

Fuzzy Inference System Algorithm of Plant Classification for Tea Leaf Recognition

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Abstract

Background/Objectives: Biologists found that the morphological, physiological, bio-chemical and molecular methods of plant identification are found to be laborious and require great amount of technical knowledge. This research paper concentrates on the identification of varieties of tea using leaf images. It aims to identify the species in an easy and an accurate manner. **Methods/Statistical analysis:** The phases involved in this work are image pre processing, feature extraction and classification. Three classification algorithms such as Fuzzy Inference system, Radial basis function network and K-nearest neighbour were used and optimized to achieve a better accuracy and execution time. **Results/Findings:** The classification algorithm K-nearest neighbor, Radial basis function neural network and Fuzzy Inference System are trained with 40 samples and tested using 20 samples. **Conclusions:** Fuzzy Inference System has a better accuracy and a lesser execution time, when compared to the other classification algorithm.

Keywords: Classification algorithm, Fuzzy Inference System (FIS), Leaf Recognition, Pre-processing

1. Introduction

In the engineering field, fuzzy inference system such as automatic control and the decision support system has been widely applied for their better performance than the conventional methods. Mainly in the business decision the information system, the financial statement plays a very important role to evaluate the management status of firms. For example, the fuzzy system realizes the non linear and smooth discriminate function so the fuzzy inference^{1,5,6,9} gives improved classification than multi-variate analysis.

The fuzzy inference system is realized as the if-then rules which mainly contain the weight in each rule and group of membership function in the antecedent. While learning fuzzy rules, the system parameters are established for minimizing the difference among the output and the prescribed value.

The most broadly consumed drink aside from water is Tea with a production of 1.8 million tones of dry leaves and consumption approximately of 40 liters beverage

per year. In our planet, between 18 and 20 billion 6 oz. cup of tea are drunk daily. Variety of leaf, growing environment, manufacturing conditions, size of ground tea leaves, infusion preparation are main quality of tea which it depends^{10,13,15}. Based on liquor (brightness, briskness, color etc.), aroma (flavor), lead appearance quality is measured. To maintain the consistency of taste, the creation of much branded tea consists of many varieties of tea. The tea taster must taste hundreds of liquors for assurance of the optimum blend^{2,7}.

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

2. Materials and Methods

The methodology proposed to classify the tea leaves using the fuzzy Inference has three phases. They are image pre processing, feature extraction and classification. The gen-

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eral architecture of automatic plant classification system performance (Figure 1).

2.1 Pre-processing

The initial processing of images is a pre-processing method³. It is used to correct the distortions, eliminate the problems from noise and cloud that are present in the data. The operation which is done previous to processing is called pre-processing and the performance of the image data arises when extracting information. The main goal of this pre-processing is to overcome the problem of distorted image data, to develop a more faithful presentation of the real leaf.

To enhance the image, number of pre-processing techniques is available. The methods used in this research to improve the quality of image are boundary enhancement, noise removal, smoothening, and filtering¹². The pre-processing steps in leaf image are shown in Figure 2.

2.1.1 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.

$$\text{gray} = 0.2989 \cdot R + 0.85870 \cdot G + 0.1140 \cdot B \quad (1)$$

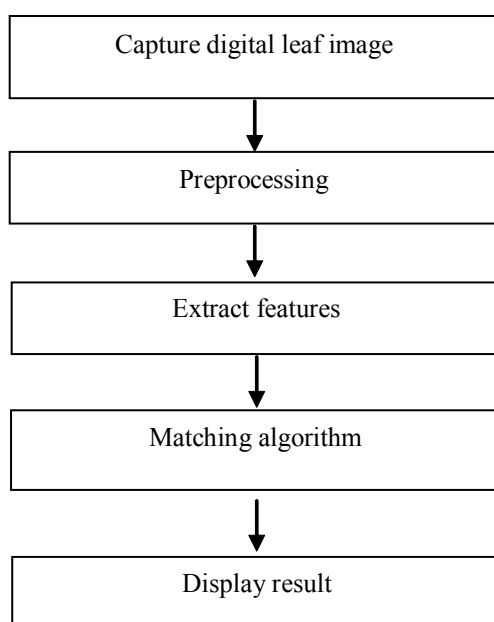


Figure 1. General architecture of automatic plant classification system.

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

2.1.2 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 [Figure 2].

To make boundary as a black curve on white background, the “0” “1” value of pixels is swapped

2.1.3 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 coefficients⁴, 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. The advantages of the DT-DWT over separable 2D DWT are that, it can be used to employ 2D wavelet transforms which are more selective with respect to orientation.

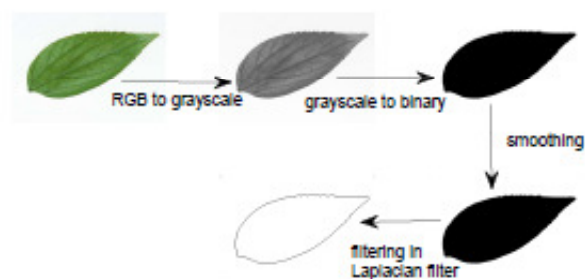


Figure 2. Pre-processing example.

2.2 Feature Extraction

A number of features are extracted to obtain the leaf contour^{8,11}. The binary image is traced to create the contour of the leaf by using classification. The ratio, length and width of leaf are obtained as shown below.

2.2.1 Physiological Length

The distance between the two terminals is the length of physiological. It is denoted as L_p . The red color line in [Figure 3] indicates the length of a leaf.

2.2.2 Physiological Width

At the physiological width, the distance among points of those intersection pairs are distinct. The red color line in Figure 4, shows the physiological width of a leaf.

2.2.3 Aspect Ratio

The L_p denotes the ratio of physiological length and W_p denotes the physiological width. This is known as aspect ratio and it is given by equation (2)

$$\text{Aspect ratio} = \frac{L_p}{W_p} \quad (2)$$

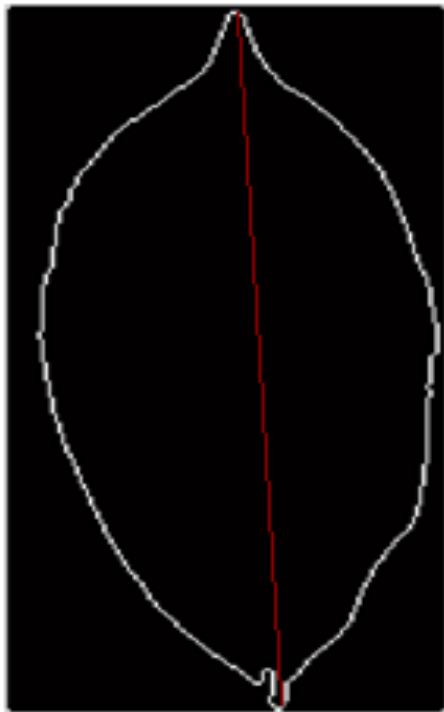


Figure 3. Physiological length of a leaf.

2.2.4 Serration Angle

The angle of a leaf can be defined using serration angle and it is given by equation (3)

$$\theta = \arccos \left(\frac{(a,b)}{|a||b|} \right) \quad (3)$$

Where, θ is the serration angle, a and b shows the length and breadth from the tip of the angle. The serration angle obtained by using equation (3) is shown in Figure 5.

2.2.5 Segment

The segment of a leaf can be denoted as the ratio of initial familiar 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'.

$$\text{segment} = \frac{a}{b} \quad (4)$$

2.3 Fuzzy Inference Systems

Fuzzy Inference System (FIS) maps the input value to the output values based on the fuzzy theory¹⁴. This mechanism of mapping is related on some set of rules, a list of

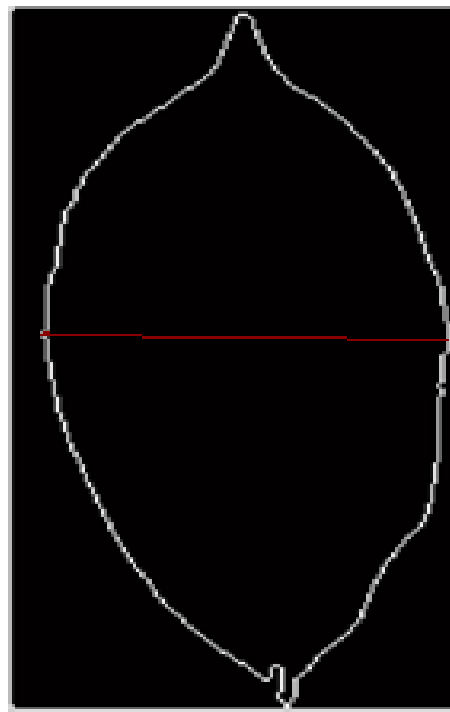


Figure 4. Physiological width of a leaf.

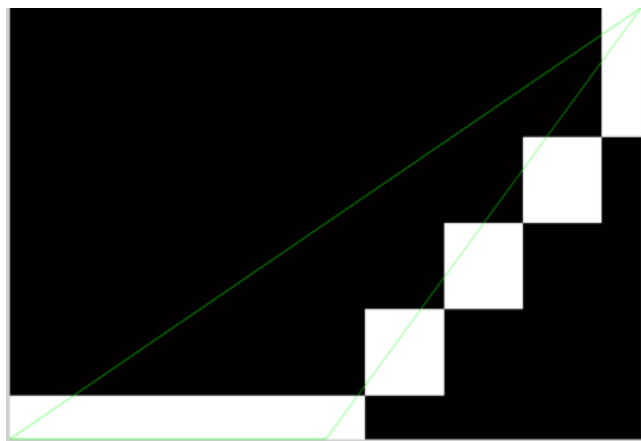


Figure 5. Serration angle obtained from the tea leaf.

if then statements. In fuzzy inference system, five steps are performed. The steps involved in Fuzzy Inference system are fuzzification of the input variables, fuzzy operator application (AND or - OR), if any, in the antecedent, inference from the antecedent to the resulting, aggregation of the rules and defuzzification.

To evaluates the output of FIS. The given inputs perform the following six steps:

1. Find out the set of fuzzy rules
2. By using the input membership functions, inputs are fuzzifying.

3. According to the fuzzy rules to perform rule strength, by combining the fuzzified inputs.
4. By combining the input and the output membership function the consequence of the rule is finding
5. Joining the value of consequence to achieve an output, and
6. Defuzzifying the output (this step is only if a crisp output (class) is needed).

The *if...then...* rule is represented in fuzzy inference system, that rule is given as follows:

If x_1 is A_{i1} and ... and x_m is A_{im} and y is w_i where, $x_j (j=1,2, \dots, m)$ is the input variable, $A_{ij} (i=1,2, \dots, n, j=1,2, \dots, m)$ is the fuzzy set, weight is denoted as w_i in i^{th} rule, and n is the number of the rules.

The standard fuzzy inference method is used in this work. The equation (5) performs the calculation of fitness function of the rule and equation (6) is used to Defuzzify the obtained inference result.

$$\mu_i = \prod_{j=1}^m \mu A_{ij}(x_j) \tag{5}$$

$$y = \frac{\sum_{i=1}^n \mu_i w_i}{\sum_{i=1}^n \mu_i} \tag{6}$$

Where, μA_{ij} is the membership function for fuzzy set μA_{ij} and μ_i is the fitness of the rule.

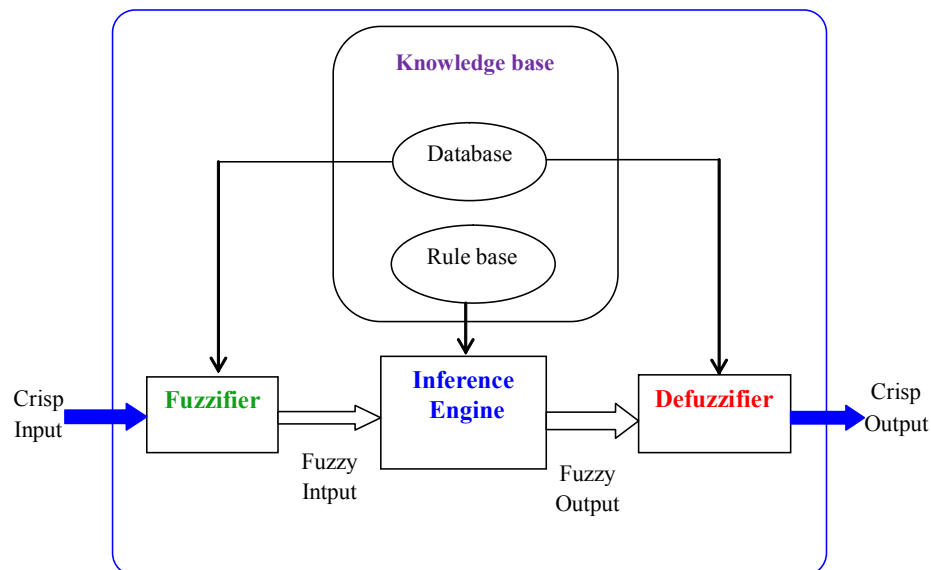


Figure 6. Fuzzy Inference System.

From equation (5) and (6), the weight and membership function is not optimized; the output of the current result does not offer accurate result. So, the weight and shape of the membership by learning is determined in this work.

3. Experimental Result

To test the proposed tea leaf recognition classifier, 20 leaves from each variety are taken from testing sets are used to calculate the accuracy. The UPASI dataset is used in this approach. The parameters of accuracy and execution time are evaluated in the proposed approach. The variety of tea leaves correctly recognized in the proposed approach is shown in Table 1.

The accuracy of the classification algorithm is shown in Table 2. The accuracy of the proposed approach FIS is compared with K- Nearest Neighbour and RBF classification approach. From the above table it is clear that the Fuzzy Inference System has high accuracy when compared with Radial Basis Function and K-Nearest Neighbour classification approach.

The graphical representation is shown in Figure 7 for the accuracy, K-Nearest Neighbour, radial basis function

Table 1. Different types of tea leaves tested in the proposed method

Tea Leaf Name	Tested Samples	Number of Correct Recognition
TRF 1	20	18
UPASI - 3	20	19
UPASI - 9	20	19
UPASI - 10	20	16
UPASI -17	20	17
UPASI - 22	20	18

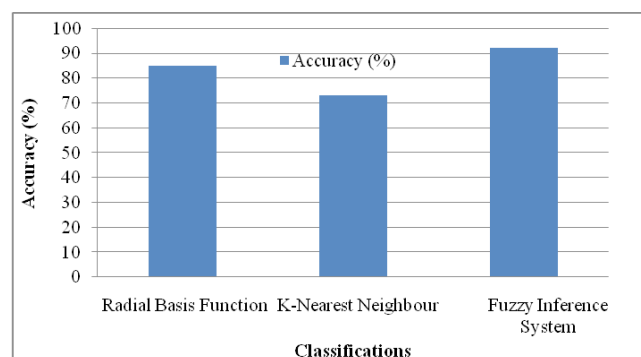


Figure 7. Accuracy for classification.

Table 2. Comparison of the classification accuracy

Classification Techniques	Accuracy (%)
Fuzzy Inference System	92
Radial Basis Function	85
K- Nearest Neighbour	73

and Fuzzy Inference System. The proposed method of Fuzzy Inference System has high accuracy compare with other methods.

Table 3 and Figure 8 show the execution time of the classification. The execution time of the proposed FIS classification approach is compared with K-Nearest Neighbor and RBF classification approach. The proposed method of FIS has less execution time when compared with the other approaches.

4. Conclusion

This work discussed a new approach of tea leaf classification. The parameters are used to minimize the difference between the given value and the output value of the system in the process of fuzzy inference system learning. The preprocessing, feature extraction and classification are the main three phases of this work. The performance of the proposed FIS classification method is measured by calculating the accuracy and execution time. The FIS

Table 3. Comparison of the execution time

Classification Techniques	Time (Seconds)
Radial Basis Function	20
K- Nearest Neighbour	18
Fuzzy Inference System	13

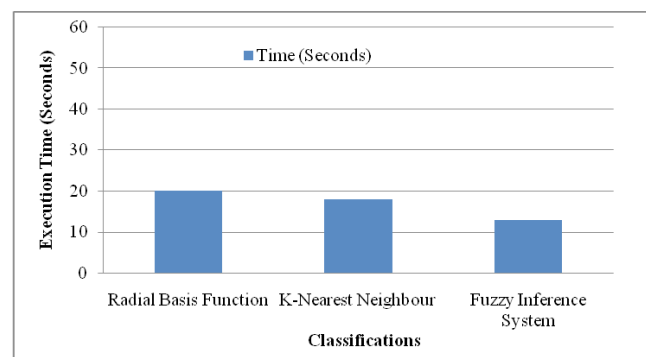


Figure 8. Execution time for classifications.

Classification produces better accuracy and takes nearly less time for execution when compared with the Radial basis function Neural Network and K-Nearest Neighbor. So, to conclude the proposed approach of Fuzzy Inference System classification has better performance and accuracy when compare with the other approaches.

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