

1. Confusion Matrix Parameters Analysis.

Determination of accuracy of HIS based on the proposed MbIE and SAbC can be done by two method.
1) Confusion matrix or Error matrix
2) Kappa coefficient

Confusion matrix and Kappa coefficient is a techniques for calculation of Accuracy assessment with MbIE and SAbC based HSI classification. It is based on the data providing the assumption on the classes of reference datasets. The datasets are classified two manner 1) reference data value and 2) ground truth data value. Moreover, The Salinas dataset confusion matrix parameters, True Positive (TP) value of 10245, True Negative (TN) value of 10724 and Kappa co-efficient of 0.99467 in Table 1. The proposed method of SSTBA performance using Confusion matrix values have been compared with statistical parameter of TP , TN and moreover for other parameters are listed in Table1. The proposed MbIE and SAbC systems has been provided for better Kappa coefficient for the given dataset is listed in Table1.

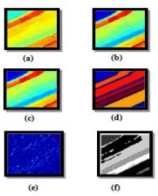

Figure 3: Output images of proposed MbIE and SAb Cclustering. (a) Input image (b) Filtered image (c) Enhanced image (d) classified image (f) Segmented image of Salinas A dataset.

Table 1: Confusion matrix values

S.No	Parameters used	Proposed
1	T_P	10245
2	T_N	10724
3	F_P	4
4	F_N	52
5	Sensitivity	99.49
6	Specificity	99.96
7	Recall	99.49
8	Jaccard Coefficient	95.04
9	Dice Coefficient	99.73
10	Kappa Coefficient	0.99467
11	Accuracy	99.73

2. Comparison for Semi supervised spectral based representation

The comparison of different Classification Accuracy CA (%) semi supervised learning has been presented in Table 2. The different values of traditional classifier of ELM [3], HERF [3], RF [3], and AHERF [3] has been compared with proposed classifier. The proposed classifier has been provided for belter classification result of Salinas A dataset of 99.97 % depicted in figure 4. Moreover in Table 3 listed the different level of training samples accuracy for proposed systems depicted in figure 5.

Table 2: Classification Accuracy (%) with different technique with proposed classier

Datasets	ELM	HERF	RF	AHERF	Proposed
Salinas A	98.40	98.63	98.0	99.21	99.97

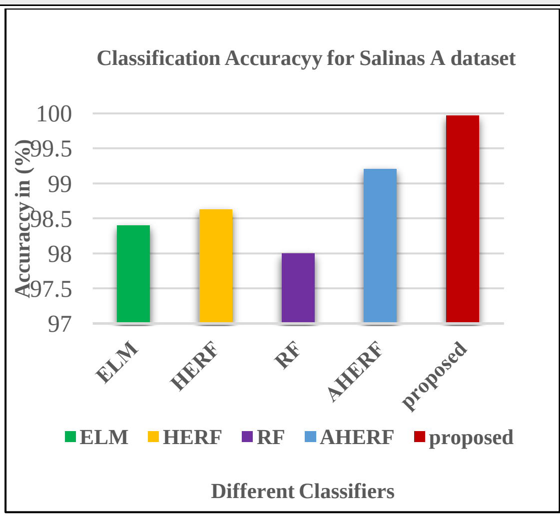

Figure 4: CA for different classification method

Table 3: Classification Accuracy (%) values of different training samples

Datasets	1%	1.5%	2%	2.5%	3%
Salinas A	97.93	98.39	98.91	99.52	99.97

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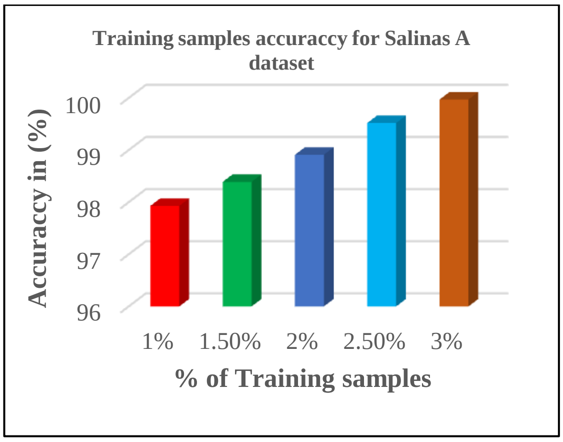

Figure 5: CA for different % of training samples

VI. CONCLUSIONS

Paper contribute, a novel dictionary learning method called MbIE and Statistical based clustering for HSI classification has been proposed. The SS representation show the outstanding ability to give better description of the HSI classification, especially exploiting MbIE and Statistical based semi supervised classifier. The experiments conducted for Salinas A datasets prove the better performance of the proposed method compared with multi-labelling image extraction methods of different HSI classification procedure.

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