International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075, Volume-9 Issue-1S, November 2019

Land Use and Land Cover Classification Using Deep Belief Network for LISS-III Multispectral Satellite Images

T.Vignesh, K.K.Thyagharajan

Abstract: Land Use and Land Cover (LULC) classification is one of the familiar applications of geographical monitoring. Deep learning techniques like deep belief networks (DBN), are used for the purpose of feature extraction and classification of multispectral images. In this proposed framework, by applying DBN, spatial and spectral features were extracted and classified with high level of classification accuracy. LISS III images of Kottayam district, Kerala were used as experimental images. This proposed framework proved that, DBN has a high ability to extract the feature and classify the multispectral images with high accuracy than traditional methods.

Keywords: Multispectral images, deep belief network, spectral features, spatial features, land use and land classification, LISS III.

I. INTRODUCTION

Land use and land cover (LULC) classification is the important sub field of land cover monitoring. LULC means, classifying the remote sensing images into various land cover classes such as water, build up area, plantation, road, forest, etc [1]. Remote sensing images have been used for the purpose of land use and land cover classification for several decades. Remote sensing images is a 2D representation of the real scene and these images captured as aerial images or satellite images. For example, aerial images are taken from aircraft and satellite images are taken from various satellites [2]. There are four different types of satellite images available for research: multilayer image, multispectral image, super spectral and hyper spectral images [3]. In this research work, we have used multispectral images for our experimental purpose. Specifically we used LISS-III images.

Multispectral image comprises various layers, each layer represent individual band image [4]. For instance, LISS-III images has four band multispectral data and identified each band as green, red, near infrared (NIR) and short wavelength infrared (SWIR) with 24 meter resolution. By using multispectral images, spatial and spectral features can be easily classified into various classes with high accuracy.

Revised Manuscript Received on November 27, 2019.

***** Correspondence Author

T.Vignesh , Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India.
Email: vigneshthangathurai@gmail.com

K.K.Thyagharajan, RMD Engineering College, Kavaraipettai, Chennai, India. Email: kkthyagharajan@yahoo.com

Mostly, LULC can be done by various approaches, specifically machine learning techniques and deep learning techniques. Around two decades before, most of the LULC was done by traditional classification techniques such as K-means clustering, C-means clustering, decision trees, rule-based classification etc [5]. Nowadays, deep learning techniques have been used in most of the LULC applications, because of the high level classification accuracy. Deep learning techniques have lot of applications such as image recognition, image classification, video surveillance, etc.

Deep learning techniques are the valuable tool for classifying multispectral images into various land cover classes and it has been using in the field of LULC and produced better result than machine learning techniques [6]. DBN is one of the kind of deep learning technique and it is proposed by Hinton et al in the year of 2006[7]. DBN is an unsupervised neural network, and each layer is created by restricted Boltzmann machine (RBM). RBM was initially proposed by Paul Smolensky in the year of 1986 and it was extended by Geoffrey Hinton and collaborators in the year of mid-2000 for fast learning process. It has been successfully used in feature extraction, classification, pattern recognition [8] etc. The organization of this paper is as follows, section 2 describes about study area and data description, section 3 illustrates about methodology, section 4 explain about experimental result, section 5 present the conclusion and section 6 describes about reference.

II. STUDY AREA AND DATA DESCRIPTION

The study area is located in Kottayam district, Kerala, India. The geographical latitude and longitude point of our study area is 9.5916° N, 76.5222° E. The total area of our study area is 2208 sq. km. Agriculture land, Built-up area, Forest, waste land and water bodies are the LULC classes of our study area. We have downloaded LISS-III (2018) data ofKottayam district, Kerala, India from USGS website which is free of cost. All the four bands of LISS-III data were merged with the use of ERDOS IMAGINE-2010 software. The merged image is the input image of DBN.

III. METHODOLOGY

In this research work DBN is used to classify the multispectral images into various land cover classes.

In this section, we briefly reviewed about DBN architecture followed by RBM, logical regression and experimental result. Basically, DBN has two different layers, such as RBM layers (Bottom Layer) and logical regression classifier (Top Layer) [9].

3.1 Deep Belief Network (DBN)

This network model was proposed by Hinton et al (2006) and it has been mostly widely used deep learning architecture classification and object recognition. This neural network architecture extensively followed deep learning architecture. DBN comprises of various levels of stacked RBM and it follows unsupervised approach for classification [10]. Figure 1 illustrates the architecture of DBN. Basically, DBN has two main parts, specifically RBM layers (Bottom layers) and LR layers (Top layers).

3.2 Restricted Boltzmann Machine (RBM)

RBM is a neural network architecture that is able to learn probability distribution along its sets of input vectors. It has two sets of phases such as visible layer and hidden layer respectively. Let us, assume that two different layers of RBM such as visible layer and hidden layer as (vl, hl) [11]. The energy function of visible and hidden layer is given in equation 1,

$$E(vl, hl) = -\sum_{i=1}^{I} a_i vl_i - \sum_{j=1}^{J} b_j hl_j - \sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij}\, vl_i hl_j \quad (1)$$

Where w_{ij} represents weights associated with visible layer vl and hidden layer hl.

Bias fields are represented as a_i and b_j.

Visible layers and hidden layers are represented as I and J.

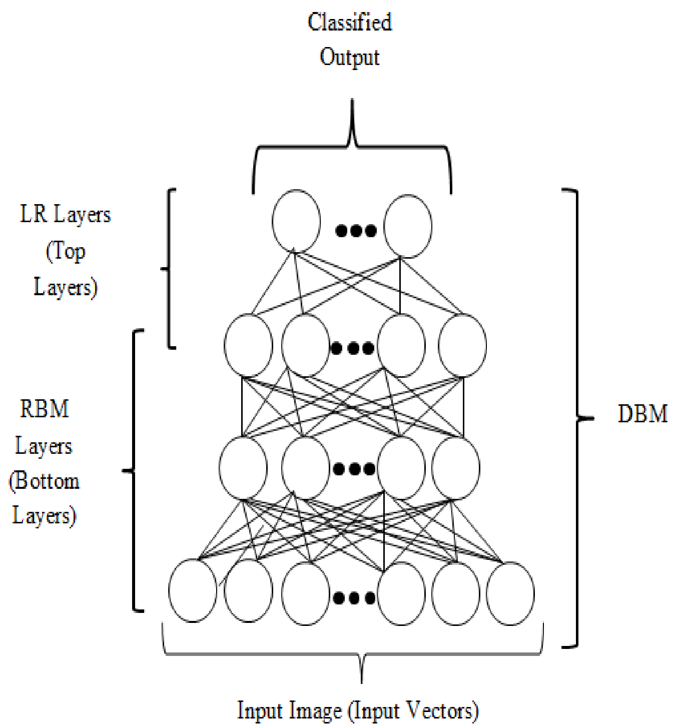


Figure 1: DBN Architecture

The probabilistic distribution of visible and hidden layers is proportional to negative power of the energy function as follows [12],

$$p(vl, hl) = e^{-E(vl,hl)} / \sum_{vl}\sum_{hl} e^{-E(vl,hl)} \quad (2)$$

The probability that hidden layer hl_j can be calculated as follows,

$$p\left(hl_j = \frac{1}{vl}\right) = \sigma(b_j + \sum_{i=1}^{I} vl_i\, w_{ji} \quad (3)$$

The probability that visible layer vl_i stimulated can be calculated as follows,

$$p\left(vl_i = \frac{1}{hl}\right) = \sigma(a_i + \sum_{j=1}^{J} hl_j\, w_{ji} \quad (4)$$

Where (x) *is represented as sigmoid function* , So, $\sigma(x) = 1/(1 + e^{-x})$

The following steps are illustrated as the training procedure of the RBM.

1. Initialize the weights and bias values, and start the iterative training phase on the training samples.
2. In the positive side of the training, training samples on the visible layers $\{vl_i\}$ and hidden layers $\{hl_j\}$ precede based on equation 3.
3. In the negative side of the training, reconstruct the visible layers $\{vl_i'\}$ based on equation 4.
4. The positive side is reconstructed to construct $\{hl_{ij}'\}$.
5. Finally, weights and biases will be based on Contrastive-Divergence (CD) algorithm (13), which can be constructed as follows,

   $$\Delta W_{ij} = \varepsilon(< vl_i hl_j > - < vl_i' hl_j' >) \quad (5)$$

   $$\Delta a_i = \varepsilon(< vl_i > - < vl_i' >) \quad (6)$$

   $$\Delta b_j = \varepsilon(< hl_j > - < hl_j' >) \quad (7)$$

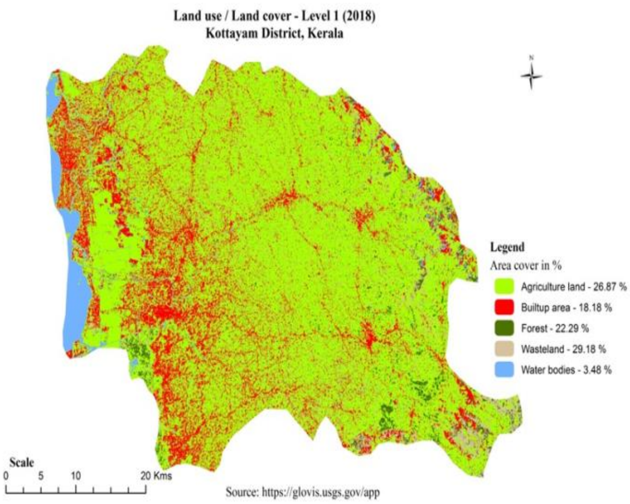
   After the training phase, LULC class samples and test samples can be predicted and outputs of RBM can be forwarded to Logical Regression (LR) layer[14].

3.3 Logical Regression Layer

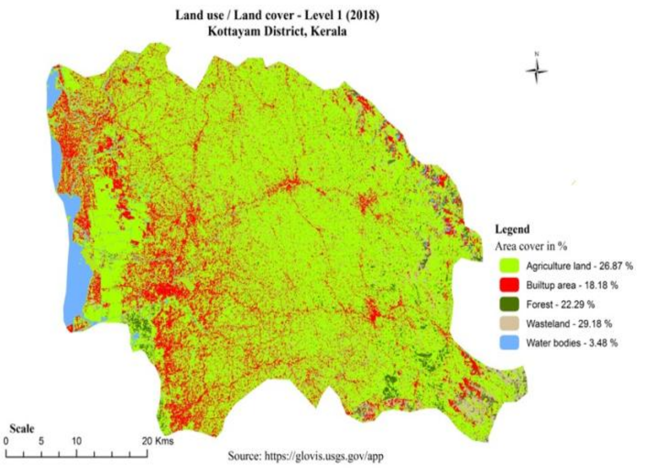
The logical regression (LR) layer is the top level layer of DFN and it is used to fine tune the samples and optimize the weights w. [15] From the LR layer, DBN can be produced the LULC classes of LISS-III images.

IV. EXPERIMENTAL RESULT

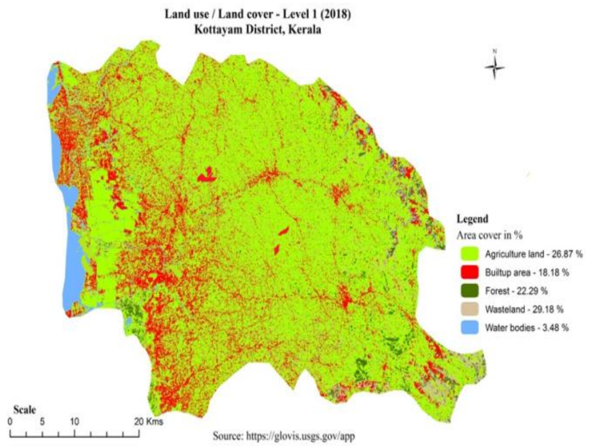
To evaluate the performance of our proposed method, comparison with other three methods such as k-means clustering (K-means+LBP), C-means clustering(C-means+LBP) Support vector machine (SVM+LBP) have been used. In the above mentioned three methods, to improve the performance of classification accuracy, we have used local binary pattern (LBP) as a feature extraction method. Figure 2 illustrates the LULC classification output of various methods and Table 1 shows classification accuracy of individual methods.



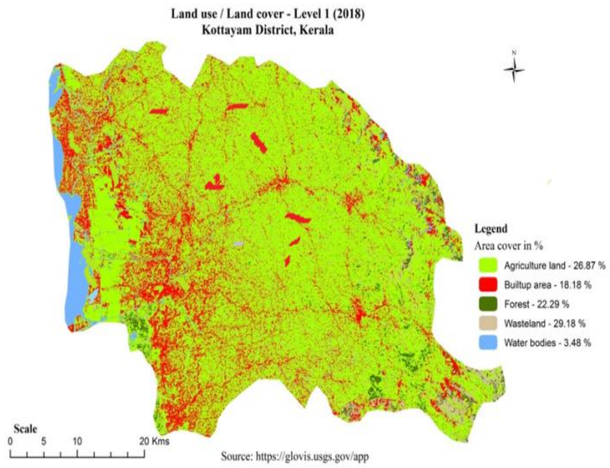
(a) DBN



(b) K-means+LBP



(c) C-means+LBP



(d) SVM+LBP

Figure 2: LULC classification of (a) DBN, (b) K-means+LBP, (c) C-means+LBP, (d) SVM + LBP

Classification methods	Total No. of pixels taken	Correctly classified pixels	Classification accuracy in %	Kappa (K^{Δ}) Coefficient
Proposed (DBN)	512	499	97.46	0.933
K-means+LBP	512	473	92.38	0.885
C-means+LBP	512	451	88.08	0.843
SVM+LBP	512	447	87.30	0.836

Table 1: Classification accuracy

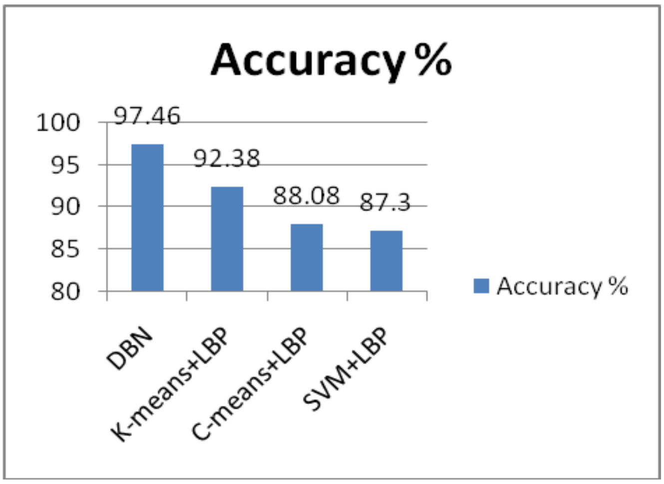


Figure 3: Classification accuracy

In our proposed method, no need to perform feature extraction as individual phase and at the same time, feature extraction and LULC classification is done by DBN. Figure 3 shows that, our proposed method produced high performance result than other three methods. For evaluation purpose, we have considered 512 pixels for each method. For DBN method, out of 512 pixels, 499 pixels were correctly classified. The overall classification accuracy of DBN method is 97.46% with kappa coefficient 0.933. For K-means+LBP method, out of 512 pixels, 473 pixels were correctly classified. The overall classification accuracy of K-means+LBP method is 92.38% with kappa coefficient 0.885. For C-means+LBP, out of 512 pixels, 451 pixels were correctly classified and overall classification accuracy of C-means+LBP is 88.08% with kappa coefficient 0.843. For SVM+LBP, out of 512 pixels, 447 pixels were correctly classified and overall classification accuracy of SVM+LBPis 87.30 with kappa coefficient 0.836. The error rates of the various methods such as DBN, K-means+LBP, C-means+LBP and SVM+LBP are respectively 2.54%, 7.62%, 11.92% and 12.7%.

V. CONCLUSION

In this paper, DBN is used for LULC classification of LISS-III data. In this proposed framework, due to the reason of deep learning techniques no need to perform feature extraction and classification in individual steps. Our experimental result shows that, DBN produced highest classification accuracy than other three methods for LISS-III multispectral satellite images. This proposed framework proved that, DBN has a high ability to extract the feature and classify the multispectral images with high accuracy than traditional methods.

REFERENCES

1. AshishGhosh, Badri Narayan Subudhi, Lorenzo Bruzzone, (2013) Integration Of Gibbs Markov Random Field And Hopfield-Type Neural Networks For Unsupervised Change Detection In Remotely Sensed Multitemporal Images. IEEE Transactions On Image Processing, 22 (8):3087-3096.
2. Zhao Meng, Bai Xiao, (2011) High-Resolution Satellite Image Classification And Segmentation Using Laplacian Graph Energy. In: 2011 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), pp 605-608.
3. T.Vignesh, K.K.Thyagharajan (2017),Soft Computing Techniques for Land Use and Land Cover Monitoring with Multispectral Remote Sensing Images: A Review, Archives of Computational Methods in Engineering, Vol.26(2),pp.275-301.
4. Roberto Vaccaro, Paul C. Smits, and Silvana G. Dellepiane, (2000) Exploiting Spatial Correlation Features for SAR Image Analysis. IEEE Transactions on Geoscience And Remote Sensing, 38(3): pp. 1212-1223.
5. D.Menaka, Dr. L. Padma Suresh, and S. Selvin Prem Kumar, (2014) Land Cover Classification of Multispectral Satellite Images Using QDA Classifier. In:2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), pp 1383-1386.
6. Claudio Persello and Alfred Stein, “Deep Fully Convolutional Networks for the Detection of Informal Settlements in VHR Images”, IEEE geoscience and remote sensing letters, vol. 14,pp. 2325-2329.
7. Y.LeCun,Y.Bengio and G.E.Hinton, “Deep Learning”, Nature, Vol.521, no.7553,pp.436-444,May 2015.
8. Ping Zhong et al, “Learning to Diversify Deep Belief Networks for Hyperspectral Image Classification”, IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 6, june 2017.
9. Chenming Li et al, “Deep Belief Network for Spectral–SpatialClassification of Hyperspectral Remote Sensor Data”, Sensors, vol.19, pp.1-13, 2019.
10. Ping Zhong et al, “Learning to Diversify Deep Belief Networks for Hyperspectral Image Classification”, IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 6, pp.3516-3530,june 2017.
11. Fang Liu, et al, “POL-SAR Image Classification Based on WDBN and Local Spatial Information”, Ieee Transactions on Geoscience and Remote Sensing, vol. 54, no. 6, pp.3292-3308, june 2016.
12. Yushi Chen et al, “Spectral–Spatial Classification of Hyperspectral Data Based on Deep Belief Network”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 6,pp. 2381-2392,june 2015.
13. G.E. Hinton, “Training products of experts by minimizing contrastive divergence,” Neural computation,vol. 14, no. 8, pp. 1771–1800, 2002.
14. Biao Leng et al, “3D Object Classification Using Deep Belief Networks”, International Conference on Multimedia Modeling, pp. 128–139, 2014, Springer International Publishing Switzerland.
15. Ahmed M.et al, “Breast cancer classification using deep belief networks”, Expert Systems with Applications Volume 46, 15, Pages 139-144, March 2016.

AUTHORS PROFILE

T.Vignesh received his M.Sc (Computer Science) and M.Tech (CIT) degree from Manonmaniam Sundaranar University, Tirunelveli, India in the year of 2006 and 2011 respectively. He also, obtained his doctoral degree from Manonmaniam Sundaranar University, Tirunelveli, India in the year of 2019. He is having around 9 years of teaching experience in various engineering college in Tamilnadu and 3 years industry experience. He has published more than 15 research papers in National and International journals and conferences. His research area includes Computer Vision, Image processing and Pattern recognition. He is a lifetime member of ISTE, IAENG, and IACSIT.

E-Mail: vignesht.sse@saveetha.com, vigneshthangathurai@gmail.com