
Hybrid Texture Feature Based Roadside Vegetation Classification

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Abstract

In the proposed technique a novel texture feature based multiple classifier technique is applied to roadside vegetation classification. It is well-known that automation of roadside vegetation classification is one of the important issues emerging strongly in improving the fire risk and road safety. The method proposes a novel texture feature based expert system for vegetation identification as dense and sparse grasses. It consist of five steps, namely image pre-processing, feature extraction, training with multiple classifiers, classification and statistical analysis. Initially, to enhance the input image, histogram equalization is applied. Then, Gray level Run length Matrix (GLRLM) and Compound Local Binary Pattern (CLBP) technique is applied in-order to obtain the texture feature relevant to vegetation in the roadside images. In the training and classification stages, three classifiers have been fused to combine the multiple decisions. The first classifier is support vector machine, the second classifier is artificial neural network and the third classifier is k-Nearest Neighbour (k-NN). The combination of multiple classifiers and fusion of classifiers have received much more attention. The strength of the proposed method is based on new descriptor and the incorporation of the multiple classifiers with majority voting. This method is more efficient and achieves high performance.

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Keywords:

Gray Level Run length Matrix (GLRLM);
k-Nearest Neighbour(k-NN);
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1. Introduction

Vegetation Classification is a useful area in research. It finds major advantage in the fire risk area identification because there is a major risk due to the roadside fires. It is essential to identify the fire risk areas and classify them. A close-area detection of roadside vegetation is important for applications such as the identification of fire hazards and the types of grass. Roadside Vegetation may include many types of crops, weeds, grasses etc. Main aim of the method is to classify the types of grasses. It involves two types of grass namely dense and sparse grasses. Chih-Wei Hsu and Chih-Jen Lin [1] describe the methods of solving multiclass SVM in one step, which requires a much larger optimization problem to decompose implementations for two such "all-together" methods. Dong-Chen H and Li Wang [2] tell about the type of features used, for vegetation classification on roadside data features extraction can be categorized into two groups – visible approaches and invisible approaches. Dymitr Ruta, Bogdan Gabrys [3] develop individual classification models, recently challenged by combined pattern recognition systems, which often show better performance. In such systems, the optimal set of classifiers is first selected and then combined by a specific fusion method. The results prompted a novel design of multiple classifier systems in which selection and fusion applied to combinations of classifiers. Faisal Ahmed *et al.* [4] tell the use of a machine-learning algorithm called support vector machine (SVM) for the effective classification of crops and weeds in digital images. It evaluate whether a satisfactory classification rate can be obtained when SVM is used as the classification model. Images were tested to find the optimal combination of features that provides the highest classification rate.

I. Harbas and M. Subasic [5] introduce the feature set consists of color features and texture features. One of the specific goals was to identify a useful texture feature set for the problem of vegetation detection. Iva Harbas and Markov Subasic [6] develop a method to detect vegetation on the basis of typical vegetation characteristics such as color, texture and shape, and researchers often try to minimize the human visual system when developing methods for automatic detection of vegetation. Image features from the visible spectrum were used to imitate, how people detect vegetation using color and texture features and allow the use of a common on-board color camera. Iva Harbas and Markov Subasic [7] describe a set of texture features based on gray level run lengths. Using this method a gray level run length matrix for runs can be computed having any direction. Jie Sun and Hui Li [8] develop a prediction method based on single classifier's uncertainty and benefit of multiple classifiers. Using majority voting process the accuracy of the method can be improved.

Joan *et al.* [9] introduce visible approaches that utilize visual characteristics of vegetation in the visible spectrum to distinguish them from other objects. It can be grouped into three categories – visible feature based approaches, invisible feature based approaches, and hybrid approaches. Hybrid approaches combine invisible and visible features for more robust performance. Kevin Woods *et al.* [10] proposed a combination of four classifiers technique that is slightly superior to the combination of five classifiers for all three data sets. This tells us that some strategy should be used when selecting three classifiers as input. Ligang Zhang and Brijesh Verma [11] introduce a new hybrid approach for vegetation classification using a fusion of color and texture features. The color intensity features are extracted from the opponent color space and the texture feature comprises of three color moments. Ludmila I. Kuncheva [12] describes a multiple classifier fusion technique which generates more accurate classification than each of the constituent classifiers. Here the classification method gives more accurate result.

Mary M Galloway [13] has introduced SVM, which attracted much attention for crop and weed classification. Satisfactory classification rate can be obtained when SVM is used as the classification model. Classification model based on support vector machine (SVM) has verified its ability to classify crop. K S H Robert Singh [14] develops run-length which may capture texture in specified directions. Run-length features are calculated from the run-length matrix that is capable of capturing the texture properties of different structures from the image data. Yang Gao [15] introduces roadside vegetation dataset in various conditions. Vegetation images can be distinguished using additional texture features. In the proposed method using the descriptor called CLBP-GLRL, the increased classification accuracy can be achieved than the other methods.

2. Research Method

The input roadside vegetation image is obtained from database and is given for the preprocessing using histogram equalization. Using CLBP, GLCM and GLRLM method the feature extraction is obtained. Finally, the multiple classifier fusion technique is applied to identify the grass as either dense grass or sparse grass. In classification, the fusion of classifier with majority voting process is introduced. Here, three types of classifier have been combined to increase the accuracy. It has been also used to differentiate two types of grasses i.e., dense and sparse. The proposed technique involve five stages namely Image acquisition, Image preprocessing using histogram equalization, texture feature extraction using GLRLM method, training and classification using classifiers, classifier fusion to differentiate the type of grass.

2.1 Feature Extraction

Vegetation is not only characterized by color information, but also by texture features. Simple color features lack discriminative power required for our problem. To solve this problem we use texture features in the feature vector. In the cases where green grasses and tree leaves share similar color, it is essential to utilize the texture features in a larger neighboring region. There are a large amount of texture descriptors presented in existing studies, such as Gabor filters, SIFT features, and filter based textons. However, these descriptors often require the calculation of statistic features in an adequately large region to reliably represent each object class. In natural conditions, this requirement cannot always be met, possibly due to low resolution of captured images or specific nature of the techniques used. A texture image can be characterized by its texture spectrum. We empirically evaluate the effectiveness of the proposed feature representation for roadside vegetation images.

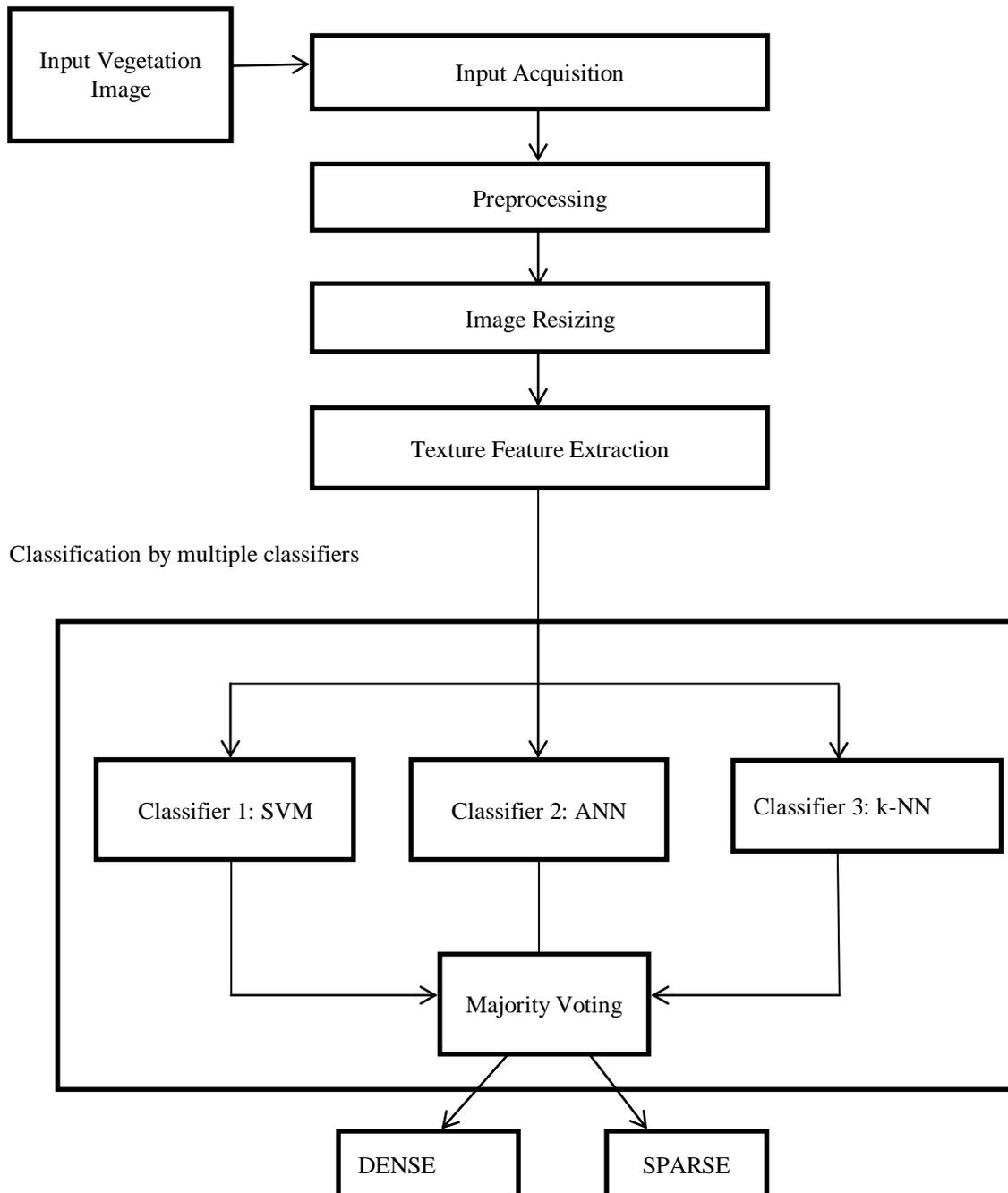


Figure1. Block Diagram of Proposed Method

2.1.1 Compound Local Binary Pattern (CLBP)

The CLBP operator combines extra Pbits with the original LBP code, which are used to express the magnitude information of the differences between the center and the neighbor gray values. Extensive experiments show the superiority of the CLBP method against some other appearance-based feature representation. Unlike the LBP that employs one bit for each neighbor to express only the sign of the difference between the center and the corresponding neighbor gray values. The proposed method uses two bits for each neighbor in order to represent the sign as well as the magnitude information of the difference between the center and the neighbor gray values. The CLBP operator is described by the equation 1,

$$s(i_p, i_c) = \begin{cases} 00 & i_p - i_c < 0, |i_p - i_c| \leq M_{avg} \\ 01 & i_p - i_c < 0, |i_p - i_c| > M_{avg} \\ 10 & i_p - i_c \geq 0, |i_p - i_c| \leq M_{avg} \\ 11 & \text{otherwise} \end{cases} \quad (1)$$

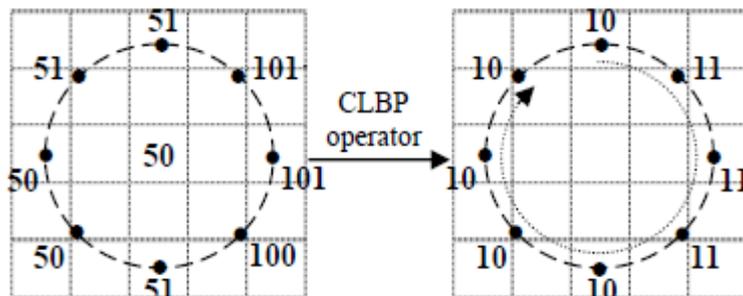


Figure2. CLBP Pattern

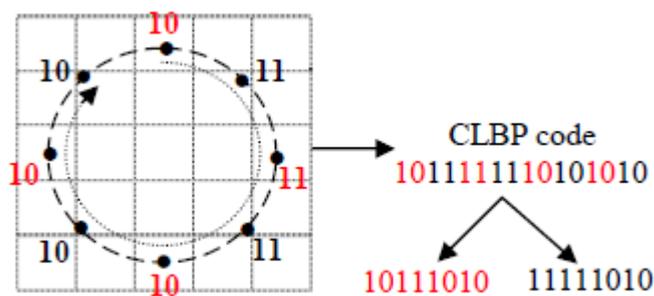
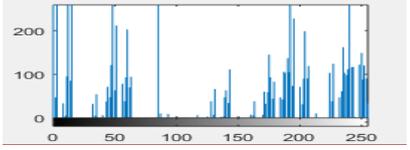
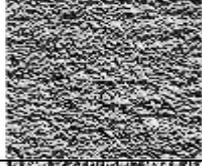
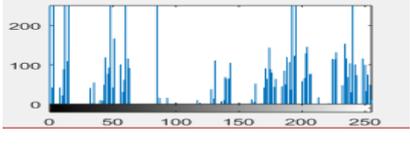
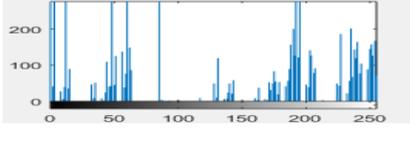
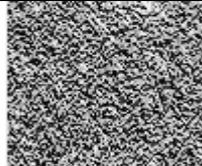
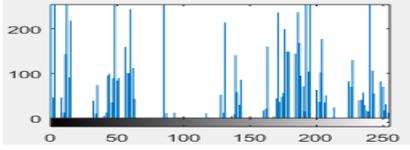


Figure3. Sub CLBP Pattern

Table 1: CLBP images with histogram

Input Image	CLBP images	Histogram images
Sparse 		
		
Dense 		
		

A 16-bit CLBP pattern is split into two 8-bit CLBP patterns, where the first CLBP pattern is obtained by concatenating the bit values corresponding to the neighbors in the north, east, south, and west directions, respectively and the second CLBP pattern is obtained by concatenating the bit values corresponding to the neighbors in the north-east, south-east, south-west, and north-west directions, respectively.

2.1.2 Gray Level Co-occurrence Matrix (GLCM)

The construction of co-occurrence matrix is achieved by forming a relative displacement vector (d). This vector describes the relative frequencies of grey-level of vectors separated by a distance. The Probabilities are in the range [0, 1] and their sum is 1.

$$\sum_{i=1}^k \sum_{j=1}^k p_{ij} = 1 \quad (2)$$

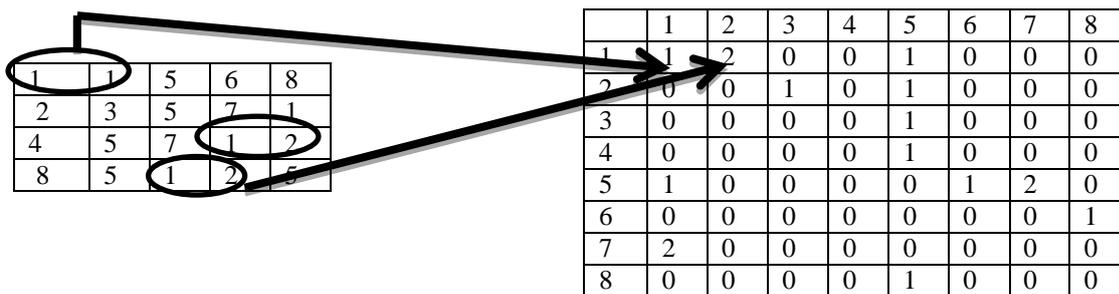


Figure4. GLCM Matrix

The figure4 shows GLCM matrix. A GLCM provides the information about how frequently a pair of pixels occurs in an image towards a particular direction. Co-occurrence matrix method is based on the repeated occurrence of some gray level configuration in the texture. This configuration varies slowly with distance in coarse texture and rapidly in fine texture. The GLCM matrix can be described with the following parameters.

Maximum Probability

It measures the strongest response of G. It's given by the formula as,

$$\max_{i,j}(p_{ij}) \quad (3)$$

Correlation

A measure of how correlated a pixel is to its neighbor over the entire image. It's given by the formula,

$$\sum_{i=1}^k \sum_{j=1}^k \frac{(i-m_r)(j-m_c)}{\sigma_r \sigma_c} p_{ij} \quad (4)$$

Contrast

Contrast is a measure of intensity contrast between a pixel and its neighbor over the entire image. It's given by the formula,

$$\sum_{i=1}^k \sum_{j=1}^k (i - j)^2 p_{ij} \quad (5)$$

Energy

A measure of Uniformity in the range [0, 1]. It's given by the formula,

$$\sum_{i=1}^k \sum_{j=1}^k P_{ij}^2 \quad (6)$$

Homogeneity

It measures the spatial closeness of the distribution of elements in G to the diagonal. It's given by the formula,

$$\sum_{i=1}^k \sum_{j=1}^k \frac{p_{ij}}{1+|i-j|} \quad (7)$$

Entropy

This Measures the randomness of the elements of G. It's given by the formula,

$$- \sum_{i=1}^k \sum_{j=1}^k p_{ij} \log_2 p_{ij} \quad (8)$$

2.1.3 Gray Level Run length Matrix (GLRL)

A set of texture features based on GLRL is described. The run length is directly proportional to the number of runs in the image. P (i, j) be the (i, j) entry in the given run length matrix. A gray-level run is a set

of consecutive, collinear points having the same gray level value. The length of the run is the number of picture points in the run.

Input image

0	1	2	3
0	2	3	3
2	1	1	1
3	0	3	0

(a) Input image

		Run length									
G						45°	1	2	3	4	
						0	4	0	0	0	
R						1	4	0	0	0	
						2	0	0	1	0	
A	0°	1	2	3	4	3	3	1	0	0	
Y	0					90°	1	2	3	4	
						0	2	1	0	0	
L	1					1	4	0	0	0	
						2	3	0	0	0	
E	2					3	3	1	0	0	
						0	4	0	0	0	
V	3					135°	1	2	3	4	
						1	4	0	0	0	
E						2	3	0	0	0	
						3	5	0	0	0	
L						0	4	0	0	0	
						1	4	0	0	0	

(b) GLRL matrix in different directions

Figure 5.a) Input image b)GLRL matrix in different directions

From an image we can compute the GLRL for the runs having any given direction. The matrix element (i, j) specifies the number of times that the picture contains a run of length j in the given direction. Various texture features can be derived from this run length matrix. A wide variety of feature has been used for texture analysis. Some of feature sets have included features based on GLRL. Table 2 describes how the GLRL matrix is calculated in four directions. The GLRL matrix can be given using the parameters as follows.

Short Run Emphasis SRE measures the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and is expected large for fine textures.

$$SRE = 1/nr \sum_{i=1}^M \sum_{j=1}^N p(i, j) / j^2 \tag{9}$$

Long Run Emphasis LRE measures distribution of long runs. The LRE is highly dependent on the occurrence of long runs and is expected large for coarse structural textures.

$$LRE = 1/nr \sum_{i=1}^M \sum_{j=1}^N p(i, j) * j^2 \tag{10}$$

Gray-Level Non-uniformity GLNU measures the similarity of gray level values throughout the image. The GLNU is expected small if the gray level values are alike throughout the image.

$$GLNU = 1/nr \sum_{i=1}^M \sum_{j=1}^N P(i, j)^2 \tag{11}$$

Run Percentage RPC measures the homogeneity and the distribution of runs of an image in a specific direction. The RPC is the largest when the length of runs is 1 for all gray levels in specific direction.

$$RPC = nr / P(i, j) * j \tag{12}$$

Run Length Non-uniformity RLNU measures the similarity of the length of runs throughout the image. The RLNU is expected small if the run lengths are alike throughout the image.

$$RLNU = 1/nr \sum_{j=1}^N (\sum_{i=1}^M P(i,j))^2 \quad (13)$$

Low Gray-Level Run Emphasis LGRE measures the distribution of low gray level values. The LGRE is expected large for the image with low gray level values.

$$LGRE = 1/nr \sum_{i=1}^M \sum_{j=1}^N P(i,j)/i^2 \quad (14)$$

High Gray-Level Run Emphasis HGRE measures the distribution of high gray level values. The HGRE is expected large for the image with high gray level values.

$$HGRE = \frac{1}{nr} \sum_{i=1}^M \sum_{j=1}^N P(i,j) \cdot i^2 \quad (15)$$

If $P \times Q$ be the size of the input gray scale image having maximum gray level say L , then the resulting GLRL matrix for this matrix is $L \times Q$. The advantage of GLRLM approach is demonstrated experimentally by the classification of two texture data sets. Comparisons with other methods demonstrate that the run-length matrices contain great discriminatory information.

2.2 Training and Classification

Three different types of classifier can be used for classification of images. They are Support vector machine, k-Nearest Neighbour and Artificial neural network. For classification, the natural color images are obtained under light. Totally 100 images are taken for dataset and 50 images are selected for test set. The output is obtained by combining the classifier with majority voting process. Finally, we can differentiate the grasses either as dense or sparse.

2.2.1 Support Vector Machine Classifier

SVM train named as kernel function is given for classifying in the kernel space. Kernel function uses SVM train to classify the images of type 1 and 2. It's a supervised machine learning algorithm which can be used for classification. It transforms data and based on transformation it finds the optimal boundary between the outputs. Compared with other methods such as artificial neural networks, decision trees, and Bayesian networks, SVM has significant advantages because of their high accuracy.

$$F(x) = w^T x + b \quad (16)$$

In the SVM classifier, an approach is used to classify the images. It has a multiple classifier combination technique that lies on both the individual performance and diversity degree of basic classifiers. SVM classifier may produce the multiple classifier output. SVM is a relatively new machine learning technique, which is developed on the basis of statistical learning theory. It is based on the principle of structural risk minimization, but not on the principle of empirical risk minimization, so SVM can better avoid the problem of over fitting.

2.2.2 k-Nearest Neighbour Classifier

k-Nearest Neighbor algorithm is among the simplest of all machine learning algorithms. K-NN classifier is also known as case based reasoning or memory based reasoning. If $k=1$, the object is simply classified as the class of the object nearest to it. When there are only two classes, k must be an odd integer. However, when performing multiclass classification k must be an odd integer. After we convert each image to a vector of fixed-length with real numbers, the most common distance function known as Euclidean distance is used for k-NN classifier.

$$d(x, y) = \|x - y\|^2 = \sum_{i=1}^k (x_i - y_i)^2 \quad (17)$$

2.2.3 Artificial Neural network (ANN) Classifier

The ANN classifier is used for biological classification. An ANN is an interconnected group of nodes, to the vast network of neurons in a brain. Each circular node in ANN represents artificial neuron and an arrow represents a connection from the output of one neuron to the input of another. Artificial neurons may have a threshold, such that only if the aggregate signal crosses that threshold then the signal is sent. Typically, artificial neurons are organized in layers. Different layers may perform different kinds of transformations on their inputs. It is a computational model based on the structure and functions of a biological neural network. Information through the network affects the structure of the ANN.

2.3 Fusion of Classifier

In fusion of classifier all the three types of classifiers are combined to provide the best accuracy output. Multiple classifier fusion may generate more accurate classification than each of the constituent classifiers. Multiple classifier outputs are usually made comparable by scaling them to the [0, 1] interval. If classifiers are built using a large number of features, good improvement is obtained.

3. Results and Analysis

Figure6 shows the input image obtained from the roadside vegetation images. The images are preprocessed by histogram equalisation to remove all the uneven illumination. Both the dense and sparse grasses are considered to be the input image.



(a)



(b)

Figure6. Input image (a) Sparse grass (b) Dense grass

3.1 Performance of GLCM

The performances of classification of dense and sparse grasses using two descriptors are compared. An overall classification process along with texture feature extraction using GLCM and GLRLM is compared. The classification of dense and sparse grass using GLRLM features and GLCM features was successfully carried out and the results were compared. Results show that GLRLM features outperforms GLCM features and the same holds good for all three types of classifiers. This shows that GLRLM features are quite appropriate as compared to GLCM features. Table 3 and 4 shows the GLCM matrix for sparse grass and dense grass.

Table 2: GLCM matrix for sparse grass

1053	318	80	137	202	132	116	318
192	93	169	226	0	0	26	144
87	14	0	0	168	80	91	143
137	35	106	84	26	13	171	345
315	147	13	29	69	73	27	156
129	69	87	167	0	0	14	98
125	32	0	0	240	178	85	231
310	142	134	272	128	90	363	1077

Table 3: GLCM matrix for dense grass

623	251	58	71	222	207	182	417
243	66	222	213	0	0	42	101
60	16	0	0	189	154	114	264
146	39	99	68	39	13	171	277
246	151	11	26	58	95	48	174
78	39	0	0	201	246	82	297
416	186	257	266	96	67	295	822

The overall performance of both dense and sparse grass is compared. The dense and sparse grass is identified with the range of GLCM values. Hence by comparing the values of matrix the particular grass is identified. CLBP-GLRL method has obtained the high level accuracy than all the other methods. It can be shown by the calculation of accuracy for all the dataset values. The accuracy of all the methods can be listed in a table and gives the final result.

Table 4: Accuracy of classifier using CLBP-GLRL method

Descriptor	Accuracy			
	$\theta = 0^\circ$	$\theta = 45^\circ$	$\theta = 90^\circ$	$\theta = 135^\circ$
GLRL	91.5	93.2	90.5	92
CLBP-GLRL	96.3	97.8	95	96.5

Table 5: Accuracy of classifier using LBP GLCM and CLBP GLRL

Descriptor	Accuracy
LBP	87.3%
GLCM	85%
LBP GLCM	91.2%
CLBP	92%
CLBP GLCM	94.5%
GLRL	93.2%
CLBP GLRL	97.8%

Table 4 shows the overall accuracy of CLBP-GLRL method in four different directions (0° , 45° , 90° and 135°). Table 5 shows the accuracy comparison of different methods and it is clear that CLBP-GLRL achieves highest accuracy than the other methods.

4. Conclusion

The proposed method provides automatic classification of images. Texture features were extracted using GLRLM and CLBP descriptor. The proposed descriptor Compound Local Binary Pattern was constructed for the identification of dense and sparse grasses effectively. In the proposed method two steps namely feature extraction and feature classification is involved. The proposed descriptor CLBP provides both sign and magnitude information of difference between center and neighboring gray values. Using GLRL method, we can compute the gray level run length for the runs having any given direction. Multiple classifier fusion technique is introduced to classify the images. The average accuracy of the classification rate was improved. Texture features were proved to give good results for the classification of the image. Overall sensitivity and specificity of the system were improved. The effectiveness of the proposed method is based on the high accuracy.

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