A Framework on Land Use Land Cover Classification of Granite Quarry Area Using Remote Sensing Images

P.Nithya
Research scholar,
Dept. of Computer Science and Engineering, Annamalai University.

Dr G.Arulselvi
Associate Professor
Dept. of Computer Science and Engineering, Annamalai University.

Abstract -Efficient land cover change detection on special data of remotely perceived information is needed for urban development and natural resources development. Recently, machine learning and deep learning tools are applied in land use and land cover (**LULC**) classification because the acquisition of high-resolution remote sensing images becomes easier due to technology development. To predict the LULC data on mining areas or quarry space from remotely perceived information could be a difficult task. The goal of this study is to compute the relative change in the area of LULC categories because of granite production. We classified the spatial structure of remotely sensed data using the modified deep convolution neural network (**CNN**) and compared this performance evaluation with traditional machine learning methods of artificial neural network (**ANN**), and iterative support vector machine (**ISVM**). In this work, unsupervised classification techniques have been used to classify the impact on granite mining using hyperspectral images. The performance efficiency of the proposed Deep convolution neural network has been developed using the optimizer SGD, Adam, and batch normalization. The overall accuracy of the DCNN framework proves that an accuracy percentage of 95.8 % whereas ANN and ISVM have an accuracy of 91.4% and 88.6 % respectively.

Keywords: Land Use Land Cover (**LULC**), Remote Sensing (**RS**), Deep Convolution Neural Network (**CNN**), Artificial Neural Network (**ANN**), Iterative Support Vector Machine (**ISVM**).Granite Quarry(GQ).

I.INTRODUCTION

Recently the deep convolution neural network is a modern technique in remote sensing applications for LULC classification. Deep learning and machine learning have yielded wonderful ends up in varied land cover recognition fields. The hyperspectral and multispectral images from different sensors has been experimented .To enhancing the vegetation index techniques ,several machine learning method such as SVM, Random Forest, K Means Clustering are used in land cover detection. In this study hyperspectral image with 230 bands has been used from the database of Google earth engine. It will be applied to the region of interest and edge thickening filter for enhancing the effective ground truth segmentation and classify the required classes. In preprocessing, data augmentation has been implemented for elastic distortion of generated hyperspectral images. The data augmentation additionally provides the diversification of remotely sensed data. . The tweaked segment data are then processed into training validation of the proposed deep learning architecture. The labelled LULC classes has been generated based on ground truth information of pre-defined Indian data pines data set .The deep learning CNN (**Resnet18**) module has been used in this planned theme to classify the LULC classes such as Quarry land, built-up land, forest land, bare land, and agriculture land.

The main objective of this research as follows: To enhance a more desirable method for the LULC classification and change in the area owing to quarry activities by implementing modified Deep learning architecture. To analyze the hyperspectral image of our study area with ground truth information of Indian pines data sets. To improve the fine-tuning of self-learning neural network by varying the hyperparameter such as the batch size of the input layer, filter size of convolutional blocks, and fixed learning rate . To evaluate the performance of the proposed architecture using different optimizers SGD, Adam, and batch normalization. To demonstrate the overall accuracy of our proposed algorithm better than the machine learning algorithms of ANN and ISVM.

This project work is organized as follows section II states the brief explanation of previous machine learning and deep learning model used in remote sensing areas. It consists of different training architectures of neural networks for the multispectral and hyperspectral images of our study. The concept of the proposed methodology has been explained in section III. Section IV provides experimental works of our planned theme and section V gives a conclusion and future work for land cover detection

II.LITERATURE REVIEW

In this framework, the previous works on LULC classification using the completely different hyperparameter of the projected classifier were discussed. The modified deep learning design has been mentioned here. To predict land cover classification in Ganji-ngzi District of Dalian city, the convolutional neural network has been applied [1] to Landsat 8 data to solve the classification on spatial information of required ground objects .This method proves that CNN has the accuracy of 93.4 % when compared to machine learning method of SVM. The land classification of another method [3] has been made by using a cascade Deep convolution neural network. The different network was tuned with cascaded features to obtain the appropriate urban supervision including the Cafe net, VGG-S net, and VGG-F net. The selective feature extraction and polychromatic of input Landsat data have been made by these three different deep convolution networks.

The cross-validation in performance evaluation of machine learning methods was tested by implementing the deep learning method of CNN [5] with fixed no of parameters mainly filter size, Relu layer, batch normalization, and drop out ratio. The hyperspectral image from AVIRIS has been analyzed based on predefined Indian data pines data set consist of 145*145(input size),220 bands,20 m of spatial resolution, and 16 classes. The used CNN architecture outperforms the traditional machine learning method of SVM, random forest, and k-nearest –neighbor. The novel concept method of BAM (best activation model) has been included to resolve the issue of underfitting during the CNN training validation of LULC classification. UC Merced Land-Use, WHU-RS19 data sets were tested with this proposed method [7] to proves that the efficient method for LULC specificity scenes.

The data is processed using modified Resnet 18 deep learning[8] projected structure for Bangla handwritten character recognition and the performance evaluation of the designed system has been experimented with three different optimize (ADAM Optimizer, SGD Optimizer, and RMSprop to enhance the fine-tuned network layer. To improve the LULC classification in neural network architecture, the modified RCNN [10] has been developed the high-resolution satellite imagery from multiple sensors for target recognition and multiclass segmentation. The methodology Alex Net and Google Net [12] was implemented in a deep convolution neural network to enhance the effective LULC classification of two datasets namely, UC Merced Land Use dataset and Brazilian Coffee Scenes dataset .the different architecture of the proposed self-learning network has proved the accuracy of 95.72% and 96.83% .the learning modalities fine-tuning CNN with the best result 93.62 % in LULC classification. The imbalanced classes of remote sensing classification have been optimized in benchmark data set by training the CNN architecture. The RGB image and DSM image of remotely sensed data[8] were used to cost functionality of urban LULC classification. The land cover detection of the Guntur region has improved using VGG 19 network [16] and high-resolution Landsat -7 images from 2013 and 2016. The accuracy of planned DCNN has been improved using parameters such as optimizer, learning rate with decay processes to obtain crop identification in the area of [18] Phulambri, Aurangabad, MH in India. The accuracy of trained DCNN architecture was also evaluated in this result as 97.58 %.To classify the hyperspectral image of the study area from the EO-1 Hyperion sensor the pre-defined Indian pines data set has been processed in this system.

A.Study area:

In this work, we have chosen two specified areas in Krishnagiri namely Londenpet and Orappam to compute the impact of granite mining activities on LULC Classes from 2009 to 2019 .the quarry area of Londenpet located at 6km away from Krishnagiri and the village of Orappam has a distance of 13.4 km from the Krishnagiri .the Londenpet is located at longitude and latitude of(**12.3028°N 78.1321°E** and **12.5079°N 78.225°E**) and Orappam is located at longitude and latitude of (**12.3254° N, 78.0987° E,** and **12.5197° N, 78.2820° E**) .the area circumference of the chosen study area of Londenpet and Orappam are **937.56** and **1005 .68** hectares.

III.METHODOLOGY

A. Preprocessing & Segmentation

The Hyperspectral remotely sensed data sets of our study area, Londenpet and Orappam have been taken from the Google earth engine database, and it consists of 230 bands with a spatial resolution of **250** m. The selected hyperspectral images of both areas Londenpet and Orappam are consists of **125*125** pixels is to apply for preprocessing to minimize the total no of bands in hyperspectral data sets for effective ground truth segmentation. To improve the LULC prediction, 130 **bands** out of **230** bands of input images are selected to collect the required area information of our study area. The input images will be resized for desirable padding and needs to remove the elastic distortion to enhance the multifariousness of spatial data by using data augmentation.

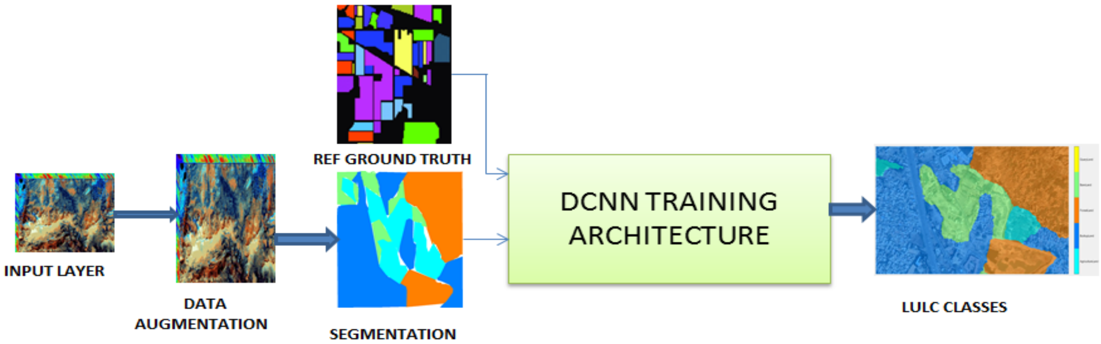
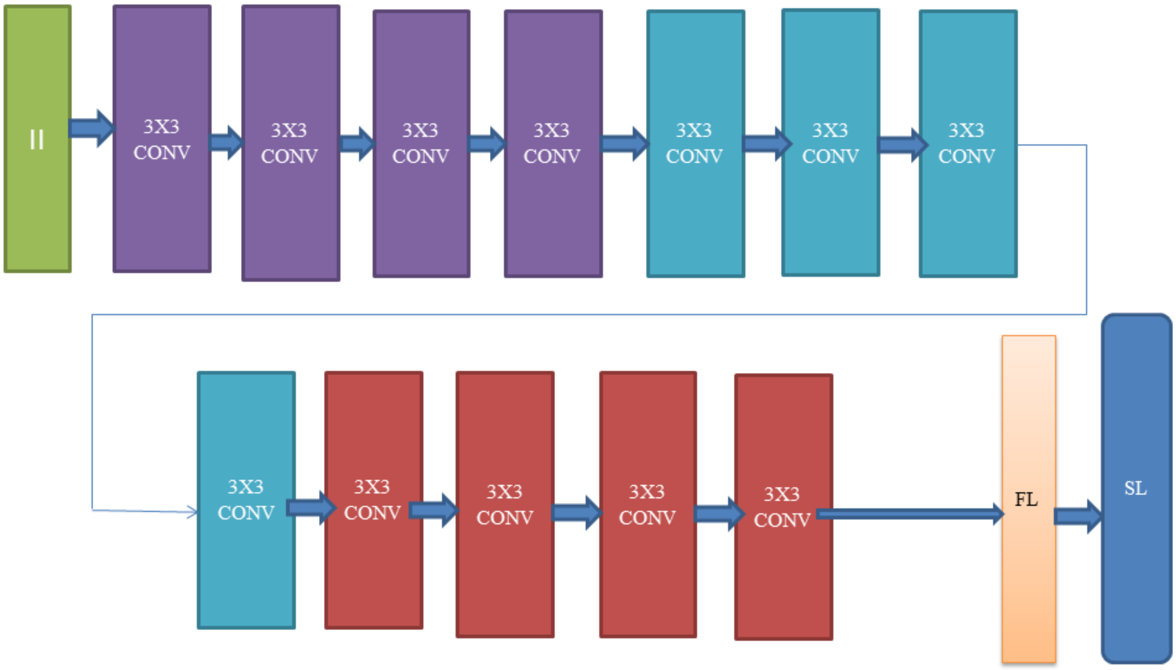


Fig .1 Frame Work Design Of Proposed Algorithm

The data augmentation adds heterogeneousness to the datasets by shifting the width and height of input samples to ensure that the network is perceptive completely different samples throughout the training phase. The standard ground truth information has been selected from Indian data pines in the dimension of 145*145*200. furthermore, it was processed to reduce the dimension of **145*145*25** To achieve the more effective result of LULC classification of 5 classes such as agriculture land, bare land, quarry land, forest land, and built up land. The input layer of our study area has given into the training validation network architecture of the Resnet18 (CNN) module with a dimension of 125*125*30. Each pixel values of input data sets are processed and labeled according to standard ground truth information.

B. DCNN Frame Work:

Deep learning modified (ResNet18) consists of integrating over loops mentioned as modules and processing the hyper spectral data. Each module consists of multiple convolutional layers with 3*3 size filters to remove the losses occur in LULC classification. In this paper, modified Resnet 18 architecture is used to efficient training validation of input image. The planned network model (Resnet 18) consists of 12 convolutional blocks of modules mentioned in fig 3. The modified Resnet architecture gets the input layer and processes the training validation segment data based on pre-defined ground truth information. The DCNN system will provide an additional layer, namely drop out layer for the convolutional layers to improve our regularization of the training module and acquire the unique result of LULC classification.



.

Fig.2 The architecture diagram of DCNN

- Input layer **- 3x3 convolution layer (64 filters)** **-fully connected layer**

- 3x3 convolution layer (128 filters) **-3x3 convolution layer (256 filters)**

- softmax layer

Table 1: DCNN parameters for our study area

Layer type	Shape
Input layer	125*125*30
Convolution layer 1	No of convolution blocks=4,Filter size 3*3 ,number of filter=64
Convolution layer 2	No of convolution blocks=4,Filter size 3*3 ,number of filter=128
Convolution layer 3	No of convolution blocks=4,Filter size 3*3 ,number of filter=256
Fully connected layer	Hidden nodes =190 ,bias =190
Output layer	Output nodes =4 ,bias =4

The Dropout layer is mainly employed between each convolution block to the optimizing problem of overfitting and underfitting of LULC observation. In this system, 3*3 max-pooling layer is maintained to compute max and min of the value of ground truth segmentation. The next layer may be a fully-connected is used to connect the previous layer neuron and collect the exchange of input layer information. It has the ability to combines all the feature extraction and self-learned information to labeling LULC classes. The final softmax layer of the architecture predicts the LULC classification possibilities by a multi logistic function. It used to compute loss parameters and activate the input function to retain the required LULC classes.

C. Parameter tuning:

The enhancing techniques such as SGD optimizer, Adam optimizer, and batch normalization are used to faster computation process of the planned architecture to attain the effective feature extraction. Additional improvement has been done in LULC classification by fixed learning rate with decay and L2 regularization for the designed network. In this project 12 convolutional blocks have been used to optimize entropy loss function occur on training validation. The training parameter of the input layer has been fine-tuned based on the Indian pines data set and study area ground truth information. The batch normalization will involve additionally developing the required LULC classes by re-scaling the LULC layers.

D. Performance metrics

The prediction of performance evaluation of designed Deep learning structure has been developed by the optimizers of SGD, Adam. The overall accuracy evaluation of proposed DCNN is compared with machine learning algorithms of ANN and ISVM by using an integrated parameter of MATLAB 9.5 software tool such as Global Accuracy, Mean Accuracy Weighted IOU, Mean IOU, Mean Bf Score .the accuracy of three classifiers can be calculated as follows

$$overall\ accuracy = \frac{\text{GA} + \text{MA} + \text{WIOU} + \text{MIOU} + \text{MBF score}}{\text{Total Test Record}} * 100$$

IV: EXPERIMENTAL RESULTS AND DISCUSSION

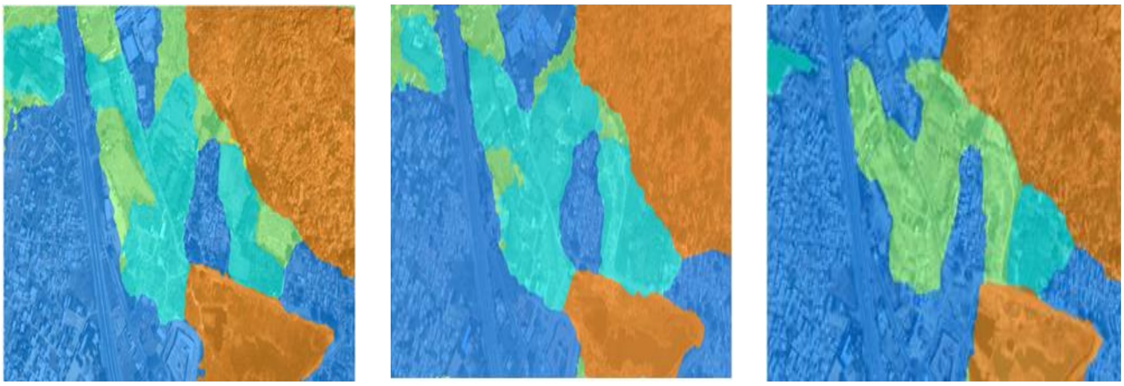
In this study, the hyperspectral image of two specified quarry areas of Londentpet and Orappam has been chosen to conduct an experimental on required LULC classes in Krishnagiri district of Tamilnadu state. The selected hyperspectral images have been taken from the Google earth engine database for the period of 2009, 2014, and 2019. It consists of 230 band and spatial resolution of 250 m .The chosen area, Londenpet and Orappam are located at the longitude and latitude of (**12.3028°N 78.1321°E** to **12.5079°N 78.225°E**) and (**12.3254° N, 78.0987° E** to **12.5197° N, 78.2820).** The proposed architecture DCNN is implementing by **MAT LAB 9.5** software tool with Intel core **i3** CPU (4GB RAM). Out of **210** bands, 130 bands of input images were selected to process with standard Indian data set to classify the LULC classes. The hyperparameter has been adjusted as learning rate(**0.0001)** and 3*3 size of 12 convolution block of the layer.

The input layer with a dimension of 125*125*30 is processed into training validation of the proposed deep learning algorithm based on ground truth information of standard Indian data pines and reference data set of our study area. The classified result of LULC classes will be labeled according to the generated feature extraction result of modified Resnet 18 architecture. Figure 3a and Figure 3b show that classified LULC classes of LONDENPET for the period of 2009,2014 and 2019. Figure 4 and Figure 4b demenstrated the classified LULC classes of Orappam for the period of 2009,2014 and 2019. From the LULC classified results, LULC classes on both areas have been computed the gain and a loss percentage of area circumference owing to granite quarry activities.

Table 2 shows that relative change in area of LONDENPET (from 2009 to 2019) in Krishnagiri district has been calculated from each pixel count of labeled LULC classes by the implementation of deep learning trained architecture. From the Fig 3,the impact of quarry activities on LULC classes states that quarry land has increased by 12.3 % from 2009 to 2019 whereas built up land and bare land has increased by 8.3 % .The loss of agriculture and forest land are 12 .63 % and13.98 % from 2009 to 2019. Table 3 shows that relative change in area of Orappam has been evaluated from designed algorithm .fig .4 clears that impact of quarries on LULC classes has been varied from 2009 to 2019 .In that quarry, built up, bare land of area has been increased by 12.5%,15.6 %, and 17 %. Respectively.

Londenpet **2009** Londenpet **2014** Londenpet **2019**

Fig 3 (a): Input Image of Londenpet (2009 to 2019)



Londenpet **2009** Londenpet **2014** Londenpet **2019**

Quarry land Forest land Built up land

Bare land Agri land

Fig 3(b) :Classified LULC Classes of Londenpet (2009 to 2019)

Orappam 2009 **Orappam 2014** **Orappam 2019**

Fig 4 (a): Input image of Orappam (2009 to 2019)

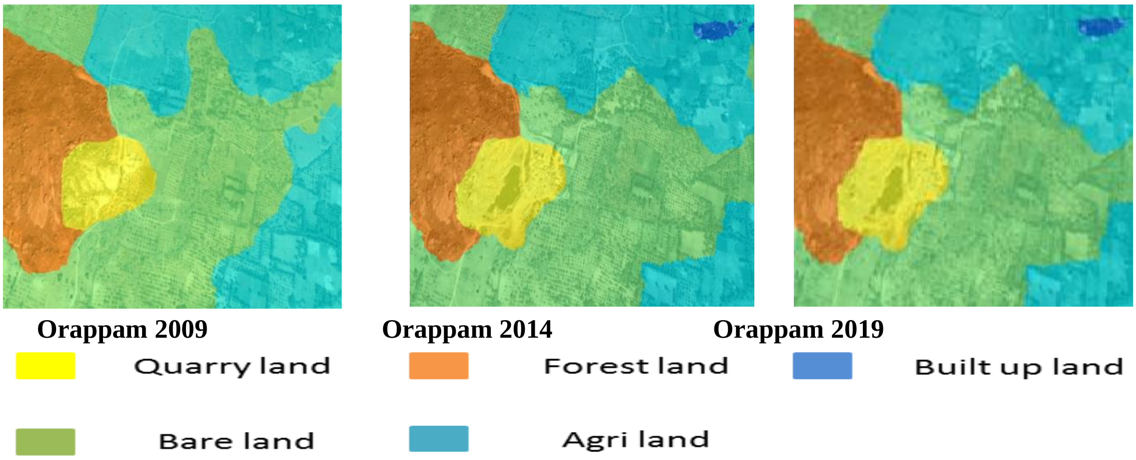


Fig 4(b): Classified LULC Classes of Orappam (2009 to 2019)

The different parameters such as batch size, filter size of each convolution block, no of convolutional block, zero paddings, and learning rate are further tuned to enhance their better classification of granite quarry area. The computation process of 125*125*30 input layer in the proposed deep learning system has been improved by utilizing such as SGD optimizer, ADAM optimizer, and batch normalization .the tested computation results of this system have been plotted as the graph shown in fig 7.

Table 2: Releative change in area of LULC classes of londenpet (2009 to 2019)

LULC classes	Change in area of LULC classes (ha)		
	2009	**2014**	**2019**
Quarry land	73.62	79.65	85.32
Bare land	278.32	289.96	296.85
Forest land	158.69	148.63	139.56
Buildup land	368.63	379.4	383.56
Agriculture land	192.32	181.32	175.63

Table 3: Releative change in area of LULC classes of Orappam (2009 to 2019)

LULC classes	**Change In area of LULC classes in (ha) over the period from 2009 to 2019 at** orappam		
	2009	**2014**	**2019**
Quarry land	32.51	39.65	42.52
Bare land	236.98	245.66	253.65
Forest land	142.63	138.96	126.35
Buildup land	332.63	341.36	349.63
Agriculture land	184.65	163.63	154.63

From the Fig 7,The graph illustrated that performance classification of optimizer SGD and ADAM are 95 % and, 96.21 % respectively. It shows that Adam optimizer is a desirable method for depicts the performance evaluation of the DCNN method.

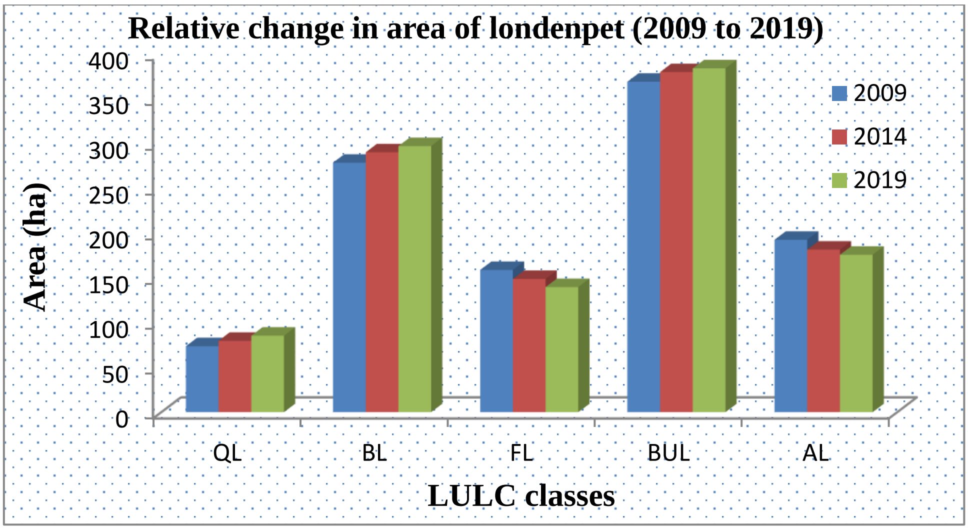


Fig 5:The change in area of LULC classes of londenpet (2009 to 2019)

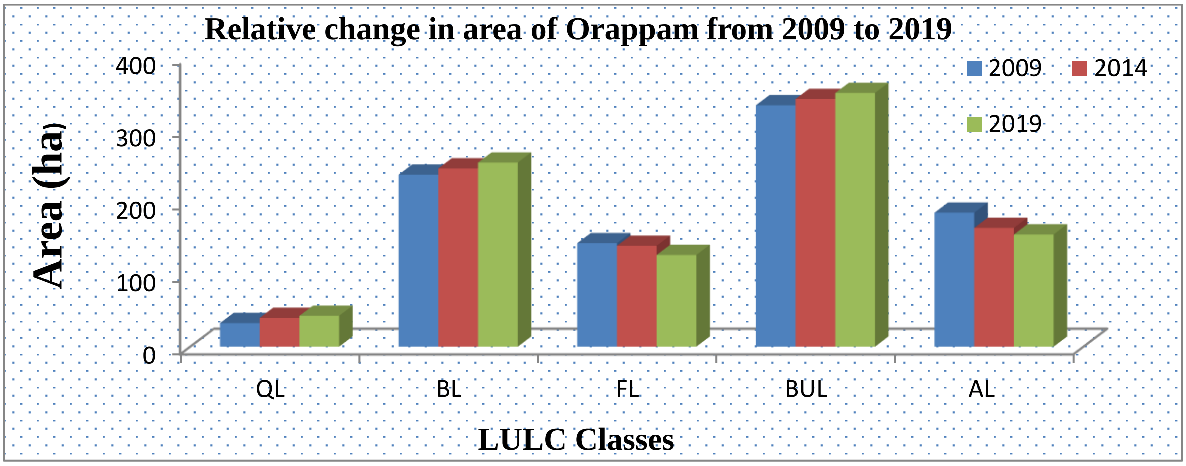


Fig 6.Releative change in area of LULC classes of Orappam(2009 to 2019)

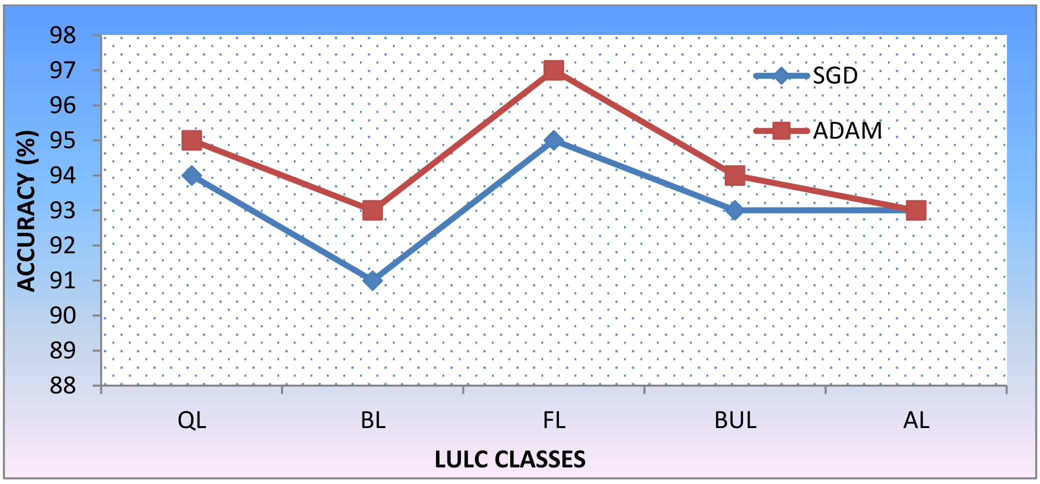


Fig 7: The accuracy efficiency of DCNN using optimizer (SGD,ADAM)

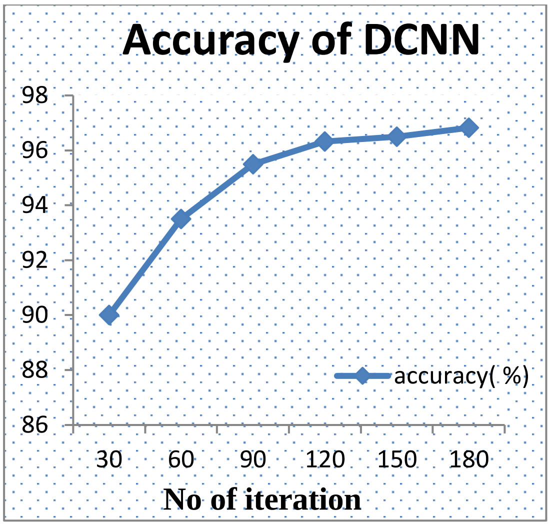


Fig 8 : Accuracy Of DCNN Vs No of Iteration

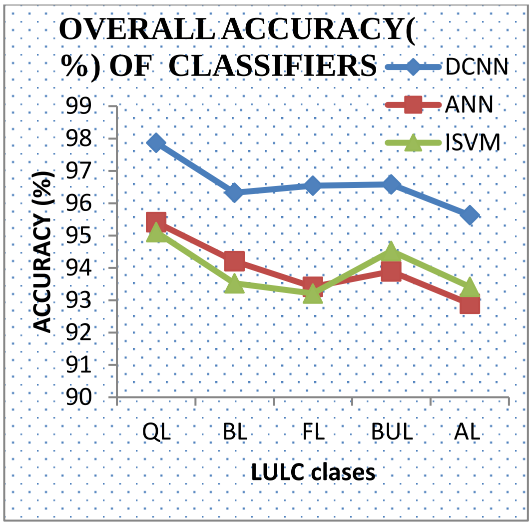


Fig 9: The overall accuracy of classifiers

Figure 8 states that the accuracy of DCNN when increasing no of iteration. Based on updated neural network parameter, The no of iteration will provides appropriate LULC prediction of 350 hyper spectral input data set of each LULC classes .It also clears that loss of input images can be decreased by improving iteration result of this designed frame work.

Table 3: The Overall perfromance metrics values of classifers

PERFORMANCE METRICS	CLASSIFIERS		
	DCNN	ANN	ISVM
GAA	0.95	0.93	0.91
MA	0.98	0.96	0.95
MIOU	0.80	0.73	0.78
WIOU	0.96	0.935	0.92
MBF Score	0.90	0.85	0.84

GAA –Global averaged accuracy **MA-Mean accuracy** **MIOU –Mean IOU**
WIOU-weighted IOU **MBF- Mean BF score**

Furthermore, we have to analyze the overall performance of the LULC classification of our proposed deep learning method with the other two machine learning methods of ANN and ISVM.The classification result was obtained using the integrated parameter of software tools (MATLAB 9.5) such as **GAA, MA, MIOU, WIOU,** and **MBF**. The result from the graph shown in fig 9 explained that the modified DCNN outperforms when compared to ANN and ISVM. We obtained the overall accuracy of the three classifiers (DCNN, ANN, and ISVM) are 95.8 %, 91.4 %, and 88.6%. Respectively.

V:CONCLUSION

In this paper, we projected a deep convolution neural network (DCNN) to analyze the LULC classification of quarry area in LONDENPET and Orappam at Krishnagiri district) by using hyperspectral datasets of remotely sensed data sets from 2009 to 2014. The objective of the planned deep learning technique of DCNN is to works on the unsupervised classification of remote sensing data effectively. It will self-recognize the extract options that are essential for the LULC classification of granite quarry activities at Krishnagiri. The experimental results clear that the impact of a quarry operation on the built-up land and the bare land area has increased by 45 % and 35% from 2009 to, 2019 whereas the agriculture and forest land area has decreased by 17 % and 16%. The quarry land optimization of LULC classes shows that expanding percentage from 7% to 9% in the study area. The performance metrics of our deep learning method (DCNN) and other machine learning methods ANN and ISVM are depicted by the computation of inbuilt parameter of software tool MATLAB 9.5 a such as global accuracy, mean accuracy, meanIOU, weightedIOU, Mean BF score. The training validation of Resnet18 (DCNN) has been improved by SGD and ADAM optimizer. The required LULC classes have been classified based on ground truth information from the predefined Indian Pines dataset. The overall results prove that The DCNN has an accuracy of 95.8% in where ANN is 91.4% and ISVM is 88.6 %. Finally, a competitive future objective might be to adapt this system to figure with consolidated information from remote sensing data in LULC classification.

REFERENCES

[1] Deshan Liu ,Ruixuan Tong ,Deqin Yan "A New Convolutional Neural Networks for Land Use Classification" 2019 IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE) DOI: 10.1109/ISKE47853.2019.9170355 2019 .

[2] F. Li, S. Li, C. Zhu, X. Lan, and H. Chang, "Specific changes detection in visible-band VHR images using classification likelihood space," in Proc. IEEE 3rd IAPR Asian Conf. Pattern Recognition. (ACPR), ,pp. 381–385. Nov. 2015.

[3] Jie Liang , Jincai Xu , Huifang Shen & Li Fang "Land-use classification via constrained extreme learning classifier based on cascaded deep convolutional neural networks", European Journal of Remote Sensing, 53:1, 219-232, DOI: 10.1080/22797254.2020.1809528,2020.

[4]M. O. Sghaier and R. Lepage, "Road extraction from very high resolution remote sensing optical images based on texture analysis and beamlet transform," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 9,no. 5, pp. 1946–1958, May 2016.

[5] Manuel Carranza-García, Jorge García-Gutiérrez,José C. Riquelme "A Framework for Evaluating Land Use and Land Cover Classification Using Convolutional",Neural Networks Remote Sens., 11, 274; doi:10.3390/rs11030274 , 2019.

[6] G. Cheng, P. Zhou, and J. Han, "Learning rotation-invariant convolutional neural networks for object detection in VHR optical remote sensing images," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 12,pp. 7405–7415, Dec. 2016.

[7] Boyang Li, Weihua Su, Hang Wu, Ruihao Li "Further Exploring Convolutional Neural Networks'Potential for Land-Use Scene Classification", IEEE international conference of Geoscience And Remote Sensing Letters ,2019 .

[8] Mujadded Al Rabbani Alif, Sabbir Ahmed, Muhammad Abul Hasan "Isolated Bangla handwritten character recognition with convolutional neural ",20th International Conference of Computer and Information Technology (ICCIT), 22-24 December, 2017.

[9] J. Han, D. Zhang, G. Cheng, L. Guo, and J. Ren, "Object detection in optical remote sensing images based on weakly supervised learning and high-level feature learning," IEEE Trans. Geoscience. Remote Sensing ., vol. 53, no. 6, pp. 3325–3337, Jun. 2015.

[10] Anirudh Potlapally, Potluri Sai Rohit ChowdaryS.S. Raja Shekhar "Instance Segmentation in Remote Sensing Imagery using Deep convolutional Neural Networks"."International Conference on contemporary Computing and Informatics' 2019.

[11]J. Han, P. Zhou, D. Zhang,G. Cheng, L. Guo, Z. Liu, S. Bu and J. Wu, "Efficient, simultaneous detection of multi-class geospatial targets based on visual saliency modeling and discriminative learning of sparse coding," ISPRS J. Photogram. Remote Sens., vol. 89, pp. 37–48,Mar. 2014.

[12] Jianwei Ma, Yayong Sun, Guohui Deng"Evaluation of different approaches of convolution neural networks for land use and land cover classification based on high resolution remote sensing images"." IEEE International Conference on Signal, Information and Data Processing (ICSIDP) 2019.

[13]G. Cheng, J. Han, L. Guo, Z. Liu, S. Bu, and J. Ren, "Effective and efficient midlevel visual elements-oriented land-use classification using VHR remote sensing images," IEEE Trans. Geosci. Remote Sens.,vol. 53, no. 8, pp. 4238–4249, Aug. 2015.

[14] Michael Kampffmeyer, Robert Jenssen,"Urban land cover classification with missing data using deep convolutional neural networks" IEEE International Geoscience and Remote Sensing Symposium (IGARSS) DOI: 10.1109/IGARSS.2017.8128164,2017.

[15]Y. Tao, M. Xu, F. Zhang, B. Du, L. Zhang, “Unsupervised-restricted DE convolutional neural network for very high resolution remote-sensing image classification,” IEEE Trans. Geosci. Remote Sens., vol.55, no.12,pp. 6805-6823. Dec.2017.

[16] Tejaswini, Pranuthi.P, Anuradha. T, Land Cover Change Detection Using Convolution Neural Network Proceedings of the Third International Conference on Electronics Communication and Aerospace Technology 2019.

[17] X. Lu, X. Li, and L. Mou, “Semi-supervised multitask learning for scene recognition,” IEEE Trans. Cybern., vol. 45, no. 9, pp. 1967–1976, Sep. 2015.

[18] Kavita Bhosle, Vijaya Musande “Evaluation of Deep Learning CNN Model for Land Use Land Cover Classification and Crop Identification Using Hyperspectral Remote Sensing Images”, Journal of the Indian Society of Remote Sensing, https://doi.org/10.1007/s12524-019-01041-2(012345678 ,2019.

[19] Y. Yuan, L. Mou, and X. Lu, “Scene recognition by manifold regularized deep learning architecture,” IEEE Trans. Neural Netw. Learn. Syst., vol. 26, no. 10, pp. 222, 2015.