Original Article

Multiobjective Convolution Neural Network Towards Soil Nutrients Classification For Crop Recommendation On Based On Spectral And Spatial Properties Using Landsat Hyperspectral Images

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Abstract

Hyperspectral Imaging Sensor Technology is employed to monitor and acquire the images or data of the remote earth surface with respect to spectral continuous data ranging of electromagnetic spectrum from visible region to short wave infrared region. Significance of the remote sensing enables the Comprehensive identification and classification of soil nutrients on account of improved spectral and spatial resolutions for crop recommendation to increase the agriculture productivity. Multiple challenges occur on processing hyperspectral images with Hughes phenomenon (curse of dimensionality) and estimation of soil nutrients in farmland on basis of the various contents. In an effort to alleviate those challenges, a new unique framework named as multiobjective Convolution Neural Network has been proposed to process the spectral and spatial properties on Landsat image along preprocessing, feature extraction and feature selection methods. Initially spectral unmixing technique is employed to identify end members (pure spectral signatures) and their end members corresponding abundances of each pixel in the HS data cube. Obtained end member is exposed to feature reduction strategy to eliminate the Hughes Phenomenon by retaining the useful endmembers using principle component analysis. The reduced features is processed in max pooling layer of the deep learning architecture to extract the maximum end members incorporate the sparse structure and Spectral low-rank structure on the pure signature of pixels of the particular region on basis of spectral analysis and spatial analysis. Identification of the soil contents such as Nitrogen, Prosperous, Potassium, pH and organic matter helps to predict the soil fertility and suitable crop for high yield production is predicted on aggregation of the spectral reflectance value of the soil nutrients contents. Classification and mapping of the soil into fertile land and bare land is done using spectral indices. The spectral indices computation of the pure spectral end members of particular region using N finder algorithm generates the type of soil with respect to the spectral and spatial value. N finder Algorithm is a change feature vector analysis on the fertility of the soil with respect to the organic matters, Nitrogen and prosperous properties. Further Convolution layers process the outcome of the N finder algorithm to gather the relating pixel of the learning image pixel together. Finally activation function using ReLu function evaluates the soil fertility in agriculture field to yield the soil fertility index for rich cultivation of various crops. Generated soil fertility index will help to identify the suitable crop for cultivation in the particular geographical region by resulting in enhanced accuracy and diversity among the soil and crop simultaneously. Experimental analysis of the proposed model has been performed out using Landsat-8 dataset which to evaluate the proposed performance of the multiobjective convolution neural network framework on the available spectral indices of the soil contents against the existing machine learning based approaches. Proposed framework produces the 99% of the accuracy on soil reflectance value against the different spectral wavelength on the soil fertility index which superior with other existing machine learning classification approaches.

Keywords: Hyperspectral Image processing, Soil Fertility Index, Landsat OSI, Soil Classification, Feature Reduction, Spatial and Spectral Indices, Crop Recommendation

1. Introduction

Hyperspectral images are an exploring salient source of information which has been originated in extensive fields to assess the object information in the particular region of interest nowadays [1]. In Particular, hyperspectral image used in Land covers analysis on the earth observation to identify the agriculture area, climate system, and ecosystem. Especially, land cover analysis in agriculture determines the soil fertility and type of the vegetation in terms of crop yield in the particular region for precision agriculture. In addition, it describes the biophysical state of the land surfaces on the wide information of the various properties in terms of spectral reflectance value of the spectral bands in the spectrum of the particular spatial location[2][3]. Moreover Soil characterization on evaluation of the soil fertility of an area is an important aspect to optimize the productivity of the soil for specific crop.

HSI usually accumulated hundreds of spectral channels and the gathered spectral reflectance information is a valuable source for soil nutrient identification and soil fertility classification. Specific Spatial and spectral analysis of the soil nutrients at regional scales is to generate the soil fertility index[4]. Traditionally chemical analysis based method has been employed for detecting the soil nutrients to identify soil fertility. However chemical analysis based method are time consuming, expensive and highly complicated. In addition, it leads to environmental pollution. In order to alleviate mentioned issues, Hyperspectral imaging spectrophotometer is employed to acquire the spectral information of the monitoring region. Obtained information is processed using machine learning architectures. Further machine learning models lags with limited number of the training samples and intraclass variability.

Deep learning architecture has been developed due to its great potential in data interpretations[5]. In this work, a new deep been proposed to process the spectral and spatial properties on Landsat image along preprocessing, feature extraction and feature selection methods. Initially spectral resolution is improved using spectral unmixing preprocessing technique to obtain pure spectral signature (end members). On obtained spectral signatures, Spectral and spatial feature are extracted using principle component analysis. PCA is feature reduction strategy to eliminate the Hughes phenomena. Feature extracted is projected to the deep learning architecture through input layer as pixel matrix.

Pixel Matrix is processed in max pooling layer to extract the maximum end members containing the sparse structure and low-rank Spectral structure on the signature of pixels of the particular region on basis of spectral analysis and spatial analysis. The spectral information is interpreted in convolution layer to identify various properties of the soil nutrients on the spectral reflectance value using N finder algorithm. It generates the type of soil with respect to the spectral and spatial value. Further ReLu activation function is been used to compute the non linearity in the properties of the soil with respect to corresponding weight and bias function to determine the quantity of soil contents such as Nitrogen, Prosperous, Potassium, pH and organic matter. Finally output layer output the soil fertility Index and suitable crop for high yield production.

Generated soil fertility index will help to identify the suitable crop for cultivation in the particular geographical region by resulting in enhanced accuracy and diversity among the soil and crop simultaneously. Classification and mapping of the soil into fertile land and bare land is done using spectral indices. The remaining of the article is sectionized as follows; related system is discussed on various performance results in the section 2. In section 3, deep learning framework has been employed for soil fertility classification of hyperspectral images is detailed. The experimental setup and performance results are depicted in section 4. Finally Conclusion of the work is summarized in section 5.

2. Related work

In this part, similar existing model for soil fertility analysis through hyperspectral image processing to yield soil fertility index and crop recommendation has been summarized and detailed on performance aspect is follows

2.1. Support Vector Machine for Classification of Hyperspectral Images

In this paradigm, various spectral resolutions of the hyperspectral images have been processed using Support Vector Machine to generate accurate land-cover classification [6]. The spectral analysis of the hyperspectral images identifies the various nutrient or minerals on the region of analysis in terms of reflectance value. Further the optimal subset of class-informative features of the soil information has been generated using feature selection technique such as genetic or Particle Swarm optimization [7]. The Spectral Classification is then performed by classifying the reflectance value of the various components into the suitable class on basis of the soil properties as indices. A class represents the soil fertility type.

2.2. Multiple Layer Perceptron for Hyperspectral Image Classification

In this paradigm, it uses the matrix representation of the HSI images to produce both spectral and spatial reflectance of the image to incorporate the long-range dependencies and extracting large spectral and spatial discriminating features. It feeds the high dimensional vectors into classes on basis of the largely spectral correlated bands, and the nonlinear complex structure of hyperspectral data. It is capable of the discriminating the feature maps with high class differences and inter class aggregations. It has ability the discriminate the soil fertility into classes suitable to various crop with high yield determinations [8].

3. Proposed Model

In this part, a multiobjective convolution Neural Network framework on composition of Spectral analysis and Spatial representation for Soil Fertility Index generation and Soil Nutrient Classification for Crop recommendation on basis of high yield prediction.

3.1. Preprocessing of Hyperspectral Images

Pre-processing of Hyperspectral Images is to enhance the image quality of the acquired image from remote sensing sensor on various processing steps. As an outcome of the preprocessing process, each pixel of the pre-processed image of the manually selected region will be resultant of the removed noises. The noise removal using gaussian based noise correction methods [9][10] against radiometric noises and geometric noises has been achieved in addition to image contrast improvement techniques. To filter the noise in the hyperspectral image, we employ radiometric correction method, it is given by

R [i, j] = Radiometric { f(i D, j D) }….. Eq.1

Image components is filter using neighbourhood condition, which is represented as D

$$g(x,y) = h_1 f(x-1, y-1) + h_2 f(x, y-1) + h3 f(x,y) .... h_9 f(x+1, y+1) .....Eq.2$$

The Image contrast techniques employed for hyperspectral images undergo on computation of histogram for color pixels. The resultant image of the preprocessing will be quality enhanced image for spectral unmixing and feature extraction.

3.2. Spectral Unmixing

Spectral unmixing is mechanism of decomposing the spectral signatures of the mixed pixels into set of endmembers which is considered as pure constituent of the material (soil) and their corresponding abundances. Spectral unmixing is processed using fully constrained least squares linear spectral mixture analysis method. It requires the material signature matrix M knowledge. It is carried out in two ways

- In the First method, Unsupervised Spectral Vector Quantization was derived using the nearest neighbor rule. It is to compute the unknown material or signals of the particular region.
- Second method is the target production process developed in the subspace projection method on the principle of orthogonality.

3.3. Feature Extraction using Markov Random Field

In this part, Markov Random Field is used to extract the hidden features of the pure spectral signatures (end members) using Spectral information criteria, Contextual content criteria and Spectral and special pair criteria [11]. It is measure of the dependency of the hidden features using Gibbs property. The distribution of features is represented as wavelet functions which are capable in separating the fine-scale properties and large dimensional information of a hyperspectral data. P(x) will be factorized due to its Markov properties which lead to following form as

$$p(x) = \prod_{C \in \Omega} \Psi_c(x) .....Eq.3$$

Large Scale Information is represented by the optimum index factor to determine the spectral bands with high spectral reflectance information and correlation of the similar spectral. The feature bands of the selected region is based on spectral reflectance content containing high representing information, but the discriminative between classes of the specific endmembers, as selected feature bands on basis of Spectral and spatial-pair separate may be highly correlated[12].

3.4. Feature Processing using Mean shift clustering

Mean Shift Clustering is projected for clustering the extracted features. The extracted features are unique spatial pure signature and ideal spectrally pure signature of a region of the interest. Clustering has been modelled to classify the Spatial and spectral reflectance value of the extracted features.

$$p(X_s = x_s \mid X_t = x_t, \forall t \in \forall s) ....Eq.4$$

Spectral features or its combinations of are correlated with possible Spectral pure spectral end members of soil types for Soil Fertility classification [13]. Soil Fertility area is mapped by computing the indistinguishable characteristics of soil, Condition of crop yielding and climate condition. Soil mapping is achieved using Soil fertility indices on the region of interest with respect to the soil contents.

3.5. Abundance Spectral Dimensionality Reduction through Principle Component Analysis

Principle Component Analysis (PCA) is employed to reduce the abundant features in the clustered set of the features. The Cluster of spectral feature is decomposed on basis of the computing the Eigen value and vector using matrix of covariance and correlation on the spectral reflectance value of the particular region or particular cluster. The computation of the most representative spectral components of the soil is assured to minimize the reconstruction error on the clustered spectral features is as follows

$$\mathrm{var}(x) = \frac{\sum_{i=1}^{n} a(xi - x)\,(xi - x)}{n-1} \quad .....Eq.5$$

Reduced features represent the highly functional information towards Soil Fertility index generation and Crop categories on the specified soil fertility. Covariance is computed for the X and Y Properties of the soil which changes together with mean is as follows

$$\mathrm{Cov}(x,y) = \frac{\sum_{i=1}^{n} a(xi - x)\,(yi - y)}{n-1} \quad ....Eq.6$$

Covariance Matrix is a N*N Matrix, where each element is given by

M_{ij}= Cov(x,y).....Eq....7

Eigen Vector of M_{ij} is a vector composed of principle feature set with values as Eigen value for Soil fertility determinations. Figure 1 represents the proposed architecture of the detailed methodology.

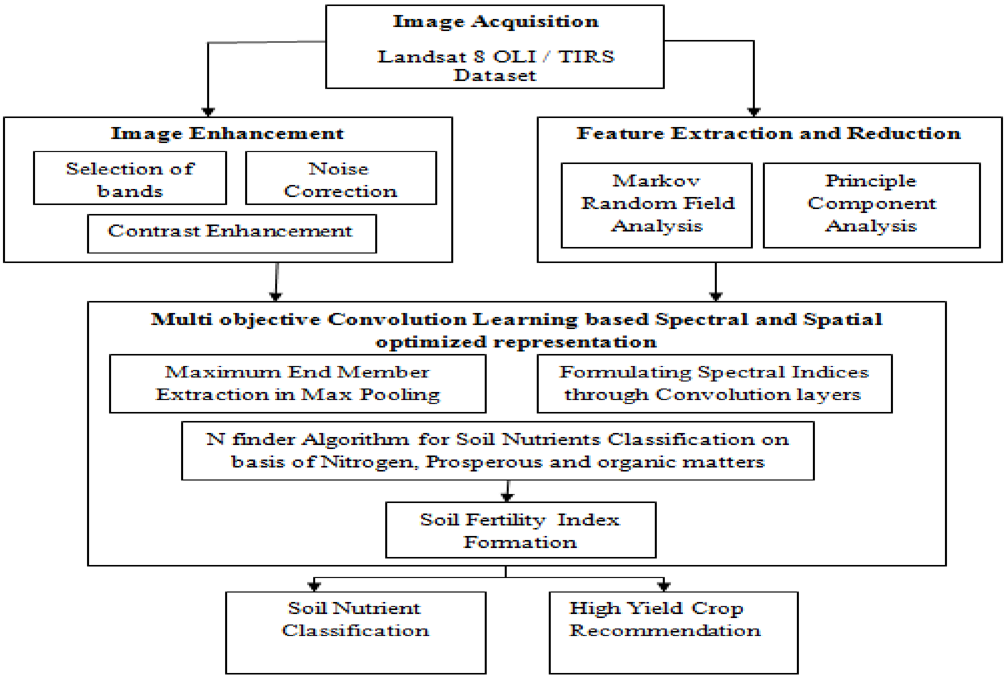

Figure 1: Proposed Architecture of Detailed methodology

3.6. Multiobjective Convolution Neural Network

The multiobjective Convolution Neural network architecture Composed of multiple convolutional layers for the volume with kernels of 3 × 3 × 3 elements has been employed for spectral analysis of the soil fertility on basis of the spectral reflectance value of the each feature of the hyperspectral image. The image is composed of band which represents the important information in terms of reflectance value and it is used for identification or classification of the various categories in the particular region [14]. HSI have three bands namely, red band, green band, and blue band. However, hyperspectral images represent the combination of bands, i.e., 100 bands, ranges from the visual to infrared.

- **Max pooling Layer**

A 2 × 2 × 2max-pooling layer is used to extract the maximum end members incorporates the sparse structure and low-rank spectral structure on the signature of pixels of the particular region on basis of spectral analysis and spatial analysis. It further increases the generalization capacity of the mechanism on the surface reflectance values [15]. Features are categorized by variations in the surface reflectance values of bands composed of two or more particular pixels. Pooling layers helps to generate the soil fertility index on the band reflectance values to separate the each component on the region of interest.

- **Convolution Layer**

The number of convolutional layers is selected exponentially on validating the performance of the model. Training iteration of the determined automatically based on the performance of the model in the validation and training set. The Convolution layers capture the soil characteristics of the high level and low level features through their inherent process on discriminating the features between the soil matters. It is capable of identifying the soil contents such as Nitrogen, Prosperous, Potassium, pH and organic matter. Crop recommendation is achieved on aspect of reflectance value of the spectral band.

Vegetation areas of the Soil with high fertility absorb in the high visible wavelength as it categorized in blue and red wavelength. It represents the Nitrogen, protein content. Similarly the soil fertility is also available in the infrared region. Soil fertility is highly characterised on the properties of Nitrogen value, prosperous value and organic matter value. In this region, fertile soil suitable for crop production is represented in green. Decrease in near infrared reflectance represents the nitrogen value and increased infrared reflectance represents the prosperous value. The spectral reflectance of the high soil fertility illustrates the highest index value whereas low fertile soil has less spectral reflectance.

- **Activation Function**

The architecture employs the rectified linear units (ReLU) to determine the non-linearity of the spectral reflectance. The N-Findr algorithm is employed to determine the spectral and spatial reflectance on various wave lengths. The spectral reflectance values of the particular region obtain the organic matter and Nitrogen value. The proposed algorithm 1 evaluates the set of pixels containing the high spectral reflectance on the pure endmembers in the particular region [16].

- .**Output Layer**

It is performs the End member classification to classify the soil on basis of its fertility constraints. Further it is useful in computing the crop to the particular soil fertility. The closest approximation of the testing sample of the HSI image may be from different Soil Fertile classes which depend on nitrogen, prosperous, pH level and organic matter derived from different convolution layers. The Soil fertility index is generated on discrete spatial distributions of the object spectra in the image. The linear variation on the spectral reflectance is measured with respect to the visible or near infrared bands..

Algorithm 1: Soil Fertility for crop Prediction
Input : feature set F={x1,x2,…xN**}**
Output: Target Label T={y1,y2..yN}
Process
While Epoch r : 1 → R do
  While feature set f: 1 → F do
    Compute the j hidden activation function using Rectified Linear Unit(ReLU)
      Generate Noise Vector n
Compute Error e
Apply Feed Forward Propagation to compute cross entropy Gradient E(θ)
cf= Convolution(F)
MP= Max_pooling(cf)
FC= Fully Connected(MP)
Class label= Spectral Reflectance (FC)
Update Network Parameter θ using gradient descent

Ground truth data is used for calibration of spectral images collected. It is also employed as verification of the materials on ground acquired in the image is utilized for materials regions mapping on cross fold validation using validation set.

4. Experimental Results

Experimental analysis has been employed out using Landsat-8 dataset to assess the performance of the proposed deep learning CNN framework on the various spectral indices against the machine learning approaches.

4.1. Experimental Set up

The Hyper spectral data contains around 220 bands and wavelength ranging from 400 nm to 2500 nm which covers all visible to infrared radiations. The spectral properties of Soil on Nitrogen status, Prosperous Status and pH level can be used for spectral estimation. Landsat 8 OLI dataset [17] were chosen to be analyzed in this work. Simulation of the work is carried on the Matlab R2018b Software. The Figure 2 shows the hyper spectral image of the Land Sat 8 Sensor.

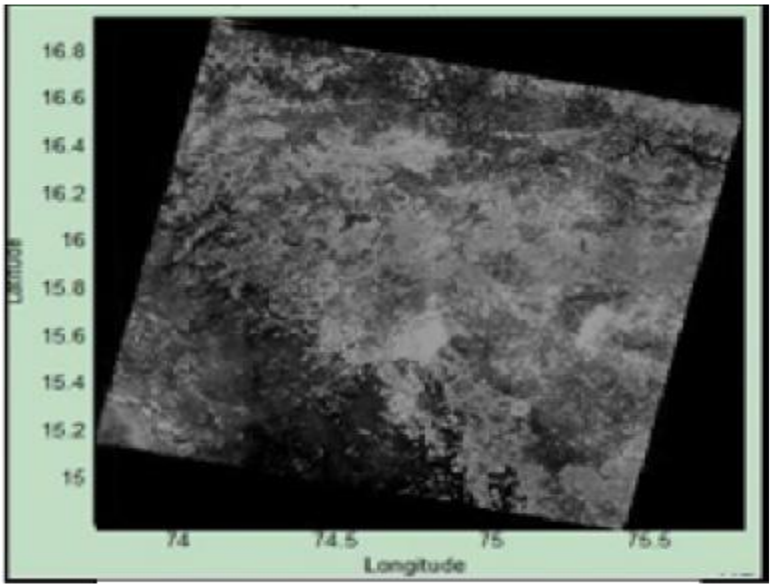

Figure 2 : Hyperspectral image

The hyperspectral image is processed using Gaussian filter towards noise removal against the radiometric and geometric noised. In this model, 'means shift clustering is used to classify the images in terms of the spectral end members which belongs properties of soil. Mean shift clustering is computed with least iterative steps by initializing the number of cluster. After selection of cluster number, the centroids have to be determined randomly. Through allocation of the centroids, each point is allocated to the closest centroids and groups of pixel nearest to centroids forms the cluster. The iteration continuous until there is no change in point of the cluster.

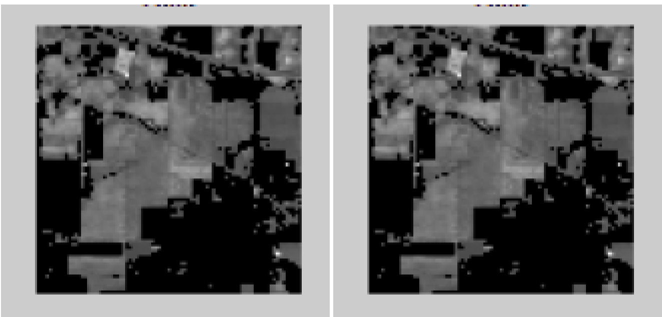

Figure 3: Cluster of hyperspectral image

The clustered image is processed later for feature extraction using bilinear feature extraction model. The feature extracted defines the properties of the soil. The N findr algorithm determines the percentage of the nitrogen values, Prosperous value and organic matters through number of pixels by considering end members. Every pixel in the image is filtered for end members and its volume provides the nitrogen percentage and prosperous percentage. Along with Nitrogen and prosperous, organic matters is identified through feature extraction model. 'N findr' algorithm calculates the spectral reflectance value of the feature.

The volume is computed for the entire pixel for each endmembers position by restoring that particular end member and determining the final maximum reflectance. The volume calculation is carried out until no end member is found. Percentage of the Nitrogen was computed or transformed as nitrogen value by usage of spectral indices such as Soil Adjusted Vegetation Index (SAVI)[18]. The SAVI varies with total nitrogen concentration and prosperous concentration which is further associated with organic matters and pH level of the soil state. Prosperous Value is computed as follows

$$\text{Prosperous Value} = -18.34*\text{NDVI}+19.370$$

Nitrogen value is computed as

$$\text{Nitrogen Value} = (\text{Prosperous value} - 2.6304)/2.483$$

The above value is computed on the reference of the ground truth data as it enables the calibration of the remote sensing data[19]. The Table 1 summarizes the organic matter Value, nitrogen Value, prosperous value for 1-210 bands of hyperspectral image of particular region.

Table 1 Spectral Values of the hyperspectral image at 1-210 bands

Bands	Organic Matter	pH level	Prosperous	Nitrogen
1-15	0.1011	0.9028	2.7771	0.0591
15-30	-0.5156	0.9021	2.7855	0.0625
30-45	0.1896	0.9020	2.7858	0.0626
45-60	0.2514	0.9010	2.8052	0.0704
60-75	0.5205	0.9007	2.8104	0.0725
75-90	0.4254	0.9005	2.8138	0.0739
90-105	-0.6283	0.9014	2.7975	0.0673
105-120	0.2296	0.9011	2.8044	0.0701
120-135	0.2941	0.9010	2.8044	0.0701
135-150	0.2868	0.9011	2.8032	0.0696
150-165	0.3461	0.9002	2.8203	0.0765
165-180	0.3692	0.9011	2.8027	0.0694
180-195	0.2419	0.9000	2.8228	0.0775
195-210	0.4197	0.9011	2.8032	0.0696
Average Nitrogen Value				0.0693
Average Nitrogen Percentage in %				6.930

The Computed value in the Table 1 provides the spectral value of soil properties for hyperspectral images of each band range. This provides the determination ability of soil fertile region of spectral reflectance. The spectral reflectance curve is to represent the soil nitrogen, prosperous, organic matter values in the given image. Spectral curve change according to the status of the climate and soil fertility. Figure 4 provides the spectral curves of the soil properties.

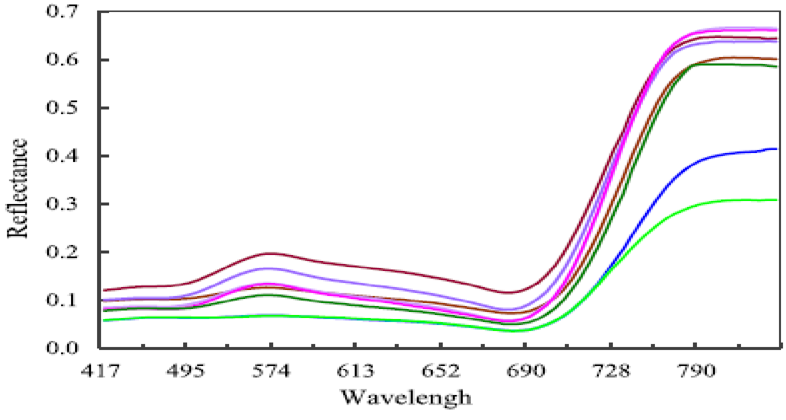

Figure 4. Spectral Curves of the Soil Properties

4.2. Performance Analysis

The performance analysis of the proposed architecture has been computed with respect to accuracy on determining the precision, recall and f measure properties. The precision, recall, Fmeasure has be identified using true positive, false positive, false negative and true negative value on different instance of classes to estimate the accuracy of the proposed model on the spectral indices of the region at different reflectance wavelength of the pixel and its is compared against existing machine learning classifier named as Support Vector Machine on Spectral value and Spatial value of the particular region[20].

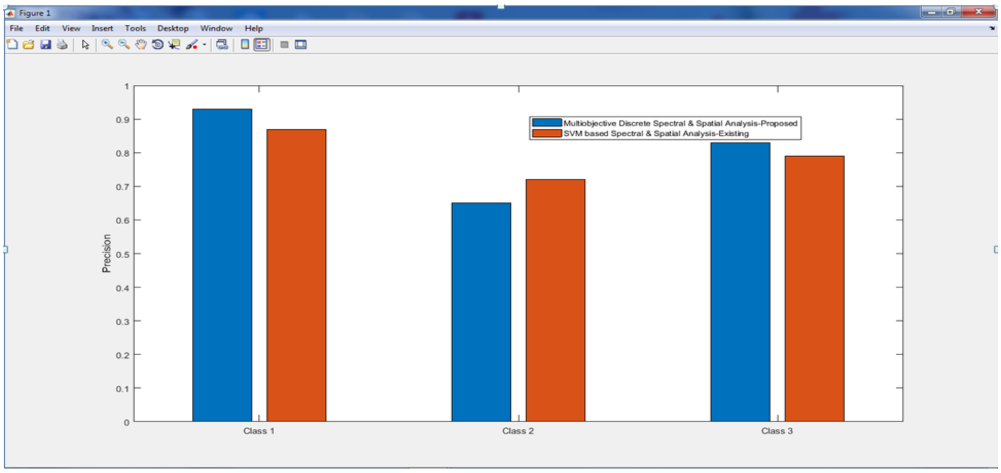

Figure 5: Performance Evaluation of Soil Fertility Classification With Respect to Precision

Figure 5 provides the performance of the classifiers with respect to the precision value for soil fertile classification to the acquired hyperspectral images and table 2 provides the performance measurement of proposed model and existing model on various spectral indices of the soil.

Table 2: Performance computation of Multiobjective Convolution Neural Network against Support Vector Machine

	MCNN-Proposed	**Existing**	**MCNN - Proposed**	**Existing**	**MCNN Proposed**	**Existing**
Metrics	**Soil Class 1**	**Soil Class 1**	**Soil Class 2**	**Soil Class 2**	**Soil Class 3**	**Soil Class 3**
True positive	78087	71014	28417	19799	55597	48995
False positive	55361	3881	9758	7994	9781	7846
False negative	11381	87889	3580	2974	9426	9157
True negative	192868	134712	234908	188456	212060	197851
Precision	0.98	0.89	0.89	0.92	0.89	0.89
Recall	0.89	0.88	0.89	0.88	0.88	0.89
F measure	0.99	0.98	0.98	0.95	0.98	0.96

Figure 6 to represents the performance of the classifier with respect to recall to the acquired hyperspectral images for soil fertile classification and table 2 details the performance measurement of the proposed model and existing model on various spectral indices of the soil. Proposed framework generates accuracy of 99% on reflectance value on the various wavelength of the soil properties on existing classification approaches on the Landset 8 OLI dataset with various spectral and spatial resolutions. This proposed paradigm can be applicable to various type dataset of hyper spectral images.

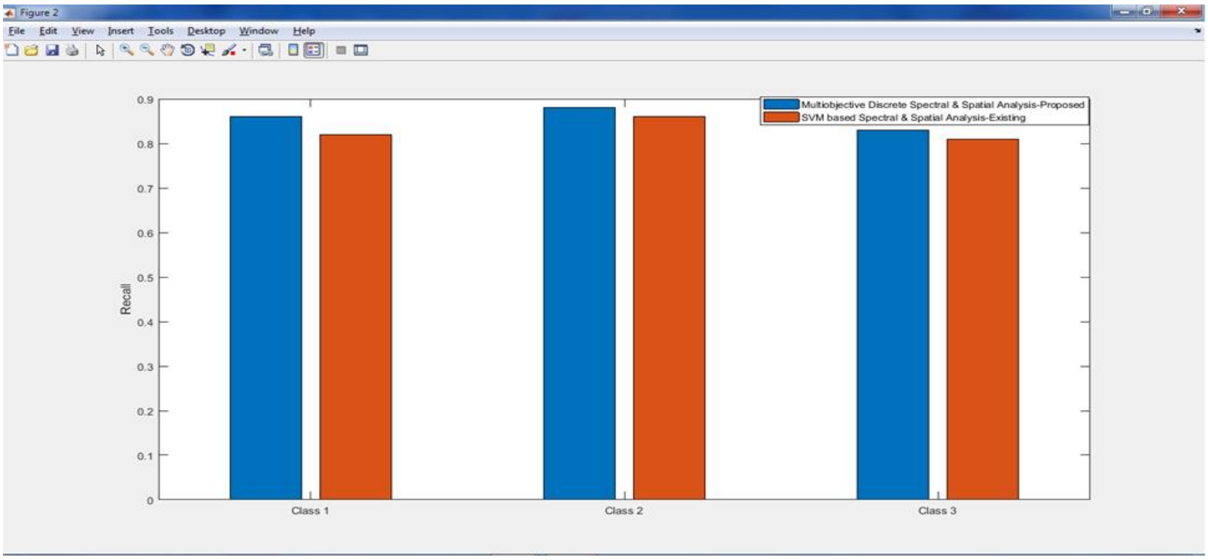

Figure 6: Performance Evaluation of Soil Fertility Classification With Respect to Precision

Figure 7 to explain the performance of the classifier with respect to Fmeasure to the acquired hyperspectral images for soil fertile classification and table 2 provides the performance measurement of the proposed model and existing model on various spectral indices of the soil. It is considered as efficient model for soil fertility estimation on spectral and spatial analysis.

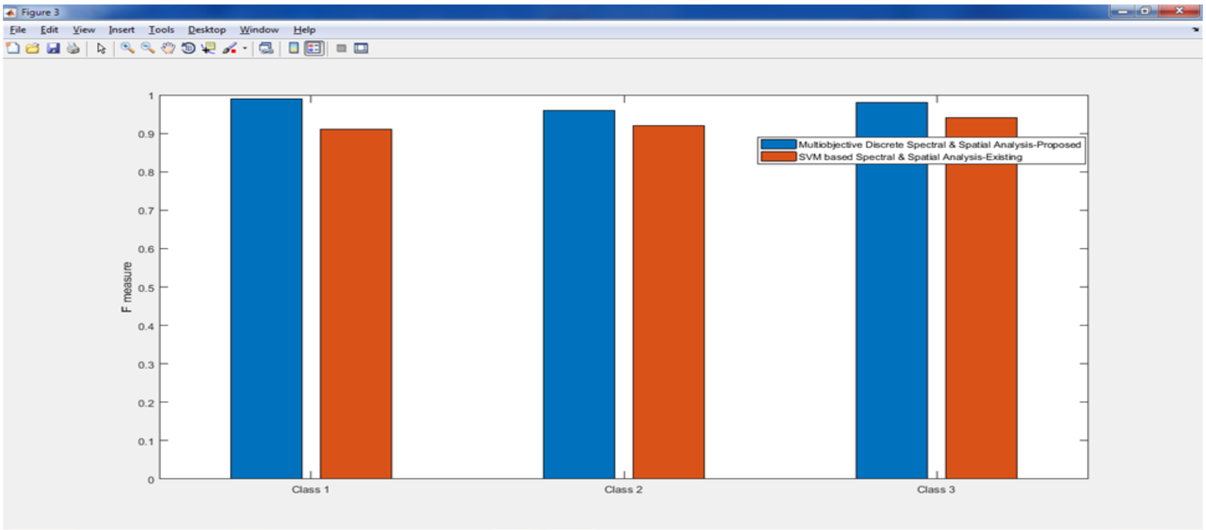

Figure 6: Performance Evaluation of Soil Fertility Classification With Respect to F measure

The obtained results depicts the effectiveness of the proposed model providing higher accuracy on comparing against existing approaches in soil fertility estimation and crop prediction for the soil with high yield. Proposed model can highly minimize data redundant and increase classification efficiency on basis of the dataset.

Conclusion

In this paper, novel multiobjective convolution neural network architecture on basis of the spectral and spatial analysis on hyperspectral images is proposed for soil fertility analysis and crop recommendation with respect to high yield productivity. Proposed model uses the error correction and image contrast improvement process in the preprocessing step. The pre-processed image is clustered using mean shift clustering on the particular region towards soil mapping. Abundant feature in the Cluster is reduced using principle component analysis. Hughes phenomena are managed using PCA. Further hidden and non linear features of the pure spectral signatures are generated in the max pooling layer of the deep learning model. In particular, output layer convolution layers identifies the soil contents such as Nitrogen, Prosperous, Potassium, pH and organic matter helps to predict the soil fertility using n finder algorithm. N finder Algorithm is a change vector analysis on the fertility of the soil with respect to the organic matters, Nitrogen and prosperous properties. Finally activation function using ReLu function evaluates the soil fertility in agriculture field to yield the soil fertility index for rich cultivation of various crops. Generated soil fertility index will help to identify the suitable crop for cultivation in the particular geographical region by resulting in enhanced accuracy and diversity among the soil fertility simultaneously. 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 architecture providing higher accuracy on comparing its performance with respect to existing machine learning approaches.

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