VOL. 2 ISSUE 2, FEB.-2013 ISSN NO: 2319-7463

Co-occurrence matrix with neural network classifier for weed species classification: A comparison between direct application of co-occurrence matrix (GLCM) and Haralick features as inputs

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Abstract: Gray level Co occurrence matrix (GLCM) texture analysis has been aggressively researched for decade for multiple applications. Co occurrence matrix retains the spatial and frequency information of the image while compresses the image into a fraction of size enabling the application of classifier engines for analysis. Haralick features are secondary features derived from GLCM. There have been countless research work done on weed classification using Haralick features outweighing the application of direct feeding of co occurrence matrix for training classifiers. Images are aquired with slight varying distances and angles to test the robustness of classifier and pre-processed using excessive Green Index method before fed into ANN (Artificial Neural Network) for training and evaluation. In this paper, we found that direct application of GLCM a column out performs the haralick feature method due to the unregulated lighting.

Key words: GLCM, Co occurrence matrix, weed classification.

1. Introduction and related works

Weed classification and autonomous weeding are by no means a new research field. Researches are pushing the limits to enhance the classification rate for selective herbicide application. On a broader view, most researchers in this area have applied varies methods of weed. With the majotrity of the related research mainly divided into Hyperspectral imaging and normal imaging system using camera. Hyperspectral imaging using infared can reveal the morphological difference in weedsalowing precise recognition and application in selective spot spraying of herbicide. While the hyperspectral system yielded good results (not necessarily better than the latter), the option of using regular cameras would lower the operation cost. Weeds can harshly reduce the productivity of crops and increase production time. Hence, weed detection and classification is a promising technology in which the application can be made into different sectors of agriculture. There is no specific definition for weeds as the weeds definition are clearly found on an economic and agricultural basis not on plant morphology basis. (Sahid, 1989). Selective herbicides normally act on two categories of plants which are the broad leaf and narrow leaf type of weeds. Countless works have focused on discriminating between these two different weed species. Some involved binarization of weeds and extract certain features – area, density, complexity and elongation of leaves (Kianni and Jafari, 2012). Others resort to texture analysis with Fast fourier transform, Gabor wavelet (Tang et.al, 2003) and Co- occurrence matrix (Kianni and Kamgar, 2011) for feature extraction on the texture of the weeds. On classification engine, various classifiers are used based on the features such as Artificial neural network (ANN) (Kianni and Jafari, 2012), SVM (Search vector machines) (Ahmed et.al, 2012).

The work featured in this paper will focus on the weed classification based on GLCM matrix and neural network comparing both direct feeding of GLCM matrix as training sets and secondary feature derivation (haralick features) as input to the neural network. Majority of the papers presented used the haralick features as proposed by original paper by Haralick et. al, 1973 such as (Kianni et.al, 2011). On a different application (face recognition), a direct application of co occurrence matrix to the classifier engine has yielded better results as compared to using haralick features. (Eleyan and Demirel, 2011)

This work is part of an on-going project to develop an autonomous crop management robot capable of selective pesticide, herbicide and disease identification in crops. Hence, image will be divided into smaller tiles in which the image tiles will be processed and suitable herbicide applied.

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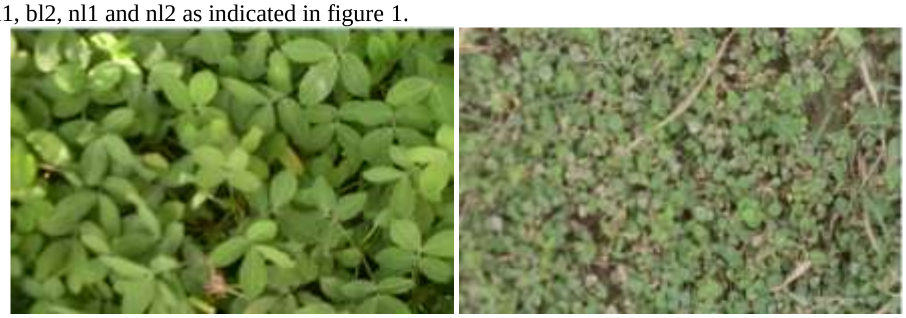
For sample/specimen acquisition, the data for input are images of weeds are captured where the captured area covers an approximate area of 8 cm by 8 cm. 20 images of each species for training is shown in figure 1. Images are acquired approximately 20cm to 30 cm.(no tripod were used) The variations are purposefully introduced to test the robustness of the classification technique. The camera used is an 8.1 megapixel Samsung S860 model. The images are captured in open area where lighting is not controlled. The species of weeds are labeled bi1, bl2, nl1 and nl2 as indicated in figure 1.



Weed species (bl1) Weed species (bl2)

Weed species (nl1) Weed species (nl2)

Figure 1: Weed species (bl1, bl2, nl1, nl2)

The diagram below shows the algorithm for the preparation of data prior to classification training. Original image is pre processed to discriminate between ground and weeds using excessive green index. The output images are intensity images with range [0,255]. For haralick features, an additional step is applied to extract Haralick feature.

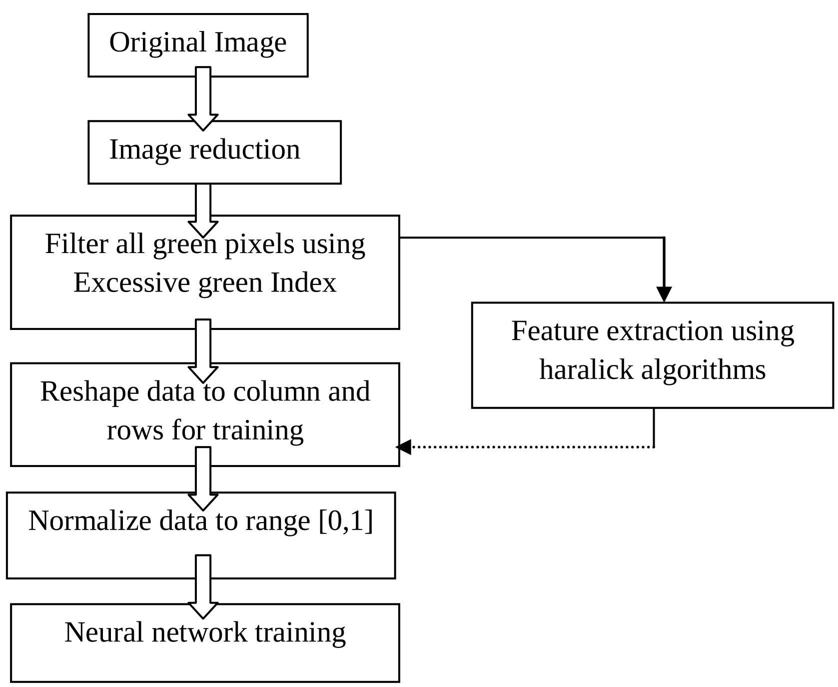


Figure 2 : Block diagram of pre processing of data prior to classification and training

2. Pre -processing

Prior to processing, the images are downsized to 10 % of its original size to reduce processing time. The original image size is 1944 x 2592 x 3, an RGB format image. After reduction, the image size is 194 x 259 x 3. Resized, the image is further processed using the Excessive green minus excessive Red Index. The equation is shown in equation (1) and (2). The advantage of using such index is to eliminate the ground image and reduce it to '0' value. The output after processing is an image with green colour values in intensity format (0,1) range.
(Ex- G) Index as proposed Meyer et.al, 1998.

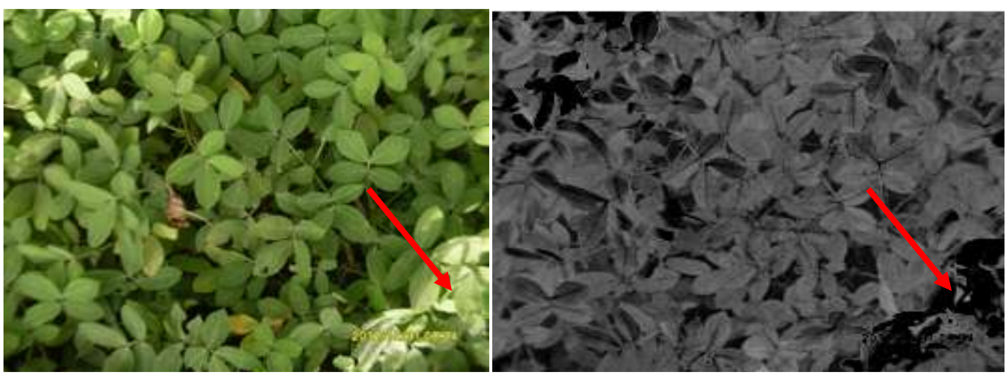
$$Ex\text{-}G = 2G\text{-}R\text{-}B \qquad (1)$$

George et.al, 2008 proposed Ex-g minus Ex-r where Ex-r is shown in equation 2. The author notes that the Ex-G minus Ex-R index is less sensitive to to different natural lighting conditions compared with other vegetation indexes. Ex- G minus Ex-R was chosen for this experiment with further plans to test other vegetation indexes used in other works.(Yang et. al, 2007) and (Ahmed et.al, 2012).

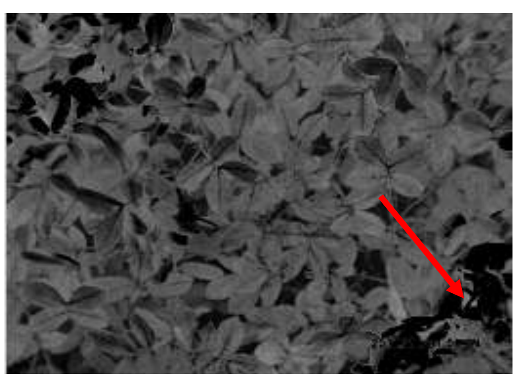
$$Ex\text{-}G\text{–}Ex\text{-}R = 1.4\,R\text{-}G\text{-}B \qquad (2)$$

where R, G, B $\in (0{,}255)$ is the Red , Yellow , Green component value in the RGB image format.

A comparison was conducted between Excessive Green Index (Ex- G) and normal grayscale yielding higher classification success rates using both Gray scale co occurrance matrix (86% for Ex-g and 85% for Gray level) and FFT (91% for ex-c and 89% for gray scale)(Ghazali et. all , 2007). After pre-processing, the ground is normalized to 0 value. However, it was also found that the proposed method converts all white spots (produced by excessive light into 0 as can be seen from figure 1. (Indicated). It is observed that the indicated position yields an RGB value of (220, 221, 210) respectively. However after preprocessing using Ex-g and Ex-g-Ex-c, it yields a 0 value.



Original Ex-g



Ex-g-ex-r Index image

Figure 3: pre –processing using Ex-g – ex-r

3. Gray level Co occurrence matrix (GLCM)

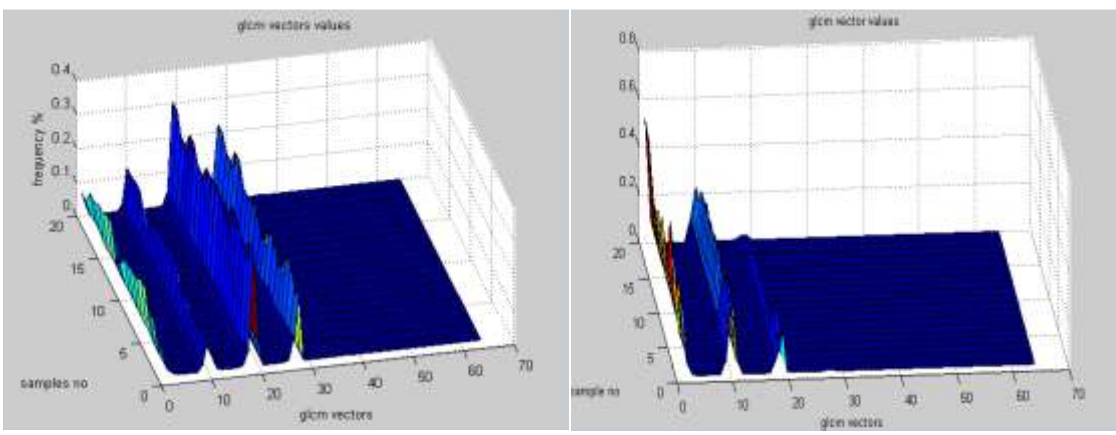
GLCM matrix by definition is a matrix showing the co-occurence of gray scale in relation to its neighbor pixels. Hence, it has rich information on its features. Both histogram and GLCM matrix is based on frequency information, however only co occurrence matrix retains the spatial information. Equation (3) shows the mathematical definition of co occurrence matrix.

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, if\ I(p,q) = i\ and\ I(p+\Delta x, q+\Delta y) = j \\ 0, otherwise\end{cases} \tag{3}$$

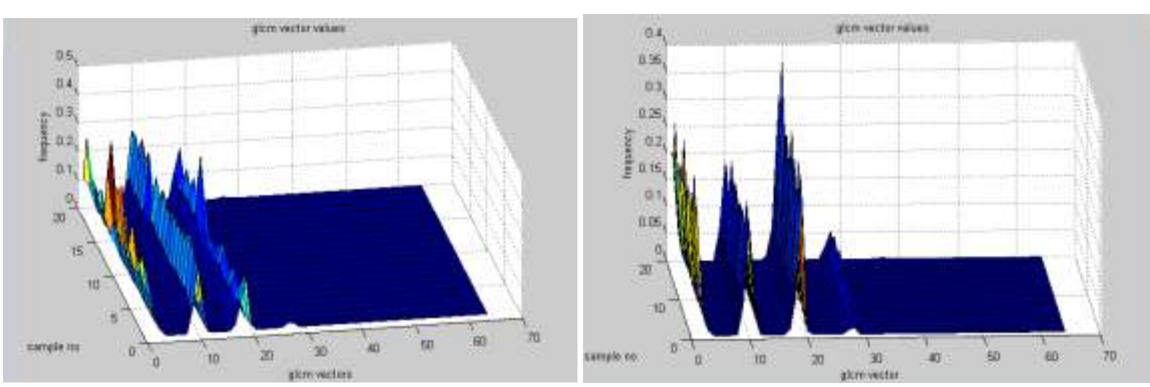
Where C, a co occurrence matrix is defined over a m x n image I , parameterized by an offset $(\Delta x, \Delta y)$. The matrix size is defined by the number of gray scale division specified. Eg . if a the total scale of (0, 255) is divided into 8 grayscale level, an 8 x 8 co occurrence matrix would be acquired. The co-occurrence matrix is rotation sensitive, therefore images are often analysed using differing offset sweeping angles$(0^\circ, 45^\circ, 90^\circ, 135^\circ)$.

Unlike features based processing, pixel based processing methods are not the prefered method of choice as compared to feature based methods due to the size of inputs. In this aspect feature based methods clearly outweights pixel based. However, Co occurrence method reduces the size of the image and simultaneously retains the spatial information. Comparatively, even after reduction using co occurrence matrix, the input size is much bigger as compared to feature based processing.

In our procedure, only horizontal sweeps (90°) across the images are performed ignoring all the other angle sweeps to minimize the inputs for training. From this point onwards, this shall be labelled as input 1. Figure 2 shows the 64 (8 x 8 cascaded into a column vector) inputs for each training image for each species of weeds. It can be observed that each species has distinctive reoccurring pixels pairs. For normalization purposes, the matrix values are divided by the number of pre processed pixels value higher than 0. This is to normalize the matrices for images of varying weed patch sizes. However, in the images of samples, they are fully covered by the weeds leave. Hence, it is normalized by dividing matrix by the number of pixel in the down sized image.



GLCM vectors of Broad leaf weed specimen (left: species bl1, right: species bl2)



GLCM vectors of Narrow leaf specimen (left: species nl1, right: species nl2)

Figure 4 : GLCM vectors of Narrow leaf specimen and broad leaf specimen.

From observation, there is no clear distinction between broad lead and narrow leaf. More work can be done in the future to investigate the difference between the two categories as many researchers have done. However, as the comparison between the training input type for classification are of concern in this research, classification according to species is acceptable.
Haralick et.al, 1973 proposed 14 features to be used for analysis of image in terms of its texture which are shown in table 1 (Index 1). 13 of the 14 feature (are selected to be fed to the neural network for training and processing which shall be labeled input 2 from this point on wards. Prior to neural network training, the inputs 2 are arranged in row vectors and normalized. The 13 features are cascaded vertically and normalized (0 ,1) using equation (4)

$$\bar{x}_{norm} = \frac{lower\ bound + (\vec{x} - \min \vec{x})(upper\ bound)}{max\vec{x} - min\vec{x}} \tag{4}$$

where the lower and upper bound are chosen range boundaries
The mathematical definition of 13 features are shown in equation (5) to (18) :

Angular Second Moment

$$f1 = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \{p(i,j)\}^2 \tag{5}$$

Constrast

$$f2 = \sum_{n=0}^{Ng-1} n^2 \left(\sum_{i=1}^{Ng} \sum_{i=1}^{Ng} p(i,j) \right) \tag{6}$$

When $|i - j| = n$

Correlation

$$f3 = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{7}$$

Sum of Squares:Variances

$$f4 = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i - \mu)^2 p(i,j) \tag{8}$$

Inverse Difference Moment

$$f5 = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \frac{1}{1 + (i-j)^2} (p(i,j) \tag{9}$$

Sum average

$$f6 = \sum_{i=2}^{2Ng} i p_{x+y}(i) \tag{10}$$

Sum variances

$$f7 = \sum_{i=2}^{2Ng} (i - f8)^2 p_{x+y}(i) \tag{11}$$

Sum entropy

$$f8 = -\sum_{i=2}^{2Ng} p_{x+y}(i) log\{p_{x+y}(i)\} \tag{12}$$

Entropy

$$f9 = -\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \log (p(i,j)) \tag{13}$$

Difference Variance

$$f10 = E\left[{P_{X-Y}}^2\right] - E[P_{X-Y}]^2 \tag{14}$$

Difference entropy

$$f11 = -\sum_{i=0}^{Ng-1} p_{x-y}(i)\log\{p_{x-y}(i)\} \quad (15)$$

Information measures of Correlation coefficient

$$\mathrm{f12} = \frac{\mathrm{HXY-HXY1}}{\max\{\mathrm{HX,HY}\}} \quad (16)$$

$$\mathrm{f13} = (1-\exp[-2.0(\mathrm{HXY2}-\mathrm{HXY})]^{1/2} \quad (17)$$

where $p_y(j) = \sum_{i=1}^{Ng} p(i,j)$,$P_{x+y}(k) = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p(i,j)$ i+j=k, k=2,3,…..,2Ng

$p_{x-y}(k) = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p(i,j) \quad |i-j| = k, k = 0,1,\ldots..Ng-1$

$\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviation of p_x and p_y.

$\mathrm{HXY} = -\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p(i,j)(\log(p(i,j))$, $\mathrm{HXY} = -\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p(i,j)(\log\{p_x(i)p_y(j)\})$,

$\mathrm{HXY} = -\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p_x(i)p_y(j)(\log\{(p_x(i)p_y(j)\})$ and Ng is the number of graylevels

5. Back propagation neural network and training results

Neural network are a class of classifier which loosely mimics the neurons in Human brain. The 80 samples (Both input 1 and input 2) are feed to the neural network. The Matlab neural network is used to test and train the samples. Training samples are divided 70 % for training, 15% for verification and 15% for testing. Table 1 and table 2 shows the results of training, verification and testing of the network. Hidden neurons are progressively increased to test the neural network. The training samples are used primarily to train the network and the weights are adjusted according to its error. The allocated sample data for verification are to measure the network generalization and to halt the training when generalization stops improving (remains stagnant).The test samples are do not effect the training and merely act to provide independent testing rate of classification. However, the data presented to the network are merely small sets and additional data sets are presented to test the data (80 data sets).

From table 1 and 2, it is very clear that the direct GLCM method is much better for classification. As can be seen, there is no additional increment of network size necessary as the external classification rate has reach 100% classification rate at 10 hidden neurons. Further comparing the input 2 neural network (haralick features), an average of 76% classification rate was achieved irregardless of the additional network size.

Table 1: results from training with back propagation neural network and testing on input2

Number of hidden Neuron	Training Classification rate (%)	Verification Classification rate(%)	Testing Classification rate(%)	Additional testing Classification rate (%)
10	98.6	100	100	76.3
15	100	100	100	76.3
20	98.6	100	100	78.8
25	100	100	100	76.3

Table 2: results from training with back propagation neural network and testing on Input1

Number of hidden Neuron	Training Classification rate (%)	Verification Classification rate(%)	Testing Classification rate(%)	Additional testing Classification rate (%)
10	100	100	91.7	100

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6. Discussion and further works.

From the results, it is clear that direct input of GLCM vector gives a higher classification rate as compared to Haralick features using neural network. Figure 5 shows the training input (80 sets) and testing inputs (80 sets) with equal samples from each class. As can be observed, the inputs are visually separable. Figure 6 shows the haralick features vector. As can be observed, the features are more inconsistent. This is due to lighting and shadows casted on the images. This shows that haralick features are highly affected by external lighting. Further investigation from the confusion matrix shows that the narrow leaf weeds species (nl2) have the highest misclassification rate with most samples misclassified as broadleaf weed 1 (bl1) and narrow leaf 1 (nl1). A controlled light scenario would definitely produce more consistent result and higher classification rate. More work can be done to investigate the performance of weed classification in regulated lighting. In conclusion, the direct feeding of GLCM vectors as compared to Haralick is much more superior for outdoor unregulated lighting. The performance of the direct GLCM vector can be further investigated for other type of weed species especially those that have similar colours.

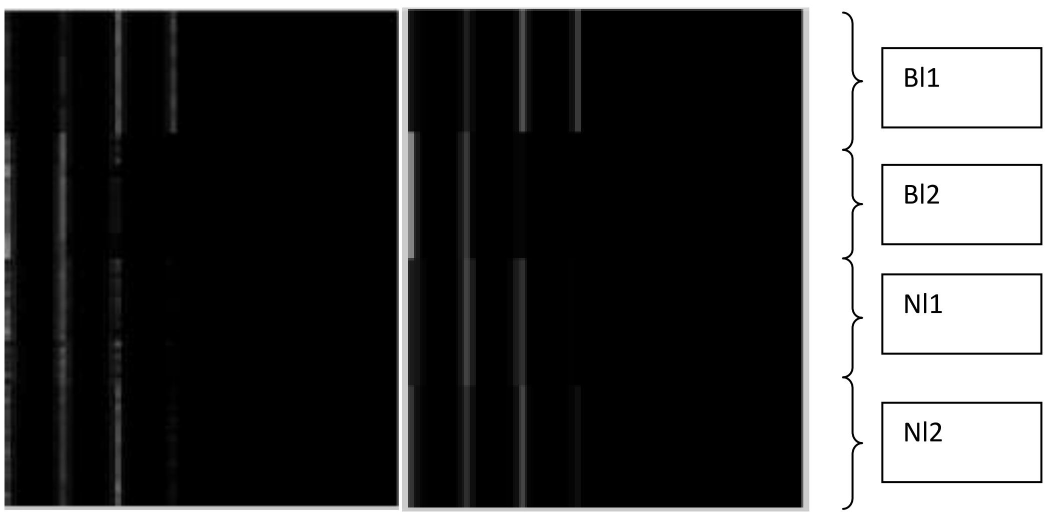

Figure 5 : GLCM vectors of samples.(Right – training sets) and(left – testing sets)

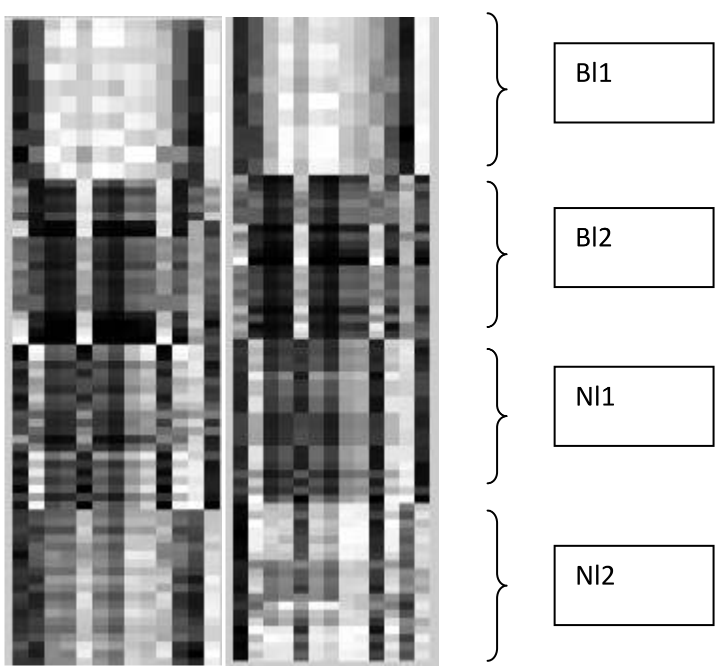

Figure 6 : GLCM vectors of Narrow leaf specimen and broad leaf specimen.

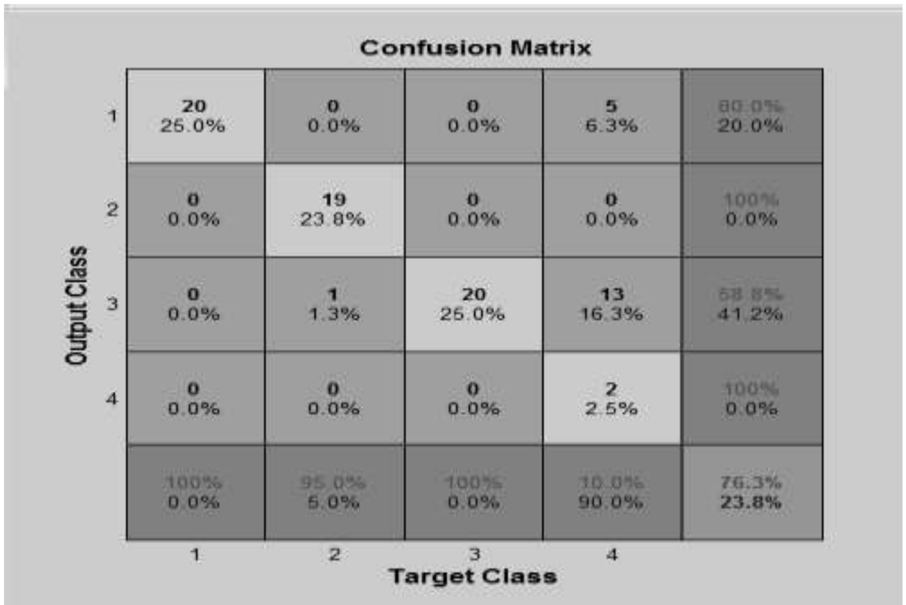

Figure 7: Confusion matrix on data input 2 (Haralick features)

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