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Dense Convolution Neural Network defined change detection and novel water indices architecture towards Water Bodies Mapping and delineation on various season and climate variation using Landsat OLI 8 Images

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***Abstract*— Classifying and mapping water bodies is more significant and essential to human life. Identifying water availability, degradation and disappearance with respect to various seasonal variations and climate variations using change detection techniques and water indices are current research challenges due to temporal variability of spectral, temporal and spatial characteristics of different reflectance bands of Landsat dataset. Especially water bodies such as sea, ocean, lakes, river and glaciers have different spectral and spatial reflectance values. Further, presence of the thematic classes in the imagery leads to misinterpretation error and it is highly complex to obtain the ground-truth data for the change in the multispectral images on the same topographical zone. In order to manage these challenges, an effective deep learning architecture is designed. In this work, a Dense Convolutional Neural Network for change detection and novel water indices is presented. Proposed model is capable of classifying the water bodies in the multispectral images in addition to detecting and quantifying the site-specific changes due to climate and seasons on the basis of spectral and spatial reflectance values. Initially endmembers considered as multivariate components are extracted using sparse principal component analysis (PCA). PCA is capable of handling of non-changing pixels and continuous narrow bands in the multispectral satellite data for various water bodies. End member selection on multivariate components is carried out using Particle swarm optimization technique. This is effective in reducing the size of multispectral data by producing the principal components and to overcome the dimensionality problem. Extracted principal endmember is applied to dense convolution neural network classifier. With the spectral values of the endmember thematic classes are generated to discriminate the water bodies on basis of its types. Finally, new water index is allotted to the water bodies on basis of the climate and season variations along the degradation rate and disappearance rate. The experimental results of the proposed model are evaluated on real-time multispectral image data sets acquired from Landsat 8 OLI dataset. Performance of the proposed model is compared with conventional approaches with respect to precision, recall and f measure on cross fold validation. From the results, it is confirmed that proposed architecture exhibits higher performance in classification accuracy with 99.43% in delineating the water bodies.**

Keywords: Multispectral Image, Deep Neural Network, Water Bodies, Water Bodies Delineation, Particle Swarm Optimization, Principal Component Analysis, Endmember, Water Index

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I. INTRODUCTION

Water bodies' delineation is essential for the human living and ecosystem towards sustainable life in the universe. However intense exploitation of the water bodies at regular intervals is found to be very imperative as it helps to access the extent and rate of degradation and disappearance due to climatic variations [1]. Delineation and classification of water bodies enhances the chances of water conservation. Manual exploitation and delineation are highly challenging due to diversity of the waterbodies. Complexity of the water bodies' detection and classification on wide range of the land regions can be minimized on utilizing the remote sensing technologies [2].

Delineation of the Water bodies using satellite images through remote sensing technology has achieved significant growth in the engineering research. Especially machine learning architectures like support vector machine [3] Random Forest and decision tree algorithms are employed to delineate the water bodies [4]. Despite of numerous advantages, machine learning architectures exhibit various challenges with respect to the illumination defects, environment changes and atmospheric aspects such as low spatial and temporal resolutions and large spatial and temporal variability and spectral signatures similarity on identifying the degradation and disappearance of the water resources among water regions such as sea, ocean, lakes, rivers and glaciers.

These limitations lead to misinterpretation error. It is a time-consuming task to identify the changes in the multispectral images on the same topographical zone. In order to mitigate these non-trivial challenges, deep learning architecture has emerged to provide advanced solutions to change detection in the water bodies. The architecture helps to detect and quantify the site-specific changes due to climate and season on basis of spectral and spatial reflectance values. Landsat OLI captures the image in nine spectral bands the spectral contextual information is used for effective discrimination [5].

In this Paper, Dense Convolution Neural Network (DCNN) is employed for change detection and novel water indices marking. Initially multispectral satellite images are preprocessed using noise removal technique against various noises and bad line replacement techniques for image replacement. Proposed model is highlighted with

- Existing Convolution neural network (CNN) algorithm
- Proposed is dense convolution neural network classifier to identify the spectral values of the end member to generate thematic classes to discriminate the water bodies

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on basis of its types by utilizing the various layers such as convolution layer, pooling layer, activation layer, embedding layer and SoftMax layer.

• Finally, new water index is generated using relief algorithm and it is used describe the water bodies on basis of the climate and season variations along with the degradation rate and disappearance rate during different seasons and climates.

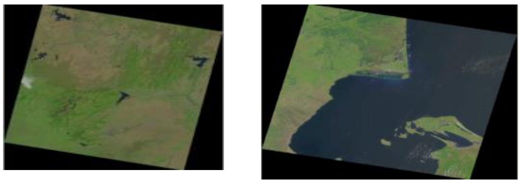


Figure 1: Multispectral Landsat OLI 8 Image from USGS earth explorer (1024 x 1024)

200 satellite images downloaded from USGS earth explore in various spatial domains. 160 images used for training and 40 images used for testing. Figure 1 represents the input Landsat OLI 8 image (1024 x 1024) download from USGS earth explorer portal.

II. Proposed Model

In this section, a new deep learning architecture named Dense Convolution Neural Network is constructed towards delineation of water bodies by processing multispectral images for change detection due to seasonal and climatic variations on the topographical region. The architecture is modelled to detect a particular water body with spectral signatures along with its changes on spatial temporal aspects.

A. Endmember Extraction – Sparse Principal Component Analysis with image preprocessing

In this work, endmember extraction is used for dimension reduction and obtain the minimum noise function. Sparse principal component analysis [7] is used for data processing and dimension reduction. So, both the techniques are used for preprocessing the data. multispectral images are represented as three dimensional images with combination of spectral and spatial bands as cube. Spectral bands contain the noise and the redundancies. This can be removed using denoising techniques. However, in spectral information, correlation between the bands of the different wavelength is complex. In order to eliminate these complexities, multiband sparse representation is done. Figure 2 represents the image preprocessing using denoising technique with slicing of multispectral image

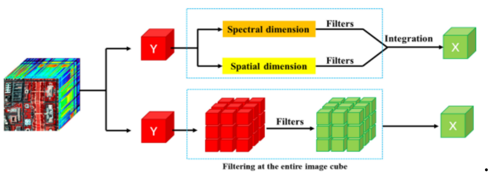


Figure 2: Multispectral Image slicing towards and spectral and spatial dimensions

Denoising technique using 3D wavelet based sliding window is employed for de-correlating the pixel dependencies with various coefficients vectorized in 2D matrix in the multispectral image slices. Rank constraints are employed in the spectral and spatial slices for approximation of the image to produce the denoised multispectral images without redundancy as well as bad lines in the image [8].

Figure 1 represents the redundancy and noise elimination in the sliced patches of the image. Rank constraints are applied to slices of the image for noise reduction as follows:

$$M_i = \frac{1}{n} R \sum_{x \epsilon C}^{n} (S - T_i) \qquad (1)$$

where R is the Rank Constraint, C is the coefficient of the image, T is the spatial dimension and S is the spectral dimension.

The first order spectral derivates of the image are reduced using the rank constraints to generate the high contrast multispectral images. Further linear combination on spatial and spectral parameters is adopted to filter the noise with averaging mechanism. Averaging of the parameters corrects the spectral and spatial bands accumulated with error.

Endmember extraction is carried out using sparse principal component analysis. Endmember extraction determines the multivariate components in the particular pixel on emphasizing the spectral and spatial signatures. Multivariate component of the pixel constructs the subspace with maximum volume to accommodate the pixels with similar spectral structure to represent the endmembers in the specified region.

Assume the multispectral Image as composition of P Pixels and L spectral bands

Assume endmember to be obtained as Ed

The Spectral signature of the N pixels is represented as Vector V

$$V = \{PL1, PL2....PLn...\} \qquad (2)$$

Covariance of the Pixel on spectral signatures is computed as

$$C_v = S_L \sum_{j=1}^{m} s(r_i - r_{i+1}) \qquad (3)$$

Correlation of the pixel on the spectral signatures is computed as

$$C_c = S_L \sum_{j=1}^{m} s(r_i + r_{i+1}) \qquad (4)$$

where m is the number of endmembers

where SL represent the spatial location of a pixel within an image. It's a variable that indicates where the pixel is situated in the two-dimensional space of the image, "i" represents the index or counter for different spectral bands or channels in a multispectral image. The subscript "i" in "ri" refers to a specific band index within that vector.

Subspace of the endmember of the neighbor spatial location is computed as

$$\mathrm{Se}_{SL} = Aggregate\ E^{\frac{|\det(e^0)|}{n!}} \quad (5)$$

where $e^0 = \left[\frac{1}{eSL1} \quad \frac{1}{eSL2} \quad \frac{1}{eSL3}\right]$

eSL= [e1,e2,......em] represents the endmember of particular spatial location .

The resulting subspace of the end-member is Abundance Ai.

$A_i = [\mathrm{Se}_{SL}]^I$ denote the abundance of the i^{th} pixels

Subspace composed of the suitable endmember representing the spectral reflectance properties of its zones. Finally, abundance map is generated to the subspace containing the spectral value of a pixel on the neighbor zones indicating as the relative abundance of an endmembers. Further Spectra fidelity is also computed to evaluate the accuracy of the abundance map generated. In Figure 3(a) represents the input image figure 3b represents the endmembers extracted principal components image.

(a) (b)

Figure 3: Endmember extraction using Principal component analysis (a) Input image (b) endmembers extracted image

A. Endmember Selection – Particle Swarm Optimization

Particle Swarm optimization is a Metaheuristic optimization technique projected to obtain the optimal endmember spectral signature in a particular location which is composed of only particular type of water body segments or spectral features. It is inspired by the social forging behaviors of the bird. Particle represents the endmembers and velocity represents the size of the endmember. In order to reduce the search space, optimization employed to generate the new population by scaling the values of the endmembers.

Assume V(t) = Velocity which represents size of end member

Assume X(t) = Particle which represent endmembers

X_{best} is the best endmember among endmembers

X_{gbest} is the best size of the endmember among the available size of the endmembers.

Fitness function of endmember is

$$V(t+1)=w*V(t)+c1*rand()*(Xbest-X(t))+c2*rand()*(xgbest-x(t)) \quad (6)$$

Selected endmembers for spatial region is represented as {e1, e2, e3...en}

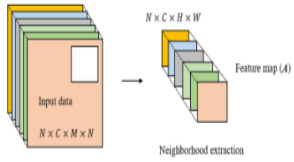
In this e1, e2 represent the best endmember of selected spatial region containing spectral signatures.

B. Water Body delineation – Dense Convolution Neural Network for Change Detection

Dense Convolution Neural Network is employed to delineate the water bodies for change detection and mapping of regions with respect to season and climate variation. It delineates the water bodies on the processing of optimal feature containing endmembers. The processing of the endmembers in the deep learning architecture undergoes various computations in the layers of the network. Change detection network aims to map the spatial correlated endmembers and identify spectral changes of the endmembers on the basis of temporal changes.

1) Convolution Layer

The convolution layer of the model contains multiple kernels to convolve with optimal endmembers to derive the feature map which is considered as activation map of the spatial correlated endmembers. Convolution is mathematical operation which illustrated as feature multiplication of the spectral signature and multiple filters. Spectral matrix of multispectral image 5*5 is multiplied with kernel size 3*3. Figure 4 represents Convolution of the spectral endmember is illustrated as



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Endmembers Matrix

1	0	1
0	1	0
1	0	1

Kernel Matrix

=

4	3	4
2	4	3
2	3	4

Feature Map

Figure 4 : Convoluted of the spectral endmember matrix with Kernel matrix

C. Endmembers Feature Map

The convolution layer yields the spectral endmembers of the mapped correlated spatial endmembers with respect to the convolution operations. Endmembers convergence into spectral map representing temporal changes of spectral values with respect to seasonal and climatic variations. Convergence map is established using no. of epochs. It enhances the endmembers on normalization of the activation function represented as ReLu to yield the linear feature map. Endmembers Distance is calculated using cosine distance.

Cosine distance of the endmembers in the convergence map is represented as

$$CD_e = C_{sp}(m^t f^t) - C_{sp}(m^t f^t) / (C_{sp}(m^t f^t) + C_{sp}(m^t f^t)) \quad (7)$$

where C_{sp} is the constraint support problem used to find endmembers in the multispectral data, ft is the filter and mt is endmembers

1) Pooling layer

Pooling layer of the network minimize the spatial dimension of the endmembers as it is termed as spatial pooling of the multispectral images. In other words, pooling layer is considered as down sampling of spatial endmembers on reducing the spatial endmembers dimension on retaining only selected weighted endmembers. The spectral reflectance value is highest in selected weighted endmembers. Due to the spectral signatures, the Max Pooling layer joins the shortened segments of the spectral endmembers. The largest number of endmembers are mapped to each spatial temporal feature using max pooling. Meanwhile it increases the model generalization. Figure 5 represents the Endmember pooling of the convoluted matrix is illustrated as

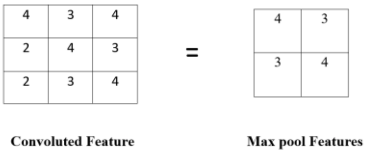


Figure 5: Endmember pooling of the convoluted matrix

2) Fully Connected Layer

Fully connected layer of the DCNN is termed as dense layer as it is capable of organizing multiple constraints to process the feature map. Feature map is an integration of the spatial and spectral endmembers of the topographical regions. Discriminative feature map is an integration of the temporal features along spatial and spectral information. Figure 6 represents Fully connected layer employs the activation function to process feature normalization to eliminate the non-linearity and over fitting issues in the feature bands. Fully connected representation of the feature bands is represented below

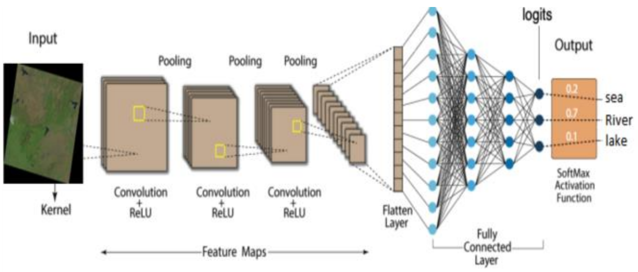


Figure 6: Fully connected model

SoftMax is implemented in the dense layer to produce the classes by deducing the feature vector into water region class vector. It is to validate the model reliability. Further loss function is integrated in fully connected layer to reduce the spatial variance on the classes of the endmembers. The testing endmembers' closest approximation, which may come from several classes, shows how the minimal residual can come from many different classes. The results based on the voting rule are integrated to get the final categorization result.

The loss function of the Multi parameters provides the SoftMax layer, which adheres to the delta rule. The spatial features' multiple linear weights are computed. Additionally, iterations can be used to determine the weight of a feature.

$$\Delta W_i = C(t\text{-net})\, x_i \qquad (8)$$

where 'C' is the learning rate 'x_i' is input weight

On the objective of minimizing the SSE (sum of squared error) and solving loss of the classifier, Delta rule is updated. In this work, spectral reflectance values of the endmembers of water bodies are used to develop new spectral indices (NSIs).

Initially it analyses the properties of each endmember with respect to the water regions and maps the value to it. Algorithm towards classification of the endmembers provided. Multibolic tangent function is given by

$$F(a) = \frac{e^a}{e^n} \qquad (9)$$

Finally, proposed delineation model based on the convolution neural network has been generated to classify the water regions into the 5 types mentioned in Table2 on updating the spectral indices of the proposed model.

III. EXPRIMENTAL RESULTS

In this part, performance analysis of the implementation outcomes is estimated and evaluated on the dataset obtained from Landsat 8 OLI sensor on the various climatic conditions. Optimal parameters for the current architecture are fixed for the water body delineation on basis of spectral reflectance values. The model is implemented in python. Landsat dataset is divided into train, test and validate the model. Especially 5-fold cross validation is carried out to increase the accuracy of the proposed model. Dense Convolution Neural Network training parameters are illustrated in the Table 1

Parameter	**Value**
Activation Function	ReLu & Tanh
Learning rate	10^{-6}
Batch size	14
Max epoch	500

Table 1: Dense Convolution Neural Network training parameters

The spectral values of the endmembers removed are measured in the multispectral pictures used for processing. To assess the effectiveness and accuracy of the existing model, spectral fidelity is successfully estimated. Figure 7 shows how the proposed model compares to the standard model in terms of precision.

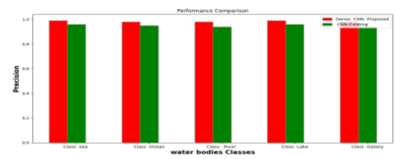


Figure 7: Performance Evaluation of the proposed model on precision

The type of water bodies with regard to the correlation of the spectral signatures is also computed during the processing stage.

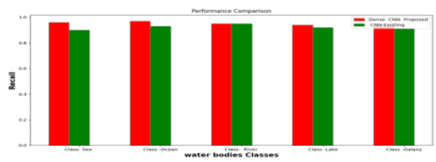


Figure 8 : Performance Evaluation of Proposed architecture against Conventional model on Recall

Figure 8 shows how well the suggested architecture performs in terms of recall on the classes when it comes to classifying multi-spectral images.

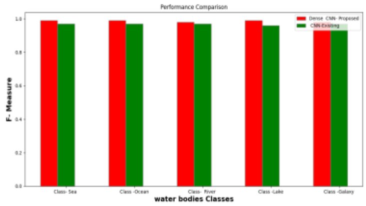


Figure 9 : Performance Evaluation of Proposed architecture against Conventional model on F measure

The suggested model's high accuracy values in the multi-objective activation functions of the classifiers' categorization of multi-spectral pictures are an intriguing finding. It organizes the water attributes that contain reflectance value's discrete spectral values and spatial values. Any form of dataset including multi-spectral images can be used with this paradigm. The performance results of the f measure on outcomes for classes with endmembers are shown in Figure 9 in detail. The proposed classifier's delineation accuracy is compared to that of the traditional classifier as shown in Table 2.

Techniques	**Classes**	**Precision**	**Recall**	**F measure**
Proposed Technique – Dense Convolution Neural Network	Sea	98.25	96.15	99.12
	Ocean	97.54	97.15	98.25
	River	98.45	95.15	97.25
	Lake	98.21	97.16	96.14
	Glacier	98.14	92.18	97.21
Existing Technique- Convolution Neural Network	Sea	91.18	90.28	92.56
	Ocean	91.14	90.01	91.23
	River	92.26	90.56	90.89
	Lake	93.18	90.25	91.45
	Glacier	94.12	90.29	90.67

Table 2: Performance computation of proposed architecture on Water bodies Delineation

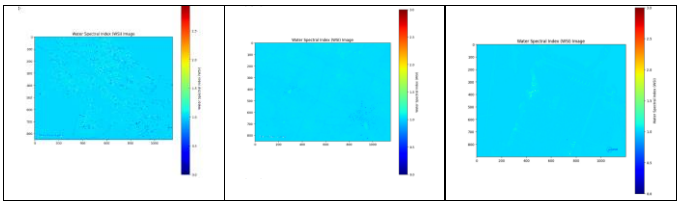


Figure 10: Change detection of water bodies in Erode district study area

Further these outputs explain that the water spectral index is able to delineate water bodies and categorize them with better reliability on various experimental and environmental conditions.

IV. Conclusion

In this work, a dense convolution neural network for water bodies' delineation employing the multispectral images is designed and implemented. Endmembers of the image is obtained using sparse principal component analysis optimal endmembers of the water bodies based on temporal changes of the images is selected using particle swarm optimization technique. Proposed classifier classifies the water bodies effectively and accurately with reference to the new spectral index generated. Proposed model is capable of identifying the lake, river, ocean, sea and glacier. In order to determine the accuracy of the implementation analysis, it is checked and verified using the Landsat 8 OLI dataset.

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