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A MACHINE VISION SYSTEM FOR ESTIMATION OF THEAFLAVINS AND THEARUBIGINS IN ORTHODOX BLACK TEA

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Abstract — Orthodox black tea quality depends upon the amount of certain organic compounds present and out of these, theaflavins (TF) and thearubigins (TR) are the most important ones While TF is responsible for attractive golden colour, increased brightness and astringency in tea liquor, TR is reddish brown, reduces the brightness of tea liquor and contribute mostly for the ashy taste of the liquor with minor improvement in astringency. The rapid estimation of TF and TR thus may resolve the problem of certain uncertainty or ambiguity that may arise during quality assessment of tea by the tea tasters. In this paper, a new method for rapid measurement of concentration of TF and TR is described using a machine vision system taking images of tea liquor and employing artificial neural networks (ANN). The results show good correlation of estimated values of TF and TR with the actual concentrations obtained using ultraviolet-visible spectrophotometer (UV-VIS).

Index Terms: Theaflavins (TF); Thearubigins (TR); Machine Vision System; Orthodox black tea; UV-VIS spectrophotometer; Generalised Regression Neural Network (GRNN); Back propagation multilayer perceptrons (BP-MLP); Radial Basis Function Network (RBFN);

I. INTRODUCTION

Orthodox black tea is mainly grown in the Himalyan foothill and Nilgiri regions in India and is a highly priced tea in the worldwide market because of its impressive colour, exciting aroma and exhilarating flavor. Orthodox black tea is rolled with machinery (popularly known as the rolling table) in a manner that mimics hand-rolling. Production of orthodox black tea involves certain processing stages like withering, rolling, fermentation, drying, grading or sorting and packaging. All the stages are associated with several bio-chemical reactions, which produce a large number of organic compounds and the concentrations of these compounds in the finished product determine the quality of made tea. During black tea processing, the conversion of catechins to theaflavins (TF) starts as soon as tea leaves are plucked from the garden. But this conversion process is very slow [1, 2]. During withering, the moisture level of plucked tea leaf is reduced to a large extent with the flow of air in a controlled manner. The main oxidation starts in the next stage known as rolling, where the cellular structure of withered leaf is broken and the enzyme ‘polyphenol oxidase’ comes in contact with catechins to form quinines followed by theaflavins and thearubigins. This continues more vigorously in the fermentation step. During drying, tea leaves are treated with hot air to kill the enzymes for arresting further oxidation and increasing shelf life. After sorting, the packaged tea is finally sent to the auction centers for valuation on the basis of organoleptic testing. [3] During organoleptic testing, human experts evaluate the quality of made tea based on its physical appearance, liquor, infusion colour, brightness, aroma, taste etc.

Table I

Chemical constituents responsible for colour formation in Orthodox BLACK Tea

Compounds	Colour
Theaflavins	Yellowish brown
Thearubigins	Reddish brown
Flavonol glycosides	Light yellow
Phephorbide	Brownish
Pheophytin	Blackish

Among several bio-chemical compounds [4] in finished tea, Theaflavins (TF) and Thearubigins (TR) are the characteristic pigments produced during tea processing and their presence contributes in the formation of the colour and brightness of tea liquor. The ratio of TF and TR is considered as an important quality index by the tea scientists [4] and in certain cases, it also helps to resolve the uncertainty and ambiguity in defining the quality scores assigned by the tea tasters during organoleptic testing [5]. Theaflavins are low molecular weight compounds and golden yellow (yellowish brown) in colour. They contribute about 0.5 to 2% of dry weight (depending on tea clone and processing parameters). On the other hand, thearubigins are high molecular weight compounds and reddish brown in colour. They constitute about 6 to 18% of dry weight [6]. In early 1960s, Woods and Roberts recognized the possible existence of relationship between black tea theaflavins and sensory evaluation [7]. Similar relationship is also reported in a few literatures [8, 9, 10, 11]. These studies led to the view that TF is the main objective quality indicator in black tea. Literature survey reveals some significant relationship between theaflavin content and the price of tea [9, 12 and 13]. A list of chemical constituents responsible for the formation of colour in black tea is shown in Table- I. [14, 16]. The presence of TF enhances the brightness and the taste of astringency in tea liquor, whereas the presence of thearubigins is responsible for reduction in brightness, adds colour and ashy taste with slight improvement in astringency [3, 5, 14, 15].

Presently in the tea industry, assessment of tea quality is carried out by the organoleptic senses of vision, nose and taste of “Tea Tasters” who may be influenced by psychological (e.g. mental state), physiological (i.e. age, sex etc) factors. Thus, the quality index assigned by the tea taster is subjective, and sometimes produces inconsistent results. Instrumental methods using spectrophotometry and High performance Liquid Chromatography (HPLC) are routinely used by the tea scientists to determine the above bio-chemical compounds [7, 16, 17, 18, 19] in tea for looking into the factors that affect tea quality. The instrumental analysis methods [20, 21, 22] are accurate, reliable and repeatable, and the repeatability and reproducibility of the analysis results are restricted only by the quality of the sample preparation. However, some major limitations of the analytical instrumental methods are high procurement cost of the instruments, longer throughput time, cumbersome methods of sample preparation, requirement of skilled operators, costly reagents for sample preparation and high maintenance cost. These factors result in limitations of the instrumental systems especially in tea auction centers and tea tasting laboratories where a large number of samples are handled every day. These motivate us thinking of a low cost, rapid and objective quality analysis instrument. Recently, the use of electronic tongue for estimation of TF [3, 5] and TR [5] was reported which uses voltametric technique to estimate the concentration of chemical compounds. Use of machine vision was reported to find out Tea Quality Index (TQI) during fermentation [23]. This paper proposes an image processing technique to calculate colour and dimensional features of tea particle to obtain Tea Quality Index. Quality analysis of tea grades is proposed by taking image of tea particle using a microscope with 5X magnification and an artificial neural network is employed to differentiate among various grades of tea. [24]. Mohit Sharma et al. [25] makes an attempt to study the colour change during fermentation using RGB (red, green, blue) colour model. Surajit Borah et al. [26, 27] describe the use of machine vision system to detect the end point of fermentation using RGB and HSI (Hue, Saturation and Intensity colour model) colour analysis. It is determined by measuring dissimilarity between the end point fermentation colour with the colour of test images under fermentation. Amit Laddi et al. [28] investigate optimum light illumination intensity for maximum discrimination of the Indian black tea varieties using machine vision. The technique involves acquisition and analysis of color information of brewed tea liquor using PCA technique with different illumination intensity. The study reveals that color attributes are significant parameters for discriminating Indian black tea varieties. Gagandeep Singh Gill et. al. [29] presents an overview of various computer vision based algorithms for colour and texture analysis with a special orientation towards monitoring and grading of made tea. Arvind Kumar et. al. [30] presents an image analysis system for analysis of tea liquor by applying L*a*b* colour model based histogram colour matching technique. B.M.T. Lekamge et. al. [31] presents a novel hybrid method to identify the stalk particles using fuzzy logic based image processing technique for colour separation. The literature review reveals that several studies have been carried out on image processing based application for quality estimation of finished tea and the tea leaves under fermentation. But, no research and development effort has been observed for estimation of TF and TR content directly from appearance of tea liquor. In this work, a machine vision system has been developed for the quantitative estimation of TF and TR in orthodox black tea which is proposed to be rapid with sample preparation technique. The machine vision system is trained first with the target data (in our case the concentration of TF and TR) which is obtained by standard instrumental technique using UV-Vis spectrophotometer. After training with known data, it can be used to estimate the concentrations of TF and TR of unknown samples. The estimations of TF and TR are considered as function approximation problem. Multilayer feed-forward neural network (also known as multilayer preceptrons or MLP) has capability to approximate any arbitrary functions [32]. This paper explores the application of different data analysis techniques i.e. Back-Propagation Multi Layer Perceptrons (BPMLP), Radial Basis Function Network (RBFN) [33] and Generalised Regression Neural Network (GRNN) [34, 35] for calibration of the machine vision system. Also the validation of the results is done by testing with different sets of tea sample using the developed machine vision system by comparing with the value obtained by instrumental analysis.

II. MATERIALS & METHODS

In this experiment, each orthodox black tea sample (made tea) was divided into two portions. One portion is used for analysis of TF and TR using spectrophotometric technique and the other portion is used to prepare the tea liquor for analysis using electronic vision system. The operational flowchart for the experimentation is shown in Fig. 1.

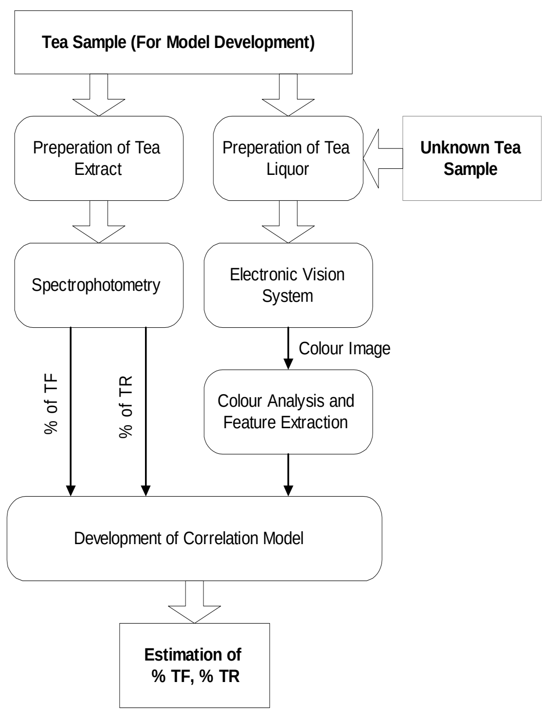

Fig. 1. Operational Flow chart of the overall experiment

The materials and the methodology to estimate the content of TF and TR are describing below.

A. Sample collection

Two leaves and a bud shoot were harvested from tea bushes (Camellia sinensis (L.) O. Kuntze) of Chinary clone with a regular plucking interval of seven days produced at Tea Experimental Farm of the Institute of Himalayan Bio-Resource Technology (IHBT), Palampur. In this experiment, a total of 36 different tea samples had been used which were produced during the three flushing seasons - Early, Rains and Backend. These tea samples were prepared from good quality clone namely Chinary produced at Kangra Vally in North India and plucked between the month of April and July. The orthodox black tea samples were processed at the Experimental Tea Factory. During processing, tea leaves were subjected to withering under ambient air at constant flow for 16-18 h; rolled using a 'peizy' roller for 0.5 h, fermented for 3 h, and dried with hot air at 95°C in a miniature dryer. 25 gm each of orthodox black tea sample, processed at different conditions in order to get wide variations in TF, TR parameters, were taken for experimentation. The TF and TR content of the each orthodox black tea sample had been determined using spectrophotometry and presented to machine vision system for image analysis. The TF values obtained among 36 samples varied from 0.354 to 0.635 with an average of 0.504 and standard deviation of 0.078. On the other hand, TR ranges obtained were 3.015 to 5.421 with an average of 3.84 and standard deviation of 0.78 which indicates the wider variation in the TR values. Also, the samples were presented to a tea taster to grade the sample based on quality score ranging from 1 to 10.

B. Estimation of theaflavins and thearubigins using spectrophotometry

Theaflavins and thearubigins were analyzed from tea infusion, prepared with boiling water. Absorbance/Optical Density (OD) of test solutions was measured on a Shimadzu ® UV-2450 UV-Vis spectrophotometer. Estimation of theaflavins and thearubigins was first developed by Ullah [36].

1) Preparation of tea extract for TF and TR analysis:

Each black tea sample was extracted in triplicate for the determination of the thearubigin fractions following the method described in Association of official Analytical Chemists (AOAC) [37]. To determine TF and TR, 50 mL of the cool, well-shaken and filtered standard tea infusion were mixed with 50 mL of ethyl acetate.

STEP 1: Preparation of Solution A: A 4 mL portion of the ethyl acetate layer was taken and made up to 25 mL with methanol.

STEP 2: Preparation of Solution B: 25 mL of the remaining initial ethyl acetate layer were partitioned with 25 mL of 2.5% aqueous sodium hydrogen carbonate and the aqueous layer is discarded. A 4 ml portion of the washed ethyl acetate layer was made up to 25 ml with methanol.

STEP 3: Preparation of Solution C: 2 mL of saturated oxalic acid aqueous solution and 6 ml of water were added to a 2 mL portion of the aqueous layer left from the first extraction with ethyl acetate, and diluted to 25 ml with methanol.

STEP 4: Preparation of blank sample is done similarly as stated above without mixing the tea extract.

STEP 5: Measurement of Absorbance: The absorbance of solutions A, B and C at 380 nm was obtained using a UV-VIS spectrophotometer-2450, Shimadzu ® against blank [36, 37].

2) Calculation of TF & TR from absorbance reading

Calculation of TF and TR value using spectrophotometry is obtained using equation (1) and (2) [36, 37].

$$\%TF = 2.25 \times E_1 \tag{1}$$

E1 = Absorbance of Solution A at 380 nm after setting the reference point of the instrument using blank.

$$\%TR = \frac{[375 * 0.02 * 6.25(AC + AA - AB)]}{[0.733 * 9 * (WDM\ /100)]} \tag{2}$$

AA= Absorbance of solution A at 380 nm after setting the reference point of the instrument using blank

AB= Absorbance of solution B at 380 nm setting the reference point of the instrument using blank

AC= Absorbance of solution C at 380 nm setting the reference point of the instrument using blank.

WDM= Weight in gm of dry matter (5 gm)

C. The Machine Vision Set up

The Machine Vision System (Fig. 2) consists of the following elements:

1) Lighting arrangement

For image acquisition, samples are illuminated using four high intensity white DOME LEDs (equivalent to D65 standard light source). Four LEDs are arranged as a square configuration, 35 cm above the sample. The light intensity inside the enclosed cabinet is measured using a light sensor (silicon based), mounted at one corner of the sample holder. A separate light intensity controller constantly compares the sensor output to the preset signal level and changes the power supply output to keep the light intensity constant irrespective of power supply voltage and any variation due to aging, ensuring uniform illumination on the system tray where tea liquor cup is placed in the predefined slot.

2) Digital camera for image acquisition

A low cost, colour digital camera, model C905 (Logitech ®) is located vertically over the sample at a distance of 30 cm. The angle between the camera lens and the lighting source axis is approximately 45 degree. The camera is interfaced with PC/ laptop using Universal Serial Bus (USB2.0) communication. To avoid the varying ambient illumination conditions, the entire system is placed inside a cabinet whose internal surface is painted. Images are taken using the following camera settings: manual mode, manually adjusted fixed focus, no zoom, no flash with resolution of 640x480 (N x M) pixels and storage in 24 bit BMP format. The white balance of the camera is set in auto mode.

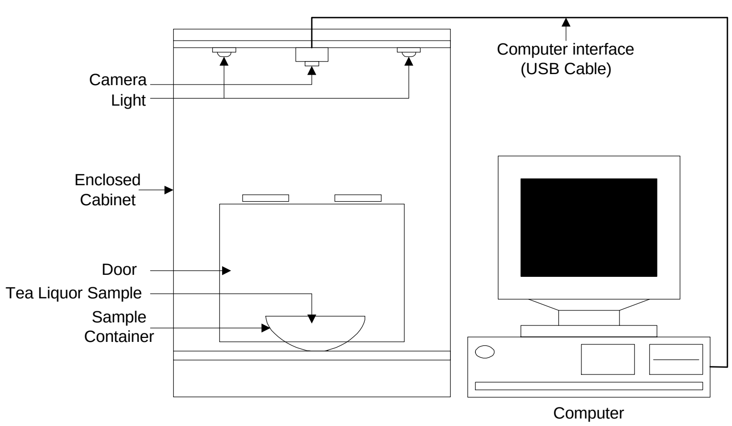

Fig. 2 Schematic diagram of Electronic Vision System

Fig. 3 Electronic Vision System (E-VISION)

D. Image analysis and feature extraction

Images of the tea liquor samples are captured by the camera. (steps for preparation of tea liquor is explained in Section E) Image processing and analysis steps are described below. Developed Electronic vision system is shown in Fig. 3.

1) Pre-processing of the Image: Though the images are taken inside a cabinet under a fixed illumination of light with intensity 110 Lux using 4 white LEDs, but, there are some noises in the image. These noises include the suspended tea particles in the liquor and the water bubbles formed during preparation of the tea liquor. To remove the above noise, a median filter with 5x5 window size is found to provide reasonably good performance. This filter operation is applied in each colour plane (Red, Green, Blue) of the image separately.

2) Segmentation of the liquor image: Experimentally, it is observed that for all the sets of the liquor images, the R (Red) value is dominating over B (Blue) and G (Green) values. So, R image plane is considered during image segmentation of the liquor image from the rest or background image. By observing the histogram of R plane of the image, a fixed threshold value is chosen. Segmented image is a binary image where ‘0’ and ‘1’ represent background and liquor image respectively. The localization of the pixel in the binary image is used to extract the liquor image in the processed RGB colour image.

3) Extraction of features: The construction of the bowl containing tea liquor is concave shape with an open top which causes the variation in depth of the tea liquor (from the liquor surface to the inside wall of the bowl) inside the bowl. As a result, the colour is more predominant and uniform in the middle portion marked as location ‘C’ in Fig. 4 when compared with any other sides, marked as N, S, E, W. More specifically, the colour values R and G are found to be decreasing from the middle region (C) to any side (N, S, E or W). But, very little change in blue (B) value is observed. The plot with average R, G, B values of the images taken at different locations in the sample holder (bowl) is shown in Fig.5.

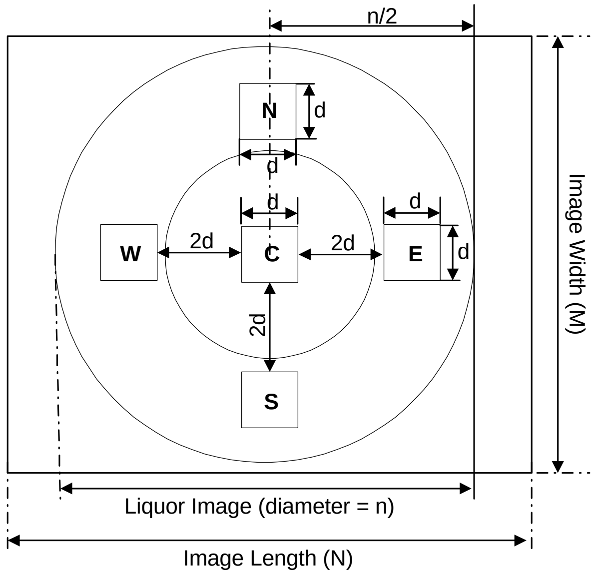

Fig. 4. Captured image with marking of different regions (C, N, W, S, E) from where colour based different image features were extracted.

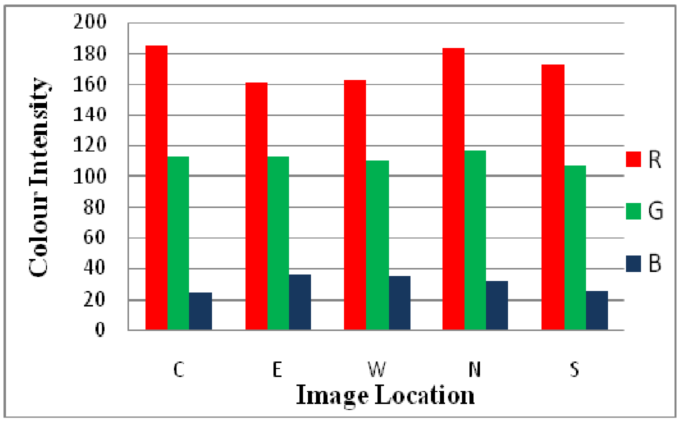

Fig.5 Average R, G, B intensity of the images at different locations in the sample holder (bowl)

The change in colour value is also observed to be a function of depth of the tea liquor in the tea tasting bowl. Therefore, colour features at five locations at C (middle), N (North), S (South), E (East), W (West) are chosen. The image of size 40 x 40 (d=40) pixels are cropped from the center of the actual image that produces almost uniform colour. Also, the image size of 40x40 (d=40) from each location (N, S, E, W) were cropped. For each cropped image, the values of R, G, B are calculated. Thereafter, the conversion is performed from device dependent RGB colour plane to device independent CIE L*a*b colour plane. The L*a*b plane is chosen as it can describe all the colours visible by the human eye and matches with human perception. ‘L’ represents the luminance or lightness component which is ranging from 0 (black) to 100 (white), ‘a’ (green to red), ‘b’ (blue to yellow) are two chromatic components varying from -128° to 127° [39]. Our objective is to estimate the TF, TR values from the colour images. Based on the assumption and initial observation, six features are selected for colour analysis for each cropped image. The features are average ‘L’, average ‘a’, average ‘b’, standard deviation of ‘L’, standard deviation of ‘a’ and standard deviation ‘b’. Considering the cropped images at five locations, we have total 30 features for each image. List of features are shown in the Table- II.

Table II

List of extracted features according to figure 4

Features	Description
Lc, ac, bc	Average L, a, b value of cropped image at location C
LN, aN, bN	Average L, a, b value of cropped image at location N
LW, aW, bW	Average L, a, b value of cropped image at location W
Ls, as, bs	Average L, a, b value of cropped image at location S
LE, aE, bE	Average L, a, b value of cropped image at location E
Lcs,acs, bcs	Standard deviation of L, a, b value of cropped image at location C
LNs, aNs, bNs	Standard deviation of L, a, b value of cropped image at location N
LWs, aWs, bWs	Standard deviation of L, a, b value of cropped image at location W
LSs, aSs, bSs	Standard deviation of L, a, b value of cropped image at location S
LEs, aEs, bEs	Standard deviation of L, a, b value of cropped image at location E

E. Preparation of tea liquor

The tea liquor samples for the vision system were prepared by boiling 100 ml of de-ionized water poured over 2.5 gm of dry tea. The solution was allowed to brew for 5 min, after which it was stirred well for mixing uniformly. The liquor was separated into another beaker so that the residual leaves remain at the bottom. The liquor was allowed to cool (at 50-60° C) before it is filtered using 'Whatman' filter paper to get a clear solution. The sample was then presented to Electronic Vision System and 5 images were recorded for each of 36 orthodox black tea samples. The same samples were also evaluated by a professional tea taster for quality evaluation.

III. DATA ANALYSIS

A. Principal component analysis (PCA)

PCA [38, 40] is a linear feature extraction technique which is used as a visualization tool for observing high dimensional data distributions into information rich, reduced dimension (typically two or three) coordinate system. By using PCA, data may be expressed and presented in a way to highlight their inherent similarities and differences. This technique calculates the projection of the input data set on the orthogonal axis those are aligned in the direction of maximum variance in the input data. The PCA technique is applied on the liquor image data after feature extraction and the plots are presented in the next section.

B. Artificial Neural Network frame work

Artificial neural network (ANN) using multi-layer perceptrons often exceeds the performance of other function approximators for arbitrary, complex and nonlinear input-output mappings. The performance of the following artificial neural network framework has been considered.

1) Back-Propagation Multi-Layer Perceptrons (BPMLP)

An artificial neural network technique like back-propagation-multi-layer perceptrons (BPMLP) can be applied to perform function approximation task for prediction of TF, TR content in a tea sample. A three layer BP-MLP model with single input and output layer and one hidden layer has been considered in our problem. The input layer has been connected with image features (30 input nodes) and the output layer has been configured with either TF or TR value. It is observed that the convergence during learning process had been found with acceptable level of accuracy with only one hidden layer with 35 neurons. In our problem, the learning rate of the hidden layer had been considered at 0.5 and 'TANSIG' is used as the activation function on hidden layer out puts. While, 'PURELIN' (linear function used in MATLAB ® 10.0) is used as activation function in the output layer and the learning rate in the output layer is considered as 0.1. Number of iteration (Epoch) was considered as 1500.

2) Generalized Regression neural network (GRNN)

General Regression Neural Network (GRNN) [34, 35] can perform estimation on any arbitrary function having linear or non-linear relationship between the dependent and independent variables. The estimated result can meet the optimal regression surface even on the samples of sparse data. GRNN is a feed forward neural network architecture implemented on supervised learning process. It has four layers - input, pattern (Gaussian Function), summation, and the output layer. Input layer receives the input signal and passes it to the pattern layer for further processing. The pattern layer calculates the Euclidean distance between the input vector and training vector and passes this value to next layer i.e. summation layer as an activation function (Gaussian Function). Summation layer has two neurons - one is the numerator and the other one is the denominator. The numerator neuron calculates the weighted sum where a weight corresponds to a training sample output. Denominator neuron calculates un-weighted sum of outputs from the pattern layer. The output layer calculates the output by dividing numerator by denominator. In our case, GRNN has 30 input nodes corresponding to 30 image features. Since, our problem is a function approximation problem, the output layer has only one node i.e, either TF or TR value. The value of spread constant is considered as 1.0.

3) Radial Basis Function Network (RBFN)

RBFN [33] consists of an input layer, a hidden layer and an output layer. Hidden nodes which are known as radial centers, implement the radial basis function i.e. Gaussian function and the output layer implements the linear summation function. During training, the weights of the hidden layer to the output layer are updated and finalized. RBFNN keeps on adding neurons to the hidden layer of a radial basis network till it reaches the acceptable level of accuracy by minimizing the mean squared error. For the development of artificial neural network using RBF, input layer consisting of 30 neurons and output layer with single neuron are considered. Implementation of RBFNN had been done using MATLAB ®, where, spread constant is considered as 1.0 and sum squared error (SSE) value is considered as 0.02. Parameters chosen for three ANN architectures are shown in Table III.

Table III

Artificial neural network architecture

BP-MLP	GRNN	RBFNN
Input Node: 30	Input Node: 30	Input Node: 30
Hidden Node: 35		
Output Node: 1	Output Node: 1	Output Node: 1
Learning rate at Hidden Layer: 0.5	Spread constant: 1.0	Spread constant: 1.0
Learning rate at output layer: 0.1		SSE: 0.02
Epoch – 1500		

IV. RESULTS AND ANALYSIS

Experiments were carried out under standard laboratory conditions with 36 tea samples using developed electronic vision system. The image of the liquor was taken five times for each sample. Thus, 180 images were captured and the images were analyzed using an image analysis program for initial processing followed by feature extraction. Finally, the data analyses were performed using MATLAB 7.0 ®.

A. Data exploration using PCA for extraction of clustering information

The PCA analysis was carried out with selected 33 orthodox black tea samples having significant variation in of TF and TR values. This would be helpful for initial exploration regarding the formation of representative clusters. The plots with TF and TR values are presented in Fig 5(a) and Fig. 5(b), respectively. The colours of markers specify values of TF and TR within the range specified by the plot legend. The PCA plots indicate the tendency to form clusters corresponding to the tea samples with closer TF and TR values, respectively. The PCA plot with Fig. 6(a) reveals the formation of good clusters produced by the tea sample with lower TF values indicated by blue (X), green (△) and red (☆) markers. Notable overlaps have been observed due to a lesser amount of variation obtained in the TF values. The cyan (*), magenta (□) markers indicating TF values overlapping with each other. Fig. 6(b) presents the PCA plot of electronic vision image analysis results for TR analysis with 33 tea samples. Formation of notable clusters have been found with the tea sample with lower TR values indicated by blue (*), red (□) and

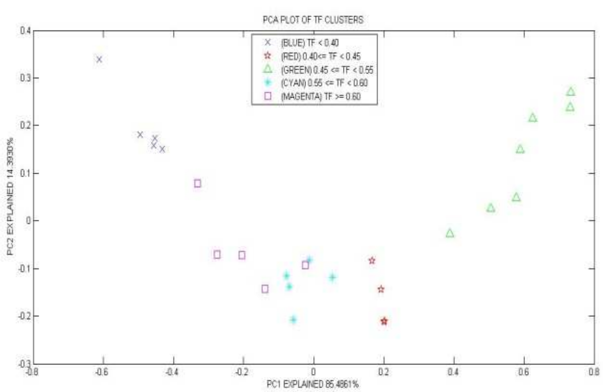

Fig. 6 (a) PCA plot showing clusters with TF

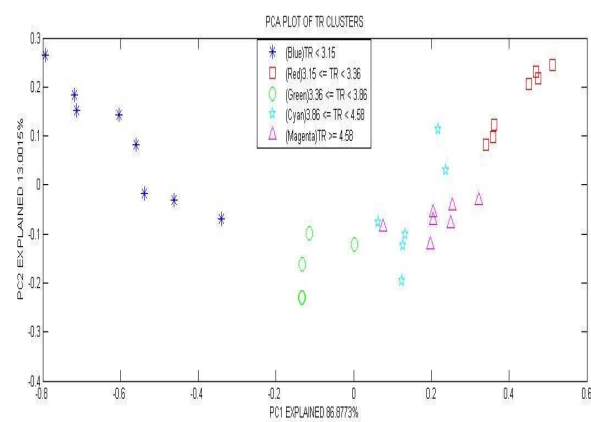

Fig. 6 (b) PCA plot showing clusters with TR green (O) markers. Though, the magenta (△) markers indicating highest TR values overlap with other group indicating by cyan (☆), but, blue (*), red (□), green (O) ones can be separable.

The PCA plot reveals a complex and non-linear relationship between the colour image features and TF- TR content. This motivates us to develop a mathematical model to differentiate among the overlapping clusters. The next section discusses about the choosing an appropriate model for efficient predication of TF and TR value.

B. Development of Artificial Neural Network models for prediction of TF and TR

1) Preparation of dataset for calibration and testing

For each of the 180 images captured, 30 image features are obtained. Thus, the total data set obtained is of size 30×180. The dataset is divided into training set of size 30×125 (70%) and test set of size 30×55 (30%). The testing results are compared with the actual values obtained using spectrophotometry. K-Fold (K=10 in our case) cross validation technique is applied to validate the neural network models.

2) Selection of the performance parameters

As indicated earlier, three types of neural networks were employed in this study. Hence, in order to compare the performance of the ANN techniques i.e. BPMLP, RBF and GRNN, the following performance parameters are considered as shown in Table IV.

Table IV

Performance parameters

Abbr.	Definition
MPPA	Mean Percentage Prediction Accuracy
MPE	Mean Prediction Error
MinPE	Minimum Value of Prediction Error
SDPE	Standard Deviation of Prediction Error
WPPA	Worst Percentage Prediction Accuracy
MSPE	Mean Square Prediction Error
MaxPE	Maximum Value of Prediction Error

These performance parameters were calculated on the results obtained after executing the 10 fold cross validation technique. The important performance indicating parameters among the above are MPPA, MSPA and WPPA, in order of priority. While MPPA and MSPA indicate the efficiency of mapping, WPPA indicates the lower bound of predication accuracy.

3) Comparison among neural network models for the prediction of TF and TR values

As mentioned earlier, a total of 180 images for 36 different tea samples have been used for testing the proposed technique of TF & TR content estimation. Three models have been validated for the whole set of data with 10–fold cross validation technique. Results of 10-fold cross validation technique are presented in TABLE V and TABLE VI for prediction of TF and TR respectively using BPMLP, RBFN and GRNN.

Table V

Result of 10 Fold cross validation for prediction average accuracy of % TF

Fold No	BPMLP	GRNN	RBFN
1	86.95	85.69	87.18
2	85.81	82.24	81.65
3	85.83	80.05	83.28
4	87.27	88.39	88.93
5	86.83	87.73	85.49
6	81.69	84.17	88.32
7	88.11	88.33	89.12
8	88.81	90.68	90.19
9	85.04	84.86	85.99
10	96.15	95.71	95.77
Average	87.25	86.79	87.59
Std	3.50	4.23	3.73

Table VI

Result of 10 Fold cross validation for prediction average accuracy of % TR

Fold No	BPMLP	GRNN	RBFN
1	92.37	92.02	91.51
2	75.54	75.10	76.27
3	73.73	77.25	76.74
4	65.16	66.33	66.55
5	92.68	93.79	91.67
6	89.76	90.46	87.76
7	92.98	92.94	92.83
8	95.07	95.90	95.23
9	92.70	92.36	92.88
10	89.11	89.05	89.98
Average	85.91	86.52	86.14
Std	10.43	9.96	9.54

4) Performance analysis on selected prediction models

Summary of the performance for prediction of TF and TR using three ANN models viz. BP-MLP, RBFN and GRNN are shown in Table VII and VIII.

Table VII

Performance summary of models developed for TF

Performance Parameters	MPPA	MPE	MSPE	SDPE	MinPE	MaxPE	WPPA
BP-MLP	87.253	0.015	0.006	0.08	0.133	0.213	66.049
RBFN	87.592	0.015	0.006	0.078	0.135	0.201	66.243
GRNN	86.794	0.016	0.007	0.081	0.136	0.198	65.98

Table VIII

Performance summary of models developed for TR

Performance Parameters	MPPA	MPE	MSPE	SDPE	MinPE	MaxPE	WPPA
BP-MLP	85.911	0.022	0.492	0.711	1.258	1.576	59.760
RBFN	86.143	0.027	0.449	0.679	1.15	1.407	62.095
GRNN	86.521	0.025	0.445	0.676	1.273	1.495	59.249

The following observations could be summarized from the above tables. The results of 10-fold cross-validation and on other performance criteria with the three models show almost similar results of high accuracy for estimation of TF and TR. In case of estimation of TF, the maximum value for MPPA has been obtained using RBFN as well as BP-MLP. On the other hand, the worst prediction accuracy (WPPA) for RBFN and BP-MLP has been calculated as 66.243% and 66.049%, respectively. Hence, the performance of RBFN being superior to that for other neural network algorithms is clearly observed for estimation of TF content in the orthodox black tea. In case of estimation of TR, the maximum value for MPPA is obtained using GRNN. But, RBFN also gives almost the same level of accuracy. It may also be observed that, the SDPE value for RBFN is more than that of GRNN. Again, the worst prediction accuracy (WPPA) for RBFN is larger compare to that of GRNN. Hence, the performance of RBFN being superior to that against other neural network algorithms is clearly observed for estimation of TR as well. The quality scores of tea samples considered in this study was given by tea tasters are plotted against the concentrations of TF and TR in Fig. 7(a) and Fig. 7(b). A positive correlation between Tea Tasters' score with TF and TR values has been clearly observed. Thus the proposed methodology for the approximate estimation of TF and TR contents can give a fair idea about the quality of Tea.

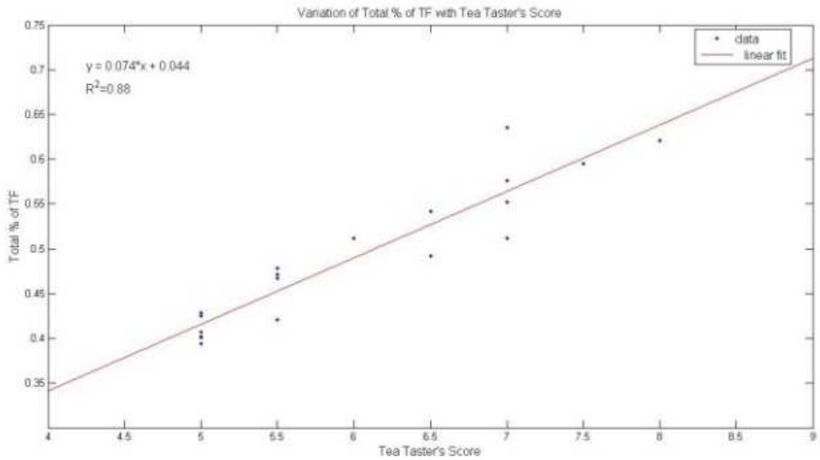

Fig.7 (a) Plot of TF (%) with Tea Tasters' Quality Scores.

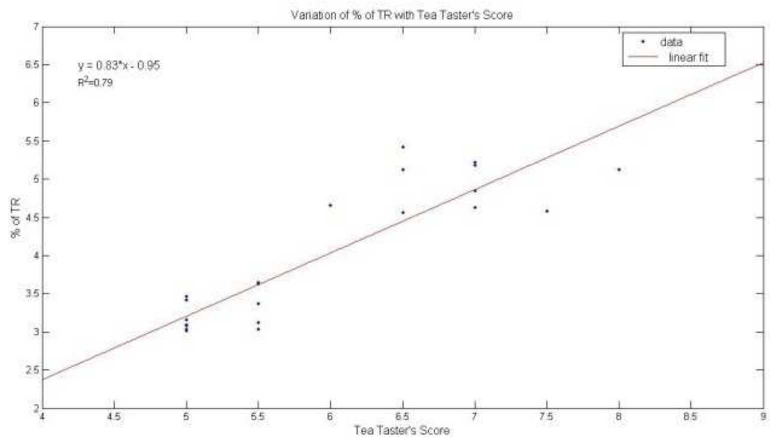

Fig. 7 (b) Plot of TR (%) with Tea Tasters' Quality Scores.

V. CONCLUSIONS

Theaflavins and Thearubigins are two very important chemical constituents for the formation of tea liquor colour and brightness and the estimation of these chemical constituents gives a fair idea about the quality of orthodox black tea. In this paper, an electronic vision system using low cost digital camera and illumination set up has been described to estimate the TF and TR content. Image of liquor sample is directly captured by the camera and image analysis techniques have been employed for extraction of different colour features. The PCA analysis shows a tendency to form different clusters. But, the formation of overlapping cluster indicates a non linear relationship among the colour image data with TF and TR values. The performance of estimation accuracy of TF and TR using three neural network techniques i.e. BP-MLP, GRNN and RBFN has been presented. The results of 10-fold cross-validation and on other performance criteria with the three models show almost similar results of high accuracy thus establishing the efficacy of the proposed solution for approximate TF and TR content. However, the performance of RBFN being superior to that for other neural network algorithms is clearly observed for estimation of TF content in the orthodox black tea. RBF models for TR shows performances better than BP-MLP and can be compared with GRNN, except for the MPPA, WPPA values. The work presented here suggests that an electronic vision can be applied to determine the approximate TF and TR content in tea. However further research is required to study the effect of other chromatic compounds like phephorbide, pheophytin and their effect on colour formation in tea liquor. All in all, the proposed electronic vision method promises a new and rapid method for quality analysis of orthodox black tea by facilitating instant estimation of important bio-chemical compounds of tea.

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