Research Article

Deep learning framework based on Spectral and Spatial properties for Land-Cover Classification using Landsat Hyperspectral Images

K. Ragul[1],Dr. N. Balakumar[2]

[1]Department of Computer Science, Bharathiar University, Coimbatore, India
[2]Department of Computer Science, Bharathiar University, Coimbatore, India

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: Hyperspectral Imaging is used to monitor the earth on basis of spectral continuous data ranges starting from visible to short wave infrared region of the electromagnetic spectrum. It enables the detailed identification and classification of minerals and land cover on basis of with improved spectral and spatial resolutions provides the opportunity to obtain accurate land-cover classification. Several challenges have been generated due to Hughes phenomenon (curse of dimensionality) and Quantification of land cover in urban area. In order to alleviate those problems, novel framework named as Deep learning framework on spectral and spatial properties on Landsat image has been proposed which composed of several techniques. Initially hyperspectral (HS) data exploitation model on identification of pure spectral signatures (endmembers) and their corresponding fractional abundances in each pixel of the HS data cube has been proposed. Feature reduction strategy based on principle component analysis has been employed to generate reduced dimensionality of the features on retaining the most useful information. The reduced features have been taken for the spectral analysis and spatial analysis using Multiobjective Discrete Spectral and Spatial optimized representation model through encompassing the sparse and low-rank structure on the spectral signature of pixels. Identification and mapping of the land cover classification categorized as agriculture area and bare land has been identified using spectral indices (end members). The spectral indices calculation provides the type of land cover on the pixel purity index and it classifies based on the spectral and spatial value using N finder algorithm. N finder Algorithm is a change vector analysis. Further Ensemble based method has been proposed in addition to generate diverse classification results and the discrete high correlation classifier method which can enhance the accuracy and diversity of a single classifier simultaneously. Finally an efficient agriculture land cover spectral evolution mapping has been proposed using Multivariate principle component analysis. It is considered as change detection method explores efficiently the context of images, which leads to a good tradeoff between wider receptive field and the use of Context towards mapping Agriculture Land cover spectral evolution. It computes the spectral correlation between two images on spectral similarity. It predicts the accurately on temporal changes of the earth surfaces. Experimental analysis has been carried out using Landsat-8 dataset to evaluating the performance of the proposed representative framework using available spectral indices against the state of art approaches. Proposed framework achieves accuracy of 99% on reflectance value against the different wavelength which superior with other existing classification approaches.

Keywords: Hyperspectral Image processing, Land Cover Classification, Landsat, Classification, Feature Reduction, Spatial and Spectral Indices

1. Introduction

Hyperspectral images are an increasingly important source of information that has found use in a wide range of fields from Earth observation to the assessment of food quality and nowadays in the medical domain [Bruzzone.L & Demir.B. ,2014]. Focusing on the earth observation, in particular on land-cover analysis identify ecosystem biodiversity, vegetation areas, water sources and climate systems. Especially, land cover analysis is to determine the distribution and type of vegetation for precision agriculture on the land surfaces and to describe the biophysical state of the surface on the burst of informative content conveyed in hyperspectral images, represented by both high spectral and spatial resolutions[Camps-Valls.G et.al ,2014][Ghamisi.P et.al, 2013]. HSI usually contains hundreds of spectral channels and the obtained spectral information is a valuable source for classification. The Spectral classifiers have been proposed for HSI classification including k-nearest neighbors, maximum likelihood, support vector machine (SVM), logistic regression, neural network, and random forest. HSI contains abundant spectral and spatial information [Hinton.G.E & Salakhutdinov.R.R ,2006]. Spatial feature extraction methods, including Markov random fields and graphical models, also contributed to the spectral-spatial classification of HSI[Hung.C, Xu.Z, & Sukkarieh.S, 2014].

Hyper spectral Image processing is employed to satellite sensor data to identify the land surface materials. Hyper spectral image obtained by the satellite sensor provides the continuous spectral curves of the materials which can obtain more feature information of the interesting objects for mineral exploration and land cover classification for precision agriculture. Precision agriculture is application to the agriculture farming with respect to soil and crop to improve the productivity. HSI data will be distributed by noise, Hughes phenomenon and complex spatial structures with high intra-class and low interclass variability's has been considered as research problem in the Agriculture land cover classification for precision agriculture[Jia.X et.al ,2013]. Multi-class imbalance learning is another major challenge to be addressed in processing high dimensional hyperspectral images. In this work, a novel framework employed deep learning framework which composed of Evolution of spectral intensities on the land cover region is termed as anomalies which is hard to predict on hyperspectral processing. Ensemble learning can be employed for classification of the hyperspectral data in order to improve the classification performance and obtain better generalization performance. Ensemble learning uses unsupervised multi classifier. It reduces the Hughes phenomena. Minority oversampling techniques for dynamically balance the class distribution has to be generated compact representation to handle class imbalance problem. Evolution in the spectral intensity can be determined using change detection models at different times provides the basis for evaluating the relationships and interactions. The rest of the paper is organized as follows; related work is presented in the section 2. In section 3, proposed paradigm named ensemble classifier has been employed for classification of hyperspectral images is described. The experimental setup and experimental results are discussed in section 4. Conclusion is presented in section 5.

2. Related work

In this section, various existing model applied to hyperspectral image towards land cover classification using spectral indices for end member extraction has been summarized and detailed as follows

2.1. Spectral and Spatial Classification of Hyperspectral Images Based on SVM

In this method, Combination of spectral and spatial resolutions of the hyperspectral images has provided the solution to obtain accurate land-cover classification. The spectral analysis becomes a fundamental part, which aims at extracting the optimal subset of class-informative features[Lin.Z et.al ,2013]. The spatial analysis is then performed by extracting spatial features to identify the end members. In this approach, the spectral indices were used to select training data, and then a machine learning classifier named as SVM has been employed to detect the land covers.

3. Proposed Method

In this section, we define a deep learning framework composed of Spectral and Spatial representation for land cover classification

3.1. Image Pre-processing

Image pre-processing is performed in order to improve the quality of original images with all preparatory steps. As a result, each pixel of the processed image of the sensed region will be processed further to classify its features based on the available of classes of land cover. The pre-processing of image becomes essential to remove the noise prior to increase the mapping and interpretability of the image using radiometric correction[Marpu .M.R et al., 2012] and geometric correction[Miao.L & Qi.H.,2007,]. Further Contrast Improvement is applied to achieve quality interpretation. Further, Image enhancement may also uses the gray scale conversion, histogram conversion, color composition and color conversion to enhance the image quality for feature selection and classification

3.2. Markov Random Field for extracting the Deep Feature

Markov Random Field using Information content criteria and class-pair separate criteria are been employed for extracting the deep feature on hyperspectral data. Projecting the signal onto a basis of wavelet functions can separate the fine-scale and large-scale information of a hyperspectral data. The former, represented by the optimum index factor selects bands with rich information and small correlation. The feature bands selected based on information content contain rich information, but the distinction between classes may not be specific, as feature bands selected based on class-pair separate may be strongly correlated[Nascimento.J & Dias.J.B,2005].

3.3. Mean shift clustering for selecting initial representative labelled training samples

Mean Shift Clustering is employed for the deep features extracted. The extracted features are spectrally unique, idealized and pure signature of an earth surface. Clustering has been employed to classify the spectral properties of the extracted features. Spectral features or combinations of spectral features with those of possible end members of vegetation types are correlated for Vegetation classification [Rodarmel.C & Shan.J,2002]. Vegetation area is mapped in carried by determining the similar characteristics of soil, crop yielding condition and climate condition. Vegetation mapping is carried out using vegetation indices over regional or national extents in the global and continental scale.

3.4. Dimensionality Reduction using PCA for abundant spectral information

Principle Component Analysis which is the decomposition of an observed set of mixture signals into a set of statistically components has been employed to initial spectral clustered features. The selection of the most representative components is assured by the minimization of the reconstruction error on the clustered features. Reduced features contain the most useful information only vegetation species and land use categories. Figure 1 represents the architecture of the proposed methodology.

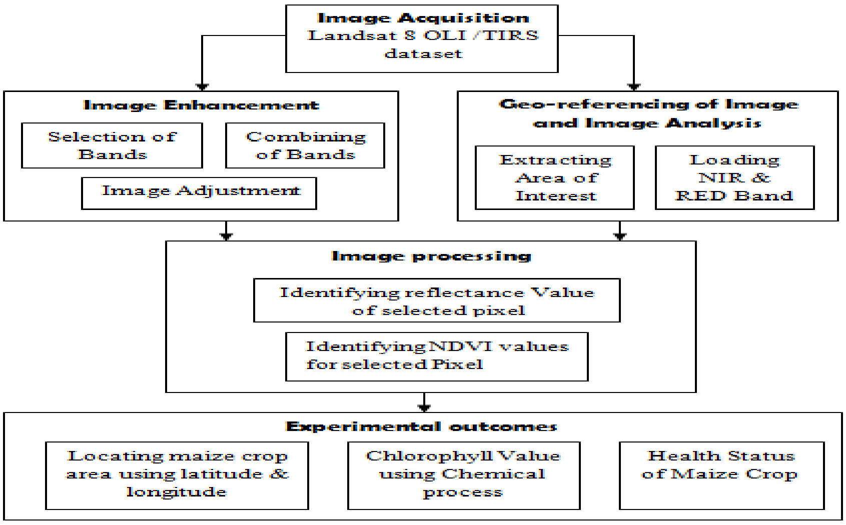

Figure 1: Architecture of proposed methodology

3.5. Joint convolution analyse and sparse Spectral feature representation- Structured Dictionary and Sparse Coefficient

The Joint Convolution analysis has been employed to Spectral characteristics of feature set. Those feature set have provided the values of the visual wavelength of the spectrum of the hyperspectral images. Analysis of number of bands has been used for the classification of the different categories. Therefore, each band of a hyperspectral image has important information. Images used in the area of computer vision have three bands, namely, red, green, and blue. However, hyperspectral images contain a number of bands, i.e., 100 bands, covering the visual and infrared spectrum.

3.5.1 Formulation of Spectral Indices

Spectral indices are used to demonstrate the relative abundance of features of interest, which are distinguished by differences in the surface reflectance values of two or more particular bands. In this Spectral indices formulated to enhance their separation based on band reflectance, the spectral reflectance between adjacent land covers must be maximized. False Color Composite[Shijin.L & Huimin.L,(2015),] used for visual interpretation of the hyperspectral images during classification.

3.6. End member Classification using Ensemble Classifier

End member classification is performed in order to improve the quality of original images. ICDA is a non-parametric method for discriminant analysis based on the application of a Bayesian classification rule on a signal composed by independent components. The method is based on the use of Independent Component Analysis (ICA) to choose a transform matrix so that the transformed components are as independent as possible. High Correlation Classifier require there to be sufficient training data available for every particular image. It is based on finding invariant representations usually cover large areas and require per-pixel labels [Tuia.Merenyi.E,Jia.X &Grana-Romay.M, 2014]. Each base learner predicts the label of the unknown sample, respectively. No prior knowledge is required unsupervised classification methods and it relies on spectrally pixel-based statistic. Finally Parallel Multiclass Support Vector Machine solves the multiclass problem in hyperspectral Image Classification.

The model locates the optimal hyper plane between the class of interest and the rest of the classes to separate them in a new high-dimensional feature space by taking into account only the training samples that lie on the edge of the class distributions known as support vectors and the use of the kernel functions made the classifier more flexible by making it robust against the outliers. On outcomes of the classifier, deep ensemble classifier objective function determines the learning model as new training samples without taking into account the on all previous learned classifier model. Meanwhile, the weight of the base learner with the smaller misclassification rate is larger, and those with the larger misclassification rate are smaller. After that, it generates a final strong classifier through a weighted combination of these base learners on above mentioned classifier.

The closest approximation of the testing sample may be from different classes, which means that the minimal residual may be derived from different classes. The finial classification result is produced by integrating the results based on the voting rule.

3.7. Agriculture Land cover spectral evolution mapping using multivariate principle component analysis

Discrete Spatial Classification using the spectra of the objects in the image on the linear variation including atmospheric and topographic effects based on wavelength. It is used to measure the distance between spectral signatures of the object towards classification with respect to near infrared with high reflectance[VanderMeer.F, 2006]. In the visible region of the spectrum, the curve shape is determined by absorption effects. The spectral indices calculation provides the type of land cover on the pixel purity index and it classifies based on the spectral and spatial value using N finder algorithm. N finder Algorithm is a change vector analysis.

Agriculture Land cover classification is based on reflectance value of the spectral band on the chlorophyll con

tent. Vegetation areas absorb high in the visible wavelength which has blue and red wavelength as it mostly contains the Chlorophyll. Health vegetation appears in the infrared region. It is characterised with Nitrogen value, chlorophyll value and protein value. In this region, healthy plants appear in green. Near infrared reflectance decreases and red reflectance increases which creates the characteristics less nitrogen and chlorophyll value to indicate it as dry region. The spectral reflectance illustrates the highest index value for vegetation whereas water and bare land have almost spectral reflectance. The N-Findr algorithm is used to obtain the graph for reflectance versus wave length (nm). The reflectance values are taken from this graph at the specified points for utilization in spectral indices to obtain the Nitrogen value. The algorithm checks for the set of pixels that has the largest volume by considering the endmembers which are the vertices for building up a simplex inside the data. The procedure started with random initial selection of pixels. Every pixel in the image was evaluated in order to filter the estimate of endmembers, checking out for the group of pixels that increased the volume of the simplex chosen by selected endmembers [Yu.C, Song.M & Chang.C.I., 2018].

4. Experimental Results

Experimental analysis has been carried out using Landsat-8 dataset to evaluating the performance of the proposed representative framework using available spectral indices against the state of art approaches. The hyper spectral images were used to measure the variation in the land cover monitoring in terms of different spectral indices is described. Landsat 8 OLI dataset were selected to be analysed in this work. The performance of the proposed model has been examined in terms of accuracy on precision, recall and f measure properties. The precision, recall, Fmeasure has be computed using true positive, false positive, false negative and true negative value on different instance of classes to determine the performance of the accuracy on the spectral indices at different wavelength of the pixel of proposed model and it is compared against SVM classification on Spectral and Spatial analysis.

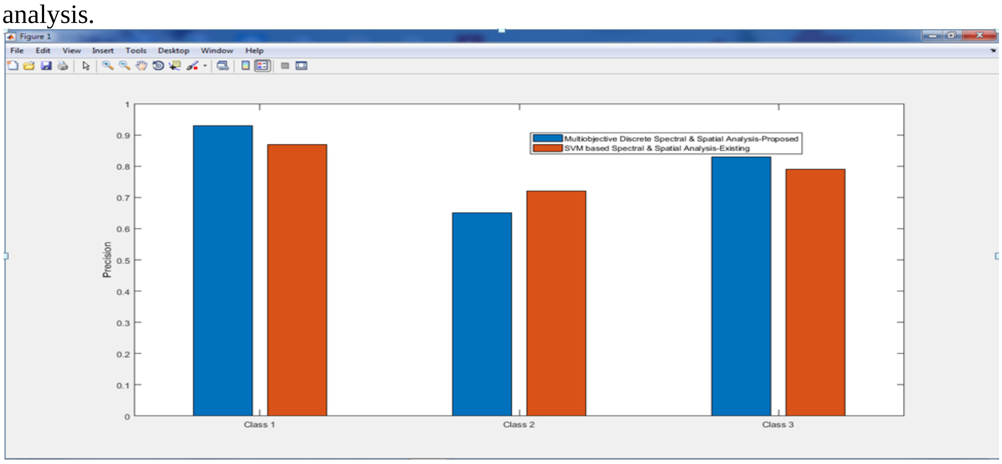

Figure 2: Performance Evaluation of Land Cover Classification Model against Precision

Figure 2provides the performance outcome of the precision value on land cover classification techniques on hyperspectral images and table 1 provides the performance computation of proposed model on spectral indices.

Table 1: Performance computation of Multiobjective Discrete Spectral and Spatial Representations

	MDSSR Proposed	**Existing**	**MDSSR Proposed**	**Existing**	**MDSSR Proposed**	**Existing**
Metrics	**Class 1**	**Class 1**	**Class 2**	**Class 2**	**Class 3**	**Class 3**
True positive	68084	61014	22412	19789	50597	47895
False positive	5461	3481	9652	7895	9681	7856
False negative	10351	8789	3700	2874	9326	9147
True negative	172768	124712	204900	189456	210060	197451
Precision	0.93	0.87	0.65	0.72	0.83	0.79
Recall	0.86	0.82	0.88	0.87	0.83	0.81
F measure	0.99	0.91	0.96	0.92	0.98	0.94

Figure 3 to explain the performance of the proposed classification of the hyperspectral images in terms of recall towards land cover classification models. It yields better results of true positive values of the computation of feature set.

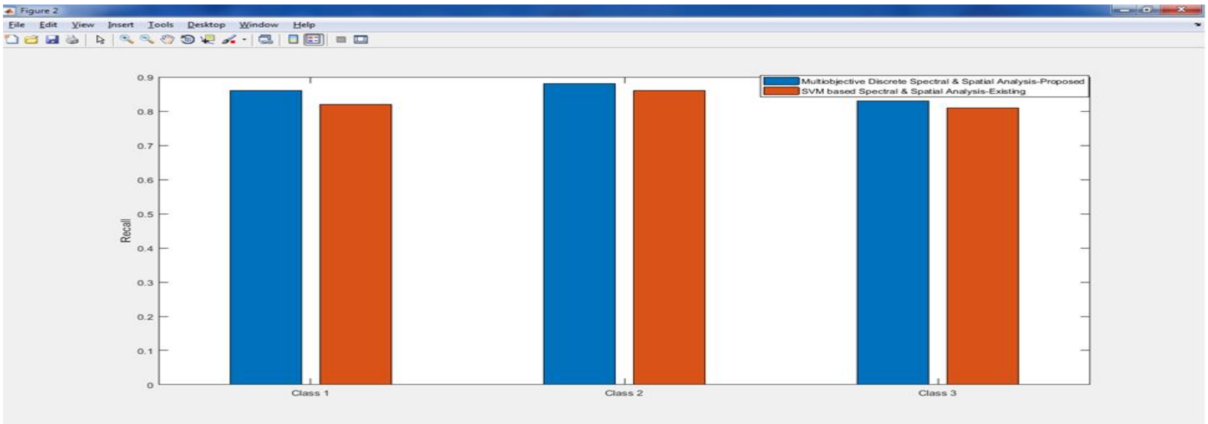

Figure 3: Performance Evaluation of Land Cover Classification Model against Recall

It is noteworthy that the accuracy values are high in the proposed classification of hyper spectral images on multiobjective discrete spectral values. This paradigm can be applicable to any type dataset of hyper spectral images. Figure 4 provides the performance outcome of the f measure value on land cover classification techniques

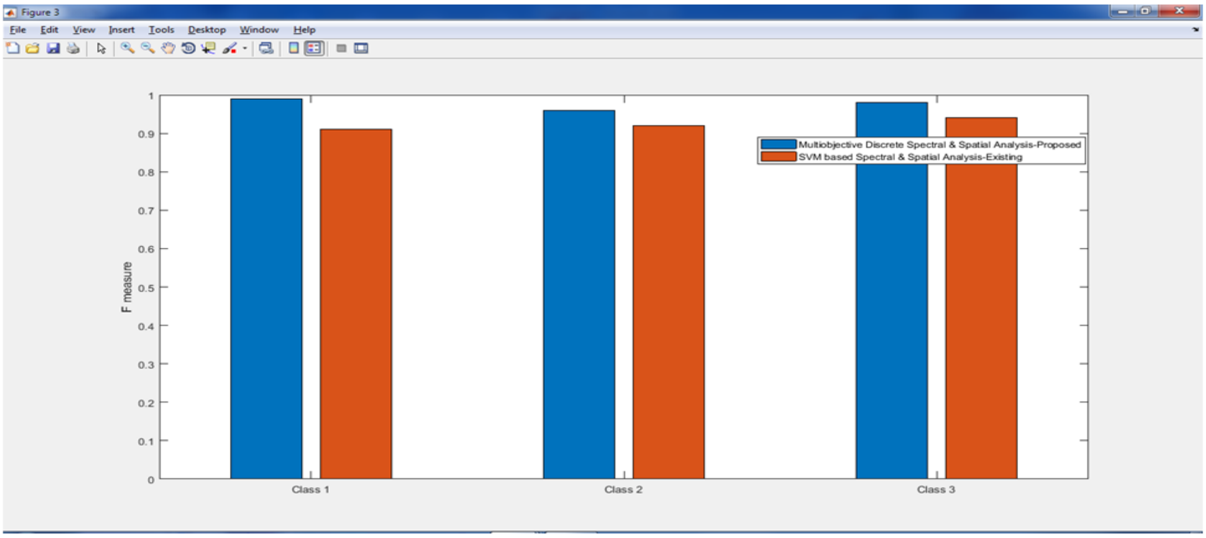

Figure 4: Performance Evaluation of Land Cover Classification Model against F measure

Proposed framework achieves accuracy of 99% on reflectance value against the different wavelength which superior with other existing classification approaches on the Landset 8 OLI dataset with different spectral and spatial resolutions. The obtained results show the effectiveness of the proposed model providing higher accuracy on comparing against state of art approaches

Figure 5: Performance Evaluation of Deep Ensemble model on F measure

In Deep Ensemble model, classifier with the increase of feature size, the classification accuracy increases, and then the accuracy remains at a certain level or ever slightly decreases. Figure 5 demonstrates the performance of the methodology on f measure using the classifier on the hyperspectral dataset.

Table 2: Performance computation of MDSSR model on spectral indices

	Ensemble Classifier-Proposed	**MDSS R-Existing**	**Ensemble Classifier Proposed**	**MDSS R-Existing**	**Ensemble Classifier Proposed**	**MDSS R-Existing**
Metrics	**Class 1**	**Class 1**	**Class 2**	**Class 2**	**Class 3**	**Class 3**
Precision	0.94	0.89	0.75	0.78	0.85	0.89
Recall	0.88	0.85	0.89	0.89	0.87	0.89
F measure	0.99	0.98	0.97	0.96	0.98	0.95

Table 2 represents the performance of the classification accuracy on ensemble classifier against state of art approach. Diversity of ensemble classifier has been represented in float values on small ranges with up and down values. Figure 6 describes the performance of the ensemble model against state of approaches.

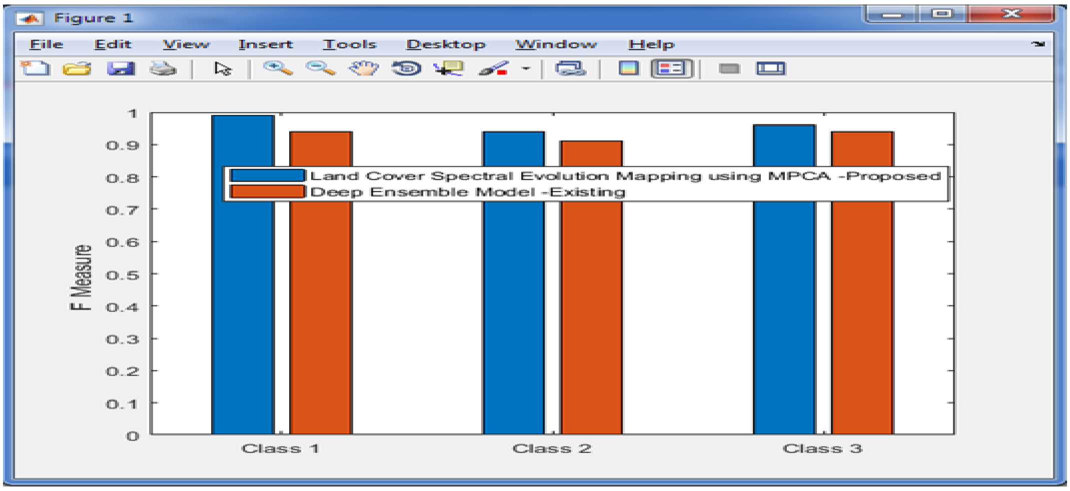

Figure 6: Performance Evaluation of the Change Detection method

Classified pixels of the spectral images have been processed further for change detection on aspect of correlation of the spectral signatures. Table 3 represents the performance of the classification accuracy on proposed classifier against state of art approach.

Table 3: Performance computation of Change Detection model on spectral indices

	Change Detection Method - Proposed	**Ensemble Classifier Existing**	**Change Detection Method Proposed**	**Ensemble Classifier - Existing**	**Change Detection method Proposed**	**Ensemble Classifier Existing**
Metrics	**Class 1**	**Class 1**	**Class 2**	**Class 2**	**Class 3**	**Class 3**
Precision	0.93	0.87	0.65	0.72	0.83	0.79
Recall	0.86	0.82	0.88	0.87	0.83	0.81
F measure	0.99	0.91	0.96	0.92	0.98	0.94

Performance of the proposed model exhibits the classification maps and corresponding accuracy[10]. Proposed model can greatly reduce data redundant and improve classification efficiency on basis of the dataset.

5. Conclusions

In this work, a novel deep learning framework for spectral and spatial analysis of hyperspectral images for land cover classification to agriculture purpose has been designed and implemented with techniques such as dynamic multiobjective classification, Ensemble Classifier and change detection method. Those methods have been employed for hyperspectral images for effective efficiency and computation on proposed dataset. Further it improves the computation time in class informative feature extraction while minimizing feature set using principle component analysis and mean shift clustering. In Particular, spectral analysis has been carried out using spectral indices on obtained feature set through markov random field. End member classification for agriculture region uses the reflectance value of chlorophyll content. The evaluation of the proposed work was tested on the Landset 8 OLI dataset with different spectral and spatial resolutions. The obtained results show the effectiveness of the proposed model providing higher accuracy on comparing against state of art approaches.

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