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CLASSIFICATION OF COLOR SATELLITE IMAGES USING COMPUTATIONAL INTELLIGENCE

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Abstract

The classification of color satellite images is presented using Multilayer Perceptron Neural Network and Support Vector Machine. Multilayer Perceptron is used for non-linear classification with 10 hidden layers using different number of epochs. A multiclass SVM is chosen for classification using radial basis function (RBF) kernel. Before performing classification, the image enhancement and feature extraction steps are carried out. The image enhancement is done using contrast stretching. The color features are extracted by using Principal Components Analysis (PCA). Classification results are obtained and testing is done by varying the number of images in the training and test datasets, the number of features and different classifiers. 100 images each obtained from Landsat satellite of NASA, US and Bhuvan geoportal of NRSC, Hyderabad are used in classification. Seven class categories, residential land, commercial land, grasslands, evergreen forest, mixed forest, sediments and clear water are identified. The results are analyzed and it is observed that SVM provides better results as compared to Multilayer Perceptron (MLP). Performance analysis is carried out with respect to classification accuracy and time.

Keywords:

Image Classification, Multilayer Perceptron Neural Network, Support Vector Machine, Landsat, Bhuvan

1. INTRODUCTION

Image classification is an important phase in an image processing system. The image classification categorizes the pixels in the digital image into one of the object classes present in the image (e.g. land, forest, grasslands, water etc.). The information obtained from classification process of remote sensing images is used in a number of applications such as determining land use patterns, environmental analysis, weather forecasting, vegetation monitoring, agriculture, natural resource management, urban planning and other related areas.

Satellite data includes geographical data in digital format. Though individual small elements may not be visible in these images but large structures are clearly visible for analysis and interpretation. Image enhancement is often required for satellite images in order to identify the objects and extract features and their coordinates from images [1]. Earlier, traditional data processing techniques were mostly utilized for satellite image processing [2]. Now, satellite image classification and interpretation are being carried out using computational techniques [3]. These techniques can work with large amounts of data. Since training and testing is involved, these techniques learn by experience.

Satellite images can be acquired by collecting data from satellites such as Landsat, Indian Remote Sensing (IRS) from Bhuvan and also from Google Earth. Landsat is a remote-sensing satellite program operated by National Aeronautics and Space Administration (NASA). It is an ongoing series of satellites that conduct Earth observations. The purpose of Landsat is to archive images of earth and gather facts about natural resources of our planet. Bhuvan, a repository of Indian satellite images, is a geoportal provided by National Remote Sensing Centre (NRSC), Hyderabad. For the research work presented in this paper, Landsat and Bhuvan multispectral color images are used. These images consist of more than one layers or bands with large amount of clear information. The multispectral satellite images are represented in digital format which can be analyzed for a range of applications with the help of computer systems. The color features in the images have been used as the basis for feature extraction and classification. A color is assigned for every object class that needs to be identified in the image [4].

This paper presents the classification of satellite images using Multilayer Perceptron Neural Network and Support Vector Machine and is organized in five sections. Section 1 provides brief introduction about Satellite images, Image Classification and various classification techniques with respect to satellite images and section 2 summarizes the literature review on computational techniques for classification of satellite images. Section 3 describes Methodology used including Design, Feature Extraction and Image Classification using Neural Network and Support Vector Machine. Results are presented in section 4. Section 5 includes the conclusions and scope for future work followed by Section 6 with references.

2. LITERATURE REVIEW

The image classification categorizes the pixels in an image into land cover classes or themes [5]. The classification algorithms are required to build a learning model using set of features for a dataset. In satellite image classification, the commonly used computational techniques for classification are Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Trees (DT) etc. Neural networks are used in various applications involving extracting land cover information through multispectral satellite images.

Ojaghi et al. [7] assessed the performance of multilayer perceptron (MLP) neural network to classify high resolution IKONOS image. MLP is a feed-forward neural network with one or more layers of neurons between the input and output layers called hidden layers and is most widely used in remote sensing applications. The output of neural network classifier has been compared with the results of support vector machine with Gaussian kernel function and Maximum Likelihood Classification (MLC) algorithm which is most commonly used in statistical approach image classification. The experimental results indicated that training data and model parameters play important role in the classification accuracy. With ANN, they obtained the accuracy of 87.75% and with SVM, 85.57% classification accuracy is achieved.

Eeti et al. [8] used Multi-Classifier System (MCS) for classification of landcover classes in a satellite image obtained from worldview-2 sensor. The authors used a group of five Artificial Neural Networks classifiers as members forming an ensemble of classifiers. They also presented a comparative study of classification results obtained through the use of principal components. The authors in [9] presented an approach for classification of 42 satellite images from Google Earth into five object classes (tree, water, greenery, rock and soil) using the decision tree. Kavzoglu et al. [10] explained the use of Multilayer Perceptron, a feed-forward ANN w.r.t satellite images and got 84.99% classification accuracy by employing 6400 pixels as training samples.

SVM is useful in handling remote sensing datasets and produce higher accuracy. Mountrakis et al. [11] presented a review on the usage of support vector machines in remote sensing. The authors depicted that SVMs are not sensitive to training sample size and have been widely used in remote sensing-based estimation and monitoring of different biophysical parameters. They also proved that as compared to alternative methods such as backpropagation neural networks, SVMs can yield comparable accuracy using a much smaller training sample size.

Bahari et al. [12] illustrated the use of Support Vector Machine for classifying multispectral satellite image from Landsat. Only land areas are identified from the satellite image. The authors classified ten land cover classes with an accuracy of 97.1%. These classes included industrial, oil palm, rubber, coastal swamp forest, coconut, dry land forest, cleared land, bare land, and sediment plumes. Different classification colors are used for showing the percentage of areas covered by above mentioned land cover classes. Accuracy analysis is done using a confusion matrix.

Tangthaikwan et al. [13] made use of multiclass SVM for classifying a satellite image form Landsat satellite. Pixel-based classification is performed by making use of SVM with RBF kernel. Seven land classes, namely red soil, cotton crop, grey soil, damp grey soil, soil with vegetation stubble, mix class and very damp grey soil are classified by the authors. Seven 1-class SVM models are generated corresponding to each of the seven classes. For each SVM, 1-label denotes output associated with that class, and a 0-label otherwise. The outputs from seven SVMs are combined to classify the image. The classification accuracy achieved is 90%.

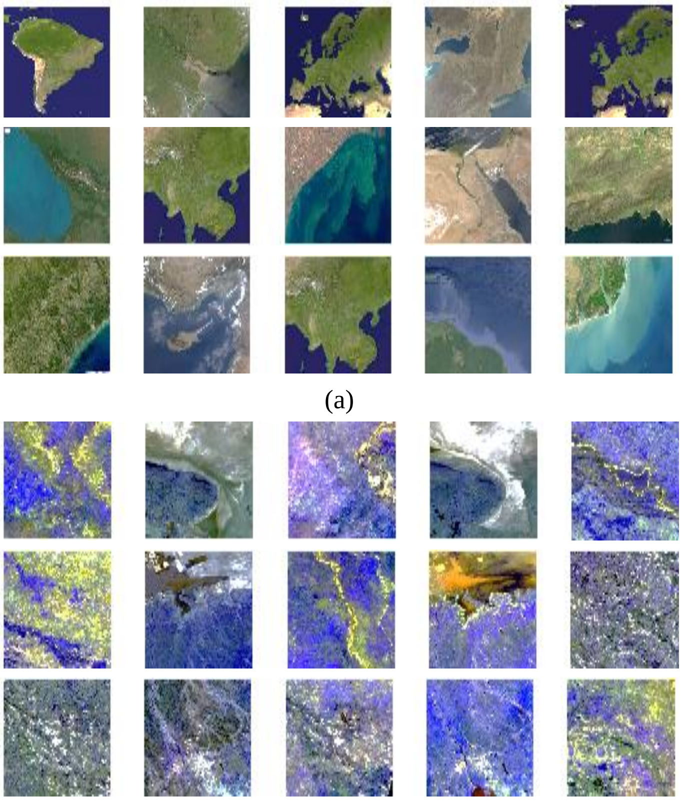
3. METHODOLOGY

This section presents the methodology followed for classification of Landsat and Bhuvan multispectral color satellite images using computational intelligent techniques: ANN and SVM. The images are selected with three macro classes land, vegetation and water containing seven class categories. The seven class categories include residential land, commercial land, grasslands, evergreen forest, mixed forest, sediments and clear water. After contrast stretching the dataset images, the enhanced images are divided into training and test datasets. These images are block-segmented into 8×8 pixel size. The image blocks are then used for extracting color features for classification. Since the satellite images contain huge amount of information in multiple bands, large number of features may be generated but only some required number are used for classification. The color features are extracted by using Principal Component Analysis (PCA) with 8×8 pixel block segments [6]. 5-fold cross validation is performed before testing. 80% of images are taken as training data and rest of 20% images are taken for test data. In cross-validation, there is an overlap of training and testing data. For classification, labelled data is created by assigning class category codes to the image block segments based on dominating color values present in the respective block [14]. For classification, different sets of images are taken for training and testing with number of color features varying between 30 and 192.

3.1 DATASET PREPARATION

The proposed research work involves interpretation of color satellite images obtained from Landsat and Bhuvan databases [19] [20]. Two datasets are created from these databases consisting of 100 images each. The digital information extracted from the Red, Green and Blue bands of these digital images is used for further processing. Landsat images are downloaded as .jpg or .tiff formats where as Bhuvan images are available in the form of band information in .tiff format. These bands are separately collected and Red, Green and Blue bands are combined to form the database images.

For Bhuvan images, layer stacking was carried out by combining band images in .tiff format. After that, using an online tiff to jpg converter, the images are converted into .jpg format and saved as a dataset. Some of the sample images of earth taken from Landsat satellite and Bhuvan Geoportal containing different classes are shown in Fig.1.



(a)

(b)

Fig.1. Sample Images from (a) Landsat and (b) Bhuvan

3.2 CLASSIFICATION OF SATELLITE IMAGES USING COMPUTATIONAL INTELLIGENCE TECHNIQUES

The algorithms used for classification using Neural Network (Multilayer Perceptron) and SVM with Radial Basis Function (RBF) kernels are presented. Both training and test features are scaled for classification of images. Testing and verification of results is carried out based on classification accuracy and time complexity.

3.2.1 Multilayer Perceptron:

Neural Network is a feed forward ANN and consists of multiple layers of perceptron as a directed graph. Multilayer perceptron is used for non-linear classification of satellite images with 10 hidden layers and 1000 epochs are used for classifying the satellite images into seven class categories. The target class labels and feature matrix for training dataset are read as input to the multilayer perceptron. The classifier requires the input class labels or targets in the format such that every row has entries corresponding to one class category. Therefore, the labels are converted into matrix form in such a manner that every row contains index entries 1 at the occurrence of instance of a particular class and 0 otherwise. Training and test features are scaled in a uniform range by computing mean and standard deviation values from feature matrix so that feature values are not biased for any particular class. The network is tested with test dataset features which are given as input to MLP. The output is converted from vector format to indices in order to check occurrences of classes. Classification accuracy is computed by comparing the output with actual test data class categories. The actual class categories are obtained by assigning color codes to the test data blocks [14].

3.2.2 Support Vector Machine (SVM):

A Multi-Class Support Vector Machine is used for classification of Landsat and Bhuvan images. With respect to class categories in land, vegetation and water, a binary classifier is not sufficient. As the number of classes is more, we have used multiclass SVM with a non-linear radial basis function kernel for classification. The input for SVM is required in a specific SVM file format. It is a set of paired values of class labels and feature values. The target labels and feature matrix for training and test images are read and saved in the file. Training and test features are scaled in the range -1 and 1 and saved in separate files. Next, for classification, the SVM format files with respect to training and test features are read. Training of SVM model is performed with specifications of training data and kernel function. The classification is carried out on test dataset using trained SVM model and the predicted output is saved. Classification accuracy is computed by comparing the results with actual class occurrences.

4. VERIFICATION AND TESTING

This section presents the results of classification of satellite images. The classification algorithms for Landsat and Bhuvan datasets are implemented using MATLAB and LIBSVM 3.24 [15] classifier tool is used for implementation of SVM with RBF kernel function. Testing is done by varying the number of images in the training and test datasets and the number of features for classification. After performing cross validation on both these datasets, the accuracy obtained is 97%. In classification, testing is performed with data different from that of training data. The number of features is varied from 30 to 192. The number of features includes equal number of features from red, green and blue component of images. For example, if there are 150 features used, it contains 50 red component features, and 50 each from green and blue components. Two parameters, time and classification accuracy are computed for both datasets. Time (in seconds), shown in the results includes total time taken for color feature extraction and classification.

4.1 VERIFICATION AND TESTING FOR LANDSAT DATASET USING MULTILAYER PERCEPTRON

The results are presented for classification of Landsat images using Multilayer perceptron. Out of 100 Landsat images, 50 are taken for training and 50 are taken for testing purpose. The color features for Landsat images are computed using Principal Components Analysis (PCA) with 8×8 pixel block segments. The classification results using varying number of color features on Landsat database are presented in the Table.1.

Table.1. Performance of MLP on Landsat images using varying number of color features.

Sl. No	Number of Features	Time Required	Classification Accuracy (%)
1	30	15m:27s	89.68
2	45	16m:38s	91.15
3	60	18m:53s	92.33
4	75	19m:11s	94.86
5	90	20m:41s	96.98
6	120	24m:23s	96.65
7	150	26m:55s	96.23
8	180	29m:34s	96.11
9	192	32m:52s	96.54

Time = Feature vector computation time + Classification time

In Table.1, as shown in the first column, 9 feature sets are used, the second column shows the number of features taken for testing, third column shows the total time for feature vector computation and classification. Fourth column shows the maximum accuracy obtained as a result of classification.

We can observe that when 90 features are taken, the classification accuracy is the highest at 96.98%. It is observed that classification accuracy is not improving significantly beyond 120 features. This is due to the reason that principal components concentrate discriminative feature values at the starting of feature vectors. It can be inferred that time taken for feature vector computation and classification is proportional to the number of features.

4.2 VERIFICATION AND TESTING FOR LANDSAT DATASET USING SUPPORT VECTOR MACHINE

The results are presented for classification using Support Vector Machine using RBF kernel function. Out of 100 Landsat images, 50 are taken for training and other 50 for testing. The color features for Landsat images are computed using Principal Components Analysis (PCA) with 8×8 pixel block segments. The classification results using varying number of color features on Landsat dataset are presented in the Table.2.

Table.2. Performance of SVM with RBF kernel on Landsat images using varying number of color features

Sl. No	Number of Features	*Time Required	Classification Accuracy (%)
1	30	15m:14s	87.81
2	45	16m:48s	92.95
3	60	18m:33s	95.42
4	75	19m:42s	95.84
5	90	21m:18s	96.58
6	120	23m:56s	97.21
7	150	25m:43s	97.00
8	180	28m:20s	96.18
9	192	31m:45s	95.11

From Table.2, it is observed that when SVM is implemented with RBF kernel, the maximum accuracy achieved is 97.21% with 120 features. It is also observed that increasing number of features beyond 120 does not make significant increase in classification accuracy.

From the classification results shown in Table.1 and Table.2, it is observed that SVM with RBF kernel provides better results as compared to MLP. The performance is analyzed based on classification accuracy for two classifiers on Landsat database when different number of features is selected for classification. The highest accuracy among the classifiers is 97.21% which is produced by SVM with RBF kernel for 120 features. The highest accuracy for MLP is 96.98% when 90 features is used. By this analysis, it is clear that choosing number of features between 90 and 120 gives best results in all classifiers for satellite images. It is also observed that for most of the datasets, the classification accuracy achieved using SVM RBF kernel is above 92%.

4.3 VERIFICATION AND TESTING FOR BHUVAN DATASET USING MULTILAYER PERCEPTRON

The results are presented for classification of Bhuvan images using Multilayer perceptron. Out of 100 Bhuvan images, 50 are taken for training and other 50 for testing purpose. The color features for Bhuvan images are computed using Principal Components Analysis (PCA) with 8×8 pixel block segments. The classification results using varying number of color features on Bhuvan dataset are presented in the Table.3.

Table.3. Performance of MLP on Bhuvan images using varying number of color features.

Sl. No	Number of Features	*Time Required	Classification Accuracy (%)
1	30	14m:52s	92.86
2	45	15m:49s	94.65
3	60	17m:42s	96.81
4	75	18m:12s	97.04
5	90	21m:48s	96.82
6	120	24m:33s	96.81
7	150	26m:52s	96.00
8	180	29m:21s	95.48
9	192	32m:08s	95.22

From Table.3, we can observe that when 75 features are taken, the classification accuracy is maximum at 97.04%. It is observed that classification accuracy does not improve significantly beyond 120 features. This is due to the reason that principal components concentrate discriminative feature values at the starting of feature vectors. It is seen that time consumption of algorithm increases with increase in number of features. It is also seen that time taken for feature vector computation and classification is proportional to the number of features.

4.4 VERIFICATION AND TESTING FOR BHUVAN DATASET USING SUPPORT VECTOR MACHINE

The results are presented for classification using Support Vector Machine using RBF kernel function. Out of 100 Bhuvan images, 50 are taken for training and 50 are taken for testing purpose. The classification results using varying number of color features on Bhuvan dataset are presented in the Table.4.

Table.4. Performance of SVM with RBF kernel on Bhuvan images using varying number of color features

Sl. No	Number of Features	*Time Required	Classification Accuracy (%)
1	30	14m:55s	92.62
2	45	16m:12s	94.13
3	60	17m:37s	96.57
4	75	18m:25s	96.84
5	90	19m:49s	96.98
6	120	23m:10s	95.76
7	150	24m:56s	95.02
8	180	26m:30s	95.18
9	192	30m:53s	95.16

From Table.4, it is observed that with 90 features comprising of 30 each from red, green and blue components of Bhuvan satellite images, the classification accuracy is maximum at 96.98%. It is also observed that increasing number of features beyond 90 does not result in significant increase in classification accuracy.

The performance is analyzed based on classification accuracy for MLP and SVM on Bhuvan database when different number of features is selected for classification. The highest accuracy among the two classifiers is 97.21% which is produced by MLP when 75 features are used. SVM with RBF kernel produces slightly lower accuracy of 96.98 at 120 features as compared to MLP. By this analysis, it is clear that choosing number of features between 75 and 120 gives best results in all classifiers for satellite images. It is also observed that for most of the datasets, the classification accuracy achieved using SVM RBF kernel is above 94%.

4.5 COMPARISON OF CLASSIFICATION RESULTS

The performance of classification algorithms is compared with the results obtained by other researchers. They also used the similar classes and multispectral images from satellites including Landsat. The comparison is based on number of classes and number of features used from satellite images. The results of comparison are shown in Table.5. From Table.5, it can be observed that the classification accuracy obtained in this study using ANN and SVM shows improvement.

Table.5. Comparison of Classification Results for Satellite Images

Authors	Images	Classes	Technique	Accuracy
Soliman et al. [16]	ASTER satellite	5	SVM	93.00%
Zhang et al. [17]	GaoFen-2	6	SVM	92.42%
Tangthaikwan et al. [13]	Landsat	7	SVM	90.89%
Bahari et al. [12]	Landsat	10	SVM	97.10%
Silva et al. [18]	HSS Sensor	5	ANN	96.20%
Proposed work	Landsat	7	ANN	96.98%
Proposed work	Bhuvan	7	ANN	97.04%
Proposed work	Landsat	7	SVM	97.21%
Proposed work	Bhuvan	7	SVM	96.98%

5. CONCLUSION AND FUTURE WORK

The average classification accuracy obtained by using Multilayer Perceptron Neural Network and Support Vector Machine is approximately 96%. It is also observed that SVM with RBF kernel function produces better results as compared to MLP. The proposed methodology is tested on image datasets created using Landsat and Bhuvan. The classification can also be performed using other classifiers like decision trees and Bayesian networks. More kernel functions like sigmoid can also be used in SVM for comparison of classification results. Images from other satellites such as QuickBird, Sentinel and IKONOS can also be used for classification.

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