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Dense connected convolution neural network for land cover classification

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***Abstract*---**Hyperspectral Imaging is employed to monitor the earth regions on basis of spectral continuous data ranges initializing from visible wave infrared region to short wave infrared region of the electromagnetic spectrum. It authorizes the detailed recognition and classification of land cover on account of spectral feature space. Hyperspectral images seemed to be presented by employing traditional unsupervised and supervised classifier with regards to classification. Various problems seemed to cause Hughes phenomenon as it represents the curse of dimensionality issues. In spite of mitigating those challenges, a deep ensemble classification model seemed to be proposed in this work. It process the data features using various convolution layers of the network along modelling the activation function as a simple structure for classification of the hyperspectral data based on the spectral values using Softmax layer and error function to minimize the losses. Dense Connected Convolution Neural Network projected in this work as it has high potential to effectively classify the spectral features with learnt weights from one individual convolution layer to convolution layers. The main idea of Dense Convolution Neural Network is to produce discriminative classification results and to enhance the accuracy and diversity of a classifier simultaneously. The methods are tested using Landsat-8 real hyperspectral imagery to classify the land cover into classes. Experimental analysis on the proposed mechanism was validated with all overall accuracy. The results demonstrate that proposed method can improve the classification accuracy and reduces the edge effects compared with existing state of art approaches.

Keywords---dense model, hyperspectral image, classification, principle component analysis, discriminate convolution neural network.

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Introduction

Hyperspectral image (HSI) classification is a considered as vital task in land cover classification as it allocates a label to each pixel in the image**.** Hyperspectral imagery provides chances for enhanced mapping, modelling, and biophysical characterization of land cover images [1]. HSI usually includes hundreds of spectral channels of the sensed image as it has been obtained with spectral information and it is considered as precious data for classification. The Spectral classifiers have been implemented 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 [2]. Spatial feature extraction methods, including Markov random fields and graphical models as it employed for to the spectral-spatial classification of HSI[3].

Many researchers have been constituted on the end member extraction using spectral indices [4]. 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. 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 [5], The soil-adjusted vegetation index (SAVI) separates vegetation and water in urban areas [6] and Tasseled Cap (TC) indices have been used to enhance the information on biophysical coastal zones, water, soil, and vegetation [7].

In this work, Dense Convolution Neural Network framework for land cover classification through ReLu activation function has been proposed for HSI spectral-spatial classification [8]. A method based on combination of those techniques was introduced to extract the complex and hidden features of HSIs which is provide high classification performance improvement. Dense Convolution Neural Network classifiers model on basis of dynamic strategies to yield efficient performance than any CNN classifiers. The land cover classification with multiple classes is considered as final outcome of the proposed model [9].

The rest of the paper is organized as follows; related work is presented in the section 2. In section 3, proposed paradigm named Dense Convolution Neural Network 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.

Related work

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

Multiobjective Convolution Neural Network inferred Spectral and Spatial Analysis

In this model, multiobjective spectral and spatial analysis of the hyperspectral images yields enhanced land cover classification with respect to the spectral and spatial features obtained using markov process [10]. A feature reduction constraint has been included to the classifier as one of the primary objective for spectral analysis, where the exploitation of earlier information coupled to the evaluation of the reconstruction error in order to enhance the identification of the effective class-of the land cover of monitored region.

Proposed work

In this section, we define Dense Neural Network framework to classify the land cover region using spatial and spectral indices of the spectral signature of pixels.

Linear Discriminant Analysis

Hyperspectral Image pre-processing is performed in order to improve the quality of original images with all preparatory steps. LDA is a non-parametric method for discriminant analysis based on the application of a Bayesian classification rule on a signal composed by Discriminative Spectral components. The method is based on the use of Linear Discriminant Analysis to determine a transform matrix so that the transformed components are as discriminant as possible [11]. Then, a non parametric estimation of the density function is computed for each discriminate spectral and spatial component. The images of size N x N, first represent each image to a 1D vector U. Vector composed of variance values of the spectral features. Variance for particular object X in an image is computed as follows

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

Covariance is computed for the X and Y object which changes together with mean is as follows

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

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

$$M_{ij} = \mathrm{Cov(\,x,y)}$$

Eigen Vector of M_{ij} is a vector composed of discriminate spectral feature set with values as eigen value for classification or recognition

Dense Connected Convolution Neural Network

In this method, these techniques require there to be adequate training data available for each specific image. It is based on computing invariant representations usually cover large areas and require per-pixel labels [12]. Each base learner predicts the label of the unspecified sample, respectively. No prior knowledge is essential for unsupervised classification methods and it depends on spectrally pixel-based statistics.

Convolution based Classifier objective function is given as

$$f(x_i) = \text{sign}(D^T x_i + C)$$

Max Pooled Margin of x_i is:

$$y_i (D^T x_i + C)$$

The significance of unsupervised classification model is to classify the image into classes composed of the connected feature. Max Pooled margin is twice the minimum functional margin for any point in the image. A complete CNN has been employed for hyperspectral image classification and mapping of the spectral signatures with multiple stage containing a convolution layer, a nonlinearity mapping layer, and a pooling operation layer for ReLU activations. A deep CNN is constructed by stacking several convolution layers and pooling layers to form a deep architecture. Figure 1 represents the architecture of the proposed framework of the efficient agriculture land classification.

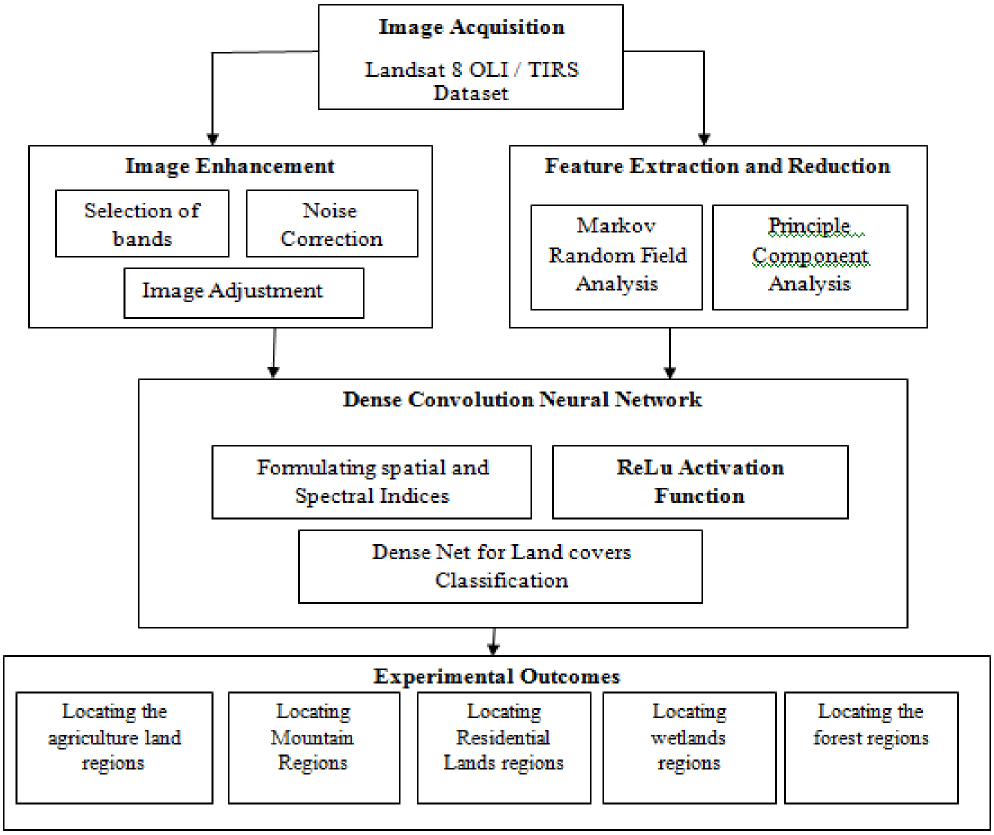

Figure 1: Architecture of the Dense Convolution Neural Network Framework

Convolution Layer

The convolution layer employs different filters to extract features from the pooling layers. It derives the feature map on the convolution operations. Epoch is used as convolution layers to converge the feature map. It enhances the feature generalization by normalizing the output of the activation function.

Cosine distance between the extracted features is given by

$$r = y\frac{D^T\mathbf{x}+C}{\|D\|}$$

Hyperspectral image data usually contains the spectral signatures. Additionally, due to the Hughes phenomenon and Convolution Layer yields the classifications based on statistical characteristics.

Activation Function

Multiple Constraints has been activated in this layer to yield the effectiveness in the land use and land cover classification on its changes of the spatial and spectral features. Classification error has been mitigated through modelling error function. Constraints have been produced through discriminative map on the change direction of every pixel between the different spatial and temporal information's. It introduces non-linearity to the network. Each activation function processed after the batch normalization to avoid the over fitting features. The closest approximation of the testing sample may be from various classes, which represents that the minimal residual may be derived from numerous classes. The finial classification result is generated by integrating the results based on the voting rule.

Pooling layer

Pooling layers transform the spectral and spatial features into large reliable and abstract features on minimizing the spatial invariance among the features extracted. Max Pooling layer connects the features into little patches on account of the spectral signatures. Max pooling is employed to compute the greatest no of the features to the each patches. It further imporves the generalization capacity of the model[13].

In multispectral analysis of the feature space, pooling layers deduces input vector into high vegetation clusters in the form of input feature vectors. The input feature vector is calculated for multivariate regression in account to yield the multi class vector. The objective function of the classifier is defined to estimate the output vector through addition of squared errors which is represented as by
The class coefficients for the feature intercept on the spectral features given by objective function as

$$Y = \beta_0 + \beta_1 X$$

Where the class coefficients are represented as

$$\beta_1 = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2}$$

The integral derivates of the class objective function with respect to the class coefficients has been extracted to estimate Error Sum of Square (SSE). Softmax layer which follows delta rule is given by loss function of the hyper parameters. It is to determine multiple linear weights of spatial features. In addition, feature weight can be computed through iterations.

$$\Delta W_i = C(t\text{-}net)x_i$$

where ***'c'*** is the learning rate
'x' is input for that weight

On the objective of minimizing the SSE and solving loss of the classifier, Delta rule will be updated.

Experimental Results

In this section, performance analysis of the experimental outcomes has been computed and validated through Indian Pines dataset on multiple spectral signatures [14]. In this work, optimal parameters for the proposed architecture have been set for the land cover classification. The model is simulated in mat lab tool. The dataset has been partitioned spectral images into train, test and validate. In this 80% of data has employed to train the proposed architecture and 20% is used to validate the proposed architecture. On 80% training data, it has been divided as 60% for train the architecture and 20% to validate the trained model. In this 5 fold cross validation is incorporated to enhance the accuracy of the training model [10]. DCNN training parameter has been represented in the table 1

Table 1: DCNN training parameters

Parameter	Value
Activation Function	ReLu
Learning rate	10^{-6}
Loss Function	Cross Entrophy
Batch size	14
Max epoch	500

The hyper spectral images taken for processing will measure the variation in the land cover spectral values in terms of different spectral indices has been represented. Spectral evolution has been computed effectively to identify the efficiency and accuracy of the proposed architecture. Figure 3 represents the performance of the proposed architecture against convention approach with respect to precision [15].

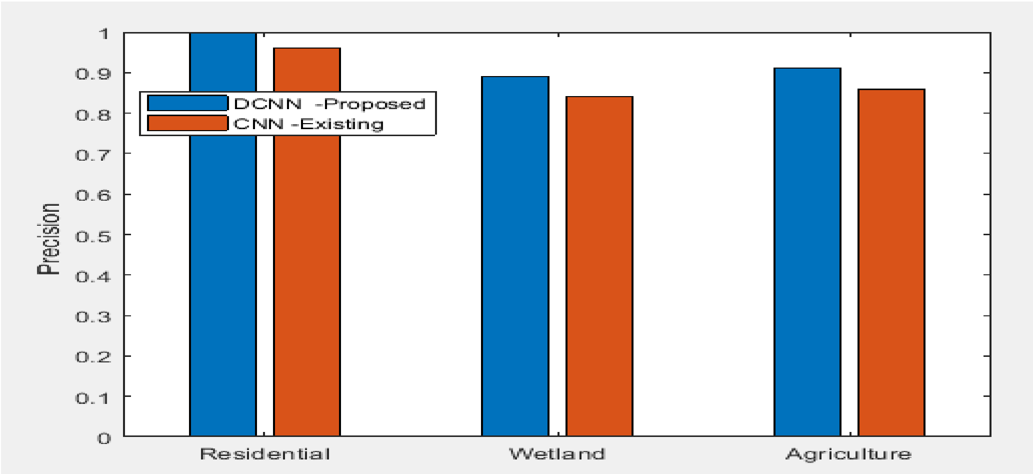

Figure 2: Performance Evaluation of the Proposed model on precision

The precision, recall, Fmeasure has be calculated using confusion matrix with parameters like true positive, false positive, false negative and true negative. Those values have been extracted from on various instances of classes to compute the performance accuracy on the spectral indices at various wavelength of the pixel of proposed architecture and it is compared with classified pixels of the spectral images. Further it have been processed to identify the change detection on aspect of correlation of the spectral signatures

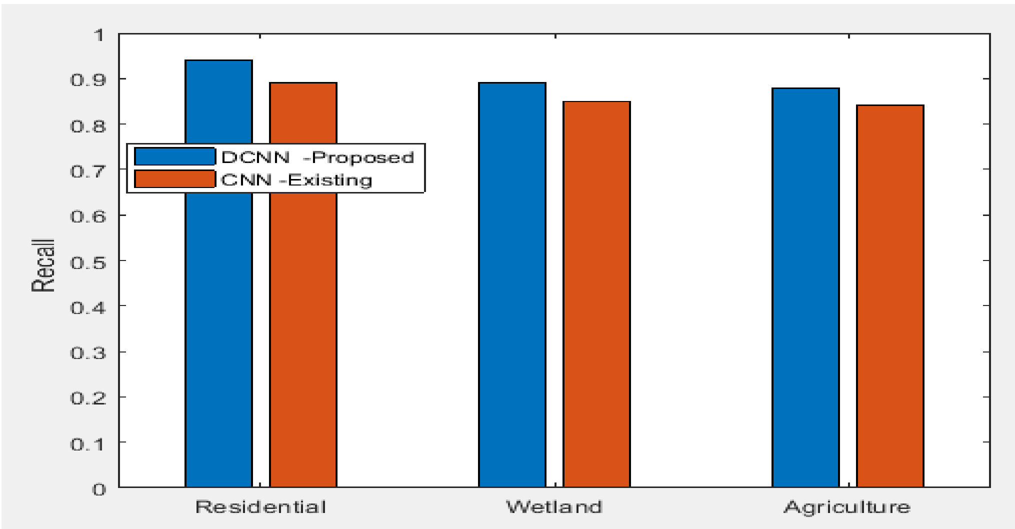

Figure 3 : Performance Evaluation of Proposed architecture against Conventional model on Recall

Figure 3 depicts the performance of the proposed architecture towards classification of the hyperspectral images in terms of recall on the classes of land cover results. On analysis, it yields effective results on true positive values computation.

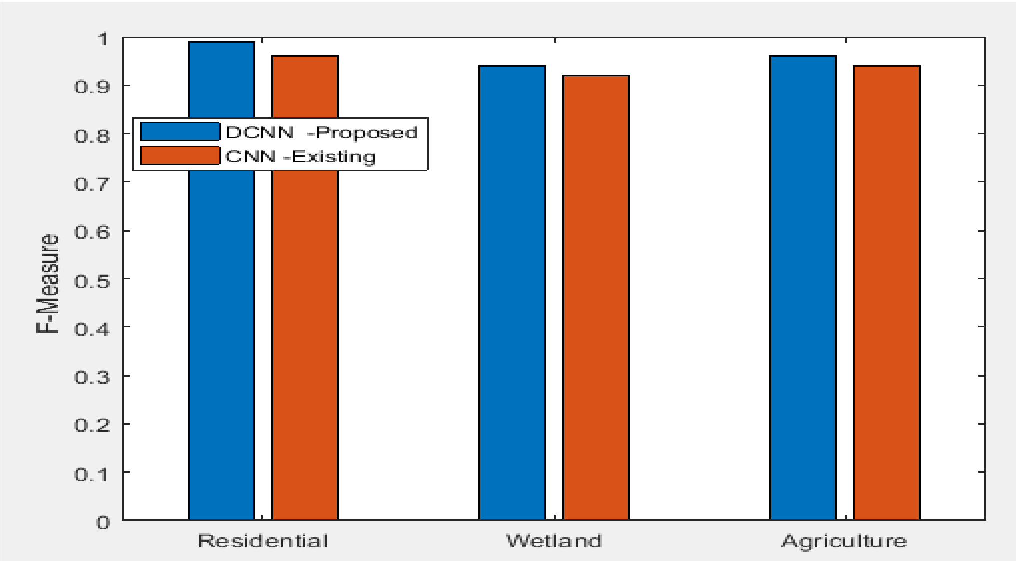

Figure 4 : Performance Evaluation of Proposed architecture against Conventional model on F measure

It is interesting that the accuracy values of the proposed model are high in the classification of hyper spectral images on multiobjective activation functions of the classifiers. It classifies the discrete spectral values. This paradigm can be applicable to any type dataset of hyper spectral images. Figure 4 provides the performance results of the f measure on outcomes of classes containing land cover. Table 2 represents the performance of the classification accuracy on proposed classifier against conventional approach.

Table 2: Performance computation of proposed architecture on land Cover Classification

Techniques	Classes	Precision	Recall	F measure
Proposed Technique – Dense Convolution Neural Network	Agriculture	0.99	0.94	0.99
	Residential	0.89	0.96	0.99
	Wetland	0.94	0.88	0.99
Existing Technique- Graph Convolution Neural Network	Agriculture	0.96	0.89	0.96
	Residential	0.84	0.94	0.94
	Wetland	0.89	0.84	0.98

Performance of the proposed approach produces the classification maps with high classification accuracy [10]. Proposed model can highly minimize the data redundancy and enhances classification efficiency on basis of the dataset.

Conclusion

In this work, a novel Dense Convolution Neural Network for land cover classification of the hyperspectral images has been designed and implemented. The proposed architecture determines the effective activation function based on spectral indices as it enhances the processing time in class informative feature classification with large feature weight. The features are reduced using pooling layer. In order to further enhance the performance of HSI classification, multiple strategies has been incorporated via convolution and softmax layer to minimize the classification error.. Finally Dense Convolution Neural Network calculates the diversity of the features effectively. The experiment analysis was evaluated and tested on the Landset 8 OLI dataset to compute its effectiveness and efficiency in terms of accuracy.

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