Object Based Classification Approach for impervious and non-impervious surfaces in satellite images

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Abstract: *In the last few years, satellite image classification is gaining more attention due to the availability of remotely sensed imagery's in high spatial resolution. This paper approached a non-linear type object classification approach based on object basis which incorporates K-Nearest Neighbour (KNN) algorithm for segmentation and classification. This proposed approach is based on object based image analysis (OBIA) technique. Spatial information is playing an important role in this technique. In this work, various features are extracted and utilized for the classification of non-linear objects. Spectral features of the training image objects are extracted using region of image (ROI) based samples which are used in KNN algorithm for segmentation and classification with a good level of accuracy. Images are classified in five types of objects such as road, building, land, water body, and vegetation also. In addition, parking lots are also having sometimes similar types of spectral reflectance as road due to similar material in both. The primarily focus of this work is to extract the non-linear objects by avoiding misclassification in a compact manner and also to improve the visibility of object.*

Keywords: Object-based Classification, Multiresolution Segmentation, K-Nearest Neighbour, Impervious surfaces; Non-impervious surfaces

Introduction

Object-Based Image Analysis (OBIA) is gaining significant attention for land use and land cover (LULC) classification, thanks to the availability of high-resolution satellite imagery. Previously, LULC classification relied solely on pixel-based methods, but OBIA has emerged as a more effective alternative, often yielding superior results. While machine learning techniques are still employed for classification, they are sometimes less effective than OBIA at various classification levels. Data extraction remains a challenging task, particularly due to the limitations of pixel resolution and the difficulty of detecting small objects in detailed satellite images. Object recognition poses numerous challenges, including variations in object appearance, different poses, complex backgrounds, and a wide range of object sizes. The exploration of spatial approaches to enhance OBIA presents an intriguing opportunity in this field.

Object based classification

In the object-based image classification (OBIC), process begins with segmenting homogeneous items from an image which are then analyzed and categorized. This segmentation creates objects that represent different land cover categories, which can vary spectrally at the pixel level. Pixels alone often fail to accurately depict features in the real world. Object-based analysis allows for the development of rule sets applicable across various scenes, effectively grouping nearby pixels into meaningful spatial and spectral regions. This approach shifts the focus from individual pixels to the spatial scale of objects, thereby enhancing the mimicking of traditional pixel-based classification methods. For example, object-based classification can employ the maximum likelihood classification approach, which either classifies objects directly by assessing their collective pixels against training classes or classifies pixels individually aggregating them into objects. In this study, we utilize a non-linear object-based classification method, primarily using eCognition software to extract non-linear features.

Literature Review

In this paper, a detailed comparative analysis of Pixel based classification (PBC) and object based image classification (OBIC) approaches related to LULC classes are mentioned in Table 1. In this connection, table 2 shows some deep learning (DL) based approaches for the classification. J.R. Anderson et al. (1976) proposed a LULC classification system for the remote sensing data. J.S. Blundell and D.W. Opitz (2006) proposed a Feature Analyst approach for Object recognition and feature extraction from imagery. R. Hamilton et al. (2007) proposed an image segmentation approach for automated stand delineation. P. Aplin and G.M. Smith (2008) proposed some advances in object-based image classification. L. Dragutet al. (2009) proposed an application to soil-landscape modeling for Optimization of scale and parametrization for terrain segmentation. Mohan and Ladha (2009) focused on classification of high resolution satellite images using ANN and contrasting two various classification methods, Object and Pixel based classifications. The accuracy results for Object based Multi-Layer Feed Forward (MLFF) NN was 87.5% and Radial Basis Function (RBF) NN was 84.7%, and for Pixel based MLFF NN and RBF NN were 79.7% and 80.8% respectively.

T.G. Whitesidea et al. (2011) had used the ASTER dataset, which shows that the research location is a portion of the Florence Creek section of Litchfield National Park in Australia's Northern Territory. They have used techniques like the NN supervised and fuzzy classification algorithm and objects utilizing training objects. The supervised pixel-based classification using the maximum likelihood classifier algorithm. For the purpose of mapping land cover, they compare the outcomes of an object-based classification to a supervised per-pixel classification.The maximum likelihood classifier algorithm was used to classify data in the supervised per-pixel classification after training areas had been chosen and accuracy shows for Object based 78.51% and for Pixel based 79.30%.C.

M. Uzar and N. Yastikli (2013) extracted building using LiDAR and aerial photographs in automatic method. Yao et al. (2017) had used the dataset of 0.5 meter resolution RGB image. They used Bayesian classification and K-Nearest Neighbor Algorithm. They used image segmentation as their method and then classify the image using the object based approach instead of traditional pixel based classification. The accuracy results show that K-NN classification and Bayes classification achieved 94.1% and 81.24% respectively.

L. Yang et al. (2019) methods used are K-Nearest Neighbor Algorithm, MLP, SVM , Pixel-based convolutional neural network, convolutional neural network + Conditional random fields ,convolutional neural network fusion MLP ,convolutional neural network features and CNN-RCRF. Their approach is to segment the image and then classify the image using different methods. The accuracy results show k-NN classification gives 67.6%, MLP is 68.3%, SVM 70.8% , pixel-based convolutional neural network is 85.4%, convolutional neural network + Conditional random fields reaches only 82.1% The accuracy of convolutional neural network fusion MLP and convolutional neural network features + MLP did not differ much from pixel-based convolutional neural network (83.6% and 84.2%, respectively), whereas CNN-RCRF provides 90.1%.

S. Shekhar and J. Aryal (2019) had used a dataset from Almeria in southern Spain. Their strategy is to determine the multiresolution segmentation approach's ideal parameters for plastic greenhouse. L. Yang et al. (2019) had used the area of Great Britain for Land Cover Map as the dataset that was utilized. A product with a 25 m spatial resolution and 5 Thematic Mapper pixels was created in 1990 using multitemporal Landsat data that additionally recorded 25 different categories of land cover. E.B.N. Bastorous (2020) extracted road network from satellite images of Egypt region.

E. Ersoy et al. (2021) had used the maps of LULC map of eight thematic classes, including artificial water surfaces, rivers, maquis, woods, agricultural regions, highways, artificial surfaces, and pastures. These classes were constructed using both categorization methods. The pixel-based classification process was carried out in ERDAS Imagine 10.4 using the closest neighbor-supervised approach, and the object-based classification process was done in eCognition Developer 64 using the maximum likelihood-supervised approach. They use high quality RapidEye satellite photos to compare the discrepancies between the outcomes of pixel and object based Land use land cover classification techniques. Overall accuracy for object classification shows 89.58% and pixel based classification shows 58.39%.

Table 1. Comparative analysis of Pixel and object based approaches

Authors & Year	Objective	Method
Makindea et al. (2016)	Land cover classification	Pixel and object based approach
Tonyaloglu et al. (2021)	LULC classes	Pixel and object based approach
Singh and Garg (2011)	LULC classification	Hybrid classifier based approach
P.P. Singh et al. (2013)	LULC classification	Expert system based approach
Singh and Garg (2013a)	Information extraction	A hybrid appraoch
Singh and Garg (2013b)	Information extraction	An integration technique
Singh and Garg (2014a)	LULC classification	ERICA based approach
Singh and Garg (2014b)	LULC classification	Spatial constraints based Fuzzy Clustering approach
Singh and Garg (2015)	LULC classes	IFPICA based approach
Gupta and Bhadauriya (2014a)	Information extraction	object based approach
Gupta and Bhadauriya (2014b)	Information extraction	object based approach using fuzzy logic
Tamta et al. (2015)	LULC classes	fuzzy based object oriented approach
Saba et al. (2013)	Land cover classification	Random forest (RF) and gradient boosted decision trees (DT) and Support Vector Machine (SVM) algorithms
G. Khadanga et al. (2016)	Extraction of cadastral parcels	OBIA approach
M.A. Aguilar et al. (2016)	Assessment of extracted greenhouses from worldview-2 imagery	Multi-resolution segmentation approach
S. Bhaskaran et al. (2010)	Urb an features mapping	PBC and OBC methods

Table 2. Comparative analysis of deep learning based approaches

Authors & Year	Objective	Method
B. Feizizadeh et al. (2021)	LULC change monitoring	Fuzzy based DL and ML approaches
C. Ye et al. (2019)	Landslide detection	DL based approach
S.O. Atik and C. Ipbuker (2021)	LULC mapping	Integrating CNN and MRS approach
X. Pan and J. Zhao (2018)	image classification	CNN and restricted conditional random field
Flanders et al. (2003)	LULC classes	CNN-MRS model
F. Pacifici et al. (2009)	LU classification	NN based approach using textual metrics

Methodology

The proposed methodology begins with a multiresolution segmentation approach, followed by the extraction of satellite image features from both the image layer and its geometry. The image layer includes statistical measures such as mean and mode, while geometric shape properties like compactness and density serve as effective features for rule formation. The entire process of non-linear object classification using the OBIA approach is illustrated in the Figure 1.

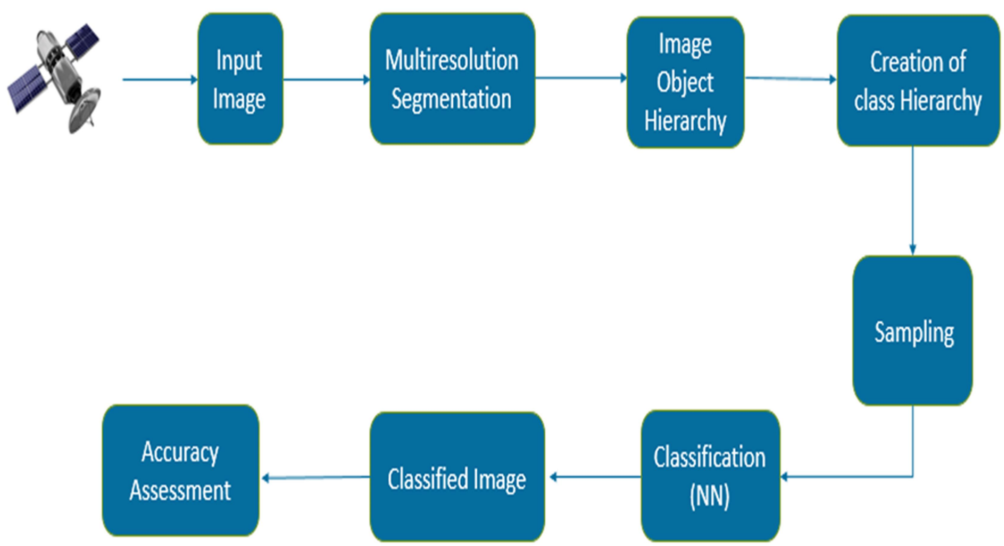

Figure 1. A framework for non-linear object classification using the OBIC

a. Multi-resolution segmentation

As long as the "Scale Parameter" is not locally exceeded, multiresolution segmentation progressively merges smaller items into larger units over several iterations. During this process, the seed object searches for the most compatible neighboring object to merge with. The best candidate becomes the new seed and seeks its optimal companion, even if the best fit isn't reciprocal. When a mutual best fit is identified, the two objects are combined. This looping process continues until no further merges are possible.

Color Heterogeneity = Sum of weighted Standard deviations for all layers (1)

Shape Heterogeneity = Deviation from a compact or smooth shape (2)

Compactness = Border Length / Area (3)

Smoothness = Border Length / Border (4)

The measurement of segmentation quality and parameter optimization is the two most pressing issues in MRS's. The segmented object's geometric and arithmetic difference from the reference item will then be used as the assessment criterion to determine the segmented object's quality. The sum of the standard deviations of the spectral values in each layer weighted with the weights for each layer is used to determine spectral or color heterogeneity:

$$he_s = \sum_{sb}^{n} w_{sb}\sigma_{sb} \quad (5)$$

Where, he_s is spectral heterogeneity, n are number of bands, σ_{sb} is the standard deviation of c spectral band's digital number and w_{sb} is given a weight of spectral band c.

In the eCognition software, a multiresolution segmentation method is used for the initial segmentation. Following a multiscale optimisation method, the data were parameterized in accordance with the particular mapping needs.In OBIA, selecting the right scale parameter is crucial. This was done in an effort to unify the dataset’s spectral, spatial, and textural aspects.The example of multiresolution segmentation with different scale parameters are given below.

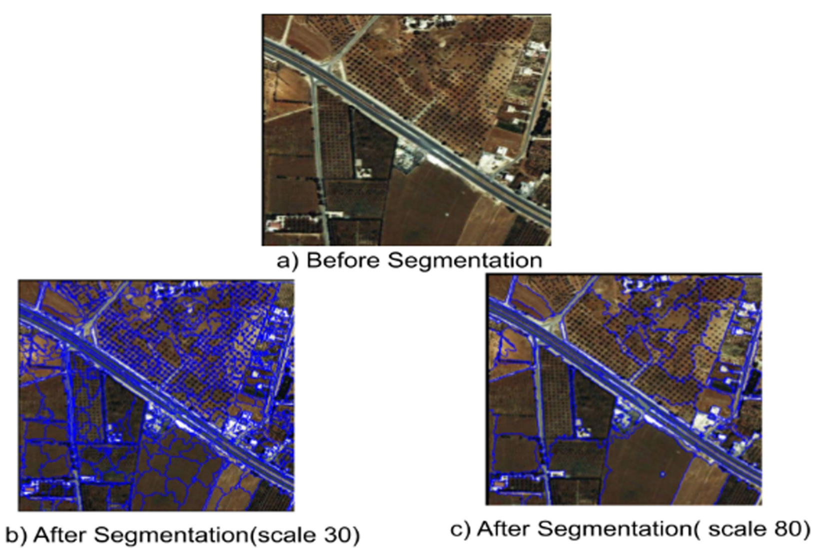

Figure 2. Different Scale Parameters Segmented Results

a. K-Nearest Neighbor (KNN) Algorithm

The k-NN algorithm is a non-parametric method used for classification and regression in pattern recognition. In both applications, the input consists of the k nearest training instances in the feature space. The outcomes vary depending on whether k-NN is employed for classification or regression:

- **Classification**: In the k-Nearest Neighbor categorization process, class membership is determined by the majority vote of the object's k closest neighbors, where k is typically a small positive number. If k = 1, the object is assigned to the class of its nearest neighbor.
- **Regression**: The k-Nearest Neighbor Regression provides the property value of an object based on the average of the values from its k closest neighbors. This method, which is a form of instance-based learning, defers computation until classification and approximates the function locally. Among all machine learning algorithms, k-NN is one of the simplest. It can be beneficial to weight the contributions of neighbors in both classification and regression, allowing closer neighbors to have a greater impact on the result than those farther away. A common weighting method assigns each neighbor a weight of 1/d, where d is the distance to the neighbor.

The suggested method utilizes a nearest neighbor (NN) classifier for classifying image objects based on the shortest distances. When applying the NN classifier, each image object is assigned a class representation of 0 or 1, indicating whether it belongs to a specific class. This approach is particularly suitable for capturing variations in high-resolution images.

$$d = \sqrt{\sum_f \left[\frac{v_f{}^{(so)} - v_f{}^{(io)}}{\sigma_f}\right]^2} \quad (6)$$

Where, d is the distance between image object o and sample object s, $v_f^{(io)}$ is value feature of image object for feature f, $v_f^{(so)}$ is the value feature of sample object for feature f, σ_f is the feature f for Standard deviation of the feature.

b. Object Features Descriptions

- ✓ **Mean**: Calculates the average of selected features for an image object and its surroundings.
- ✓ **Brightness**: Determined from positive-value channels only; negative pixel layers can be included if specifically chosen.
- ✓ **Geometry**: Based on the shape of an image object derived from its pixels; values can vary with rotation due to the raster nature of images.

- ✓ **Asymmetry**: Measures the difference in shape between a roughly elliptical image object and another, with higher values indicating greater asymmetry.
- ✓ **Border Index**: Indicates jaggedness; higher values suggest more jagged edges, calculated by comparing border lengths to the smallest enclosing rectangle.
- ✓ **Compactness**: Describes how compact an image object is; calculated as the product of length and width divided by pixel count, with more compact objects appearing to have smaller borders.
- ✓ **Density**: Describes pixel distribution within an object; a square is the most dense, calculated as the ratio of pixels to estimated radius.
- ✓ **Rectangular Fit**: Measures how well an image object fits within a rectangle of the same proportions, ranging from 0 (no fit) to 1 (perfect fit).
- ✓ **Roundness**: Indicates how closely an image object resembles an ellipse, calculated by the difference between the radii of the smallest enclosing and largest enclosed ellipses.
- ✓ **Shape Index**: Gauges the complexity of a shape, with values of 1 for compact shapes and increasing for more irregular shapes, calculated as the border length divided by four times the square root of the area.

Results and Discussion

The experiment is conducted using eCognition software version 10.2 on utilizing the wikimapia dataset with a spatial resolution of 1 meter. These images are from the developed Suburban as shown in the figures 3(a) and 4(a). The areas are used for classification, including classes such as roads, vegetation, land, water, parking lot, and buildings. The process begins with the user selecting segments to serve as training or sample areas. MRS is applied by utilizing shape and compactness parameters. After the segmentation stage, image objects are created (see figure 2).

Object features such as image layer texture and geometry are incorporated to develop the object images further. The object hierarchy consists of five classes' road, vegetation, water, land, parking lot and Building in the results. Each class is assigned different colors for easy identification, allowing users to recognize which class each object belongs to. Standard K-NN classification algorithms are subsequently applied to classify the image objects. During this classification process, some areas merge as they identify the nearest sample object based on spectral, spatial, and feature properties. Each image object sample is then manually selected to determine the actual class, followed by the use of an export confusion matrix algorithm to save the results in a 'csv' file.

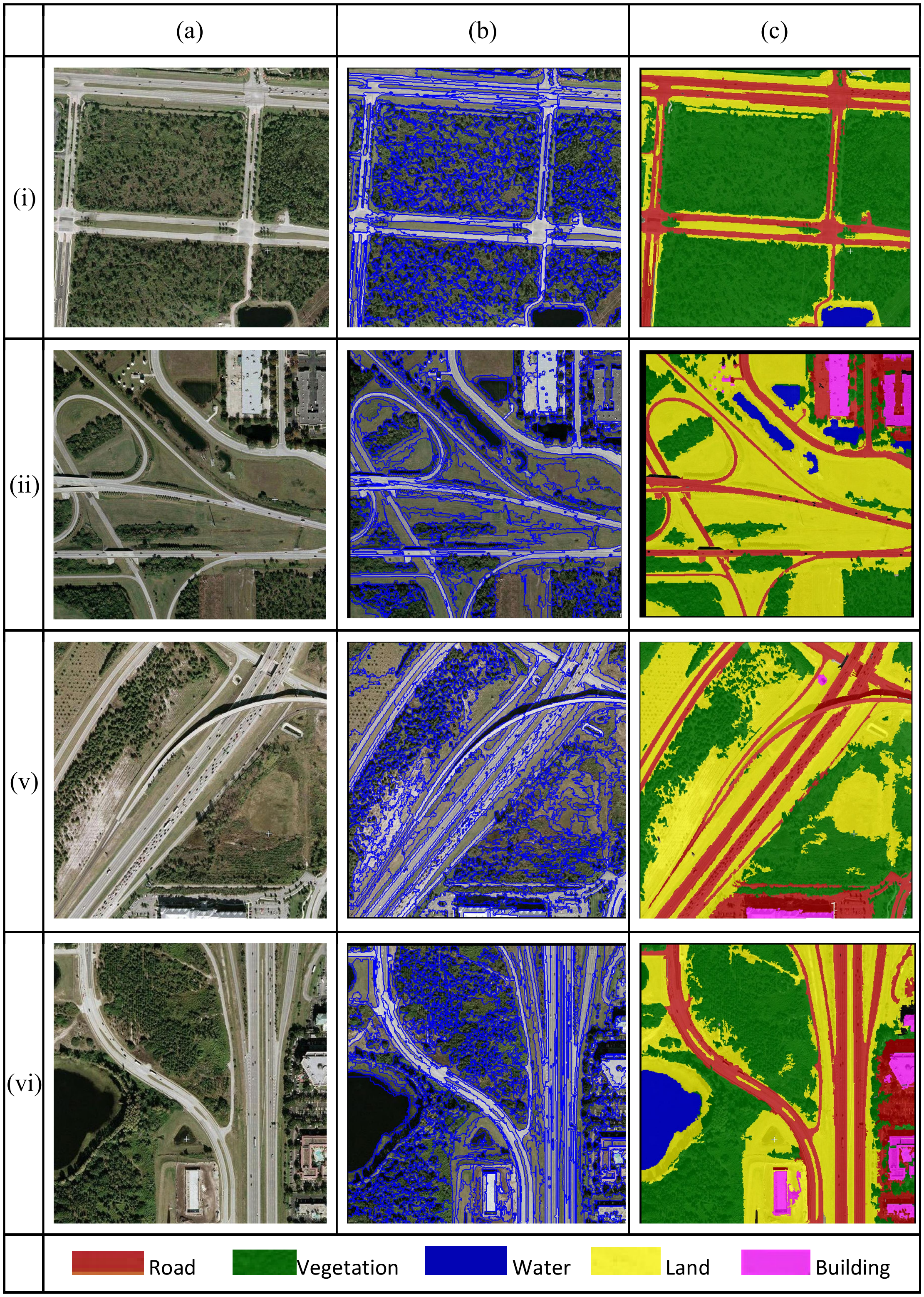

Figure 3. Developed Suburban images: (a) input image, (b) segmented images, (c) classified images in road, vegetation, water, land and building objects.

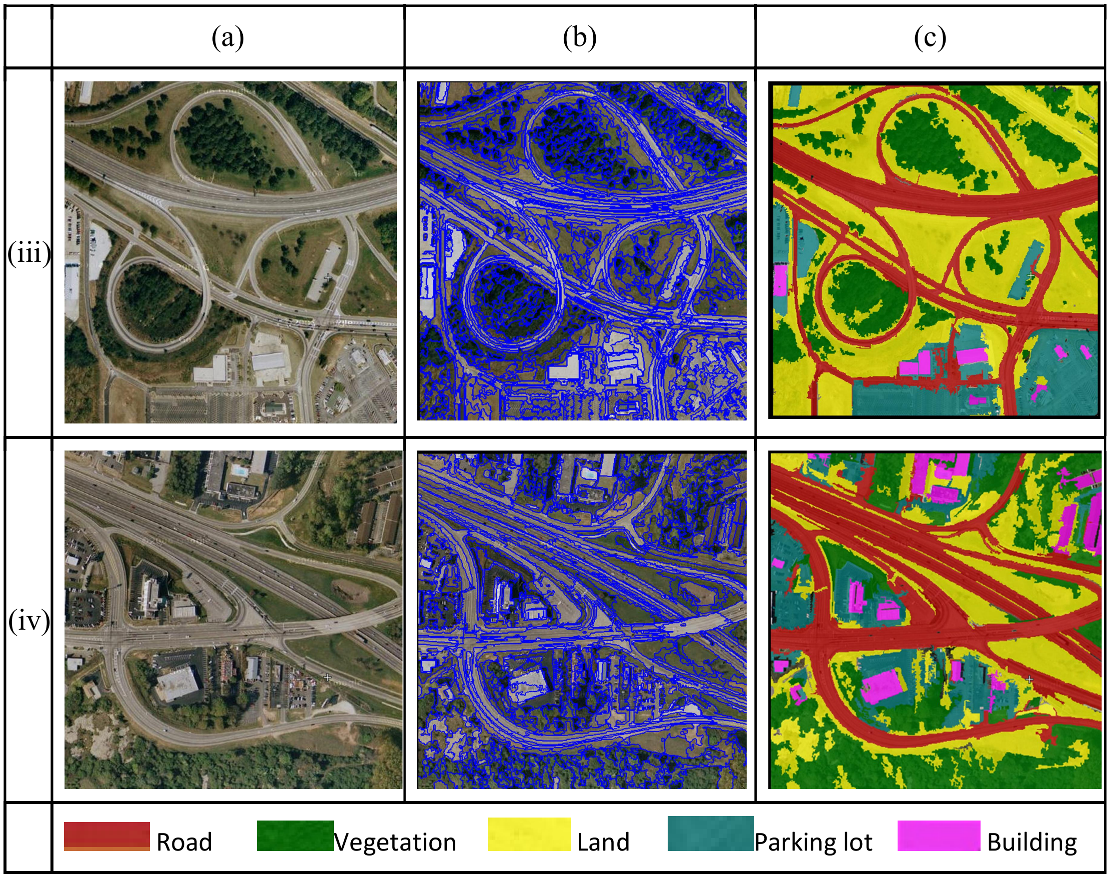

Figure 4. Developed Suburban images: (a) input image, (b) segmented images, (c) classified images in road, vegetation, land, parking lot area and building objects.

a. Accuracy Assessment:

After getting the visual results of the classified images as shown in the figures 3(c) & 4(c), there is an indeed of accuracy assessment. Table 3 and 4 are showing metrics of producer's accuracy, user accuracy, Hellden, short and kappa values for the results as shown in figures 3 and 4 respectively. Overall accuracy and kappa value for all the image results are shown in table 5. The quantitative assessments are shown in the table 3 & 4 for the classified results (see figures 3 & 4).

- ✓ Producer’s accuracy: The producer’s accuracy refers to a false negative, where objects or pixels belonging to a specific class are categorized differently other than the reference class.
- ✓ User’s accuracy: The user's accuracy refers to false positives, which occur when pixels or objects are mistakenly assigned to a known class.

- ✓ Hellden: Hellden index measures mean accuracy which expresses the likelihood that a randomly selected user class point will correspond to that class in the same position in the sample or reference data.
- ✓ Short: The intersection of the estimated and sample or ground truth classes to their union is calculated using the Short's mean accuracy.
- ✓ Kappa per class: While Kappa for each class computes in agreement at the per-class level, Cohen's Kappa coefficient indicates the expected level of agreement when classes are completely independent.
- ✓ Overall accuracy: The percentage of pixels from the ground truth or reference locations that are successfully mapped in classified objects is determined by the overall accuracy.

Table 3. Quantitative evaluation of the classified results in road, vegetation, water, land and building classes

		Class objects				
		road	**vegetation**	**Water**	**Land**	**Building**
Producer Accuracy	**Fig. 3(i)**	0.87	0.97	1.00	0.92	-
	Fig. 3(ii)	0.86	0.96	1.00	0.88	0.96
	Fig. 3(v)	0.73	0.9357	-	**0.79**	**1**
	Fig. 3(vi)	0.5446	**0.9103**	1	0.8384	0.7097
User Accuracy	**Fig. 3(i)**	0.88	0.99	0.50	0.89	-
	Fig. 3(ii)	0.89	0.91	0.71	0.97	0.81
	Fig. 3(v)	0.7612	**0.9143**	-	0.8636	0.4167
	Fig. 3(vi)	0.7639	**0.9181**	0.4	0.7685	0.44
Hellden	**Fig. 3(i)**	0.87	0.99	0.67	0.90	-
	Fig. 3(ii)	0.88	0.93	0.83	0.92	0.89
	Fig. 3(v)	0.7445	0.9249	-	0.8261	0.5882
	Fig. 3(vi)	0.6358	**0.9142**	0.5714	0.8019	0.5432
Short	**Fig. 3(i)**	0.78	0.96	0.50	0.82	-
	Fig. 3(ii)	0.78	0.87	0.71	0.85	0.79
	Fig. 3(v)	0.593	0.8602	-	0.7037	0.4167
	Fig. 3(vi)	0.4661	**0.8419**	0.4	0.6684	0.3729
Kappa per class	**Fig. 3(i)**	0.8514	0.9213	1.00	0.9021	-
	Fig. 3(ii)	0.8298	0.934	1.00	0.811	0.9598
	Fig. 3(v)	0.6624	0.8683	-	0.7195	1.00
	Fig. 3(vi)	0.4615	**0.8217**	1.00	0.7898	0.6749

Table 4. Quantitative evaluation of the classified results in road, vegetation, land, parking lot area and building classes

		Class objects				
		road	**vegetation**	**Land**	**Parking lot**	**Building**
Producer Accuracy	**Fig. 3(iii)**	0.8487	**0.957**	0.9261	0.5164	0.7778
	Fig. 3(iv)	0.8085	0.80	**0.9352**	0.6667	1.00
User Accuracy	**Fig. 3(iii)**	0.7866	0.9468	0.8868	0.759	0.28
	Fig. 3(iv)	0.8941	0.9697	0.8783	0.875	0.4242
Hellden	**Fig. 3(iii)**	0.8165	**0.9519**	**0.906**	0.6146	0.4118
	Fig. 3(iv)	0.8492	0.8767	**0.9058**	0.7568	0.5957
Short	**Fig. 3(iii)**	0.6898	0.9082	0.8282	0.4437	0.2593
	Fig. 3(iv)	0.7379	0.7805	0.8279	0.6087	0.4242
Kappa per class	**Fig. 3(iii)**	0.7998	**0.9403**	**0.8921**	0.4482	0.7692
	Fig. 3(iv)	0.7589	0.7369	**0.9102**	0.6228	**1.00**

Table 5. Overall accuracy and kappa value of the classified results of Figures 3(i-vi)

Input images	**Classified results**	
	Overall Accuracy	**Kappa value**
Fig. 3(i)	95.07%	0.8993
Fig. 3(ii)	90.85%	0.8723
Fig. 3(iii)	84.08%	0.7875
Fig. 3(iv)	83.05%	0.7833
Fig. 3(v)	85.38%	0.7684
Fig. 3(vi)	80.30%	0.7022

Conclusion and Future scope

This study highlights that image segmentation and classification are crucial steps in OBIC. The choice of an appropriate segmentation method significantly impacts the accuracy of classification results. In the eCognition, MRS is demonstrating strong performance over the other segmentation algorithms available. When challenging MRS in the eCognition Developer, the K-NN classifier is used for achieving a classification accuracy of 95.07% and a kappa value of 0.8993 as shown in Figure 3(i)(c). However, the outputs in other figures indicate that the accuracy is not yet optimal. Future studies will explore different object feature variables and focus on improving classification accuracy. Efforts will be made to reduce misclassifications, potentially incorporating a wider range of features and exploring various deep learning algorithms to enhance rule application.

References

B. Feizizadeh, K.M. Alajujeh, T. Lakes, T. Blaschke, & D. Omarzadeh, (2021). A comparison of the integrated fuzzy object based deep learning approach and three machine learning techniques for land use/cover change monitoring and environmental impacts assessment. *GIScience & Remote Sensing, Volume 58-2021.*

B.K. Mohan & S.N. Ladha, (2007). Comparison of Object based and Pixel based classification of high resolution satellite images using Artificial Neural Network. *National symposium on security and soft computing, 29-31 March 2007, Surat, India*.

C. Yao, X. Luo, Y. Zhao, W. Zeng, & X. Chen, (2017). A review on image classification of remote sensing using deep learning. *3rd IEEE International Conference on Computer and Communications (ICCC), 13-16 December 2017, Chengdu, China*.

C. Ye, Y. Li, P. Cui, L. Liang, S. Pirasteh, J. Marcato, & J. Li, (2019). Landslide detection of hyperspectral remote sensing data based on deep learning with constraints. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Volume 12-2019.*

D. Flanders, M. Hall-Beyer, & J. Pereverzoff, (2003). Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing, Volume 29-2021*.

E.B.N. Bastorous (2020). ROAD NETWORK EXTRACTION FROM SATELLITE IMAGES IN EGYPT. Egypt: Doctoral dissertation, Assiut University

E. Ersoy Tonyaloglu, N. Erdogan, B. Cavdar, K. Kurtsan, & E. Nurlu, (2021). Comparison of pixel and object based classification methods on rapideye satellite image. *Turkish Journal of Forest Science, Volume 5 -2021*.

E.O. Makindea , A.T. Salamib , J.B. Olaleyea , O.C. Okewusi, (2016). Object Based and Pixel Based Classification using Rapideye Satellite Imagery of Eti-Osa. *Geoinformatics FCE CTU, Volume 15-2016*.

F. Pacifici, M. Chini, W.J. Emery, (2009). A neural network approach using multi-scale textural metrics from very high-resolution panchromatic imagery for urban land-use classification. *Remote Sensing of Environment, Voulme 113-2009*.

F. Saba, M.J. Valadanzouj, & M. Mokhtarzade, (2013). The optimization of multi resolution segmentation of remotely sensed data using genetic algorithms. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-1/W3, 5-8 October 2013, Tehran, Iran*.

G. Khadanga, K. Jain, & S. Merugu, (2016). Use of OBIA for extraction of cadastral parcels. *International conference on advances in computing, communications and informatics (ICACCI), 21-24 September 2016, Jaipur, India*.

J.R. Anderson, E.E. Hardy, J.T. Roach, & R.E. Witmer, (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data, Geological Survey Professional Paper: Vol. 964. Washington: US Government Printing Office. https://doi.org/10.3133/pp964

J.S. Blundell, & D.W. Opitz, (2006). Object recognition and feature extraction from imagery: The Feature Analyst approach, *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XXXVI-4/C42, 4-5 July 2006, Salzburg University, Austria*.

K. Tamta, H.S. Bhadauria, & A.S. Bhadauria, (2015). Object-oriented approach of information extraction from high resolution satellite imagery. *IOSR Journal of Computer Engineering (IOSR-JCE), Volume 17-2015.*

L. Yang, L.R. Mansaray, J. Huang, & L. Wang, (2019). Optimal segmentation scale parameter, feature subset and classification algorithm for geographic object-based crop recognition using multisource satellite imagery. *Remote Sensing, Volume 11-2019*.

L. Dragut, T. Schauppenlehner, A. Muhar, J. Strobl, & T. Blaschke, (2009). Optimization of scale and parametrization for terrain segmentation: An application to soil-landscape modeling. *Comput. Geosci., volume 35-2009*.

M. Uzar, & N. Yastikli, (2013). Automatic building extraction using LiDAR and aerial photographs. *Boletim de Ciências Geodésicas, Volume 19- 2013*.

M.A. Aguilar, F.J. Aguilar, A.G. Lorca, E. Guirado, M. Betlej, P. Cichón, & C. Parente, (2016). ASSESSMENT OF MULTIRESOLUTION SEGMENTATION FOR EXTRACTING GREENHOUSES FROM WORLDVIEW-2 IMAGERY. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, Volume XLI-B7, 12-19 July 2016, Prague, Czech Republic.*

N. Gupta, & H.S. Bhadauria, (2014a). Object based information extraction from high resolution satellite imagery using eCognition. *International Journal of Computer Science Issues (IJCSI), Volume 11-2014*.

N. Gupta, & H.S. Bhadauria, (2014b). Object-oriented approach of information extraction from panchromatic satellite images based on fuzzy logic. *5th International Conference-Confluence The Next Generation Information Technology Summit (Confluence), 25-26 September 2014, Noida, India.*

P. Aplin, & G.M. Smith, (2008). Advances in object-based image classification. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XXXVII Part B7, 3-11 July 2008, Beijing, China.*

P.P. Singh, & R.D. Garg, (2011). Land Use And Land Cover Classification Using Satellite Imagery: A Hybrid Classifier And Neural Network Approach. *International Conference on Advances in Modeling, Optimization and Computing, 5-7 December, 2011, IIT Roorkee, India*.

P.P. Singh, R.D. Garg, & P. L. N. Raju, (2013). Classification of High Resolution Satellite Imagery: An Expert System Based Approach. *34th Asian Conference on Remote Sensing (ACRS), 20-24 October, 2013, Bali, Indonesia*.

P.P. Singh, & R.D. Garg, (2013a). A Hybrid approach for Information Extraction from High Resolution Satellite Imagery. *International Journal of Image and Graphics, Volume 13*-2013.

P.P. Singh, & R.D. Garg, (2013b). Information Extraction from High Resolution Satellite Imagery Using Integration Technique. Second international conference on Intelligent Interactive Technologies and Multimedia (IITM), 9-11 March, 2013, IIIT Allahabad, India.

P.P. Singh, & R.D. Garg, (2014a). Classification of High Resolution Satellite Images using Equivariant Robust Independent Component Analysis. *Second International Conference* *on Advanced Computing, Networking and Informatics (ICACNI), 24-26 June, 2014, Kolkata, India*.

P.P. Singh, & R.D. Garg, (2014b). Classification of high resolution satellite image using spatial constraints based fuzzy clustering. *Journal of Applied Remote Sensing, Volume 8*-2014.

P.P. Singh, & R.D. Garg, (2015). Fixed Point ICA based approach for maximizing the non-gaussianity in remote sensing image classification. *Journal of the Indian Society of Remote Sensing, Volume 43*- 2015.

R. Hamilton, K. Megown, T. Mellin, & I. Fox, (2007). Guide to automated stand delineation using image segmentation. RSAC-0094-RPT1. Salt Lake City, UT: USDA Forest Service, Remote Sensing Applications Center.

S.O. Atik, & C. Ipbuker, (2021). Integrating convolutional neural network and multiresolution segmentation for land cover and land use mapping using satellite imagery. *Applied Sciences, Volume 11-2021.*

S. Shekhar, & J. Aryal, (2019). Role of geospatial technology in understanding urban green space of Kalaburagi city for sustainable planning. *Urban Forestry & Urban Greening, Volume 46 -2019*.

S. Bhaskaran, S. Paramananda, & M. Ramnarayan, (2010). Per-pixel and object oriented classification methods for mapping urban features using Ikonos satellite data. *Appl Geogr., Volume 30-2010*.

T.G. Whitesidea, G.S. Boggs, S.W. Maier, (2011). Comparing object-based and pixel-based classifications for mapping savannas. *International Journal of Applied Earth Observation and Geoinformation, Volume 13*- 2011.

X. Pan, & J. Zhao, (2018). High-resolution remote sensing image classification method based on convolutional neural network and restricted conditional random field. *Remote Sensing, Volume 10-2018*.