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Multiobjective Discrete Spectral and Spatial Optimized Representation for Land-Cover Classification using Landsat Hyperspectral Images

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Abstract: ***The availability of hyperspectral images with improved spectral and spatial resolutions provides the opportunity to obtain accurate land-cover classification. . The changes in land cover largely affect the terrestrial ecosystem, thus information on land cover is important for understanding the ecological environment. Quantification of land cover in urban area is challenging due to their diversified activities and large spatial and temporal variations. In order to improve urban land cover classification and mapping, a novel framework named as Multiobjective Discrete Spectral and Spatial optimized representation for end member extraction has been proposed in this paper. It is considered as 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. High dimensionality of the data leads to computational complexity as it represents the Hughes phenomenon. 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. 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.

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I. 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[1]. 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[2][3]. Further changes in the biophysical state of the land surface have noticeable impacts on the quality of the environmental analysis[4]. Many researches have been constituted on the end member extraction using spectral indices[5]. However classification of land cover by many existing machine learning model based on the pixel and object wise has imposed by challenges due to the large spatial and temporal variation on the diversified activities. Although various land cover classification approaches are available, modelling of appropriate novel model using spectral indices has become mandatory as spectral indices demonstrate the relative abundance of features of interest. Moreover, the spectral index values primarily characterize a particular land cover[6]. Various spectral indices have been developed and used to detect different land cover types, such as the normalized difference vegetation index (NDVI) to extracts vegetation and biomass information[7], The soil-adjusted vegetation index (SAVI) separates vegetation and water in urban areas[8] and Tasseled Cap (TC) indices have been used to enhance the information on biophysical coastal zones, water, soil, and vegetation[9]. In order to improve urban land cover classification and mapping, a novel framework named as Multiobjective Discrete Spectral and Spatial optimized representation for end member extraction has been proposed in this paper to address those issues on land cover classification. In this model, Hughes phenomena have been eliminated on application of principle component analysis on decreasing the dimensionality of the feature space by retaining the most useful information.

Reduced feature set processed on encompassing the sparse and low-rank structure on the spectral signature of pixels. New Spectral Indices calculated will be used to classify the land cover region in terms of pixel purity index and it classifies based on the spectral and spatial value using N finder algorithm. The rest of the paper is organized as follows; related work is presented in the section 2.

In section 3, proposed paradigm named Multiobjective Discrete Spectral and Spatial optimized representation for end member extraction is described. The experimental setup and experimental results are discussed in section 4. Conclusion is presented in section 5.

II. 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

A. 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[10]. 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.

III. PROPOSED PARADIGM

In this section, we define a Multiobjective Discrete Spectral and Spatial optimized representation for end member extraction to classify the land cover region using spectral indices of the spectral signature of pixels.

A. Hyperspectral Image Enhancement

Hyperspectral Image enhancement 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 to assign the land cover class. In addition, it has become primary to make the image compatible spatially and spectrally on time series and area of the imagery which encompassed by many images [11]. In hyperspectral image pre-processing, a set of operation named as bad line replacement, radiometric correction and geometric correction has been carried out.

- **Bad line Replacement – Image Repairing process**

Bad line replacement in the hyperspectral image is carried out to improve the overall quality of the image by analysing the image band by band against finding the missing data lines and image repairs. The analysis of the bad line or missing line has been employed on the Landsat 8 images by injecting the blocks of missing line through procedure that produces a line above, below or with an average of the two and data in the each band of the image region [12].

- **Radiometric Corrections**

The Radiometric correction is employed to the fidelity of the brightness values on the hyperspectral image in order to correct the radiometric errors. In addition, it provides the mathematical function to eliminate the distortions of satellite images. The distortion of the image produced due to Seasonal phonology, ground conditions and atmospheric conditions in terms of variation in spectral responses and temporal responses [13]. Most cases, radiometric correction are strong to minimize the effects of ground and atmospheric conditions on the spectral signals of the satellite images. Further, radiometric correction has been utilized to estimating the absolute reflectance of monitoring region of land cover and also to calibrate the sensor value on atmospherics properties.

- **Geometric Corrections**

Geometric correction is another major image enhancement method to satellite images towards eliminating the distortion in the hyperspectral images[14]. Geometric correction has been established as a relationship between the image coordinate system and the geographic coordinate system and it has been calibrated on the measured position through altitude and the ground control points. Map projection and reference system is employed to geometric correction on inclusion of selection and co registration of the image data with other GPS data.

Calibration is done with plus or minus operations on the pixel of its true position to eliminate the distortion and error for achieving the accurate spatial assessment and measurements of the data. In addition, nearest neighbor re-sampling method has been used to assign the value of the closest pixel to output pixel value and first-order transformation has been introduced to transfers original data values without averaging them.

- **Contrast Improvement**

Contrast Improvement is applied to achieve quality interpretation. Satellite image is characterized by contrast. Contrast is created by the difference in luminance reflected from two adjacent surfaces of the images. The contrast is the difference in visual properties that makes an object distinguishable from other objects in the particular spectral band. 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.

B. Feature selection and Reduction

Feature Selection and reduction employed to the pre-processed hyperspectral image towards extracting land cover information by interpreting images in terms of filters or through inclusion of similarity interpreting elements such as image color, texture, tone, and pattern and association information. Features are extracted by exploiting the discrimination information of the pixel which represented as Spectral Signature. The extracted features in terms of spectral signature were taken for image classification with reference to signature libraries.

- **Feature Extraction using Markov Random Field**

Markov Random Field using Information content criteria and class-pair separate criteria are most widely employed method for feature selection of hyperspectral data. Projecting the signal onto a basis of wavelet functions can separate the fine-scale and large-scale information of a hyperspectral signal. 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.

- **Feature Reduction using Principle Component Analysis**

Principle Component Analysis which is the decomposition of an observed set of mixture signals into a set of statistically components. The selection of the most representative components is assured by the minimization of the reconstruction error. Reduced features contain the most useful information only vegetation species and land use categories.

Algorithm 1: Feature Reduction using PCA

Random variables of the feature is represented as $x_1(t), x_2(t) \ldots x_n(t)$

Where t is the time or sampled index, Local maxima of nongaussianity is

$$Y = Wx,$$

where

'*W*' is some unknown matrix Random variable s_k instead of time signal

$$x_j = a_{j1}s_1 + a_{j2}s_2 + .. + a_{jn}s_n, \text{ for all } j$$

$$\mathbf{x = Bs}$$

Intependent components(IC) of the Input data.

Spectral features or combinations of spectral features with those of possible end members of types are correlated for land cover classification. It produces following properties

- Effectiveness and efficiency in classification
- To avoid redundancy of data
- To smartly identify useful spatial as well as spectral features
- To maximize the pattern discrimination

C. Multiobjective Discrete Spectral and Spatial optimized representation

End member extraction is been computed using Multiobjective Discrete Spectral and Spatial optimized representation. It measures the changes in the land cover on utilizing the reduced feature set on terms of spectral analysis and spatial analysis. It computes 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).

- **Discrete Spectral Classification**

Spectral characteristics of feature set have provided the values of the visual wavelength of the spectrum of the hyperspectral images. Analysis of number of bands to use for the classification of 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. Therefore, it is important to analyze different combinations of bands for the land cover classification. The spectral signature in terms of spectral bands can be used to identify measure and monitor the region of interest. The spectral bands are processed to identify the condition of region through cost effective and computationally efficient procedures.

- **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 used for visual interpretation of the hyperspectral images during classification. The False Color Composite is generated using spectral bands. It refers to a group of color rendering methods used to display images in color which were recorded in the visible or non-visible parts of the electromagnetic spectrum.

The band reflectance profile indicates that shortwave infrared (SWIR) band 1 has the highest reflectance for bare land, but that the reflectance for vegetation and impervious areas is almost the same. Absorption, Emittance and reflection play an important role in the spectral signature formation. It has unique pattern for each spectral lines. The figure 1 represents the architecture of the proposed paradigm. The SWIR band 2 shows clear distinctions between all land cover types; bare land has the highest reflectance and has a significant mean difference from impervious areas.

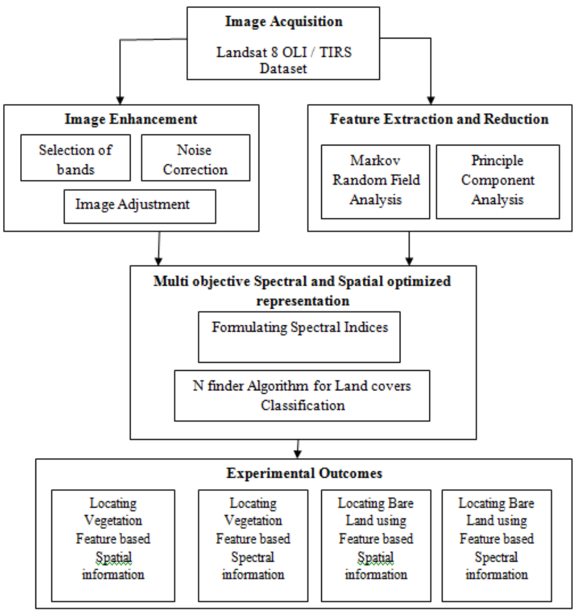

Fig 1. Architecture of the Proposed Paradigm

In contrast, in the blue band, impervious areas have the highest reflectance. The mapping is generally carried out through characterizing, modelling and classifying. Land Cover Classification is carried out on spectral signatures.

- **Discrete Spatial Classification**

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.

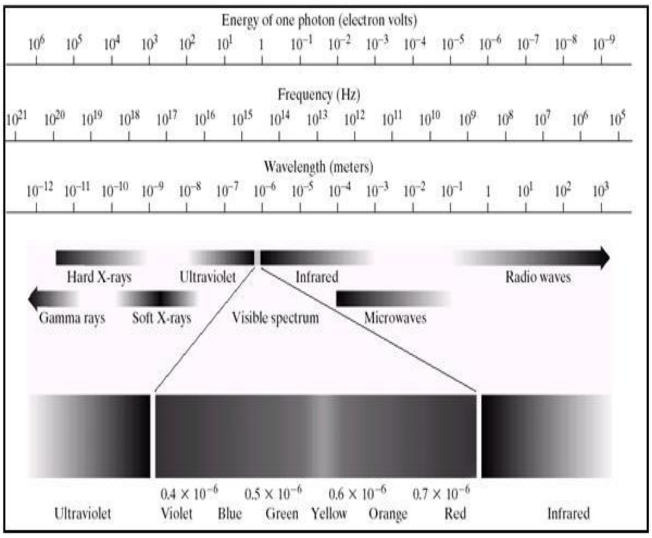

Fig 2. Spectral reflectance of Electromagnetic Spectrum

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. Vegetation areas absorb high in the visible wavelength which has blue and red wavelength as it mostly contains the Chlorophyll. The particular wavelength produces a small reflectance for infrared wavelength. Figure 2 represents the Spectral reflectance of the spectrum.

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.

- **N finder Algorithm**

The N-Finder 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.

Algorithm 2: Multiobjective Discrete Spectral Classification - Landover Extraction

Input: F(s) & Ground Truth SI
Output: Classes of F(s)
Process
  Compute SI for F(S)
    Assign Reflectance Value for SI
      Reflectance Value $R_v = p\ L_1 d_2 / \cos q_s\ E_{s,1}$
    Where P = Pi
        L = Mapper Spectral reflectance at wavelength
        E_s = Spectral irradiance at particular Wavelength

$$T = p(x) = \prod_{C \in \Omega} \Psi_c(x)$$

Classify C = Split($R_v\, x_i$ + T)
Where T is threshold for various spatial regions.
C is classes Containing the Vegetation, Bare land and Water feature

The volume was calculated for every pixel for every end member's position by replacing that particular endmember and finding the resulting maximum volume. When the replacement results showed increase in the volume, then the end member was replaced by the pixel. Thus the process was repeated until there were no more end member replacements.

IV. 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 in this section.

A. Dataset Description

Landsat 8 OLI dataset were selected to be analyzed in this work. Data was collected from the western part of the Indiana containing dense forest, farm lands and bare lands with number of bands ranging from 400nm-2500nm which covers all wavelengths from near visible band to infrared region[15]. The Indian Pines scene contains two thirds agricultural, and one-third forest or other natural perennial vegetation

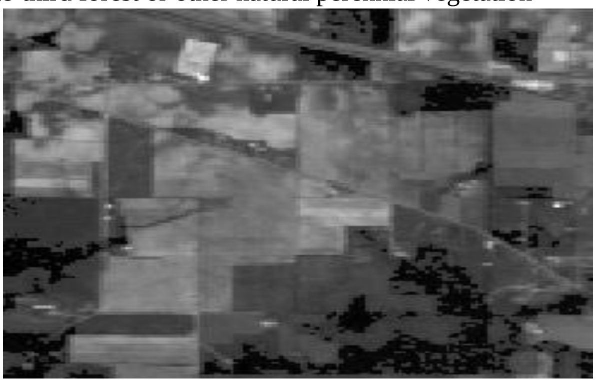

Fig 3. Hyperspectral Image

The Land cover corresponds to the different reflectance spectra to the electromagnetic wavelength has been measured. The Figure 4 describes the reflectance spectra of the different types of land cover. The reflectance value of the hyper spectral image on different region is computed with reference of ground truth data. Ground truth data relates to the feature of the hyperspectral image. The spectral indices can be calculated using the spectral curve of the reflectance value and it corresponds to the wavelength.

The hyperspectral image consists of 145×145 pixels and 224 spectral reflectance bands in the wavelength range 0.4 – 2.5nm. The bands indicate spectrum ranges and color represents region under monitoring with different colors to represent as vegetation and non vegetation regions such as B4 is red (0.64–0.67 µm), B3 is green (0.53–0.59 µm), B2 is blue (0.45–0.51 µm).

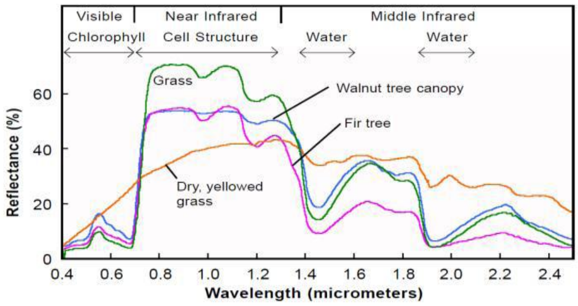

Fig 4. Reflectance Spectra of the Hyperspectral Image

The hyper spectral images were taken with fixed spatial dimensions, and it pre-processed for the contrast improvement and noise removal to process further for feature extraction and classification. To generate a feature, hyperspectral value of the image was derived through Markov Random field. The extracted feature has been processed using PCA for feature reduction on retaining the most useful information. Spectral Indices value ranges of the different region of interest has been tabulated in table 1.

Table- I: Spectral Values of Region of Interest

Region	Spectral Value Range
Rock, Sand and Snow	< 0.1
Shrubs and Grasslands	0.2 – 0.3
Crops or forest	0.4-0.9

Multiobjective discrete Spatial and Spectral optimized representative classifies the subset of feature reduced using PCA has been computed with spectral indices towards classification. The spectral signature in terms of spectral bands can be used to identify measure and monitor the region of interest based on pixel purity index. Classification of the region is computed on the surface reflectance values of two or more particular bands.

Spectral indices formulated as ground truth has been used for their separation based on band reflectance, the spectral reflectance between adjacent land covers. Despite the differences among the identified indices, characteristic of the region used to classify the land cover. The performance of the proposed model has been examined in terms of accuracy on precision, recall and f measure properties.

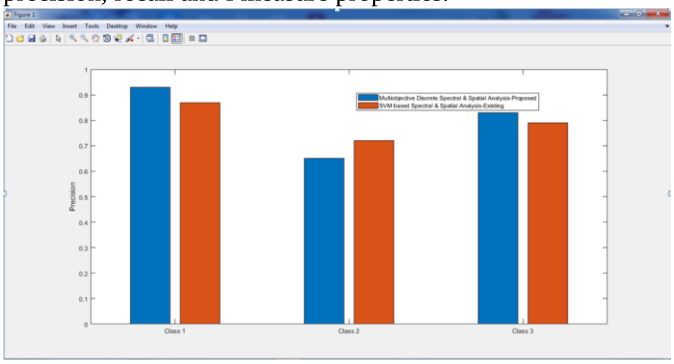

Fig 5. Performance Evaluation of Land Cover Classification Model against Precision

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 5 provides the performance outcome of the precision value on land cover classification techniques.

Table- II: Performance computation of proposed model on spectral indices

	Proposed	Existing	Proposed	Existing	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

The classification accuracy is summarized in the Table 2 and described in figure 6 to explain the performance of the proposed classification of the hyperspectral images in terms of recall towards land cover classification models. It yield better results of true positive values of the computation of feature set.

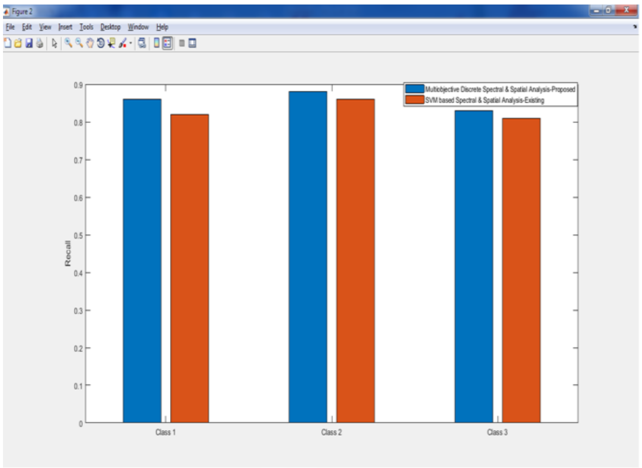

Fig 6. Performance Evaluation of Land Cover Classification Model against Recall

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 7 provides the performance outcome of the f measure value on land cover classification techniques

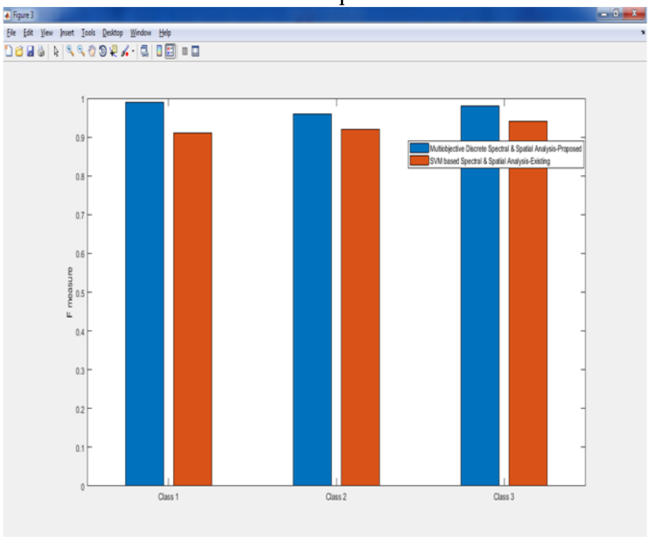

Figure 7: Performance Evaluation of Land Cover Classification Model against F measure

Proposed framework achieves accuracy of 99% on reflectance value against the different wavelength which superior with other existing classification approaches.

V. CONCLUSION

In this work, a novel paradigm for spectral and spatial analysis of dynamic Multiobjective classification of the hyperspectral images has been designed and implemented. The presented model improves the computation time in class informative feature extraction while minimizing feature set using principle component analysis. In Particular, spectral analysis has been carried out using spectral indices on obtained feature set. Spectral analysis produces the higher classification accuracy on the Multiobjective representatives for the discrete features. Importantly proposed model provides the land cover classification on environmental studies. 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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