

## Research Article

### Comparison of Soft Computing Approaches for Texture Based Land Cover Classification of Remotely Sensed Image

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**Abstract:** Texture feature is a predominant feature in land cover classification of remotely sensed images. In this study, texture features were extracted using the proposed multivariate descriptor, Multivariate Ternary Pattern (MTP). The soft classifiers such as Fuzzy k-Nearest Neighbor (Fuzzy k-NN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM) were used along with the proposed multivariate descriptor for performing land cover classification. The experiments were conducted on IRS P6 LISS-IV data and the results were evaluated based on error matrix, classification accuracy and Kappa statistics. From the experiments, it was found that the proposed descriptor with SVM classifier gave 93.04% classification accuracy.

**Keywords:** ELM, fuzzy k-NN, MTP, SVM, texture descriptor

## INTRODUCTION

Major land cover types on the earth's surface are water, land and vegetation. The knowledge about the land cover types obtained through land cover classification can help the authorities of a nation to take vital decisions related to conservation of natural resources. Texture based studies (Lucieer *et al.*, 2005) prove that texture features are quite suitable for land cover classification of remotely sensed images and give high classification accuracy. In this study, the multivariate texture descriptor MTP is proposed and used for feature extraction. Like feature extraction technique, the choice of classifier is also vital for achieving high classification accuracy. Classification algorithms are responsible for grouping samples that belong to the same class. The classifier should also minimize error and separate outliers which lead to over fitting prior to classification. Soft classifiers in particular, incorporate fuzziness and classify pixels that lie on boundary accurately. Among the classification algorithms used in this study, the fuzzy k-NN classifier uses fuzzy samples for classification. Each fuzzy sample has a vector of fuzzy membership probabilities for each land cover class. The SVM classifier allows a marginal region on both sides of the linear or non linear boundary of separation of classes and classifies the pixels within the support regions based on measures of uncertainty and reliability. The ELM algorithm is a single shot feed forward neural network. The parameterization of ELM is computationally simple as

the weights of hidden layer are assigned randomly. The ELM algorithm converges quicker than other neural networks. The objective of the research work is to conduct a comparative study of fuzzy k-NN, ELM and SVM classification algorithms with the proposed Multivariate descriptor (MTP) in performing land cover classification of remotely sensed images.

**Motivation and justification of the proposed approach:** A variety of texture descriptors are found in literature. Local Binary Pattern (LBP) texture descriptor plays an important role in classification of texture images. The classification accuracies of LBP (Ojala *et al.*, 2001) and its derivatives were found better in many applications. In Multivariate Local Binary Pattern (Lucieer *et al.*, 2005), nine pattern units incorporating cross relations between bands were added to form the feature vector of the color image. To provide better pattern discrimination, Advanced Local Binary Pattern (Liao and Chung, 2007) was developed where the single minimum value obtained through applying repeated left circular shift operation on LBP pattern unit was used as a texture descriptor. A new algorithm using Hidden Markov Model (Younis *et al.*, 2007) was formulated for co-segmentation and analysis of 3D-MRI and MRSI data. Xiaoyang and Bill (2007) proposed Local Ternary Pattern for face recognition under difficult lighting conditions. In our earlier work, we did a comparative study (Jenicka and Suruliandi, 2008) of texture descriptors for segmentation of gray level images and later proposed Modified Multivariate

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Local Binary Pattern (MMLBP) for classification of remotely sensed images. Local Texture Pattern (LTP) (Suruliandi and Ramar, 2008) was developed for gray level images and later extended to remotely sensed images as Multivariate Local Texture Pattern (MLTP) (Suruliandi, 2009). Dominant Local Binary Pattern (Liao *et al.*, 2009) uses histograms of dominant patterns for pattern description. Local Derivative Pattern (Raju *et al.*, 2010) captures pattern unit in different angles. A novel face descriptor named Local Color Vector Binary Pattern (LCVBP) (Jae *et al.*, 2012) was introduced for face recognition to meet face images with challenges. Two color local texture features like Color Local Gabor Wavelets (CLGWs) and Color Local Binary Pattern (CLBP) (Seung *et al.*, 2012) were developed for face recognition and both were combined to maximize their complementary effect of color and texture information respectively. In study (Jenicka and Suruliandi, 2008), land cover classification was performed using the existing texture models namely MLTP, MLBP, MALBP, gabor and wavelet and it was proved that MLTP outperformed other models in giving high classification accuracy.

Among many classification algorithms used for classification of remotely sensed images, Fuzzy k-Nearest Neighbour, Support Vector Machine, Relevance Vector Machine (RVM), Self Organizing Map and Extreme Learning Machine are reported in recent literature. The supervised, unsupervised and semi supervised classification of remotely sensed images was performed with several fuzzy classifiers including fuzzy

k-NN (Wen and Minhe, 2010) and promising results were obtained. Hermes *et al.* (1999) suggested that SVM was more suitable for heterogeneous samples for which only a few numbers of training samples were available. Qiu *et al.* (2008) concluded that the SVM classification approach was better than k-NN classification approach. Demir and Erturk (2007) used RVM classifier for fast classification of hyperspectral images. Turtinen *et al.* (2003) suggested that the combination of LBP and SOM gave better performance when log likelihood distance was used as a dissimilarity measure instead of Euclidean distance. In another study, it was substantiated that the performance of the proposed hybrid 2D and semi 3D Texture Feature Coding Method (TFCM) and ELM (Tanyildizi, 2012) methodology for classification of 2D and 3D color textures was better than that of wavelet feature extractor and an ANFIS classifier. In our earlier work (Jenicka and Suruliandi, 2011), we performed a comparative study of classification algorithms on remotely sensed image using MMLBP and concluded that support vector machine classification algorithm performed better. Lu and Weng (2007) performed a detailed survey of various classification algorithms including pixel based, sub pixel based, parametric, non parametric, hard and soft classification algorithms. From the various classification algorithms mentioned so far, it is observed that fuzzy and neural network based classifiers perform better than other classifiers. A study to unravel the better soft classifier is the need of the

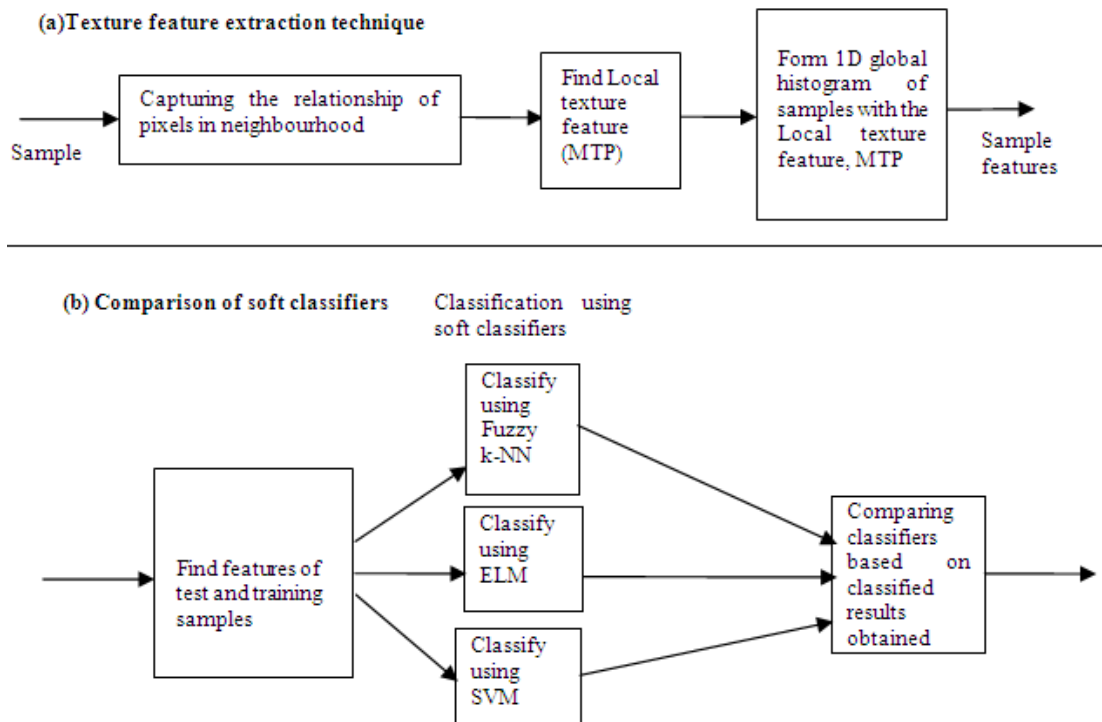


Fig. 1: An overview (a) texture feature extraction technique, (b) comparison of soft classifiers

hour. Motivated by this, the multivariate texture descriptor MTP is proposed and a comparative study of soft classifiers like Fuzzy k-NN, ELM and SVM was conducted in performing land cover classification with the proposed Multivariate descriptor (MTP). It is also expected that when a multivariate texture descriptor is combined with soft classifiers, promising results can be obtained. Justified by this fact, the performance evaluation of soft classification algorithms on land cover classification of remotely sensed images was carried out.

**Outline of the study:** The proposed approach has texture feature extraction part as shown in Fig. 1a and classification part as shown in Fig. 1b. During feature extraction, the neighbour pixels (around a centre pixel) of each 3×3 neighbourhood of a training sample is assigned a Pattern label using the proposed local texture descriptor (MTP) with the help of three discrete output levels such as 0, 1 and -1. The 1D histogram of the sample characterizes the global feature of the sample. A comparison of soft classifiers is performed in the classification phase.

**METHODOLOGY**

**Feature extraction technique:** In this section during feature extraction, the local descriptors of every pixel along with its neighbours are computed as local texture descriptor. Then the global description of the image or sub image can be obtained by accumulating the occurrence frequencies of the proposed local texture descriptor in a 1D histogram as described in subsection below.

**Multivariate Ternary Pattern (MTP):** The local texture descriptor extracts local texture information from a neighbourhood in an image. Let us take a 3×3 neighbourhood X, where the value of the centre pixel is  $g_c$  and  $g_1, g_2, \dots, g_8$  are the pixel values in its neighbourhood. The relationship between the centre pixel and one of its neighbour pixels is described by discrete output levels as shown in Eq. (1) below:

$$P(g_i, g_c) = \begin{cases} -1 & \text{if } g_i < (g_c - m) \\ 0 & \text{if } (g_c - m) \leq g_i \leq (g_c + m) \\ 1 & \text{if } g_i > (g_c + m) \end{cases} \quad (1)$$

where, ‘m’ is the threshold (a small positive integer). The discrete output levels 0, 1 and -1 characterize neighbourhood pixel relation. So, concatenation of these levels in a neighbourhood gives us a pattern unit. A sample calculation of pattern unit for n = 5 is shown in Eq. (2) below:

$$\begin{bmatrix} 206 & 194 & 201 \\ 203 & 201 & 198 \\ 212 & 210 & 202 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 0 \\ 0 & & -1 \\ 1 & 1 & 0 \end{bmatrix} \rightarrow 1 \ -1 \ 0 \ -1 \ 0 \ 1 \ 1 \ 0 \ (\text{Pattern Unit}) \quad (2)$$

The pattern unit with discrete output levels is used to form a unique value to characterize the pattern in the chosen 3×3 local region. The total number of patterns considering all combinations of three output levels with number of Pixels in the neighbourhood (P) equal to 8 will be 3<sup>8</sup>. This will lead to increase in number of bins required when these local patterns are accumulated to characterize global regions. In order to reduce the number of possible patterns, a Uniformity measure (U) is introduced as defined in Eq. (4). It corresponds to the number of circular spatial transitions between output levels like 0, 1 and -1 in the pattern unit. Patterns for which U value is less than or equal to three are considered uniform and others are considered non uniform patterns. The gray scale TP for 3×3 local region is derived as in Eq. (3). The value PS stands for sum of all positive output levels and NS stands for the absolute sum of all negative output levels. To each pair of (NS, PS) values, a unique TP value is obtained from the lookup table ‘L’ for all uniform patterns and 46 will be assigned for non uniform patterns:

$$TP(X) = \begin{cases} L(NS, PS) & U \leq 3 \\ 46 & \text{Otherwise} \end{cases} \quad (3)$$

where,

$$PS = \sum_{i=1}^8 p(g_i, g_c) \quad \text{if } s(p(g_i, g_c)) \geq 0$$

$$NS = \sum_{i=1}^8 p(g_i, g_c) \quad \text{if } s(p(g_i, g_c)) < 0$$

and,

$$U = \left| s(g_8 - g_c) - s(g_1 - g_c) \right| + \sum_{p=2}^8 \left| s(g_p - g_c) - s(g_{p-1} - g_c) \right| \quad (4)$$

where  $s(x, y) = \begin{cases} 1 & \text{if } |x - y| > 0 \\ 0 & \text{if otherwise} \end{cases}$

Table 1: Lookup table (L)

NS/PS	0	1	2	3	4	5	6	7	8
0	1	2	3	4	5	6	7	8	9
1	10	11	12	13	14	15	16	17	0
2	18	19	20	21	22	23	24	0	0
3	25	26	27	28	29	30	0	0	0
4	31	32	33	34	35	0	0	0	0
5	36	37	38	39	0	0	0	0	0
6	40	41	42	0	0	0	0	0	0
7	43	44	0	0	0	0	0	0	0
8	45	0	0	0	0	0	0	0	0

Table 2: Proposed descriptor, TP extended to different sizes of neighbourhood

Size of neighbourhood	Number of points in the neighbourhood	Total number of possible patterns	Total number of uniform patterns
(3×3)	8	73	46
(5×5)	16	145	118
(7×7)	24	217	190

The lookup table L is generated and shown in Table 1. The maximum Negative Sum (NS) is 8 (absolute value) as there can be eight 1's. So the size of the lookup table is (9×9). Zero entries in the lookup table show that the patterns will never occur. All other entries are entered sequentially starting from 1.

The proposed ternary pattern can be extended for 3×3, 5×5 and 7×7 neighbourhoods based on the uniformity condition. The total number of possible patterns and uniform patterns for the proposed univariate descriptor are shown in Table 2.

The proposed univariate TP operator for gray scale image is extended as Multivariate TP (MTP) for remotely sensed images. Among the multispectral bands, three most suitable bands for land cover classification are chosen and combined to form a RGB image. Nine TP operators are calculated in the RGB image. Out of nine, three TP operators describe the local texture in each of the three bands R, G and B individually. Six more TP operators describe the local texture of the cross relation of each band with other bands (GR, BR, RG, BG, RB and GB). For example, the GR cross relation is obtained by replacing the centre pixel of R band in its neighbourhood with the centre pixel of G band. Nine TP operators thus found are arranged in a 3×3 matrix. Then MTP is found by calculating TP for the 3×3 resulting matrix as shown below. This MTP histogram has only 46 bins:

$$MTP = TP \begin{bmatrix} TP^{RR} & TP^{GR} & TP^{BR} \\ TP^{RG} & TP^{GG} & TP^{BG} \\ TP^{RB} & TP^{GB} & TP^{BB} \end{bmatrix} \quad (5)$$

**Global description through histogram:** The steps for global description of a multispectral image are given below:

- Find local texture descriptor (MTP) by using a sliding window neighbourhood (of size 3×3) that runs over the multispectral image from top left to bottom right.
- Compute the occurrence frequency of MTP into a 1D histogram within a sub image of size (z×z).

**Classification algorithms:** A training set is formed initially in all classification algorithms under study. Training set is a matrix of training samples in which each row holds the global features and the actual class label of a training sample. In other words, the actual class labels of training samples are positioned in the last

column of training set and the remaining columns hold the global features. Each classifier has got two phases namely training and testing phase. Each classifier has got two phases namely training and testing phase. The steps performed within the two phases of each classification algorithm are explained in their respective sections.

**Fuzzy k-NN:** The Fuzzy k-NN algorithm proposed by Keller *et al.* (1985) further improves the classification accuracy obtained using k-NN algorithm. In fuzzy k-NN, each training sample can be a mixture of two or more classes. The classification principle using fuzzy k-NN algorithm is listed below.

**Training phase:**

- Extract global features of fuzzy training samples.
- The membership values of a known fuzzy sample 'x' in class 'i' can be found using the formula below:

$$\mu_i(x) = \begin{cases} .51 + \left(\frac{n_j}{k}\right) \times .49 & \text{if } i = j \\ \left(\frac{n_j}{k}\right) \times .49 & \text{if } i \neq j \end{cases} \quad (6)$$

where,  $n_j$  is the number of neighbours within 'k' closest neighbours belonging to class 'j'. The fuzzy membership values are found based on two conditions. The condition  $i = j$  means that the classified land cover class is the same as the actual land cover class and  $i \neq j$  means otherwise.

**Testing phase:**

- Extract global features of test sample
- Find log likelihood distance between the test sample and each training sample as given in equation below:

$$G = 2 \left[ \begin{aligned} & \left[ \sum_{s,m} \sum_{i=1}^n f_i \log f_i \right] \\ & - \left[ \sum_{s,m} \left( \sum_{i=1}^n f_i \right) \log \left( \sum_{i=1}^n f_i \right) \right] \\ & - \left[ \sum_{i=1}^n \left( \sum_{s,m} f_i \right) \log \left( \sum_{s,m} f_i \right) \right] \\ & + \left[ \left( \sum_{s,m} \sum_{i=1}^n f_i \right) \log \left( \sum_{s,m} \sum_{i=1}^n f_i \right) \right] \end{aligned} \right] \quad (7)$$

where,  $s$  and  $m$  are two histograms of test sample and training sample,  $n$  is the number of bins and  $f_i$  is the frequency at bin  $i$ :

- Pick up ‘ $k$ ’ closest training samples.
- The final membership of an unknown test sample is found using the formula given below:

$$\mu_i(x) = \frac{\sum_{j=1}^k \mu_{ij} \left( \frac{1}{\|x - x_j\|^{\frac{2}{m-1}}} \right)}{\sum_{j=1}^k \frac{1}{\|x - x_j\|^{\frac{2}{m-1}}}} \quad (8)$$

where,

$\mu_{ij}$  : The membership of training sample of  $i^{\text{th}}$  class to  $j^{\text{th}}$  class

$\|x - x_j\|$  : The distance between the training sample  $x$  and  $x_j$  ( $j^{\text{th}}$  nearest neighbour) and

$m$  : Weight attached to the distance  $\|x - x_j\|$

The test sample ‘ $x$ ’ is assigned to the class label based on the value of the expression that goes as,  $\max_n^{i=1} (\mu_i(x))$  where  $n$  is the number of classes.

**Support vector machine:** The SVM classifier is a supervised binary classifier which can classify pixels that are not linearly separable. Support vectors are the samples closest to the separating hyper plane and SVM orientates this hyper plane ‘ $H$ ’ in such a way as to be as far as possible from the sure candidates of both classes. The parameter ‘ $C$ ’ is the penalty assigned by user for training errors. The optimization problem of finding support vectors with maximal margin around separating hyper plane is solved subject to the tolerance value ‘ $C$ ’ entered by the user. The classifier solves optimization problem with the help of one of the kernels like linear, sigmoid, radial basis function, polynomial, wavelet and frame. A kernel specific parameter ‘ $\lambda$ ’ is assigned prior to optimization. Each new testing sample is classified by evaluating the sign of output of SVM.

Multiclass classification is done in SVM following two approaches namely one against one and one against all. We have used one against one approach in this study. In one against one approach, one SVM per each pair of classes is used. The whole set of patterns is divided into two classes at a time and finally the patterns which get classified into more than one class are fixed to a single class using probability measures. The steps involved in multiclass classification are as follows:

**Training phase:**

- If ‘ $s$ ’ is the number of classes, then ‘ $sC_2$ ’ support vector machines are needed and each SVM is denoted as  $SVM_{i,j}$  where ‘ $i$ ’ and ‘ $j$ ’ are the pair of classes.
- The SVM classifier is trained with the 2D histograms of known samples and their class labels. The known samples and class labels must belong to the corresponding pair of classes of SVM.

**Testing phase:**

- The 2D histogram of unknown sample is given as input to all SVM’s.
- The output of each SVM (per pair of classes) is mapped to a local probability value.
- Then the global posterior probability is found from the individual probabilities to decode the class label of the unknown sample.

The overall working principle of multiclass SVM is outlined in Fig. 2 where  $Cl_1, Cl_2, \dots, Cl_s$  are classes.

**Extreme learning machine:** The ELM classifier was proposed by Huang (2003) and Huang *et al.* (2004, 2006). The algorithm for classification of remotely sensed image using ELM classifier is listed below.

**Training phase:**

- Extract the global features of training samples.
- Normalize the global features of training samples to lie between 0 and 1 using the equation given below:

$$x_{Normalized} = \frac{x - \min}{\max - \min} \quad (9)$$

where,  $x$ , ‘ $\min$ ’, ‘ $\max$ ’ and  $x_{Normalized}$  stand for, the feature value to be normalized, minimum feature value, maximum feature value and normalized feature value, respectively.

- Prepare a training set with the normalized features of training samples along with its class labels.
- The ELM classifier has  $r$ -input neurons,  $r/2$ -hidden neurons and  $o$ -output neurons where  $r$  is the number of input features and ‘ $o$ ’ is the number of land cover classes. A suitable activation function for the ELM classifier is chosen.
- The initial weights between the input and hidden layer are set randomly.
- The ELM classifier is trained with the normalized features of training samples. The output of hidden layer is found based on chosen activation function.
- During the learning process, the weights between the hidden layer and output layer are adjusted in

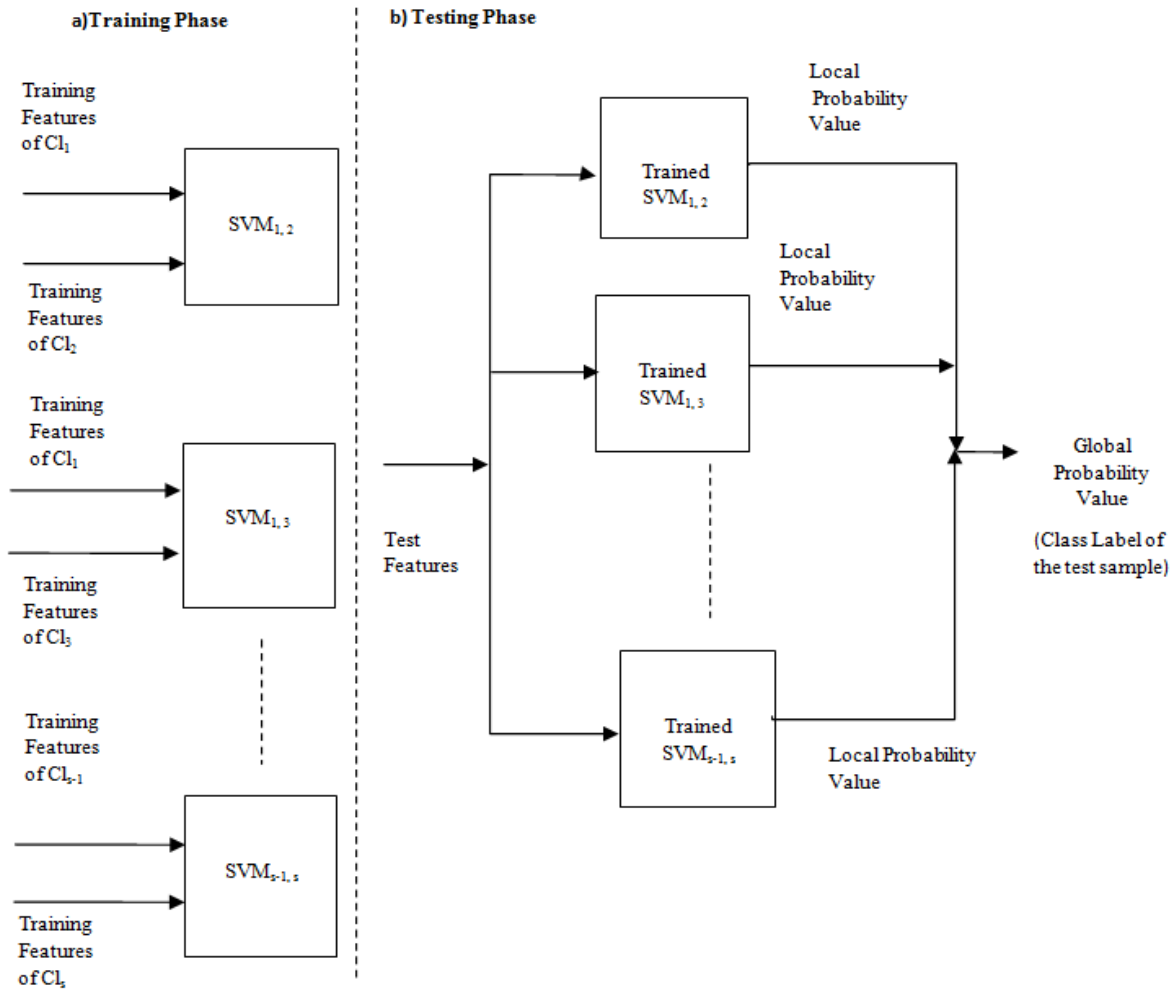


Fig. 2: Working principle of SVM

accordance with the input features and the land cover class to which the features belong.

**Testing phase:**

- Extract the global features of test sample.
- Normalize the global features of test sample using the equation given in ‘(9)’.
- The normalized features of test sample are given as input to ELM and the classifier returns the class label of test sample based on prior learning.

**EXPERIMENTS, RESULTS AND DISCUSSION**

This section describes the experiments, results and discussion on land cover classification of remotely sensed image using MTP texture model with Fuzzy k-NN, SVM and ELM classifiers.

**Experimental data:** The remotely sensed image under study is a IRS P6, LISS- IV image (26) supplied by



Fig. 3: IRS P6, LISS-IV remotely sensed image

Table 3: Training samples and their descriptions

Class No.	Actual class	Sample used	Description
Class 1	Vegetation-1		Rice crops with tender sprouts
Class 2	Vegetation-2		Thick vegetation
Class 3	Vegetation-3		Mature and ripe rice crops
Class 4	Settlement		Residential area
Class 5	Water		Water in rivers and ponds
Class 6	Soil		Barren land with sparsely and randomly scattered shrubs

National Remote Sensing Centre (NRSC), Hyderabad, Government of India. The image has been taken in July

2007 and is of size 2959×2959. It is formed by combining bands 2, 3 and 4 of LISS-IV data (Green, red and near IR) and is shown in Fig. 3. It covers the area in and around Tirunelveli city located in the state of Tamil Nadu in India. An updated geological map has been selected as a reference for ground truth study of the same area.

The experimental classes or training samples are the areas of interest extracted from source image in Fig. 4 and are of size 16×16 as shown in Table 3.

In experiments for performing land cover classification of remotely sensed image, the size of training and testing samples were kept as small and close as possible to get better classification accuracy. So the window size of the test sample was also fixed to 16×16. The threshold (n) and size of neighbourhood were fixed heuristically to 5 and 3×3, respectively. For ground truth verification, a set of stratified random samples comprising of 2400 pixels were taken from the remotely sensed image and used for building error matrix. Classification accuracy and kappa statistics were computed from the error matrix and used for performance evaluation.

**Performance metrics:** The overall classification accuracy ( $P_o$ ), Kappa coefficient (K) and error matrix

are the performance metrics for evaluating the classified images in land cover classification.

**Experimental setup:** The overall classification procedure followed in all experiments is described as follows. In the training phase, training samples of size 16×16 were extracted from the remotely sensed image. In each training sample, for each 3×3 neighbourhood, the Multivariate local Texture feature (MTP) was found. The 1D histogram was formed for global description of a training sample. Then the 1D histograms of training samples were used to train the classifier. In the testing phase, test sample of size 16×16 was extracted from the remotely sensed image using a sliding window that runs from top left to bottom right in the remotely sensed image. The 1D histogram of test sample was found following the same procedure used in training samples. Then the 1D histogram of test sample was given as input to the classifier and the classifier returned the class label. The performances of land cover classification experiments conducted using MTP descriptor with Fuzzy k-NN, ELM and SVM classifiers are evaluated in this section.

**Experiments:**

**Experiment I-classification using fuzzy k-NN and MTP:** Adequate number of fuzzy samples belonging to different land cover classes was chosen for training the

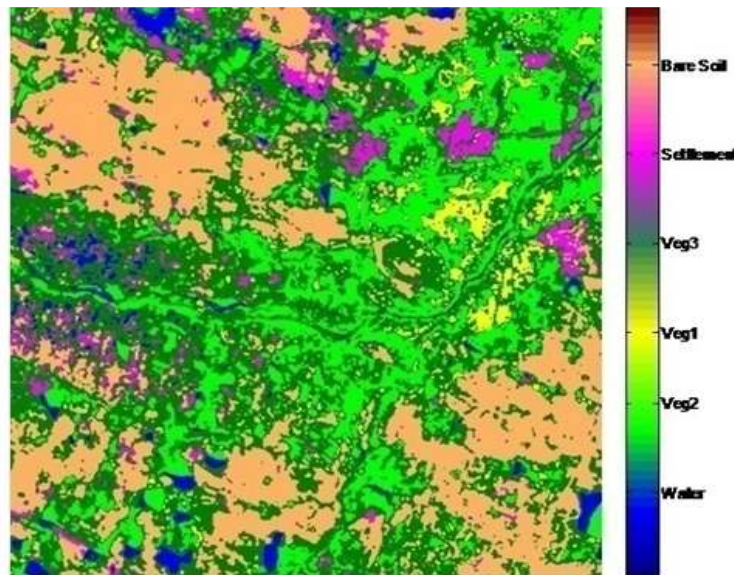


Fig. 4: Classified image using fuzzy k-NN

Table 4: Error matrix of MTP with fuzzy k-NN

Classified total	Back ground	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Row total
Class 1	0	80	1	27	1	10	1	120
Class 2	0	8	262	34	0	0	0	304
Class 3	0	11	2	541	99	0	2	655
Class 4	0	0	1	27	247	0	0	275
Class 5	1	0	0	5	0	239	0	245
Class 6	2	0	0	37	1	0	761	801
Column total	3	99	266	671	348	249	764	2400



Table 5: Accuracy totals of MTP with fuzzy k-NN

Class name	RT	CT	NC	PA (%)	UA (%)
Background	1	0	0		
Class 1	99	120	80	80.81	91.95
Class 2	266	304	262	97.74	86.38
Class 3	671	655	541	69.60	84.60
Class 4	348	275	247	79.31	77.97
Class 5	249	245	239	98.39	94.59
Class 6	764	801	761	95.16	85.83
Totals	2400	2400	2130		

Overall accuracy = 88.75%; Overall kappa = 0.8547; RT: Reference total; CT: Classified total; NC: Number correct; PA: Producer's accuracy; UA: User's accuracy; BG: Back ground

fuzzy k-NN classifier. Fuzzy membership values of each training sample to belong to the land cover classes were found using Eq. (6). In Eq. (8), the k value was fixed to 3 while the weight (m) attached to the distance between the training sample and its k-nearest neighbour is set to 2. The experiment was conducted and the classified image is shown in Fig. 4. For the classified image in Fig. 4, the error matrix and accuracy totals (P<sub>o</sub>-Overall accuracy, K-Kappa) were found. The results are shown in Table 4 and 5, respectively.

The thin diagonal line tracing water is clearly seen. All texture classes are discriminated well and seen in the remotely sensed image. In fuzzy k-NN, the number of fuzzy training samples was varied to improve

classification accuracy. The subtle difference of Settlement being a micro texture and Vegetation-3 being a macro texture is reflected in a few places on either sides of the perennial river where some pixels of Vegetation-3 class are misclassified to Settlement class.

#### Experiment II-classification using ELM and MTP:

The global features of remotely sensed image were initially normalized to values from 0 to 1. The λ parameter (a kernel specific parameter) was chosen as 1. The Radial Basis Function Kernel (RBFK) was used as the activation function in the hidden layer. The experiment was conducted and the classified image is shown in Fig. 5. For the classified image in Fig. 5, the error matrix and accuracy totals were found. The results are shown in Table 6 and 7, respectively.

The classified image shows clear discrimination various classes. In ELM, the number of hidden neurons was varied in the range n/2 ±20 to get optimal result. The merit of ELM classifier is that it is faster than other classifiers. The settlement class is densely classified. But in the left end of the image across the river some pixels of Vegetation-3 class are misclassified as Settlement class. The slight drop in

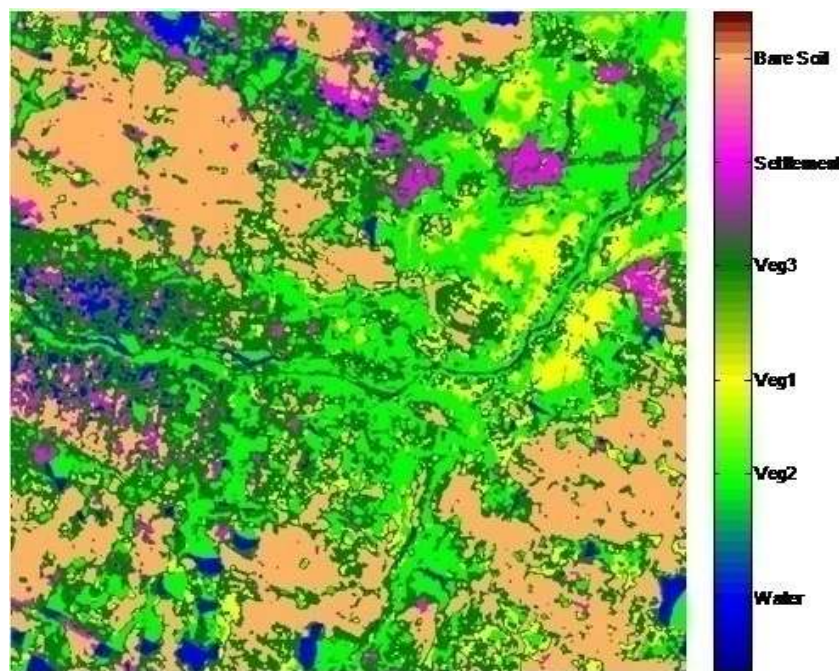


Fig. 5: Classified image using ELM

Table 6: Error matrix of MTP with ELM

Classified total	Back ground	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Row total
Class 1	0	80	1	6	0	0	0	87
Class 2	0	4	260	37	0	0	0	301
Class 3	0	15	3	467	26	4	37	552
Class 4	0	0	2	76	276	0	0	354
Class 5	2	0	0	12	0	245	0	259
Class 6	2	0	0	73	45	0	727	847
Column total	4	99	266	671	347	249	764	2400



Table 7: Accuracy totals of MTP with ELM

Class name	RT	CT	NC	PA (%)	UA (%)
Background	1	0	0		
Class 1	99	87	80	80.81	91.95
Class 2	266	301	260	97.74	86.38
Class 3	671	552	467	69.60	84.60
Class 4	348	354	276	79.31	77.97
Class 5	249	259	245	98.39	94.59
Class 6	764	847	727	95.16	85.83
Totals	2400	2400	2055		

Overall accuracy = 85.63%; Overall kappa = 0.8146

Table 8: Error matrix of MTP with SVM

Classified total	Back ground	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Row total
Class 1	0	64	5	14	0	0	5	88
Class 2	0	0	261	30	0	0	0	291
Class 3	1	1	7	527	8	2	37	583
Class 4	0	0	1	24	367	0	5	397
Class 5	0	1	2	18	1	248	1	271
Class 6	1	0	0	0	3	0	766	770
Column total	2	66	276	613	379	250	814	2400

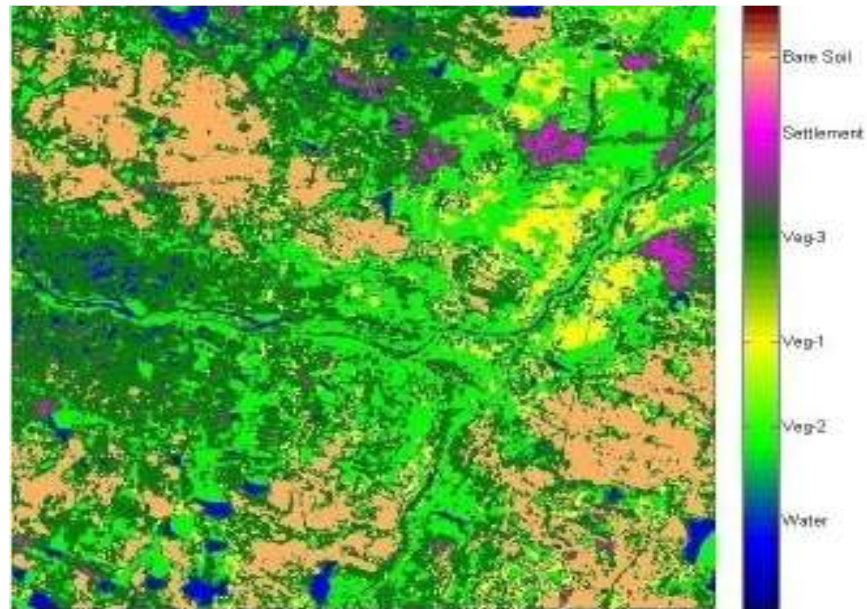


Fig. 6: Classified image using SVM

Table 9: Accuracy totals of MTP with SVM

Class name	RT	CT	NC	PA (%)	UA (%)
Background	0	2	0		
Class 1	88	66	64	96.97	72.73
Class 2	291	276	261	94.57	89.69
Class 3	583	613	527	85.97	90.39
Class 4	397	379	367	96.83	92.44
Class 5	271	250	248	99.20	91.51
Class 6	770	814	766	94.10	99.48
Totals	2400	2400	2170		

Overall accuracy = 93.04%; Overall kappa = 0.9104

accuracy of the ELM classifier is due to the fact that it fails to trace the fuzzy boundaries between classes.

### Experiment III-classification using SVM and MTP:

The optimization problem of minimizing error (equal to expected output minus actual output) in SVM is solved using polynomial kernel. The values  $\lambda$  and 'C'

explained in above section were fixed to 0.000000001 and 1000, respectively. Larger values of C mean imposing high penalty to errors. The experiment was conducted and the classified image is shown in Fig. 6. For the classified image in Fig. 6, the error matrix and accuracy totals were found. The results are shown in Table 8 and 9, respectively.

The proposed algorithm of MTP with SVM gives a high classification accuracy of 93.04% and a kappa coefficient of 0.9104. The model performs well because the hyper plane of separation exactly fits in to separate pixels belonging to different land covers.

### PERFORMANCE EVALUATION

The classification accuracies obtained for MTP with SVM, Fuzzy k-NN and ELM are 93.04, 88.75 and

85.63%, respectively. The kappa coefficients obtained for the above mentioned methods in the same order are 0.9104, 0.8547 and 0.8146 respectively. In the experiments, the major difference in classification accuracy is caused by the abilities of classifiers to discriminate between the Settlement and Vegetation-3 classes. In the classified images obtained using ELM and fuzzy k-NN, some pixels of vegetation-3 class were misclassified to settlement class. Only SVM classifier densely classified the vegetation-3 class matching the ripe crop area of the reference map. So among the three classification algorithms evaluated, SVM is found better based on error matrix, classification accuracy and kappa statistics.

### CONCLUSION

A Multivariate Texture Descriptor (MTP) is proposed for land cover classification of remotely sensed images. The merit of the work is double fold. In order to find a suitable soft classifier for land cover classification of remotely sensed images, the performances of the chosen classifiers (Fuzzy k-NN, ELM and SVM) have been evaluated in this study with the proposed MTP descriptor. From the experiments, it is proved that the proposed descriptor with SVM classifier outperformed other classifiers and gave 93.04% classification accuracy.

The work can be extended in the following ways. The proposed descriptor can be used for extracting texture features in other applications like medical image processing and face recognition as well. For each application, the performance evaluation of soft classifiers with the proposed descriptor can be performed to find a suitable classifier.

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