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A Novel Optimized Land Cover Classification Framework Using Data Mining Techniques

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Abstract: The main purpose of this study is to highlight the importance of data mining techniques for the classification of land cover (LC) types such as fertile cultivated land, green pasture, desert-rangeland, bare land and Sutlej-river land. A novel framework is designed to classify the subjective land cover types. Visually three selected land cover, desert rangeland, Sutlej river land and bare land have almost similar physical features and remaining two, fertile cultivate land (cropland) and green pasture (grass) have also to some extent similar physical features. It seems very difficult to discriminate these vast land cover areas when remotely sensed. For this study, data have been acquired by handheld crop scan device Multispectral Radiometer (MSR5) in the form of five spectral bands such as, blue (B), green (G), red (R), near-infrared (NIR) and shortwave infrared (SWIR), while texture data have been acquired from the digital photograph at the same site and location in the region of Bahawalpur Punjab Pakistan. Feature selection and reduction techniques are employed on statistical texture data to get an optimized set of features, while for MSR5 dataset, there is no such type of processing is required. These both type of data sets are deployed to WEKA software version (3.6.12) for classification. A comparative analysis is performed on the results of Multilayer Perceptron (MLP), Random Forest (RF), j48 and Naïve Bayes (NB). It is observed that MLP outperformed exceptionally and received an overall accuracy of 97.333% for texture dataset and 96.66% for multispectral dataset respectively.

Keywords: Textural Features, Remote sensing, MLP, Multi-spectral,

1. INTRODUCTION

Data mining techniques have a significant role in image processing and remote sensing for betterment of the agriculture (Parihar, *et. al.,* 2006). This study combines the data mining with remote sensing to extract the useful knowledge in the given datasets, Recently it has been used to classify the vast land use/cover area into different classes and for the estimation of crop yield assessment models (Blaschke, *et.al.,* 2000) .This would be helpful not only for the current needs but also for future prediction. In this century, world is facing the different challenges of human survival such as, lack of food, poverty, drought and different catastrophic events. (Rundquist, 2000).These issues can be tackled in the better planning of food, water, environment, security and increase in crop production with utilization of cultivated land properly. The LC information is essential for better planning and utilization purposes. It is trying to enhance the cultivation area with better varieties of crops. Scientists are trying to get the benefits of information technology by involving it in different domain such as, engineering, agriculture, economics and environmental sciences etc. (Walter-Shea *et.al.,* 1992). Conventionally, cultivated lands are monitored through field base survey (Foody, 2002), Which requires a heavy financial investment along with large human resources. Hence for developing countries such as Pakistan, it is not so easy to spend a huge amount on such projects. As per geographical distribution, it is observed that land is categorized into different types like bare, fertile, rocky, salinity and sandy etc. In Pakistan, the conventional field based survey system could not been successful due to both financial and technical limitations. Although almost half of the total population of these countries is associated with agriculture profession (Pakistan, 2000). For this reason, data mining with remote sensing and image processing technology could not been implicated for natural resource organization as was suggested by different scientists (Kureshy, 1995). Similarly the Chinese Academy of Sciences (CAS) with collaboration of different research teams developed a model for land use dataset of temporal data (Gao *et.al.,* 1999). (Liu *et.al.,* 2002). (Liu *et.al.,* 2003). Shifa with his fellows discriminate the cotton and sugarcane plants by using multispectral data and observed 98% overall classification accuracy (Shifa, *et.al.,* 2011). Rehmani and his companions acquired two types of remote sensing data (radiometric and photographic) of five different wheat varieties and compared the classification accuracy 96%for radiometric data and 93.14% for photographic data (Rehmani, *et.al.,* 2015). A two layer Conditional Random Field (CRF) model for land cover and land use classification was proposed by

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(Albert, *et. al.*, 2014). Similarly a multilayer conditional random field (MCRF) land classification model was suggested. It was used for multi temporal with multi scale remote sensing data (Hoberg *et.al.*, 2012). A texture features with variable window size images were used for four land cover of aerial data. Different statistical features were used to classify the land cover data (Helmholz *et.al.*, 2014). A supervised pixel-based classification method was developed by implementing Markov Random Field (MRF) method to differentiate the agriculture land cover data (cropland and grass land) (Caridade *et.al.*, 2008). In data mining, classification is an ultimate objective. classification is achieved in training dataset to predict the class of future objects whose class label are not known (Bayardo, 1997). (Di, *et.al.*, 2000).Image segmentation gives the lot of object information not only for spectral but also about the spatial or shape features (Blaschke, 2010). (Hussain, *et.al.*, 2013). Hu and Wang, Compared between object-based approaches and traditional pixel-based approaches. They observed that Object-based approaches outperformed in the overall classification accuracy. (Hu *et .al.*, 2013). Classification of photographic urban land-used data in four classes such as office, industrial, public, and transportation are discussed and applying decision tree and achieved an accuracy of 61.88% (Di, *et.al.*, 2000). They described the data mining algorithms to get information from GIS database by using inductive learning methods to improve land use classification of images. In this study, it is tried to compare the performance of two types of data (multispectral and texture) for the classification by using data mining techniques, before this study, there is no such type of datasets are developed by using data mining techniques for land cover classification. All discussed issues emphasize the significance of the proper land classification, administration and better utilization. The objective of this study is to build up a simple, concise and outstanding framework to classify the above discussed land cover types. Both types of data sets are acquired in an open environment and used optimized set of spectral and statistical parameters for classification. For the completion of this study, we used texture features for photographic data and spectral features for MSR5 (multispectral) data.

2. MATERIAL AND METHODS

This study focuses the land cover classification through remote sensing data by using data mining techniques. This research is conducted at The Islamia university of Bahawalpur province Punjab (Pakistan), located at 29°23′44″N and 71°41′1″E.. This data are acquired by using a device named Multispectral Radiometer Crop Scan (MSR5). It provides data equivalent to Satellite Landsat5 TM (Thematic Mapper). Its output data consists of five spectral bands including B, G, R, NIR and SWIR, ranges from 450 nanometer to 1750 nanometer, where as photographic data are acquired by a digital NIKON camera.

2.1 Proposed Methodology

An optimized land cover classification framework (OLCF) is proposed for subjective (LC) types. To complete this study the following steps of image pre-processing, feature extraction, selection, reduction and classification are adopted, which are discussed in the following sections. The proposed methodology has been implemented using data mining tool, **WEKA software versions(3.6.12)** [http://www.cs.waikato.ac.nz] with MaZda software versions 4.6 (Szczypiński *et.al.*, 2009). All experimentation has been performed on Intel(R) Core i3 processor 2.4 Giga Hertz (GHz) with 2 Giga Bytes (GB) and 64-bit Windows operating system. The proposed optimized land classification framework (OLCF) is described in given below (**Fig-1)**.

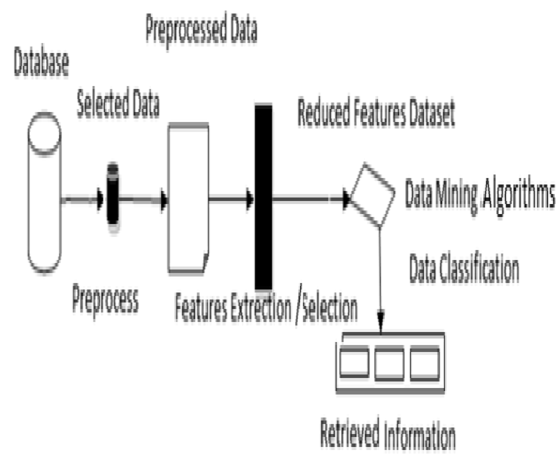

Fig. 1. Proposed Optimized Land Cover Classification Framework (OLCF)

2.2 Digital Photographic Data Acquisition

Digital photographs of subjective LC are taken by digital camera of Nikon Company; model COOLPIX having a resolution of 14.1 megapixels. The 12 colored photograph of each type of LC with the dimensions of 4288×3216 pixels and 24 bits depth having jpg format are acquired. To increase the dataset, 5 non overlapping regions of interests (ROIs) of window size (512x512) on each image are developed, in this way total 300(60×5) sub images data are arranged for the analysis. The photographic data are taken at the height of 4 feet from the ground surface. Whole data collection process is completed during the months of April to December in 2015 at noon time (12.00 pm to 2.00 pm) under natural sunlight. For better overall experimental accuracy the sunlight intensity is measured by digital Luxmeter MS 6610, MATECH.

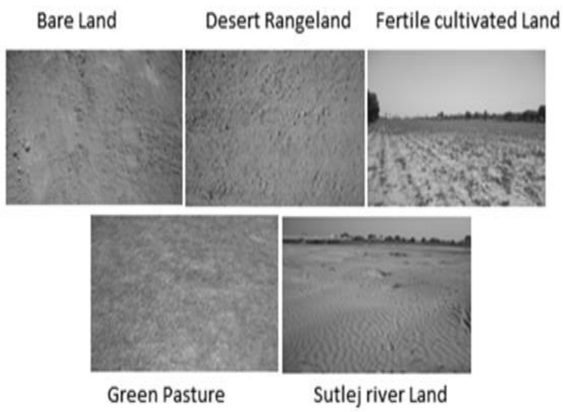

Fig. 2.Photographic Land Cover Data

2.3 MSR5 Data Acquisition

Radiometric data are acquired by Multispectral Radiometer (MSR5) made-up of CROPSCAN Inc. (USA). MSR5 has the quality to provide compatible data to satellite LANDSAT5 TM. It provides five different segment of spectrum, including B (450 to 520 nm), G (520 to 600 nm), R (630 to 690 nm), NIR (760 to 900) and SWIR (1550 to 1750 nm). MSR5 crop scan data have been previously used for the crops classification (Svotwa *et.al.* 2014). (Garatuza-Payan *et.al.,* 2003). (Shifa *et.al.,* 2011). and vegetation cover estimation and crops disease identification (Taghvaeian *et.al.,* 2012). (Taghvaeian *et.al.,* 2013). For this study, we have been acquired 60 MSR scans of each plot at 4 feet height of subjective land cover types. These scans have been taken at the same sites where the digital photographic data are acquired of these LC types. Each MSR5 scan composed of five spectral bands, three visible (B, G, R) and two invisible NIR and SWIR. Five different types of LC contain total 300 spectral data instances (CROPSCAN, 2001).

2.4 Proposed Optimized Land Cover Classification Framework (OLCF)

After acquiring both multispectral and photographic data, then the proposed optimized land cover classification framework (OLCF) is used to implement for further processing and analysis. For photographic data, each image contains some extraneous portion, so before starting to further processing, applicable image portion is acquired. By using image converter software, the obtained images are transformed to gray level (8 bit) and stored in bmp format. The MaZda software version (4.6) is used to calculate texture features (Szczypiński *et.al.,* 2009). For this study total 234 texture features are calculated for each region of interest (ROI). These feature are divided as first order 9 parameters and 11 second order (Haralick) parameters resulting from gray level co-occurrence matrix (GLCM) in all four directions (0^{o}, 45^{o}, 90^{o} and 135^{o}) up to 5 pixel distance 220 (11×4×5) (Haralick *et.al.,* 1973) and 5 Auto regression parameters . It means that each ROI has described by 234 features and statistically the data are accessible in 70200(300×234) dimensional features vector space. It is important to describe here that all of the obtained features are not equally significant for subjective land cover classification. So, it is necessary to reduce the feature dimensionality to obtain the most discriminate features, which has the ability to separate and categorize the LC classes accurately.

2.5 Features Selection

We have used three supervised feature selection techniques Fisher Co-efficient (F), Probability Of Error plus Average Correlation Co-efficient (POE+ACC) and Mutual Information Co-efficient (MI).These techniques are available in MaZda software version (4.6). Each technique gives 10 most discriminate features in descending order as per their significance. In this way total 30 features (10 features by each technique) are selected. As discussed by (Shahid *et.al.,* 2014) the combined set of features give better classification results, hence all the above mentioned techniques are merged together (F+PA+MI) to get the most discriminate features, in this way a set of 30 features are obtained for further analysis.

Table1. Feature Table (F+PA+MI) for ROI (512x512)

F+PA+MI		
1 S(0,4)InvDfMm	11 S(0,2)SumEntrp	21 S(0,3)Correlate
2 S(0,5)InvDfMm	12 S(0,5)DifEntrp	22 S(0,3)Contrast
3 S(0,3)InvDfMm	13 Perc.01%	23 S(0,4)Correlat
4 S(4,4)InvDfMm	14 S(1,0)Correlate	24 S(2,2)Correlate
5 S(0,2)InvDfMm	15 S(5,5)Entropy	25 S(2,2)Contrast
6 S(5,5)InvDfMm	16 S(5,5)SumAverg	26 S(0,4)Contrast
7 S(3,3)InvDfMm	17 Skewness	27 S(0,1)Entropy
8 S(2,2)InvDfMm	18 S(0,3)AngScMom	28 S(0,5)Correlate
9 S(3,3)InvDfMm	19 S(0,2)SumVarnc	29 S(0,2)Correlate
10 S(0,1)InvDfMom	20 S(1,0)InvDfMom	30 S(0,3)SumVarnc

2.6 Features Reduction

Before classification, the data have been processed to minimize the consequence of unnecessary disparity within the data due to outliers and other objects by applying feature reduction techniques. The combined feature selection techniques (F+PA+MI), only picks the most important features, but does not directly state the level of discrimination power. To find the data clustering, the selected 30 features data are deployed to non-linear discriminant analysis (NDA) available in B11 software which is integrated with MaZda software. It is observed that texture dataset has been given better results on NDA, While for MSR5 datasets, linear discriminant analysis (LDA) is provided the better results for data clustering and analysis. The objective of linear discriminant analysis (LDA) is to get a linear transform matrix (Zapotoczny, 2011).

2.7 Classification

Classification is the key feature in data mining, which is used in many applications. Classification is an ongoing process for assigning a given part of information into any of the known classes. In data mining, actually it is the procedure to acquire the information in the huge volume of data (Han and Kamber, 2006). In this study different classification methods of data mining are employed on two different types of LC dataset. We have applied different classification algorithms by using WEKA software version (3.6.12) such as Multilayer Perceptron (MLP), Naïve Bayes (NB), Random Forest (RF) and J48. These classifiers are employed on two types of dataset such as texture and spectral. All the classifiers are implemented after applying feature selection and reduction techniques due to get the better overall accuracy results. For processing in Weka software, both types of dataset are arranged into the Attribute Relation File Format (ARFF).

2.7.1 Multilayer Perceptron (MLP): It is known as Artificial Neural Network (ANN). It is a feed forward neural network with one or more layers between input and output layer. It has three layers: input layer, hidden layer and output layer. Hidden layer is the middle layer it may be more than one. In each layer every neuron or node is associated to every neighboring layers node. The training or testing parameters are depends on the input layer, and additional processing depends the hidden and output layers.

2.7.2 Random Forest (RF): It is an ensemble learning technique for classification; t is mostly used for large datasets. It also has the capability to handle the large volume of features without deleting in the dataset. For unsupervised data clustering, RF can also be used for better classification results.

2.7.3 J48: It is the optimized form of C4.5 classifier. Its result is decision tree which is same as tree structure. It contains different nodes such as root node intermediate node and leaf node. Every node in a tree contains a decision and as a result all the nodes describe the decision tree (Di *et.al.,* , 2000)

2.7.4 Naive Bayes (NB): Naive Bayes classifier is a set of supervised learning algorithms dependent on employing 'Bayes theorem'. Naïve Bayes is also called a conditional probability model: this classifier is very fast as compared to others complicated classifiers. Naive Bayes classifiers have worked excellent in many real-time datasets, famously document classification and spam filtering. They require a small amount of training data to estimate the necessary parameters.

3. <u>RESULTS AND DISCUSSIONS:</u>

In this study by using WEKA software, we have selected above discussed four data mining classification algorithms. We have built and compared the results on both types of datasets. These data mining techniques have the abilities to analyze the large datasets. For both types of dataset (texture and spectral), we have split dataset into 66% for training and 34% for testing with 10 fold cross validation method. We have also measured some other performance measuring parameters such as true positive (TP), false positive(FP), receiver-operating characteristic (ROC), mean absolute error (MAE), root mean squared error (RMSE), Confusion matrix, time complexity (T) and overall accuracy (OA). At first we have taken the texture dataset for land cover classification. We have employed different data mining classifiers that showed different accuracy results. Texture data classification results are acquired with the 10 fold Cross-validation method by using classifiers including MLP, RF, NB and J48 with an optimized set of 30 texture features. The classifier MLP demonstrates the highest overall accuracy of 97.6667% as compared to the others deployed classifiers. As a result, it represents the higher overall accuracy (OA) with others performance evaluating parameters including kappa coefficient, TP, FP, ROC, MAE, RMSE and time complexity factor. All the texture base land cover classification results with performance oriented parameters are shown in the given **(Table-2)**.

Table-2: Texture data classification table

Classifiers	Kappa Statistics	TP Rate	FP Rate	ROC	MAE	RMSE	Time (sec)	OA
Multilayer Perceptron	**0.9708**	**0.977**	**0.006**	**0.998**	**0.0197**	**0.0971**	2.37	**97.6667%**
RandomForest	**0.8792**	**0.903**	**0.024**	**0.988**	**0.0836**	**0.1767**	**0.38**	**90.3333**
J48	**0.7542**	**0.803**	**0.049**	**0.886**	**0.0845**	**0.2756**	**0.19**	**80.33%**
NaiveBayes	**0.6958**	**0.757**	**0.061**	**0.938**	**0.0989**	**0.3063**	**0.02**	**75.6667%**

Table-3 represents a confusion matrix of texture data; it includes the information which is actual and predicted data for MLP classification system. MLP shows the best overall accuracy among different employed classifiers.

Table-3: Multilayer Perceptron (MLP) texture data confusion table

Classes	Bare land	Desert Rangeland	Fertile Cultivated land	Green pasture	Sutlej River Land
Bare land	**59**	**1**	**0**	**0**	**0**
Desert Rangeland	**1**	**57**	**2**	**0**	**0**
Fertile Cultivated land	**0**	**1**	**58**	**0**	**1**
Green pasture	**0**	**0**	**0**	**60**	**0**
Sutlej River Land	**0**	**0**	**1**	**0**	**59**

Texture data classification graph of MLP is shown in **(Fig-4)**. It shows that each LC type has 60 data instances (ROIs) and these ROIs or data have shown into their respective classes. Given **(Fig-4)** explained the land data classification MLP graph.

For the multispectral dataset, the same data mining classifiers were deployed as in above discussed texture dataset. The 10 fold Cross-validation approach with additional 5 spectral features were used for data classification. Here MLP classifier also showed the highest overall accuracy as compared to the others deploying classifiers. As a result, the deployed multispectral features provided the higher overall accuracy with others performance evaluating parameters including kappa coefficient, TP, FP, ROC, MAE , RMSE and time complexity factor. Given below (**Table-4**) shows different classifiers results for multispectral data set.

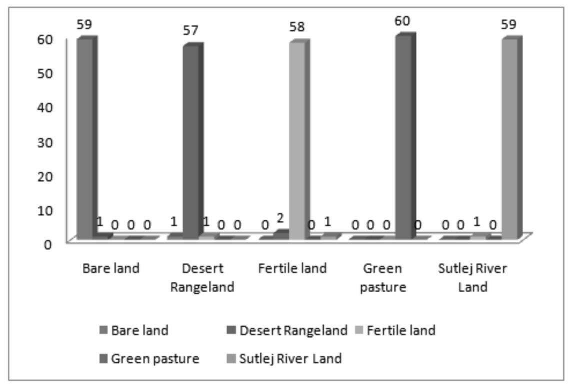

Fig-4: Multilayer Perceptron (MLP) texture data classification graph

Table-4: Multispectral data classification table

Classifiers	Kappa Statistics	TP Rate	FP Rate	ROC	MAE	RMSE	Time (sec)	OA
Multilayer Perceptron	**0.9542**	**0.963**	**0.009**	**0.997**	**0.0236**	**0.0903**	**0.44**	**96.3333%**
Random Forest	**0.9333**	**0.947**	**0.013**	**0.992**	**0.0396**	**0.1323**	**0.12**	**94.6667%**
J48	**0.9167**	**0.933**	**0.017**	**0.965**	**0.0295**	**0.1609**	**0.02**	**93.3333%**
Naïve Bayes	**0.7708**	**0.817**	**0.046**	**0.962**	**0.0729**	**0.255**	**0.01**	**81.6667%**

It contains the information which is actual and predicted data for MLP classification system. MLP shows the best overall accuracy among different employed classifiers for multispectral datasets. Multilayer Perceptron confusion table for multispectral data is shown in **(Table-5)**.

Table-5: Multilayer Perceptron (MLP) Multispectral data confusion table

Classes	Bare Land	Desert Rangeland	Fertile Cultivated Land	Green Pasture	Sutlej River Land
Bare Land	**57**	**2**	**0**	**0**	**1**
Desert Rangeland	**2**	**53**	**5**	**0**	**0**
Fertile Cultivated Land	**0**	**0**	**60**	**0**	**0**
Green Pasture	**0**	**0**	**0**	**60**	**0**
Sutlej River Land	**0**	**0**	**1**	**0**	**59**

Multispectral data classification graph for MLP classifier is shown in **(Fig-5)**. It shows that each LC type has also 60 data instances (ROIs) and these data have moved into their respective classes. Given below **(Table-5)** explains the data classification of MLP classifier for Multispectral data. All above discussion shows that, better data acquisition, preprocessing, optimized selected features and different data mining classifiers can also impact on results for classification. By implementing this optimized land classification framework (OLCF) rather than traditional qualitative parameters we can accurately classify different land cove types into their appropriate classes (Armstrong *et.al.,* 2007).

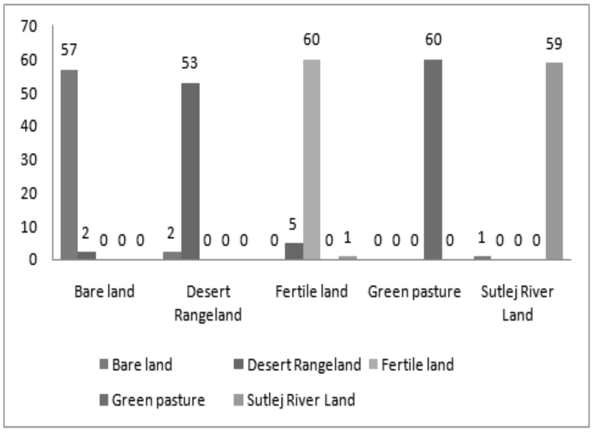

Fig-5: Multilayer Perceptron (MLP) multispectral data classification graph

4. CONCLUSION

In this study five different types of land cover datasets are classified into their appropriate classes. A comparative study of four data mining classifiers such as MLP, RF, NB and J48 has been performed after implementation on texture and multispectral dataset. Both types of land cover dataset (texture and multispectral) classification has been observed in the sense of overall accuracy with others performance oriented parameters as discussed above. All the classifiers have given satisfactory results but multilayer perceptron has outperformed exceptionally.

After deploying multilayer perceptron, an overall accuracy of 96.333% for multispectral data and 97.666% for texture data have been observed. It is the best overall accuracy among all the remaining deployed classifiers results of five different types of land cover datasets including fertile land, green pasture, desert rangeland, bare land and Sutlej river land. In this study, it is important to discuss here that in digital photographic dataset, if texture feature space would not been optimized by employing combined set of feature selection techniques (F+PA+MI) and feature reduction by non linear discriminant analysis (NDA) then it looks very difficult to achieve such an excellent overall accuracy . Although it is lengthy, time consuming and complex procedure but it will lead to better accuracy results which is almost equal or better in some cases for analysis and classification as compared to multispectral data. In future we may enhance this study as a data fusion for combining both textural and multispectral dataset for better classification results.

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