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# A New Framework For Tea Plant Recognition Using Extreme Learning Machine With Very Few Features

**Arunpriya C. and Antony Selvadoss Thanamani**

*P.S.G.R Krishnammal College for Women*
*Coimbatore, India*
*arunpriya.bs@gmail.com*

*Nallamuthu Gounder Mahalingam College,*
*Pollachi, India.*
*selvadoss@yahoo.com*

## ABSTRACT

Due to more and more tea varieties in the current tea market, rapid and accurate identification of tea varieties is crucial for tea quality control. Tea quality mainly depends on the variety of leaf, growing environment, manufacturing conditions, size of ground tea leaves and infusion preparation. In the past few years, tea cultivar has been assessed by morphological assessment coupled with pattern recognition. This paper uses an efficient machine learning approach called Extreme Learning Machine (ELM) for the classification purpose. The proposed approach consists of four phases which are as preprocessing, feature extraction, feature clustering and classification. Additionally, this work proposes an iterative algorithm for feature clustering and applies it to leaf recognition. Feature clustering is a powerful tool to reduce the dimensionality of the selected feature. For improving the accuracy and performance of tea leaf recognition, ELM is implemented. The classifier is tested with 20 leaves from each variety and compared with k-NN and RBF approach. The proposed ELM classification produces effective results.

**Keywords:** Leaf Recognition, Extreme Learning Machine (ELM), Preprocessing, Feature Extraction, Feature clustering and Classification.

## 1. INTRODUCTION

Tea is the most widely consumed beverage aside from water. In general, plant leaf contains carbohydrates, protein, lipids, enzymes, several biochemical intermediates and structural elements which are normally associated with the plants for their growth and various metabolic functions. In addition, tea leaf is distinguished by its remarkable content of methyl xanthine and polyphenols. These two groups of compounds are predominantly responsible for those unique properties of tea that account for its popularity as beverage. The most important chemical constituent that influences the taste and flavour in tea infusions are polyphenols, flavonols, caffeine, sugars, organic acids, amino acids and volatile flavour compounds. Tea quality mainly depends on the variety of leaf, growing environment, and manufacturing conditions, size of ground tea leaves and infusion preparation. Quality is measured on the basis of liquor (brightness, briskness, color etc.), aroma (flavour) and leaf appearance. The production of most branded tea involves blending of many varieties of tea to maintain the consistency of taste. A tea taster has to taste hundreds of liquors for assuring the made tea quality and optimum blend.

In this work, ELM is introduced as it is a fast method for training neural networks and in some sense closer to a kernel method in its operation. A fully trained neural network has learned a mapping such that the weights contain information about the training data. ELM uses a fixed mapping of data to feature space. This is similar to a kernel method, except that instead of some theoretically derived kernel, the mapping ELM uses a random kernel method. Therefore, the individual weights of the ELM hidden layer have little meaning, and essential information about the weights is captured by their variance.

The review of this research is organized as follows. Section 2 summarizes the concepts of literature survey. Section 3 discusses the proposed method, section 4 provides the experiments and its results. Finally, Section 5 presents the conclusions of the work.

## 2. LITERATURE SURVEY

The aim of Toshima *et al* (2010) was to identify α-glucosidase inhibitors in the anti hyper glycaemic tea product. Characterization and quantification of anthocyanins into black (aerated) and green (unaerated) tea products were carried out by Kerio *et al* (2012). A method based on online liquid chromatography was developed by Li *et al* (2010) to screen and identify α-glucosidase inhibitors from pu-erh tea, eagle tea. Valliammal and Geethalakshmi (2012) describe an optimal approach for feature subset selection to classify the leaves based on Genetic Algorithm (GA) and Kernel Based Principle Component Analysis (KPCA). High-performance liquid chromatography (HPLC) has been used by Xu *et al* (2012) to quantify levels of free amino acids, catechins, and caffeine in green tea. Joulin *et al* (2010) combine existing tools for bottom-up image segmentation with kernel methods commonly used in object recognition. Boureau *et al* (2011) introduced that a common trait found in much recent work in image recognition or retrieval is that it leverages locality in feature space on top of purely spatial locality. Support vector machine (SVM) as the pattern recognition was applied by Zhao *et al* (2006)to identify three tea categories. An investigation has been made by Yu *et al* (2008) to determine the grade of different tea samples. Trace metals in tea were determined by Moreda *et al* (2003) using inductively coupled plasma-atomic& mass emission spectrometry.A new on-line evolving clustering approach for streaming data is described by Baruah *et al* (2012). Wu *et al* (2012) suggested an improved ELM based on the affinity propagation clustering, which does not need to define the number of hidden nodes. In view of the good properties of the ELM feature mapping, the clustering problem using ELM feature mapping techniques is studied by He *et al* (2014). Kim *et al* (2012) introduced a new hybrid intelligent modeling using context clustering and Extreme Learning Machine (ELM) mechanism. Pan *et al* (2012) recommend an iterative framework for figure-ground segmentation by sampling-learning via simulating human vision.

Typically, a recognition system needs to classify an unknown input pattern into one of a set of pre-specified classes. However, the problem can become very difficult if the number of classes is very large or if members in the same class can look very different. So, this research motivates the technique using ELM classifier for recognition of tea leaf accurately.

## 3. METHODOLOGY

The tea leaf recognition method used in the proposed approach consists of four phases namely image preprocessing, feature extraction, feature clustering and classification. The general architecture for automatic plant classification through leaf recognition is given in Fig.1.

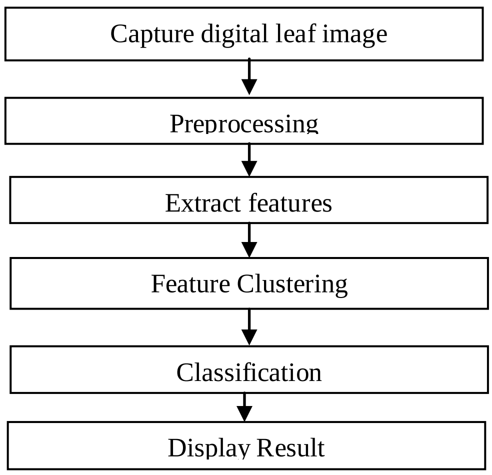


**Fig 1. General architecture of automatic plant classification system**

### 3.1 Preprocessing

The preprocessing refers to the first step of processing an input leaf image. It is used to correct the geometric distortions, regulate the data radio metrically and reduce the noise and clouds that are present in the data. These operations are called preprocessing because they are normally carried out prior to the real analysis and manipulations of the image data in order to extract any specific information. The main aim is to correct the distorted or degraded image data to create a faithful representation of the real leaf. Several pre- processing techniques like boundary enhancement, smoothening, filtering, noise removal are applied to improve the quality of the leaf image. The following Fig. 2 shows the pre-processing steps in leaf image.

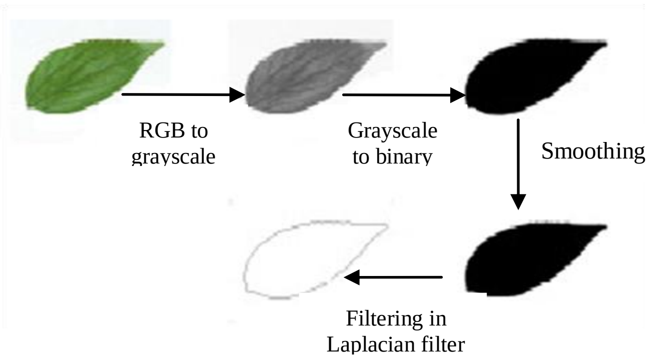


**Fig 2. Pre-processing example**

### *A. Converting RGB image to binary image*

The leaf image is obtained through scanners or digital cameras. All leaf images are in 800 x 600 resolutions. An RGB image is firstly converted into a grayscale image. Equation 1 is used to convert RGB value of a pixel into its grayscale value.

$$gray=0.2989*R+0.85870*G+0.1140*B \quad (1)$$

Where R, G, B correspond to the color of the pixel, respectively.

### *B. Boundary Enhancement*

The margin of a leaf is highly focused in this pre processing step. Convolving the image with a Laplacian filter of 3 × 3 spatial mask. An instance of image pre-processing is illustrated in Fig 2. To make boundary as a black curve on white background, the “0” “1” value of pixels is swapped

### *C. Fuzzy Denoising Using Dual Tree Discrete Wavelet Transform*

The denoising is done through Fuzzy shrinkage rule. In image denoising, a trade-off between noise suppression and the maintenance of actual image discontinuity is made, solutions are required to detect important image details and accordingly adapt the degree of noise smoothing. With respect to this principle, a fuzzy feature for single channel image denoising is used to enhance image information in wavelet sub-bands and then using a fuzzy membership function to shrink wavelet coefficients, consequently.

Dual Tree Discrete Wavelet Transform (DT-DWT) is used as a fuzzy denoising algorithm which provides both shiftable sub-bands and good directional selectivity and low redundancy.

The 2-D dual-tree discrete wavelet transform (DT-DWT) of an image is employed using two critically-sampled separable 2-D DWT's in parallel .[16] The advantages of the dual-tree DWT (DT-DWT) over separable 2D DWT is that, it can be used to employ 2D wavelet transforms which are more selective with respect to orientation.

### 3.2 Feature Extraction

The features are defined as the function of measurements each of which specifies some quantifiable property and it is computed such that it quantifies the significant characteristics of a tea leaf image. Features like color, texture and shape are independent feature in leaf image recognition. All the features are classified into low-level and high-level features. The low-level features can be extracted directly from the original image whereas the high-level feature extraction must be based on low-level features. The feature extraction performed here is to obtain the leaf contour. The image-threshold operation is applied to the gray scale image to obtain the binary image of the leaf shape. The binary image is traced to produce the contour of leaf by making use of the border tracing algorithm. The features that are extracted in the proposed method are described as follows.

#### *A. Physiological Length:*

The distance between the two terminals is the physiological length. It is represented as $L_p$.The red line in the Fig. 3 indicates the physiological length of a leaf.

#### *B. Physiological Width:*

At the physiological width, the longest distance between points of those intersection pairs is defined. The distance between the two terminals is the physiological length. The red line in the Fig. 4 indicates the physiological width of a leaf.

#### *C. Aspect Ratio:*

The ratio of physiological length $L_p$ to physiological width $W_p$ is called aspect ratio and it is given by,

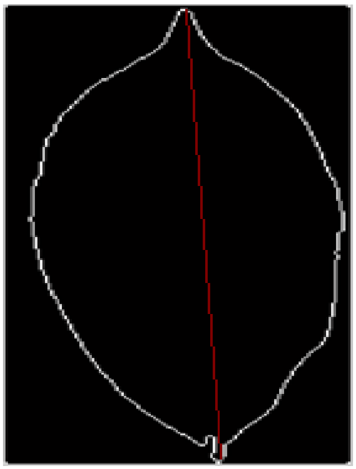

**Figure 3: Physiological length of a leaf**

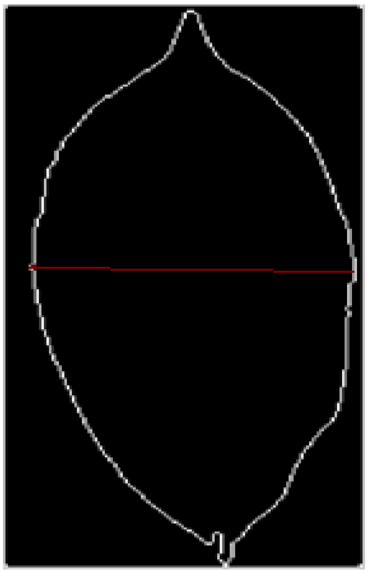

**Figure 4: Physiological width of a leaf**

$$Aspectratio = \frac{L_p}{W_p} \quad (2)$$

*D. Serration Angle:*

The teeth angle of a leaf can be defined using serration angle.

$$\theta = arc\cos\left(\frac{(a.b)}{|a||b|}\right) \quad (3)$$

Where θ is the serration angle, *a* is the length of first recognizable teeth from the tip of the angle and b is the breadth of first recognizable teeth from the tip of the angle

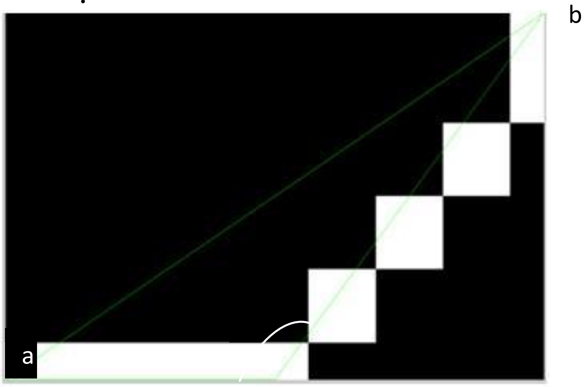


**Figure 5: Serration angle obtained from the tea leaf**

The serration angle obtained from the tea leaf using equation 4 is shown in the Fig. 5.

### *E. Segment*

The segment of a leaf can be defined as the ratio of first recognizable teeth in the left side from the tip of the angle 'a' to the first recognizable teeth in the right side from the tip of the angle 'b'.

$$segment = \frac{a}{b} \tag{4}$$

### *F. Segment maximum width to Physiological length ratio*

The leaf is divided into 10 segments as shown in the Fig. 6. Each segment width to the physiological length ratio can be determined for all the 10 segments.

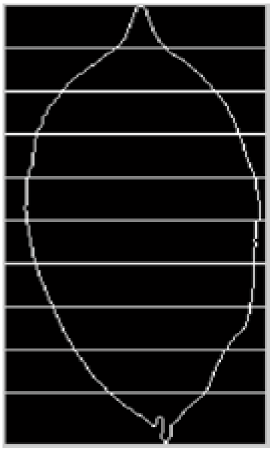

**Figure 6: Segment of a leaf**

### *G. Tip Angle*

The angle which is formed from the tip of the leaf to the first recognizable teeth on either side of the leaf is called tip angle.
The tip angle can be calculated using the formula,

$$\theta = arc\cos\left(\frac{(a.b)}{|a||b|}\right) \tag{5}$$

Where θ is the tip angle, a and b are the first recognizable teeth from the tip of the angle on left and right side respectively. The tip angle formed from the tea leaf is shown in the Fig. 7.

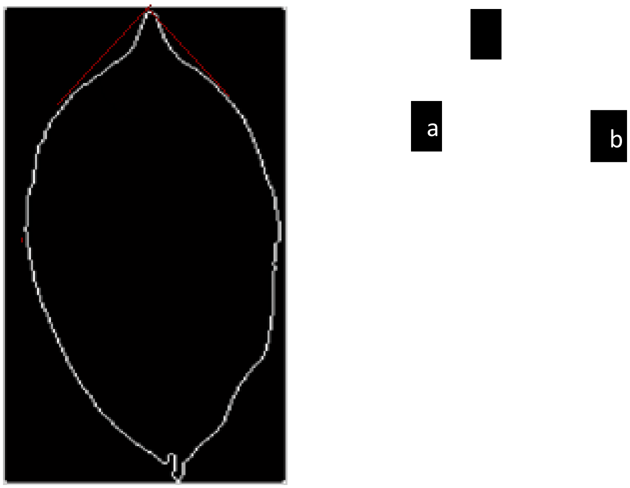


**Fig 7: Tip angle obtained from the tea leaf**

Feature clustering is an essential task, as it is an essential after the feature extraction. The input for feature extraction is the pre-processed data, wherein the features are stripped off. The output of feature extraction is used as the input for feature clustering. The feature clustering is one of the techniques which is used to identify the number of cluster centers in less iteration. It is possible to find the similar points without actually knowing the labels and hence these measures contribute to the points being similar to others as well as those which make it dissimilar from others. Therefore, feature extraction process based on clustering criterion will reduce the dimensionality of the input tea leaf samples.

### 3.3 Feature Clustering

The objective function is not convex in preceding RBF kernel algorithm. It is observed that the modified similarity matrix will lead to a nonlinear optimization problem which is very difficult due to the nonlinearity introduced by RBF kernel function. In order to overcome, this research introduced an iterative feature clustering algorithm and it will clearly define the objective function and can be solved iteratively. The weight assigned to each feature has direct relation to the clustering task. The clustering quality of the integrating method essentially depends on similarity matrix formed by the linear combination of individual kernel matrix constructed from each feature.

Iterative feature clustering is an efficient approach for feature reduction, which groups all features into some clusters, where features in a cluster are similar to each other. The proposed feature clustering strategy allows us to aggressively reduce the number of features associated with each node in the hierarchy. Therefore, feature clustering is an attractive option when training data is limited. The pseudo-code of the feature clustering is given in Algorithm 1.

The final discrete feature clustering result is obtained by applying k-means on the rows of the relaxed clusterindicator matrix L.To compare different features clustering in this process one must stick with the classifier to make the result comparable. This work selected an ELM as a flexible and well established classifier. Therefore, the ELM classification process is the final phase in the leaf recognition system. Almost all methods that have beenproposed in this phase are to retrieve the processinginput in a vector value format from the extractionprocess.

**Algorithm 1: Iterative Feature Clustering**

Input: **X**, k, $\in$

Output:**L**,**w**

Step 1: Construct $\boldsymbol{K}_p = (p = 1, \dots, d)$ with RBF kernel function using only the $p$-th row of **X**, and normalize each kernel matrix as: $\boldsymbol{K}_p \leftarrow \boldsymbol{D}_p^{-\frac{1}{2}} \boldsymbol{K}_p \boldsymbol{D}_p^{-\frac{1}{2}}$, where $\boldsymbol{D}_p$ is a diagonal matrix with the row sum of $\boldsymbol{K}_p$ iin the diagonal;

Step 2: Set the initial weight vector **w** to$e_d/\|e_d\|_2$;

Step 3: **While***the **relative** change of the objective function value* $\geq \in$***do***

Step 4: Update **L** as in$max_{\boldsymbol{L}} trace\left(\boldsymbol{L}^T \widetilde{\boldsymbol{K}} \boldsymbol{L}\right) s.t. \boldsymbol{L}^t \boldsymbol{L} = \boldsymbol{I}_k$;

Step 5: Update **w** as in $max_w \sum_p w_p trace\left(\boldsymbol{L}^T \prod_n \boldsymbol{K}_p \prod_n \boldsymbol{L}\right) s.t. w_p \geq 0, \|\boldsymbol{W}\|^2 = 1$

Step 6: Record the objective function value in $max_{w,\boldsymbol{L}} Q(\boldsymbol{L}, \boldsymbol{w}) = max_{w,\boldsymbol{L}}\, trace\left[\boldsymbol{L}^T \prod_n \left(\sum_p w_p \boldsymbol{K}_p\right) \prod_n \boldsymbol{L}\right] s.t. w_p \geq 0, \|\boldsymbol{W}\|^2 = 1, \boldsymbol{L}^t \boldsymbol{L} = \boldsymbol{I}_k$.

Step 7: end

Step 8: return **L**,**w;**

### 3.4. Proposed Extreme Learning Machine Classification

The proposed ELM classification uses a fixed mappingfrom data to feature space. This is similar to a kernelmethod, except that instead of some theoreticallyderived kernel, the mapping ELM uses is random.Therefore, the individual weights of the ELM hiddenlayer have little meaning, and essential informationabout the weights is captured by their variance.

#### *A. Extreme Learning Machine*

If there are N samples ($x_i$, $t_i$), where $x_i = [x_{i1}, x_{i2} \dots x_{in}]^T \in R^n$and $t_i = [t_{i1}, t_{i2}, \dots, t_{im}]^T \in R^n$, then the standard SLFN with N hidden neurons and activation function g(x) is defined as:

$$\sum_{i=1}^{\bar{N}} \beta_i\, g\left(w_i . x_j + b_i\right) = 0_j, j = 1, \dots \dots, N., \quad (6)$$

Where $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ represents the weight vector that links the ith hidden neuron and the input neurons, $ß_i = [ß_{i1}, ß^{i2}, \dots, ß^{im}]^T$represents weight vector that links the ith neuron and the output neurons, and $b_i$ represents the threshold of the ith hidden neuron. The "." in $w_i . x_j$indicates the inner product of $w_i$and $x_j$. The SLFN try to reduce the difference between $o_j$and $t_j$.

More in a matrix format as Hß = T, where

$$H(a_1, \dots, a_{\tilde{N}}, b_i, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} g(w_1, x_1 + b_1) & \cdots & g(w_g, x_g + b_g) \\ \vdots & \ddots & \vdots \\ g(w_1, x_1 + b_1) & \cdots & g(w_g, x_g + b_g) \end{bmatrix}_{N*\tilde{N}} \tag{7}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N}*m} \text{and} T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{N}}^T \end{bmatrix}_{N*m}$$

The result reduces the norm of this least squares equation is

$$\hat{\beta} = H^{+}T$$

Where $H^{\dagger}$ is known as Moore-Penrose generalized inverse. Initially, the input weights and hidden biases are created with the help of AHP technique. Next, the corresponding output weights are analytically determined with the help of ELM algorithm during the first iteration and randomly generate the output hidden biases. Therefore, if actual output is out of range than preferred output or likewise, errors are huge so, it converges to preferred output with large steps. In the same way, when quantity of error is very less then, actual output approaches to preferred output with soft steps. Thus, error oscillation and dimensionality is greatly reduced.

## 4. EXPERIMENTAL RESULTS

The proposed ELM classifier is used for recognizing the cultivars of tea leaf. For each type of tealeaf, 20 leaves from testing sets are used to test the accuracy. The UPASI dataset is used in this approach to test the classifier. The five parameters commonly used for calculation purposes are accuracy, execution time, precision, recall, and error rate. These parameters are evaluated in the proposed approach. The different tea leaves taken in the proposed approach and the number of correct recognitionin each sample is shown in the Table 1. Table 2 shows the accuracy and execution time of the classification algorithms. The accuracy and execution time of the proposed ELM classification is compared with K- Nearest Neighbor and RBF classification approach.

The calculation for accuracy and execution time for classification techniques k-NN, RBF and ELM for leaf recognition are estimated as shown in the table 2. The numbers of leaves in testing sets are splitted into 10, 25 and 50 sets to estimate the accuracy and execution time. The accuracy of proposed ELM method for all features is 92, 83, & 78 in values and for reduced features are 98, 89 &85 values which are higher when compared to the k-NN and RBF methods. The execution time for proposed ELM with all features is 17,20,32 and with reduced features is 8,16,25. The time taken by ELM is very low when compared to the other methods. From the above table it is clear that the proposed ELM has high accuracy and less execution time for tea leaf recognition.

**Table 1. Different Types of Tea Leaves Tested in the proposed method**

| Tea leaf name | Tested Samples | Number of Correct Recognition |
|---|---|---|
| TRF 1 | 20 | 20 |
| UPASI - 3 | 20 | 21 |
| UPASI - 9 | 20 | 21 |
| UPASI - 10 | 20 | 14 |
| UPASI -17 | 20 | 19 |
| UPASI - 22 | 20 | 20 |

**Table 2. Comparison of the Classification Accuracy and Execution time**

| Testing Sets | Accuracy (%) | | | | | | Execution Time (Seconds) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All Features | | | With Reduced Features | | | All Features | | | With Reduced Features | | |
| | k-NN | RBF | ELM | k-NN | RBF | ELM | k-NN | RBF | ELM | k-NN | RBF | ELM |
| 50 | 54 | 68 | 78 | 66 | 75 | 85 | 58 | 46 | 32 | 45 | 33 | 25 |
| 25 | 65 | 79 | 83 | 71 | 78 | 89 | 52 | 41 | 20 | 38 | 27 | 16 |
| 10 | 72 | 87 | 92 | 85 | 89 | 98 | 49 | 35 | 17 | 30 | 21 | 8 |

**Precision and Recall**

Precision and recall are the common measures in tea leaf recognition. They are based on the comparison of an expected and the effective results of the evaluated system. Recall is the ratio between the number of documents retrieved and considered relevant, and the total number of documents considered relevant in the collection and Precision is the ratio between the number of documents retrieved and considered relevant, and the total number of retrieved documents. The precision and recall formula for proposed ELM as,

$$\text{Precision} = \frac{\#(\text{relevant items retrieved})}{\#(\text{retrieveditems})} = \mathrm{P}(\text{relevant} \mid \text{retrieved}),$$

$$\text{Recall} = \frac{\#(\text{relevantitemsretrieved})}{\#(\text{relevantitems})} = \mathrm{P}(\text{retrieved} \mid \text{relevant}),$$

**Table 3. Comparison of Precision and Recall for classification**

| Testing Sets | Precision (%) | | | | | | Recall (%) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All Features | | | With Reduced Features | | | All Features | | | With Reduced Features | | |
| | k-NN | RBF | ELM | k-NN | RBF | ELM | k-NN | RBF | ELM | k-NN | RBF | ELM |
| 50 | 65 | 73 | 81 | 72 | 79 | 85 | 92 | 86 | 79 | 88 | 74 | 63 |
| 25 | 69 | 77 | 84 | 76 | 83 | 92 | 87 | 82 | 75 | 81 | 69 | 58 |
| 10 | 74 | 82 | 89 | 80 | 86 | 99 | 84 | 77 | 72 | 76 | 64 | 55 |

It is observed from the table 3 that the proposed ELM classification approach outperforms the k-NN and RBF techniques. The testing sets for all features and with reduced features are estimated for precision and recall. The high dimensionality is reduced using the feature clustering and tests the features in three levels. In testing sets the number of leaves is divided into 10, 25 and 50. Using fewer sets in training sets, the proposed ELM values are higher with reduced features for precision (99%), recall (55%) than the overall features for precision (89%), recall (72%) are estimated. Therefore, the precision and recall values for proposed ELM are calculated for all features and with reduced features which is higher than the other previous methods like k-NN and RBF.

## 5. CONCLUSION

The preprocessing, feature extraction, feature clustering and classification are the main four phases for tea leaf recognition. This work discusses about the feature clustering and new classification approach of tea leaf recognition. The enhanced clustering results improved leaf image classification accuracies especially at lower number of features. When the training data is sparse, this proposed feature clustering achieves higher classification accuracy than the maximum accuracy achieved. The performance of the proposed ELM approach is evaluated using UPASI datasets and compared with k-NN and RBF method. The proposed algorithm has produced better accuracy and takes very less time for execution. Further enhancement can be made by incorporating the non-linear interaction among features into this proposed algorithm.

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