Optimizing Fermentation Time And Color Evolution Prediction With color Transition Forecasting Segmentation Technique (CTFS)

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ABSTRACT
Fermentation plays a crucial role in determining the quality of black tea. This stage of the process is responsible for enhancing the appearance, aroma, liquor, and infusion characteristics of the finished tea. During fermentation, the grassy scent gradually transforms into a floral aroma due to complex biochemical reactions within the tea leaves, while the greenish color transitions to a rich coppery brown hue. Detecting the optimal fermentation time is essential for tea manufacturers, as under-fermentation or over-fermentation can lead to inferior tea quality. Hence, it is imperative to halt the fermentation process at the optimal time, determined by monitoring changes in aroma (using an electronic nose) and color (using nine value analysis). This paper investigates the changes in aroma index and color during the fermentation process of valparai region black tea, aiming to identify the optimal fermentation time using Color Transition Forecasting Segmentation Technique(CTFS).

Keywords: Segmentation, Color Change, Aroma, Black Tea, Fermentation

1. INTRODUCTION

Tea (Camellia sinensis) is presently one of the most widespread and widely consumed beverages globally, with a daily intake exceeding 2 million cups. Its popularity stems from its medicinal benefits, including reducing heart diseases, aiding weight management, preventing strokes, lowering blood pressure, preventing bone loss, and boosting the immune system, among others. Historical records suggest that the tea plant originated in China and Burma, among other regions [14]. India is the second country for tea producing. Despite tea's significance to the country, its sector grapples with a multitude of obstacles. These challenges encompass high production costs, mismanagement, unfavourable agricultural practices, the impact of climate change, market competition from other countries, low price margins, and a deficiency in automation, among various other factors[15].

Table 1 illustrates the current leading tea-producing nations. Tea encompasses various types, such as Oolong tea, black tea, white tea, matcha tea, sencha tea, green tea, and yellow tea, among others. The processing methods employed determine the type of tea produced. Globally, Kenya is the primary producer of black tea, which remains the most popular category, constituting approximately 79% of the total global tea consumption .[16].

Tea, a globally cherished beverage, is celebrated for its invigorating properties and myriad health benefits. Its diverse array of types, including black, green, and oolong tea, distinguishes itself by the extent of oxidation of polyphenolic compounds. Black tea, having undergone complete oxidation, undergoes a meticulous production journey involving withering, rolling, fermentation, drying, and sorting/packaging. Among these steps, fermentation emerges as a pivotal stage, wielding significant influence over the final quality of black tea.

During fermentation, a complex interplay of chemical constituents and enzymes with oxygen triggers the production of polyphenolic compounds, spurred by the stress induced by plant cell rupture. Environmental factors such as humidity, temperature variations, and the thickness of the fermentation bed exert notable effects on the quality of the tea. Fermentation facilitates the amplification of theaflavin (TF) and thearubigin (TR) levels through the oxidation of catechins and gallates. Notably, TR consistently outweighs TF, maintaining an optimal TR:TF ratio of 10:1. TF levels peak during fermentation before gradually declining, while thearubigin levels continue to escalate over time. The luminous golden hue observed in tea liquor signifies a high TF content, while a lacklustre appearance indicates over-fermentation. Proper fermentation, essential for preserving tea quality, necessitates meticulous attention to achieve the optimal duration[7].

Table 1. The top tea-producing nations worldwide

Rank	Country	Estimates tonnes produced yearly
1	China	2 400 000
2	India	1 320 000
3	Sri Lanka	439 000
4	Kenya	349 600
5	Vietnam	260 000

2. Fermentation Process In Tea Production

The fermentation (oxidation) process involves enzymatic oxidation. When the cells of the tea leaves are ruptured, exposing the cell sap, chemical constituents and enzymes react in the presence of atmospheric oxygen. Fermentation commences as soon as rolling or maceration begins. This process is exothermic, releasing heat, moisture, and carbon dioxide[8].

The enzymes polyphenol oxidase (PPO) and peroxidase (PO) act on catechins in the presence of oxygen, leading to the formation of oxidized polyphenolic compounds such as theaflavins (TF) and thearubigins (TR). Theaflavins (TF) comprise simple theaflavin (TF), theaflavin-3-gallate (TF3G), theaflavin-3'-gallate (TF3'G), theaflavin-3,3'-digallate (TF33'DG), isotheaflavin, and neotheaflavin[9].

Catechins combine in pairs to produce various compositions of theaflavins. The structures of thearubigins (TR) are not well understood, and no definitive structures have been identified to date. However, it has been suggested that the B-ring interflavonoid bond (2'-2' as found in bisflavanols) may form the backbone of all thearubigins or a portion of them[10].

Important Sensory characteristics in Fermentation process

Color

Throughout the fermentation process, the green hue of tea leaves transforms into a coppery brown shade. Theaflavins (TF) contribute to the brightness, briskness, and overall quality of the tea liquor, while the content of thearubigins (TR) influences the color, taste, and body of the tea. TF and TR are associated with the formation of two primary color pigments: orange-red and reddish-brown, respectively.

Smell

In the Indian tea industry, the fermentation process is assessed using two distinct smell peaks known as the first nose and second nose. Experienced floor supervisors rely on their senses to detect these peaks, identifying the intense emission of volatile compounds by manually smelling the teas. Initially, the ruptured tea leaf is green in color and emits a raw smell, which gradually diminishes over time. As fermentation progresses, a fruity aroma emerges at a specific point in time, known as the first nose. Subsequently, as the tea leaves transition from green to coppery brown, a more pronounced fruity aroma develops, indicating the second nose. Once the second nose is detected, signaling the heightened fermentation stage, the fermentation process is terminated. However, such practices are subjective and susceptible to human error due to variations in individual perception[11].

Taste

High-quality black tea infusion is distinguished by its vibrant reddish-brown color, brisk and robust taste, and rich flavor profile (Chaturvedula and Prakash, 2011).

Time

The duration of fermentation is crucial as it significantly influences the quality of black tea (Muthumani and Kumar, 2007). The fermentation time is predetermined and varies depending on factors such as the type of tea, extent of maceration and rolling, degree of withering, and standard of plucking.

Temperature

Maintaining the fermentation temperature within a specific range is essential for producing high-quality tea, as fermentation conducted at excessively low or high temperatures can result in the inactivation of enzymes.

Under-fermented Fermented Over-fermented

Figure 1. Examples of color change of the tea fermentation

3. RELATED WORK

Kimutaiet.al(2020) [1]introduced a deep learning model called TeaNet, which is based on Convolution Neural Networks (CNN). TeaNet utilizes images from the tea Fermentation and Labelme datasets as input data. Comparative analysis was conducted on the performance of TeaNet against various standard machine learning techniques, including Random Forest (RF), K-Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Naive Bayes (NB). Results indicate that TeaNet outperformed the other machine learning techniques in classification tasks. However, the researchers plan to further assess the stability of TeaNet in classification tasks through future studies, particularly when deployed in a tea factory in Kenya. Additionally, the research has made available a tea fermentation dataset for use by the community.

Kimutai et.al (2021)[2]investigates the application of Internet of Things (IoT), deep convolutional neural networks (CNNs), and image processing techniques using majority voting in detecting the optimal fermentation of black tea. A prototype system was developed using Raspberry Pi 3 models equipped with a Pi camera to capture real-time images of tea during fermentation. The prototype was implemented and tested at the Sisibo Tea Factory for training, validation, and evaluation purposes. Upon evaluation of the deep learning model on offline images, it achieved perfect precision and accuracy scores of 1.0 each. When evaluated on real-time images, the deep learning model achieved the highest precision of 0.9589 and accuracy of 0.8646. Furthermore, when employing a majority voting technique for decision-making, the deep learning model attained an average precision of 0.9737 and accuracy of 0.8953. The results demonstrate that the prototype system is capable of effectively monitoring the fermentation process of various tea types, including Oolong and black tea. Moreover, the system can be expanded by retraining it to monitor the fermentation of other crops such as coffee and cocoa, thus showcasing its versatility and potential for broader agricultural applications.

Jolvis Pou, K. R. (2016)[3] suggested that maintaining an optimal ratio of TF (Theaflavins) to TR (Thearubigins) at 1:10 is crucial for producing a high-quality cup of tea. Concentrations of TF and TR, along with desired quality attributes, increase with fermentation time, reaching optimal levels before diminishing with prolonged fermentation. Effective control of oxidation conditions is necessary during this process. Although specific environmental conditions for fermenting tea leaves are not standardized, typical parameters include temperatures of 24-29°C for 2-4 hours or 55-110 minutes for orthodox tea or crush, tear, and curl (CTC) black tea, respectively. These conditions are maintained under high relative humidity levels of 95-98% with sufficient oxygen supply. In conclusion, polyphenolic compounds found in black tea, including TF, TR, and unoxidized catechins, contribute to the health benefits associated with tea consumption.

The identification of aroma compounds present during tea fermentation was conducted using gas chromatography-mass spectrometry (GC-MS), while their specific characteristics (floral, grassy, sweet, etc.) were determined through gas chromatography-olfactometry (GC-O). Various studies utilizing GC-MS have identified over 70 different chemical compounds contributing to tea aroma. However, the high cost of GC-MS instruments limits their availability in many tea factories. Moreover, oxidation continues during transportation to the laboratory unless samples are frozen, posing challenges for integrating GC-MS into regular quality checks on the production line.

Currently, traditional methods involve human observation of color changes in tea particles and detecting the development of a fruity aroma to determine the optimum fermentation time in Sri Lankan tea factories. However, this approach lacks consistency due to subjective variations among individuals. Hence, there is a growing demand to develop a system capable of monitoring tea fermentation with minimal human intervention, addressing the need for standardized and reliable quality control measures.

4. PROPOSED METHOD

Each tea sample weighing 30 ± 0.5 g is extracted and evenly distributed within a sample pool of diameter Φ80 mm. The sample pool is placed under uniform lighting conditions to facilitate image acquisition. From each image captured, a section measuring 3000 × 2000 pixels is automatically segmented with pixel point (1728, 1152) as its central reference. The color characteristics of this section are then analyzed. Before conducting further analysis, the image processing module automatically eliminates background shadows using a predefined threshold setting. These shadows, caused by underexposure of lower leaves due to light projection onto the surface of the table, are identified and removed. Digital images can be categorized into various types, including grayscale, RGB, index, and binary images. Grayscale images, represented as a two-dimensional data matrix, store pixel grayscale values ranging from 0 to 255, where 0 denotes pure black and 255 signifies pure white. In this experiment, a threshold value of 30 is set. Pixels with grayscale values lower than 30 are deemed shadows and consequently removed. The remaining pixels within the Region of Interest (ROI) are used to calculate the average color characteristics. Nine color indexes are then extracted through color model conversion among RGB, HSV, and CIE Lab. These include the mean values of the red (R), green (G), and blue (B) channels, as well as hue (H), saturation (S), luminance (V), a* component, b* component, and lightness component (L*). Color transformation is performed based on established formulasEqn(1) and (2).The TFs and TRs content is quantified following the guidelines outlined in The Measurement of Tea Leaf's tea pigment—High Performance Liquid Chromatography (GB/T 30483-2013). Sample preparation involves freeze-drying and grinding.

Algorithm :Color Transition Forecasting Segmentation Technique(CTFS)

Step1:Sample Preparation

Take 30 ± 0.5 g of tea from each sample.
Evenly spread the tea in a sample pool of diameter Φ80 mm.

Step 2: Image Acquisition

Embed the sample pool under uniform light for image acquisition.
Capture digital images of the sample pool.

Step 3: Partition Image Section

```
#Define the desired section size
section_width = 3000
section_height = 2000
# Define the center pixel coordinates
center_x = 1728
center_y = 1152
# Calculate the starting and ending pixel coordinates for the section
start_x = max(0, center_x - section_width // 2)
end_x = min(image_width, center_x + section_width // 2)
start_y = max (0, center_y - section_height // 2)
end_y = min(image_height, center_y + section_height // 2)
```

Step 4: Remove Background Shadow

```
# Define the threshold value
        threshold_value = 30
# Convert the captured image to grayscale
        grayscale_image = convert_to_grayscale(captured_image)
# Apply thresholding to identify shadowed pixels
        shadow_mask = threshold_grayscale_image (grayscale_image, threshold_value)
# Invert the shadow mask to identify non-shadowed pixels
        background_mask = invert_mask(shadow_mask)
# Apply the background mask to the captured image to remove shadows
        shadow_removed_image = apply_mask (captured_image, background_mask)
# Display the shadow-removed image for verification
        display_image(shadow_removed_image)
```

Step 5:Extract Color Features

```
#Convert the processed image to grayscale.
        grayscale_image = convert_to_grayscale(processed_image)
# Define the Region of Interest (ROI) coordinates
```

roi_start_x = 100, roi_end_x = 500, roi_start_y = 200, roi_end_y = 700
#Calculate the average grayscale value of remaining pixels in the Region of Interest (ROI).
total_pixels = (roi_end_x - roi_start_x) * (roi_end_y - roi_start_y)
average_grayscale_value = sum(sum(roi)) / total_pixels
#Extract the following color indexes using color model conversion among RGB, HSV, and CIE Lab

Step6: Color Transformation

Perform color model conversion using the following formulas:
RGB to HSV conversion for H, S, and V components.

$$\overbrace{\begin{array}{l} V = \max(R,G,B) \\ S = \begin{cases} V - \min(R,G,B)/V & if\ V \neq 0 \\ 0 & otherwise \end{cases} \\ H = \begin{cases} 60(G-B)/(V-\min(R,G,B)) & if\ V = R \\ 120 + 60(B-R)/(V-\min(R,G,B)) & if\ V = G \\ 240 + 60(R-B)/(V-\min(R,G,B)) & if\ V = B \\ H + 360 & if\ H < 0 \end{cases} \end{array}}^{RGB\ to\ HSV}$$

→(1)

RGB to CIE Lab conversion for a*, b*, and L* components.

$$\overbrace{\begin{array}{l} \begin{vmatrix} X \\ Y \\ Z \end{vmatrix} = \begin{vmatrix} 0.433910 & 0.376220 & 0.189860 \\ 0.212649 & 0.715169 & 0.072182 \\ 0.017756 & 0.109478 & 0.872915 \end{vmatrix} \times \begin{vmatrix} R/255 \\ G/255 \\ B/255 \end{vmatrix} \\ L^* = \begin{cases} 116 \times Y^{1/3} & Y > 0.008856 \\ 903.3 \times Y & Y <= 0.008856 \end{cases} \\ \begin{cases} a^* = 500 \times (f(X) - f(Y)) \\ b^* = 200 \times (f(X) - f(Y)) \end{cases} \\ \text{where } f(t) = \begin{cases} t^{1/3} & t > 0.008856 \\ 7.787 \times t + 16/116 & t <= 0.008856 \end{cases} \end{array}}^{RGB\ to\ CIE\ Lab}$$

→(2)

Output:
Store the extracted color features for further analysis.

5. RESULT AND DICUSSION

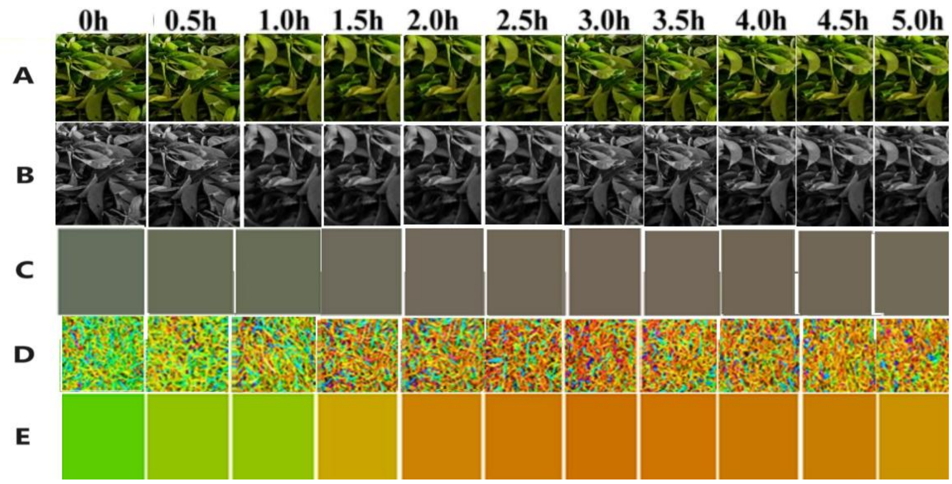

Figure 2. (**A**) Fermentation time images; (**B**) Average of Gray Color (C)Average color; (**D**) Strengthened images; (**E**) Average color of the strengthened images.

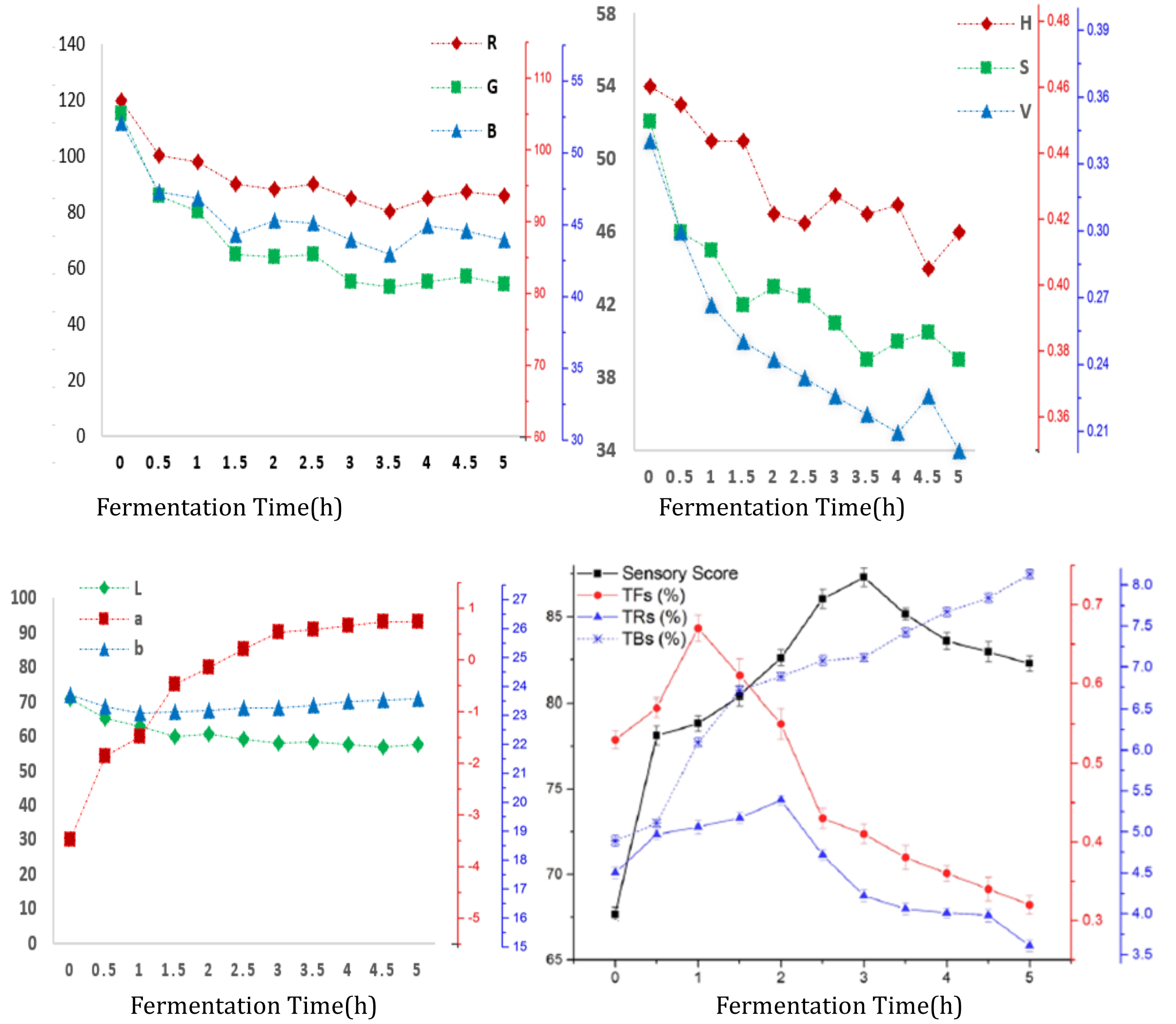

Figure 3. (a)RGB eigen value (b)HSV eigenvalue (c)Lab eigenvalue (d)Quality indices in the context of fermentation

To better understand the changes in foliage color during fermentation, this study initially examined the overall visual alterations. Images captured at various fermentation stages were organized chronologically, and the average color of these images was calculated. The findings are depicted in Fig. 2(A) and (B) revealing discernible color variations corresponding to different fermentation durations, perceptible to the human eye. To enhance the differentiation of these variations, image saturation and brightness were intensified. Subsequently, RGB images were converted to HSV color models, where the saturation (S) channel values were tripled, and the value (V) channel values were doubled before being converted back to RGB images. The resulting images are presented in Fig. 2(C) and (D), illustrating the gradual transition of foliage color from green to reddish-yellow, eventually to tan, over the fermentation period. Notably, during the 2.5–3 hour interval, the presence of red color is most pronounced. Following this, various color features of the images were extracted to elucidate the micro-level change patterns of foliage colors during fermentation, as demonstrated in Fig. 3. Throughout the fermentation process, these analyses unveil comprehensive insights into the dynamic alterations in foliage color.

Eigenvalues are a distinct collection of scalar values typically linked with a set of linear equations, often found within matrix equations.The color eigenvalues exhibited an overall downward trend of "fast-slow-stable" except for the a* value, which displayed a general upward trend (initially quick, then backing off slowly). Between the 0 to 1.5-hour mark, all color features underwent significant changes, commonly referred to as the "red stain" in tea production. By the 3-hour mark, the a* and H values reached their respective peaks, positive and negative, resulting in the foliage displaying the highest degree of redness. Post the 3-hour mark, the redness (R, H, and a*) of the fermented leaves experienced slight changes, while the b* value representing the yellow-blue spectrum continued to decrease. The "brown stain" of the fermented leaves intensified, leading to a decline in the sensory quality of the black tea.

6. Performance Evoluation
In order to signify the performance of the algorithm developed for segmentation of color change prediction, the performance is measured using the metrics—such as sensitivity, specificity, dicecoefficient, jacquard similarity and accuracy. The results obtained out of the proposed method is equated with the metrics measured with the existing method, such as Graphcut method and FRFCM.

Accuracy
The metric which define show accurate a system can predict is measured by Accuracy.Higher the value of accuracy the model is said to be more robust and performs better.Accuracycan beobtained by using the following equation (3)

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \rightarrow (3)$$

Here True and negative is TN, True and positive is TP, False and negative FN andFalse and positive FP. The Hypothesis of the segmentation is to find the fermented color change region from the fermentation process.
True Positive (TP) defines the ratio of Correctly recognized as Fermented color change prediction ratio. False Positive (FP) is the ratio of incorrectly recognized as Fermented color change. True Negative (TN) is the ratio of correctly recognized as under-fermented color region. False Negative(FP)is the ratio of incorrectly recognized as under-fermented color region

$$\text{Sensitivity} = \frac{TP}{TP + FN} \dashrightarrow (4)$$

$$\text{Specificity} = \frac{TN}{TP + FN} \rightarrow (5)$$

$$\text{Dice coefficient} = \frac{2|X \cap Y|}{|X| + |Y|} \dashrightarrow (6)$$

$$\text{Jaccard Similarity} = \frac{A \cap B}{|A \cup B|} \dashrightarrow (7)$$

Table 2. Comparison of Metrics

Test Image	Method	Sensitivity	Specificity	DC	JS	Accuracy
Image1	**CTFS**	**0.985**	**0.974**	**0.986**	**0.973**	**98.73**
	Graph-cut	0.773	0.755	0.784	0.784	74.47
	FRFCM	0.542	0.787	0.555	0.535	64.27
Image2	**CTFS**	**0.978**	**0.996**	**0.956**	**0.967**	**98.68**
	Graph-cut	0.723	0.731	0.776	0.744	73.43
	FRFCM	0.578	0.543	0.589	0.567	64.21
Image3	**CTFS**	**0.985**	**0.978**	**0.989**	**0.987**	**98.65**
	Graph-cut	0.783	0.679	0.756	0.687	74.43
	FRFCM	0.556	0.556	0.598	0.557	64.21
Image 4	**CTFS**	**0.995**	**0.966**	**0.988**	**0.985**	**98.74**
	Graph-cut	0.773	0.689	0.766	0.677	74.53
	FRFCM	0.557	0.586	0.578	0.567	64.61
Image 5	**CTFS**	**0.983**	**0.987**	**0.977**	**0.987**	**98.55**
	Graph-cut	0.763	0.669	0.756	0.697	74.43
	FRFCM	0.566	0.546	0.578	0.567	64.11

Image-1 exhibits a sensitivity of 0.98, specificity of 0.97, Dice coefficient of 0.98, Jaccard Similarity coefficient of 0.97, and an accuracy of 98.73 for the proposed method, which surpasses Graph-cut (78.47) and FRFCM (78.27) in terms of accuracy. Similarly, in Image-2, the sensitivity is 0.97, specificity is 0.99, Dice coefficient is 0.95, Jaccard similarity is 0.96, and accuracy is 98.68, outperforming Graph-cut (73.43) and FRFCM (74.21) in accuracy. Image-3 showcases a sensitivity of 0.98, specificity of 0.97, Dice coefficient of 0.98, Jaccard similarity of 0.98, and an accuracy of 98.65, superior to Graph-cut (75.43) and FRFCM (75.21) in accuracy. Image-4 and Image-5 also demonstrate similar performance trends in sensitivity, specificity, Dice coefficient, Jaccard similarity, and accuracy, outperforming Graph-cut and FRFCM in accuracy.

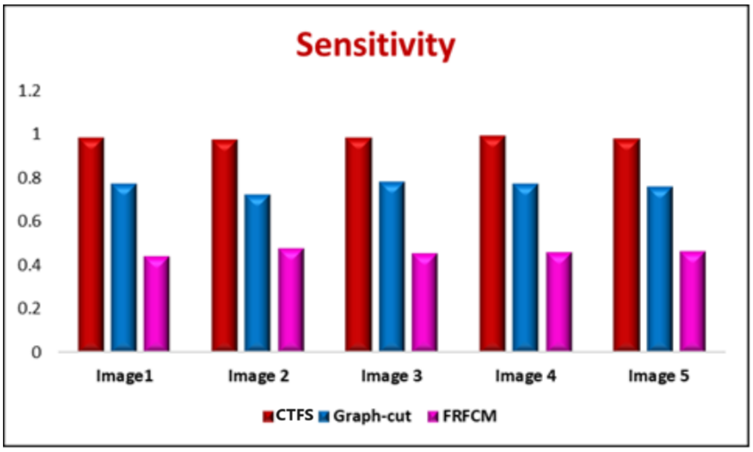

Figure 4. illustrates the Sensitivity Comparison of Segmentation Algorithms.

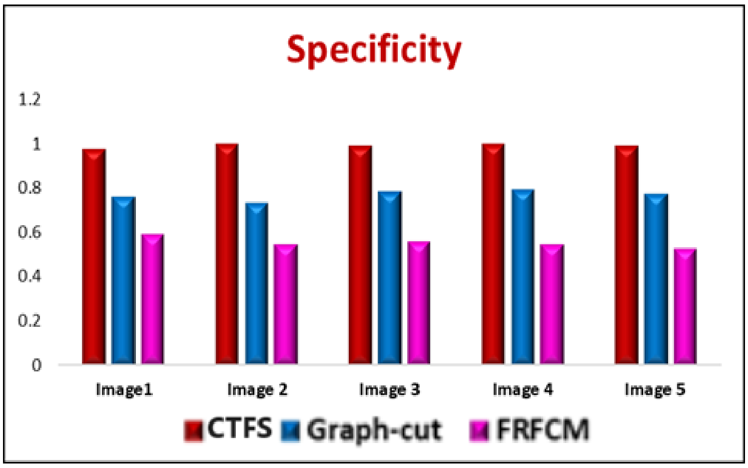

Figure 5. Comparison of Specificity of Segmentation Algorithms

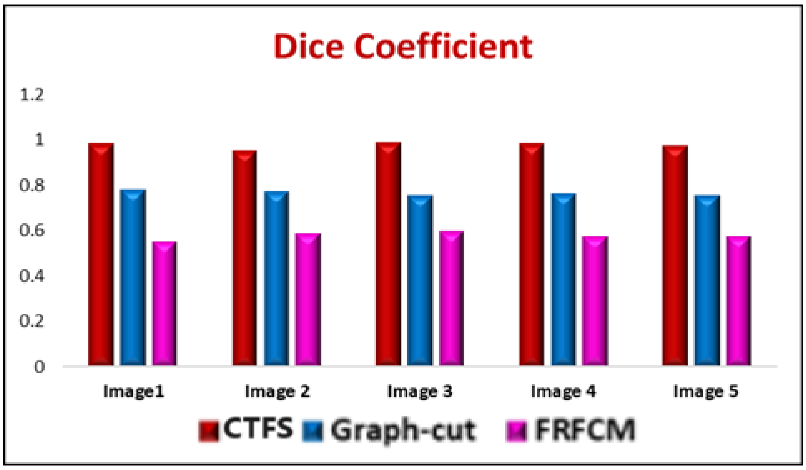

Figure 6. Comparison of Dice Coefficient of Segmentation Algorithms

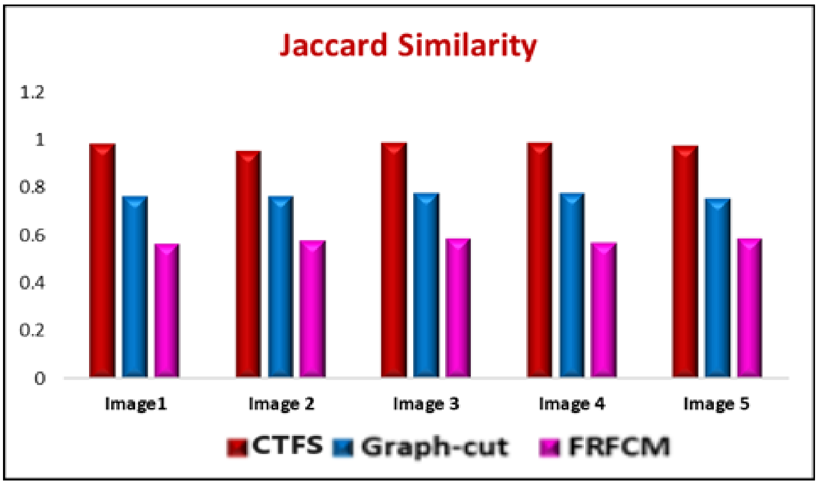

Figure 7. Comparison of Jaccard Similarity of Segmentation Algorithms

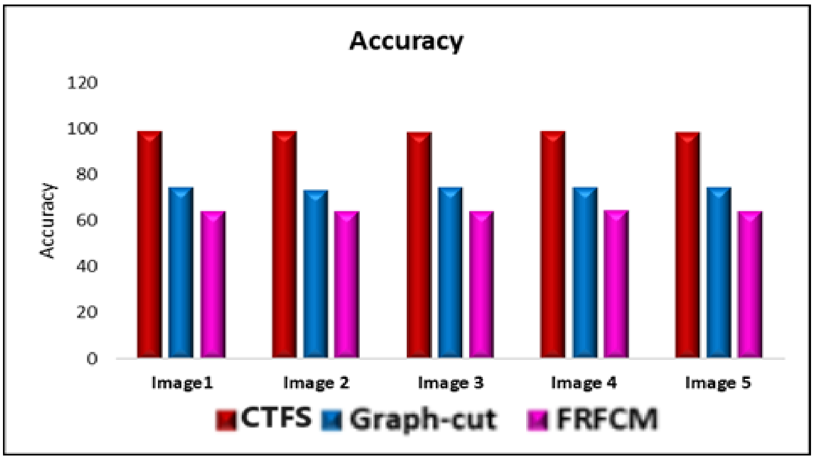

Figure 8. Comparison of Accuracy of Segmentation Algorithms

7. CONCLUSION

Utilizing machine vision technology and color change segmentation algorithms, this research developed a nondestructive and rapid quantitative testing method for assessing tea pigments and sensory quality indices during black tea fermentation. By performing spatial color conversion on images, the study identified nine color variables (R, G, B, H, S, V, L, a*, and b*) as characteristic parameters for evaluating fermentation quality. The research analyzed the change patterns, discrepancies, and correlations between image colors and quality indices. The findings indicate significant differences in color features and quality indices at various fermentation stages, while also highlighting significant correlations between them. The proposed method perfectly identified the fermentation color change and time. The proposed method is compared with performance metrices also. The proposed method scored high accuracy value than other existing method.

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