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Applications of Data Mining Techniques in Improving the Classification Accuracy of High Resolution Satellite Data

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Applications of Data Mining Techniques in Improving the Classification Accuracy of High Resolution Satellite Data

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15	Abstract/Key words	The commonly used automatic methods of satellite image classification, supervised or unsupervised classification algorithms, are good enough when used with low to moderate resolution remotely sensed (RS) data. But, in the case of high resolution images like IRS P6 LISS IV, IKONOS or CARTOSAT, showing a diversity of land cover forms, the traditional algorithms have not been found adequate to obtain satisfactory results, because of high variance in the data. The report is comprised of four sections. Section-1 reports the Introduction of RS classification techniques along with the objectives. Comprehensive review of related works is presented in the Section-2. Section-3 presents the methodology of two proposed object-based image classification (OBIC) techniques (OBIC based on NNC and Hybrid approach of OBIC) along with experimental experimental demonstration. Concluding remarks are given in Section-4. **Keywords:** RS, OBIC, NNC			

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Foreword

With the rapid development of remote sensing (RS) technology in the last two decades, the limitation of RS applications is becoming weaker because of the availability of multiple RS data sources with finer spatial, temporal, spectral and radiometric resolutions. Scientists and practitioners have made outstanding efforts in developing advanced classification approaches and techniques for improving classification accuracy. Major drawback found for traditional '*hard*' classifiers is that they require training data to be normally distributed. Typically, they have considerable difficulties dealing with the rich information content of high resolution data; they produce a characteristic, inconsistent classification, and they are far from being capable of extracting objects of interest. The development and application of new classification techniques for RS multispectral imagery is currently a highly important research area and application issue.

I congratulate project team for initiating and completion of the project entitled 'Applications of Data Mining Techniques in Improving the Classification Accuracy of High Resolution Satellite Data'. It provides a comprehensive survey on RS data classification methods reported since last two decades along with two proposed object-based image classification (OBIC) methods. I hope, proposed OBIC methods developed using data mining techniques and tools can be effectively used for accurate classification of high resolution RS data.

Director, NESAC

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1. Introduction

With the rapid development of remote sensing (RS) technology in the last two decades, the limitation of RS applications is becoming weaker because of the availability of multiple RS data sources with finer spatial, temporal, spectral and radiometric resolutions. RS data of the earth may be analyzed to extract useful thematic information. A thematic map shows the spatial distribution of identifiable earth surface features and provides an informational description over a given area, rather than a data description[1].

1.1 Classification of RS Data

RS data classification is an important means of information extraction to make thematic maps from imagery. Classification of RS data is an important issue, and effective selection of appropriate classifier is especially significant for improving classification accuracy[2]. RS imagery, covering a large geographic area with high temporal frequency, offers a unique opportunity for deriving land use and land cover information through the process of image interpretation and classification. Large number of RS image classification techniques have been developed since 1980[3,4,5] where the pixel value is treated as the basic unit of the analysis. Literatures on the RS data analysis approaches and few survey articles have pointed out the recent advancements of classification algorithms and associated feature extraction techniques. It has been noticed that all the major classification algorithms have been experimentally tested on multispectral and hyperspectral RS data. Further significant advances of these algorithms have been marked in terms of classification accuracy, robustness and stability.

1.2 Soft Computing Techniques in Data Mining

With the launch of very high resolution RS sensors like IKONOS and QuickBird, data mining based-techniques have been developed since late 1990s, where, soft computing approaches are becoming more relevant in RS applications. Soft computing is a term used in computer science to refer to problems in computer science whose solutions are unpredictable. Soft computing deals with imprecision, uncertainty, partial truth, and approximation to achieve practicability, robustness and low solution cost. Soft computing became a formal area of study in computer science in the early 1990s[6]. Components of soft computing, mainly include artificial neural network (ANN[7]), fuzzy set theory[8, 9], evolutionary computation[10], Chaos theory[11] and rough set.

1.2.1 Classification Using ANN

The motivation of working on ANN is from the interception of the recognition that the working way of computing or estimation of conventional digital computer and the human brain are entirely different[12]. The human brain has the ability to arrange its constituent structures called neurons in such a way which can perform certain computations such as recognition of pattern or perception. ANNs process records one at a time, and "learn" by comparing their classification of the record (which, at the outset, is largely arbitrary) with the known actual classification of the record. The errors from the initial classification of the first record is fed back into the network, and used to modify the network algorithm for a number of iterations.

1.2.2 Fuzzy Set Theory

Fuzzy sets were introduced by Lotfi A. Zadeh and Dieter Klaua in 1965 as an extension of the classical notion of set[13]. In classical set theory, the membership of elements in a set is assessed in binary terms, according to a bivalent condition-an element either belongs to or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval [0, 1]. The fuzzy set theory has an effective use in a wide range of domains, including RS data classification in which information is incomplete or imprecise.

1.2.3 Rough Sets

Rough set theory (RST) is an extension of classical set theory. It is used to compute in the existence of vagueness or imprecision in the data. A rough set is related to working on the boundary regions of a set[14] Usually, rough sets are used in system of classification where the knowledge of the system is incomplete[15] In other words, rough set is applied to any classification task to form various classes where each class contains objects which are not distinguishably different.

1.2.4 Evolutionary Computing

Evolutionary computing or genetic algorithm (GA) is a computational model on the basis of principles of evolution and natural selection. Evolutionary computation uses iterative progress, such as growth or development in a population. This population is then taken in a guided random search using parallel processing to reach the desired goal. Such processes are often inspired by biological mechanisms of evolution. In a GA, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible[16] GAs are very effectively applied in some specific application of RS[17].

1.2.5 Chaos Theory

Chaos theory concerns deterministic systems whose behavior can in principle be predicted. Chaotic systems are predictable for a while and then appear to become random. The amount of time for which the behavior of a chaotic system can be effectively predicted depends on three things: how much uncertainty, we are willing to tolerate in the forecast; how accurately, we are able to measure its current state; and a time scale depending on the dynamics of the system.

The phenomenon of sensitivity to initial conditions brings up the question of differing outcomes from the predicted process. In the classification work, the expected outcome is the most precise definition of the content and the satisfaction of the users. Unforeseen differences can occur due to the shortcomings of the classification system and due to human factors (errors). Chaos theory helps to understand the origins of errors that may happen during any process[18].

1.3 Motivation

Remote sensing research focusing on classification of RS imagery has long attracted the attention of the RS community because classification results are the basis for many environmental and socioeconomic applications. Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy[19]. Major drawback found for traditional '*hard*' classifiers is that they require training data to be normally distributed[20]. Typically, they have considerable difficulties while dealing with the rich information content of high resolution data: they produce a characteristic, inconsistent classification, and they are far from being capable of extracting objects of interest. The development and application of new classification techniques for RS multispectral imagery are currently a highly important research area and application issue[21]. Still, the greatest challenge is to deal with very high-spatial-resolution multispectral and hyperspectral data. The capability of producing a high degree of classification accuracy with a minimal set of training data is now highly desirable from advanced classification approaches.

1.4 Objectives

Following are the objectives identified for the study-

- A systematic and comprehensive survey on RS data classification approaches and methods reported since last two decades.

- Object-based image classification (OBIC) using multi-resolution segmentation and nearest neighbor-classifier approach (NNC) for extraction of linear objects like drainage, roads and railway lines from high resolution India satellite imageries. NNC attempts to classify an unknown object based on the best class separation distances in the feature space.

- Hybrid OBIC method realized through the fuzzy set theoretic approach of NNC and knowledge-based classification for extraction of land uses from the fused images of high resolution panchromatic Cartosat-I image and low resolution multispectral Landsat Enhanced Thematic Mapper Plus (Landsat ETM+) image.

2. Related Works

During 1980s and 1990s, most classification techniques employed the image pixel as the basic unit of analysis, with which each picture element is labeled as a single land use land cover category. With the pixel as the basic analysis unit, a series of classification techniques, such as unsupervised (i.e., *K*-means and ISODATA), supervised (i.e., MLC, ANN and SVM) and hybrid classification (i.e., fusion of supervised and unsupervised) have been developed. These pixel-wise classification approaches have certain limitations, when applied to heterogeneous regions as the size of an object may be much smaller than the size of a pixel. In particular, a pixel may not only contain a single land use land cover type, but a mixture of several land use land cover types[22]. As a result, fuzzy classification and spectral mixture analysis techniques have been developed in 1990s as a subpixel classification to address the mixed pixel problem[23].

2.1 Taxonomy

Lu and Weng[24] characterized the category of RS classification approaches in supervised, unsupervised, parametric, non-parametric, per-pixel, subpixel, object-oriented, per-field, hard, soft, spectral, contextual and spectral-contextual based on classification criteria and apply. We organize classification approaches of the above categories in four main categories; they are supervised, unsupervised, hybrid and ensemble.

In the terminology of machine learning[25], classification is considered an instance of supervised learning, i.e., learning where a training set of correctly identified observations is available. Supervised classification methods require pre-classified data (or training data). The corresponding unsupervised procedure is known as clustering, and involves grouping data into classes based on some measures of inherent similarity or distance.

Traditionally, the hybrid classification system utilizes more than one classification system of either supervised or unsupervised. On the other hand, ensemble approaches may use a set of supervised as well as unsupervised learning algorithms to achieve better predictive accuracy.

2.2 Existing Approaches

Recent researches on image classification have shown that conventional 'hard' classification techniques, which allocate each pixel to a specific class, are often inappropriate for applications where mixed pixels are abundant in the image[26]. Traditional per pixel supervised methods like MDC, MLC and K-NNC often ignore the impact of the mixed pixel. They have considerable difficulties in dealing with the rich information content of high resolution data; they produce a characteristic, inconsistent classification, and they are far from being capable of extracting objects of interest. Major problem found for such approaches is that they need normal distribution of training as well as input data. Even so, they are providing satisfactory performances in the classification of low and low-moderate resolution RS data.

The limitations of these conventional classifiers have been recognized and the potential of alternative approaches have been evaluated[27, 28]. Non-parametric classifiers such as ANNs and DTs are becoming important approaches for multi-source data classification[29]. On the other hand, DT models are found to be efficient for a particular classification problem, however, DTs are very sensible to the training data and often creates over-complex trees that do not infer the data well[30]. Further, when compared to some of non-parametric classifiers, namely DT and ANN, SVM does not require the generation of rules that heavily depend on the knowledge from experts. This is crucial for achieving high classification accuracy[31]. However, the biggest limitation of the SVM lies in the choice of the kernel and often faces high computational expenses both in training and testing[32].

Most commonly used ensemble approaches like boosting and bagging often over-fit the training data. Besides lack of interpretability is one major disadvantage of bagging. On the other hand, RFs are creating new vistas in machine learning applications. RFs are composed of DTs for class prediction and characterized by bagging for random selection of features and are efficient choices as it avoids overfitting by creating a great number of trees[33]. Recently, OBICs approaches have been offered as an alternative to the pixel-based classification approaches for very high spatial resolution images. The problem occurred due to the mixed pixel[34] can be addressed through segmentation of images at different scale levels.

The existing major classification approaches are categorically given in the Table 1.

Table 1: Existing major multispectral approaches

Category	Existing major approaches
Supervised	MLCs[35,36,37,38], fast MLC[39], spatial-spectral mixing with MLC[40], MLC and expert system[41], MDCs[42,43], ANN[44], dynamic learning ANN[45], RBF ANN and *K*-means[46], Fuzzy ANN[47], contextual ANN[48], back propagating ANN[49,50], ANN with multi-scale texture metrics[51], DTs[52,53,54,55,56,57] refined DT[58], boosted DT[59], DT using Waikato environment for knowledge analysis (WEKA[60]), SVMs[61,62,63,64], SVM by kernel dependence measure[65], spatial-contextual SVM[66], etc.
OBIC	OBICs[67,68,69,70,71,72,73], image segmentation and object-based classification[74], multiresolution and object-oriented fuzzy classification[75], contextual OBIC[76], OBIC for extraction of linear features[77], feature extraction from fused image[78], the effective fuzzy approach of NN-classifier[79], OBIC with machine learning methods[80], etc.
Unsupervised	*K*-means[45,81], ISODATA[82,83], Unsupervised classification based on independent component analysis (ICA) mixture model[84], SOMs[85,86,87], FLVQ[88,89,90], FCM[91], improved FCM[92], semi-supervised FCM[93],Gaussian kernel based FCM[94], FCM based on feature divergence[95], FCM based on Markov random field[96], etc.
Hybrid	The combination of MLC and neural network using Bayesian techniques[97], the combination of MLC and DT[97], combined supervised and unsupervised classification[98], a hybrid system based on rough set theory[99], Bayesian and Hybrid classifier[100], hybrid algorithm of genetic algorithm and back propagation ANN[101] etc.
Ensemble	RFs[102,103,104,105,106], ensemble of discriminant analysis, DT, SVM, MLP, and radial basis function ANN[107], ensemble of soft computing[108], bagging and boosting[109,110], AdaBoost[111,112]etc.

3. Methodology

Two types of OBIC frameworks proposed based on the classification criteria and applications.

- OBIC-based on nearest neighbour classifier (NNC)
- Hybrid approach of OBIC

3.1 OBIC Based on NNC

It is mainly comprised of multi-resolution segmentation, features extraction and classification. Multiresolution segmentation was introduced in different scales to create hierarchies of objects for extraction of linear objects. NNC was applied in object-based domain which defines classification decision boundary based on the class separation distance of the training samples. For evaluation of performances of the proposed method in comparison with its other counterparts such as MLC and conventional NNC, overall accuracy (OA) and kappa index analysis (KIA) have been used.

3.1.1 Datasets Used

The study presented here is for two dissimilar types of terrain data in order to determine the variation of classification performance. Ortho-rectified Cartosat-I (Panchromatic) and LISS-IV of Resourcesat-2 sensor's (multispectral) data are used. G, R, NIR bands are used in case of multispectral images.

Table 2: Specifications of Cartosat-I and LISS-IV sensor's data

Sensor	Pixels size	Spectral (μm)	Spatial (m)
Cartosat-I (Plain areas)	12000x 12000	0.5-0.85	2.5
LISS-IV (Hilly terrain)	12288x 12288	0.5-0.59 (G) 0.62-0.68 (R) 0.77-0.86 (NIR)	5.8

Cartosat-I: The image of the test site is a plain terrain in Sibsagar district of Assam, India comprised of rural settlements surrounded by agricultural areas.

LISS-IV: It is mainly a hilly terrain in Meghalaya, India comprised of settlements surrounded by mainly forest.

3.1.2 Multiresolution Segmentation

Multi-resolution segmentation is an agglomerative region growing technique starting with one pixel object forming one image object for each of the bands of the image, merging decision is based on local homogeneity criteria (h), describing the similarity of adjacent image objects[113]. It is comprised of spectral (h_{spec}) and shape (h_{sh}) homogeneity. The shape (h_{sp}) homogeneity is associated with compactness 'h_{comp}' and smoothness 'h_{sm}'. Here, S of each segmentation level determines the maximum allowed heterogeneity for the resulting image objects.

3.1.3 OBIC Based NNC

In OBIC based NNC, the decision boundary between a sample object $O_i \in O_s$ and an unknown object O_u can be defined based on the class separation distance or feature distance between O_i and O_u. The class separation distance can be computed between any O_i and O_u in k-dimensional feature space as follows[90]:

$$class\_sep\_dist_{O_i, O_u} = \sum_{f=1}^{k} \left(\frac{V_f^{O_i} - V_f^{O_u}}{\sigma_f} \right)^2$$

where $V_f^{O_i}$ and $V_f^{O_u}$ are values of feature f for the sample objects O_i and O_u respectively. Feature values of varying range is standardized by using standard deviation (σ_f) of all features.

Here, O_u is classified by a majority vote of its neighbors, with the object being assigned to the class of O_i most common amongst its k nearest neighbors.

3.1.4 Experimental Results

The classification is exclusively performed for previously classified land use. for which training data had been collected in the same vegetation period. The training dataset had been prepared with reference to the existing classified map. other satellite data sources of the same period. We have supplied the training datasets in the form of Geographic information system (GIS) layers and 40% of the total training datasets had been used as test datasets for performance assessment of the OBIC based NNC in comparison to the other traditional classifiers like MLC and NNC.

Linear features like roads and drainage may not be prominently visible in the hilly terrain because of terrain condition. atmospheric or other sensor related problems. Similarly. same thing happened while attempting to separate out metalled roads from the dry river. Separation of roads from river or roads from railway line can be possible only when segmentation takes place on different scale parameters. Few test results are presented in the Figure 1 and Figure 2.

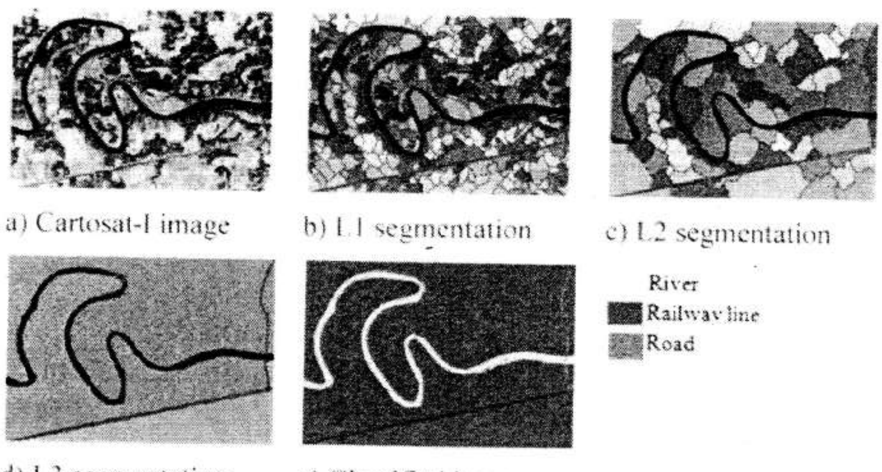
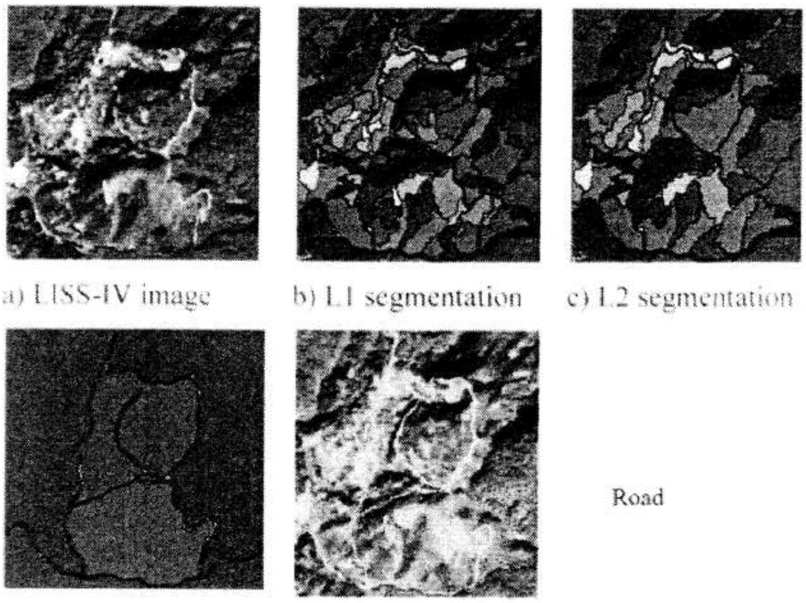


Figure 1: Segmentation and classification of Cartosat-I image



a) LISS-IV image b) L1 segmentation c) L2 segmentation

d) L3 segmentation e) Extraction of road

Figure 2: Segmentation and classification of LISS-IV image

The comparative performances of all the classifiers are given in the Table3 in terms of OA (in %) and KIA. It is observed that the performances of MLC and NNC are comparable with each other. The proposed OBIC based NNC outperforms the other in classifying both the datasets. It is observed that the performances of all the classifiers are significantly lower while classifying the hilly area image (LISS-IV).

Table 3: Comparative assessment of different classifiers

Classifiers	Cartosat-I (Plain area)		LISS-IV (Hilly area)	
	OA	KIA	OA	KIA
MLC	77	0.74	71	0.69
NNC	78	0.76	71	0.68
OBIC based NNC	91	0.88	81	0.78

3.2 Hybrid Approach of OBIC

Wavelet transform (WT)-based fusion, multi-resolution segmentation, selection of the optimal set of features, fuzzy logic based NNC (FNNC) and knowledge based classification approach are the basis of this method.

3.2.1 Datasets used

High resolution panchromatic Cartosat-I data with a spatial solution of 2.5m and the multispectral data of Landsat ETM+ sensor with 30m spatial resolution with three spectral bands (G: 0.52-0.60 μm, R:0.63-0.69 μm and NIR:0.77-0.90 μm) of the same region were used for the study. The test site is a plain area characterized by mainly tea garden areas mixed with grasslands and agricultural fallow lands.

3.2.2 Methods

Panchromatic Cartosat-I data was fused with the multispectral data of Landsat ETM+ sensor using WT-based fusion technique. When applying WT to images, one rough image and three precise images are obtained. Rough image contains the spectral information of multispectral image and three precise images contribute the information related to spatial resolution of the panchromatic image according to directivity. The basic logic is to replace the rough image of low resolution image from that of high resolution image and then carries out a wavelet reverse transformation using a rough image of low resolution images and precise images of high resolution images.

Multi-resolution segmentation was applied to the fused image based on spectral and shape homogeneity criterion, where, scale of each segmentation level determines the maximum allowed heterogeneity for the resulting image objects. It defines the occurrence or nonoccurrence of certain object class where the same type of objects appears differently at different scales.

Once the fused image is segmented to set of image objects, then a number of features characterizing the fused image can be derived from the image objects to define the class description of training datasets. However, all the features are not relevant in improving the classification performance. Also, the choice of the optimal set of features for classification of unknown image objects is a very crucial step and really important for projecting an effective classification system. We applied feature space optimization (FSO) to select the optimial set of features. FSO defines the optimal set of features in terms of best class separable distances. It requires training samples and computes the best class. separable distance in k dimensional feature space. A feature or a feature set can be said optimal if it has maximum class separable distance.

On the other hand, introduction of expert knowledge into the classification system can contribute significant performance of the system. The established scientific indices, expert knowledge, experimental observations can make the basis of knowledge-based features. We have used Normalized difference vegetation index (NDVI) of each of the image objects to carry out the first level classification (i.e. Discrimination of vegetation and non-vegetation).

The conventional NNC was enhanced by fuzzy membership functions, where, the decision boundary is defined by the fuzzy membership function on the feature distance between each of the training sample objects and unknown objects formed during segmentation of the image.

3.2.3 Experimental Results

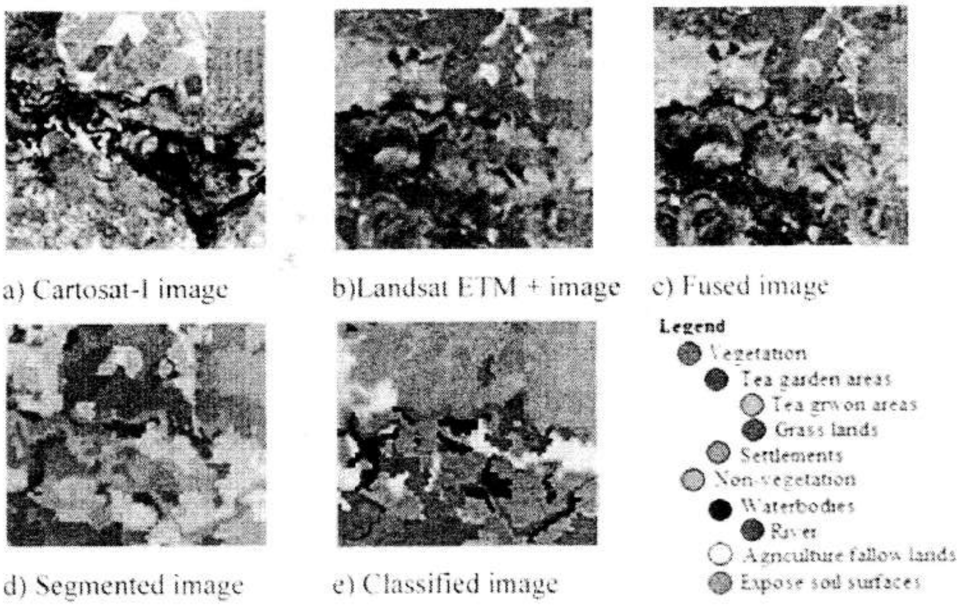
We have presented a typical example of feature extraction from WT-based fused images of Cartosat-I and Landsat ETM+ sensors. For discussion, we have cited the example of existing tea garden areas with actual tea grown areas and grasslands, agriculture fallow lands, exposed soil surfaces, water body with river and settlements mixed with vegetation. Initially, the classification was initiated based on knowledge. Image objects falling under the categories of vegetation and non-vegetation are having distinct spectral characteristics because of their reflectance properties. We have used mean NDVI of segmented image objects to discriminate between the image objects of vegetation and non-vegetation.

A set of random sample datasets representing each of the classes participating in the classification process has been used as reference or test dataset for assessment of the performances of the proposed method in comparison with other existing classifiers like MLC, ANN and SVM. The comparative assessment of performance of all the classifiers is given in the Table3.1. The hybrid approach of OBIC outperformed the all the other classifiers investigated here.

Table 3.1: Comparative assessment of different classifiers

Approaches	OA	KIA	P	ROC
MLC	70	0.66	0.68	0.88
ANN	78	0.76	0.77	0.89
SVM	80	0.77	0.78	0.89
Hybrid OBIC	88	0.85	0.87	0.95

Images of Cartosat-I and Landsat ETM + sensors and the corresponding fused image along with the segmented and the final classified image is depicted in the Figure 2.



a) Cartosat-I image b)Landsat ETM + image c) Fused image

d) Segmented image e) Classified image f) Step5: Classification

Figure 3: Images of Cartosat-I, Landsat ETM+ with corresponding fused image along with segmented and final classified images

4. Discussion

Recent researches on image classification have shown that conventional 'hard' classification techniques, which allocate each pixel to a specific class, are often inappropriate for applications where mixed pixels are abundant in the image. Traditional per pixel supervised methods like MDC, MLC and K-NNC often ignore the impact of the mixed pixel. They have considerable difficulties in dealing with the rich information content of high resolution data: they produce a characteristic, inconsistent classification, and they are far from being capable of extracting objects of interest. On the other hand, no significant developments in the advancement of hybrid approaches reported in the recent literatures. It involves a lot of computational cost as it requires fusion of supervised and unsupervised learning. However, some of the hybrid classification models are found very efficient in terms of classification accuracy, but the computational complexity suffers a lot. Most commonly used ensemble approaches like boosting and bagging often over-fit the training data. Besides lack of interpretability is one major disadvantage of bagging. Bagging models are also suffering from computational complexity. On the other hand, boosting has been proven to give better accuracy than bagging, but it also inclines to be more likely to over-fit the training information. AdaBoost is sensitive to noisy data and outliers. On the other hand, RFs are creating new vistas in machine learning applications. RFs are composed of DTs for class prediction and characterized by bagging for random selection of features and are efficient choices as it avoids overfitting by creating a great number of trees. Recently, OBICs approaches have been offered as an alternative to the pixel-based classification approaches for very high spatial resolution images. In addition, OBICs have many advantageous features over other existing classifiers, because, classification component of OBIC can be realized through powerful fuzzy logic, SVMs, and RFs. However, there are certain other issues affecting the performance of the OBIC; a scale factor of segmentation algorithm and selection of relevant features are few major issues.

In this study two object-based methods are proposed: i) NNC method for extraction of linear objects like drainage, roads and railway lines from high resolution Indian satellite imageries and ii) Hybrid method of OBIC realized through the fuzzy set theoretic approach of NNC in conjunction with knowledge-based classification for extraction of land use classes from the fused image of high spatial resolution panchromatic and low resolution multispectral images.

The NNC-based method outperforms the other approaches with encouraging classification accuracy. However, further attention requires in the improvement of the classification algorithm. Likewise, the choice of the optimal set of features is required in achieving the higher performances. On the other hand, the hybrid OBIC method using Gaussian membership function in conjunction with knowledge classifier has been established to be effective for classification of fused images while comparing with the other counterparts like MLC, ANN and SVM.

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Form GFR 19-A

(See Government of India's Decision (1) below Rule 150)

FORM OF UTILIZATION CERTIFICATE

Sl. No.	Letter No. & Date	Amount Rs.
1	No. NESAC/EOAM-MC/46/2007 dated November 5, 2008	83,000/-
	Total	83,000/-

Certified that out of the amount of Rs. *Nil* received during the year **2010-11** in favour of **Registrar, Tezpur University** towards collaborative project '**Applications of data mining techniques in improving the classification accuracy of high resolution satellite data**' under NESAC letter no given in the margin and Rs. 27,412 on account of unspent balance of Previous year, a Sum of Rs. 27,412 has been utilized for the purpose for which it was sanctioned.

Certified that I have satisfied myself that the conditions on which the amount was sanctioned have been duly fulfilled and that I have exercised required checks to see that the money was actually utilized for the purpose for which it was sanctioned.

15/12/10

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