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CURRENT CHALLENGES, AND FUTURE OPPORTUNITIES FOR FERMENTED TEA LEAF SEGMENTATION, CLASSIFICATION, AND OPTIMIZATION

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ABSTRACT

Fermented tea leaves emerged as a significant agricultural commodity on the global scene. This type of product experiences segmentation, classification, and optimization due to the different textures, different stages of fermentation, and environmental influences. The article reviews the progresses and limitations made by automatic systems in the realm of image-based analysis of fermented tea leaves, machine learning algorithms, and optimization methods. The challenges of high segmentation accuracy in heterogeneous samples, robust classification among diverse tea varieties, and scaling of optimization strategies for quality enhancement are some key challenges. Apart from hybrid optimization algorithms designed to interpret the gap, future areas of opportunities that utilize deep learning and multimodal fusion. Highlights from different hyperspectral imaging approaches and AI-driven models providing quick solutions with high accuracy and cost-effectiveness.

Keywords: Fermented Tea Leaves, Image Segmentation, Classification Algorithms, Quality Optimization, Deep Learning, Hyperspectral Imaging, Agricultural Automation

1. INTRODUCTION

Tea ranks among the most consumed affordable drinks. Over 3 billion cups of tea are consumed daily by people. The prominence arises from the health benefits, such as helping to prevent breast cancer [1], skin cancer [2], colon cancer [3] neurodegenerative problems [4], and prostate cancer [5] along with many other ailments. Tea also impacts diabetes prevention and ramps up metabolism [6]. Due to the manufacturing process that teas are labelled as green, black, oolong, white, yellow, or compressed tea. Black tea accounts for some 70% of the total tea produced in the world [7]. People cherish the unique taste and strong aroma and health benefits. Pu-erh Kombucha and Myanmar's Laphet are teas that vastly different cultural roots and unique ways of fermentation [8]. These teas preserve traditions while satisfying the rising demand for functional and artisanal beverages.

When fermentation occurs, the chemical structure of tea leaves changes. This increases the levels of active components in fermented teas, such as antioxidants, probiotics, and flavours [9]. This attracted health-conscious individuals to prefer fermented tea more often. Maintaining a relatively consistent quality in tea is challenging. Such that variations in quality of tea may result from factors like environmental conditions, types of microbes, and length of time of tea fermentation [10].

One of the most challenging aspects of sorting and categorizing fermented tea on its various varieties [11]. The chemical structure of the tea leaves varies that undergo fermentation, which in turn creates a significant degree of variability in the texture and appearance, which adds to the confusion criteria to use and classify them. The other variables, such as the quality of the soil, the conditions of the weather, and the microbial species involved, further complicate the categorization process [12]. The traditional way of sorting and categorizing tea leaves is through visual inspection. This method tends to be highly subjective and often prone to errors [13]. For example, deep learning techniques, within a very short time, classify tea diseases through RGB and hyperspectral images, boasting remarkable levels of accuracy. In the same manner, machine vision systems have been developed for judging fermented black tea by studies examining colour and texture, with some researchers finding the methods to be perfectly accurate [14]. The flavours and nutritional benefits of the fermented tea leaves entirely down to an intricate balance of fermentation time, temperature, and various microbial species activity [15].

To overcoming the contemporary challenges of segmentation, classification, and optimization, a possibility transformation for the fermented tea leaf industry while contributing to sustainable food production and enhancement of traditional products [16]. Comprehensive reviews prompted research on such topics in tea industries with applications of computer vision and machine learning in critical stages such as cultivation, harvesting, and processing [17]. The insights reiterate the importance of encapsulating this upgraded technology for increased productivity and quality in tea production [18].

During fermentation, tea catechins undergo oxidation catalysed by enzymes like polyphenol oxidase and peroxidase, thereby giving rise to two primary groups of pigments: Theaflavins (TFs) and Thearubigins (TRs) [19]. TFs are responsible for the briskness, strength, and brightness of the tea infusion, while TRs give the red colour to both the tea leaves and infusion. Both TFs and TRs are key indicators of black tea quality [20]. Another group of pigments, Theabrownins (TBs), forms through the oxidation, polymerization, and coupling of polyphenols, TFs, and TRs. While TBs contribute to brownish tea, the buildup is associated with over-fermentation leading to dark and turbid infusions [21].

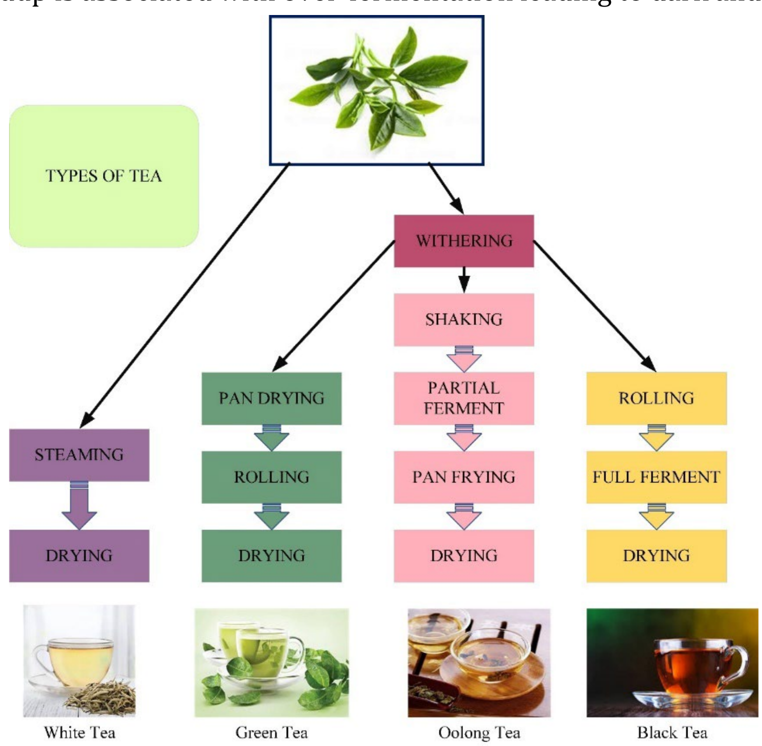

Figure 1: Processing pathways for different types of tea

Figure 1 is a presentation of the processing methods for different types of tea based on tea leaves are processed into white on the one hand, green tea, Oolong tea, and Black tea. The process begins with fresh tea leaves and grey into white tea processed with certain steps like steaming and drying; green tea cooked pan drying, rolling, and drying; partial fermentation withering, shaking, and pan-fried; the Black tea is withering, rolling, full fermentation, and then drying. Each pathway enables researchers to understand the unique combination of steps imparting the flavour, aroma, and appearance of the tea type.

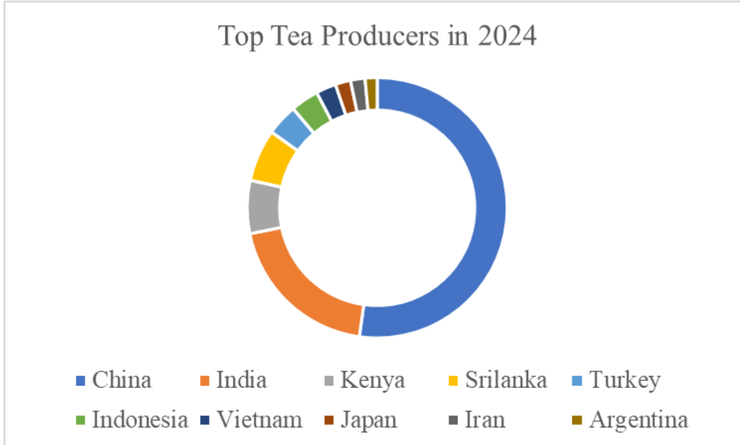

Figure 2: Global Tea Production by Country in 2024

Figure 2 showcasing the leading tea-producing countries and the relative contributions to global production. China, represented in blue, holds the largest share, emphasizing its dominance in tea production, followed by india as the second-largest producer. Kenya, Sri Lanka, and Turkey also make significant contributions, while countries like Indonesia, Vietnam, Japan, Iran, and Argentina, depicted in green, dark blue, and shades of brown, account for smaller portions.

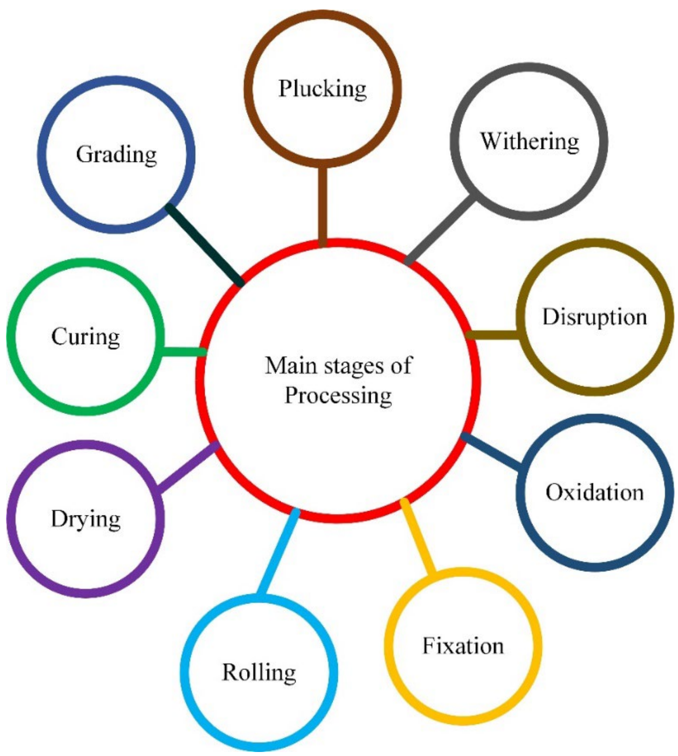

Figure 3: Key stages in tea processing

Figure 3 shows the key stages in tea production. These steps include Plucking, tea leaves are plucked, followed by Withering to reduce moisture. The leaves are disrupted to release important components, oxidized to develop flavour, and fixed to keep the desired properties. After rolling and drying, the product is cured to enhance flavour, grading sorts the product according to quality, guaranteeing a refined and high-quality tea.

2. OVERVIEW OF FERMENTED TEA LEAF PROCESSING

Fermented tea leaf processing consists of many stages: plucking, withering, rolling, and oxidation. This is important to bring flavour, aroma, and colour to the tea [22]. Based on enzymatic activity, the fermentation process varies with black or oolong teas; it varies with temperature, humidity, and quality of leaves [23].

2.1. TEA FERMENTATION PROCESS

Fermentation of tea refers to the complex biochemical and microbial transformation of tea leaves, which acts as a significant step during the processing of varieties of fermented tea such as Pu-erh, black tea, and Laphet [24]. Fermentation, unlike the enzymatic oxidation of green or partially fermented teas, is mostly dependent on microbial activity to impart changes in characteristics such as the chemical, physical, and sensory properties of tea leaves. The unfermented tea leaves are subjected to a controlled environment of temperature, humidity, and time for growth of microorganisms [25]. Different microorganisms, such as fungi-the Aspergillus spp., Penicillium spp., bacteria-the Lactobacillus spp., Acetobacter spp., etc., for polyphenols, amino acids, and carbohydrates in the tea leaves-produce bioactive compounds and flavour-enhancing metabolites [26]. This conversion increases the levels of theaflavins, thearubigins, and other secondary metabolites responsible for the colour, flavour, and health benefits of tea [27]. During fermentation, a lot of physical changes happen. Due to microbial action, leaves are usually dark, supple, and have a strong aroma [28]. The communities of microorganisms, intervals of fermentation, and environmental conditions like the availability of oxygen determine the quality of the final product [29].

2.2. IMPORTANCE OF SEGMENTATION AND CLASSIFICATION

To ensure high-quality production and consistency in fermented tea products, segmentation and classification play pivotal roles.

2.2.1. SEGMENTATION FOR UNIFORM PROCESSING

The size and shapes of tea leaves within the same batch vary, and vary in maturity. Segmentation into proper grades takes into account that leaves of different qualities and characteristics benefit from various processing conditions. Old, mature leaves perhaps have longer fermentation periods than younger tender leaves-both on the basis of maturity required for transformation being optimum. Segmentation becomes critical when mass production is employed to ensure uniformity and avoid waste due to the mixing of batches. One way to accelerate uniform processing is to employ advanced segmentation tools, such as computer vision systems, that automatically country-leaves according to dimensions, colour, and texture, leaving them basically clean [31].

2.2.2. CLASSIFICATION FOR QUALITY ASSURANCE

Classification helps categorize tea leaves by variety, grade, and fermentation stage; quality assurance is important for keeping conformity in batches along production and selling by available market standards. Poorly classified and arranged leaves, introduce off-flavours or unwanted appearance qualities which considerably decrease the marketability [32]. Such new classification methods apply machine learning and computer vision for high accuracy. For instance, hyperspectral imaging and deep learning algorithms is used to classify leaves based on differences in chemical and physical properties. The greater classification accuracy and real-time quality controlling of manufactured products, rendering them in large-scale production [33].

2.2.3. ENHANCING PROCESS OPTIMIZATION

Segmentation and classification directly influence the optimization of fermentation conditions. By knowing the needs of the different categories of leaves, producers able to alter the processes of fermentation to yield a consistent product. For instance, it has been found in research that segmented leaves would show more desirable compounds like theaflavins when more optimally applied parameters for microbial inoculation and fermentation have been used up and levels of undesirable microbial by-products have been reduced [34].

Table 1: Research gap for the overview of fermented tea leaves processing

Research Gap	Solution
Lack of Standardized Segmentation Criteria Across Varieties	Examine standardized segmentation, which takes dimensions, texture, and maturity into consideration. Additionally, more sophisticated machine learning models would increase the accuracy of segmentation.
Incomplete Classification Based on Chemical and Microbial Properties	Development of a classification system that use hyperspectral imaging integrated with the information obtained from chemical and microbial profiling to classify tea leaves according to the chemical composition and microbial community for improved fermentation technology.
Suboptimal Process Optimization Due to Limited Real-Time Adaptation	An introduction of systems for real-time monitoring and the feedback using IoT sensors, computer vision, and machine learning algorithms allow dynamically determining the conditions during fermentation.
Limited Understanding of the Interactions Between Microbial Communities and Leaf Characteristics	Explore the interplay of microbial species along with tea leaf composition. Microbiome profiling and data analytics would allow for optimizing fermentation protocols directed by such interactions.

3. SEGMENTATION TECHNIQUES

Segmentation is a notable approach to tea-leaf analysis and processing that function toward quality assurance and optimization for fermentation. Segmentation is the process of further classifying or processing tea leaves based on some established features like size, shape, colour, or texture, which is applied to partitioning of images or a physical batch of tea leaves. Advances in segmentation-and-the shift from the original manual approach to be more sophisticated fully automated systems-have definitely increased analysis efficiency concerning tea leaves.

3.1. TRADITIONAL APPROACHES

Manual & Semi-automatic methods are the only mode of tea leaf segmentation research in the beginning stages. These methods are based on simple image processing techniques as well as human in order to extract or segment out regions of interest in images taken from leaf samples.

1) **Thresholding:** Thresholding, the pixel intensity values separate them from tea leaves and background [37]. Learning one of the global threshold examples that separate light-coloured leaves from dark background. After that, improve accuracies by using other variants (e.g, Otsu's method for determining thresholds automatically [38] in order to segment better).
2) **Edges Detection Techniques:** Regarding Tea leaf edge detection to extract the edge of the tea leaves by pixel intensity changes in sharp places. Previously reported techniques are tailored for sharp edged leaves, failed with overlapping leaves, occlusions, and blur [39].
3) **Region Growing:** While region-growing techniques split leaves, which segregated pixels in neighbourhood that had same colour or texture attributes. This approach is good for uniform things such as tea leaves but computationally expensive and noisy for anything in real life [40].

3.2. COMPUTER VISION AND DEEP LEARNING APPROACHES

Computer vision and deep learning have tremendously revolutionized tea leaf segmentation with accurate, strong robustness & matured scaling. These approaches take advantage of advanced algorithms and models that are able to extract features directly from data, less human intervention required.

Feature-Based Computer Vision Techniques: In earlier stages of automation [41], segmentation is done through traditional computer vision methods Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) widely implemented. These algorithms take primitive features such as edges, corners and gradients in order to determine regions of interest. SIFT is able to reveal key points on leaves with success, and HOG did extract texture information to discriminate leaves from background [42]. However, overpowered by dynamic lighting, complex patterns, and tea leaf classes with significant intra-class variation.

Machine Learning Approaches: Supervised models Support Vector Machines (SVMs) and Random Forests introduced by machine learning. Manually features [43] are used in classification of pixel or image regions, these models as machine learning helped improving segmentation accuracy over classical methods feature generation is the biggest pinpoint of this peripheral and error prone heavy feature engineering [44].

Deep Learning Methods: Deep learning, in particular CNNs, completely altered image segmentation by having a feature extraction and learning from the raw data automatic with inferenced layers of each input. Effective deep learning approaches for tea leaf segmentation are:

U-Net: Image segmentation is among the most popular architectures of U-Net particularly for agricultural purposes. Encoder-decoder design helps in preserving spatial and contextual features from the network to provide very accurate segmentation. In tea leaf processing, the approach has been leveraged for de-blurring leaves that are overlapping and separate leaves from stems with accuracy [45].

Mask R-CNN

Mask R-CNN object detection model which inherits segmentation as a segment. This helps with instance segmentation individual leaves even in the overlapping cases are separated. Mask R-CNN showed state-of-the-art results on tough tea leaf datasets with classification and segmentation output back-to-back [46].

Fully Convolutional Networks (FCNs):

FCNs is a popular deep learning approach for semantic segmentation. FCNs, by replacing fully-connected layers with convolutional layers makes the model do pixel-wise classifications which is useful in tea leaf segmentation with fine details [47].

3.3. COMPARATIVE INSIGHTS

Although traditional methods such as thresholding and edge detection are basic and low computation, that cannot deal with the complexities including leaf overlap, variable illumination and leaf textures etc [48,49]. In contrast, deep learning methods such as U-Net and Mask R-CNN reach state-of-the-art performance with very high computational power due to large data sets. Coming from different environments these are more general and able to drop human segmentation with minimum intervention in an industrial setting [50,51].

Tea industries take an initiative to step towards automation and optimization of the quality control as well as fermentation process by segmenting in real-time with true precision using cutting edge computer vision and deep learning.

Table 2: Research gap for the segmentation techniques

Research Gap	Solution
Traditional segmentation methods are not very effective in dealing with overlapping leaves and occlusions.	Use deep learning models, such as Mask R-CNN and U-Net, to segment instances accurately, even when there are complicated structures and overlapping leaves.

Large-scale datasets cannot be efficiently processed using manual and traditional methods.	For pixel-level segmentation, use completely automated deep learning techniques like FCNs and DeepLab to handle big datasets with little assistance from humans.
Traditional techniques are sensitive to changes in the environment, such as changes in illumination.	In order to ensure consistent segmentation performance under a range of environmental variables, use robust deep learning models, like DeepLab, that extract multi-scale features.
Machine learning techniques' reliance on human feature extraction, which results in inefficiencies.	Use CNN-based architectures, such as U-Net, to increase accuracy and efficiency by automating feature extraction and learning straight from raw data.
Difficulty recognizing individual leaves in intricate patterns or differentiating leaves from stems.	To accurately separate individual leaves and differentiate leaves from stems in complex or overlapping patterns, use Mask R-CNN for instance segmentation.

The major research gaps in tea leaf segmentation as tabulated in table 2 include the inefficiencies of conventional methods used to handle overlapping leaves, large datasets, and environmental variations. Suggested solutions comprise the use of sophisticated deep learning methods like U-Net and Mask R-CNN, FCNs to automatically integrated feature extraction, segmentation accuracy improvement and the provision of robust performance in challenging scenarios and commercial settings.

4. CLASSIFICATION TECHNIQUES

Tea leaf fermentation is an essential step in the production of various types of tea, particularly in the processing of black and oolong teas [51]. During this stage, enzymatic and microbial actions lead to the transformation of the chemical composition and flavour profile of the tea leaves. The detailed explanation of the classification techniques in the context of tea leaf fermentation:

4.1. TRADITIONAL CLASSIFICATION METHODS

Traditional methods are historical in practice and have refined with the test of time. These methods are largely empirical and rely heavily on visual, sensory, and physical cues to decide the extent and quality of fermentation.

- **Visual Classification:** Tea leaves are grouped according to appearance after fermentation. Colour changes of the leaves from green to reddish-brown or dark brown reflect the level of fermentation [52].
- **Sensory Classification:** Tasting is the traditional method the experts use to test the flavour profile of tea using the sense perception after the fermentation process [53]. Completely fermented black tea generally tends to possess rich, full-bodied flavour characteristics while a more minimally fermented oolong has more floral or fruity profiles.
- **Oxidation and Moisture Content:** The level of oxidation and moisture contents are also used in the classification of tea fermentation. More robust flavour obtained from over-fermented leaves, while under-fermented leaves result in lighter teas with more vegetal notes [54].

4.2. ADVANCED MACHINE LEARNING TECHNIQUES

Machine learning techniques have indeed revolutionized tea leaf fermentation classification for a more objective and efficient method. Through algorithms, different features, ranging from chemical to visual and then fermentation conditions [55], define the patterns required for classification in tea.

Image Recognition: Computer vision techniques, like CNNs, analyse images of tea leaves at various stages of fermentation to classify the level of fermentation by detecting the minor changes in colour, texture, and shape of the leaf [56].

Spectroscopic Analysis: Machine learning algorithms analyse spectroscopic data acquired using techniques like near-infrared and UV-VIS in order to categorize tea leaves according to the chemical composition. Spectroscopic analysis detects any variation in content related to key compounds, and polyphenol content that indicate fermentation [57].

Data Fusion: Data fusion achieved with the integration of data from a multivariate source: image data, chemical analysis, environmental conditions for the fermentation process. This enhances the accuracy level of classification from machine learning models. Techniques in these lines include the use of Random Forest, SVM, and neural networks [58].

4.3. HYBRID APPROACHES

Hybrid approaches tend to take on the benefits of traditional techniques while incorporating newer techniques of machine learning to obtain more accurate classifications with robustness. Hybrid approach is helpful to combine strengths to analyse better about tea leaf fermentation [59].

- **Sensory-Machine Learning Hybrid:** Human specialists occasionally combine machine learning algorithms with sensory techniques. For instance, machine learning algorithms use sensory information, like flavour characteristics, as input features to more accurately classify the type of tea or forecast the degree of fermentation [60].
- **Feature Fusion:** A hybrid approach could be combining visual features of image recognition with chemical features from spectroscopy. The combination of these data types offers a better understanding of the fermentation process and gives a better classification performance [61].
- **Ensemble Methods:** Applying ensemble learning techniques such as boosting or bagging, multiple classifiers like decision trees or support vector machines are used to make predictions, the results are combined to boost accuracy. These methods assist in the reduction of bias levels of individual classifiers and also improve robustness [62].

4.4. CURRENT CHALLENGES IN CLASSIFICATION

While improvements in classification techniques have enhanced the accuracy and efficiency of tea leaf fermentation classification, there are still a number of challenges:

- **Data Quality and Labelling:** Accurate and labelled data is necessary for machine learning model training. Obtaining a complete dataset containing a variety of tea kinds, fermentation conditions, and expert-labelled data is challenging when it comes to tea leaf fermentation.
- **Complexity of Fermentation Process:** Some of the variables that determine the dynamic course of fermentation are temperature, humidity, and enzyme activity. Large data sets and careful feature selection are required to successfully model such complexity by applying machine learning techniques.
- **Environmental Variability:** Environmental factors are those that differ from batch to batch, from season to season, and from area to region. This generally affects the fermentation process. Environmental viability is hard to develop models that generalize effectively under a number of circumstances considering this heterogeneity.
- **Interpretability of Models:** Though very accurate, most machine learning models are black boxes. In tea production, the interpretability is important to understand the underlying factors that influence fermentation and for explaining the classification results to people who are not experts.
- **Real-Time Classification:** The challenge in the classification of real-time tea leaf fermentation, particularly in production, lies in acquiring data, processing, and decision-making in the shortest time possible. Therefore, real-time classification challenging to develop a machine learning model that is effective and efficient for real-time operation in the production environment.

Table 3: Research gap for the classification techniques

Research Gap	Solution
Insufficiently complete and standardized datasets for machine learning model training.	To enhance the training of models, create and manage a variety of well-labelled datasets that include different tea types, processing settings, and opinions of experts.
The difficulty of simulating dynamic fermentation processes that are impacted by several variables.	Use cutting-edge machine learning methods, such as deep learning combined with feature development, to model and depict the intricacy of the methods of fermentation.
Variability in the environment has an impact on the generalizability of the model and fermentation results.	Create reliable models of machine learning using domain adaption strategies to take batch-specific, seasonal, and regional variances into consideration.
Machine learning algorithms for classifying tea fermentation lack clarity.	Develop explainable AI (XAI) frameworks to identify key features influencing fermentation and provide insights to the tea production experts.
Real-time classification throughout the tea-making process presents difficulties.	To ensure real-time monitoring and classification, use edge computing and Internet of Things devices to provide quick data collection and processing.

Table 3 presents common obstacles in the application of machine learning on Fermenting Tea. Some of them are limited data, high-model complexity, shift in environmental states, complexity of the model, and issues with real-time classification. Explainable AI, advanced AI tools, curating of data diversity, strong model robustness, and IoT supported by edge computing for real-time analysis.

5. OPTIMIZATION TECHNIQUES

One of the key steps in tea processing especially for black tea and all oolong teas is the fermentation of tea leaves. The oxidation of polyphenols like catechins happens which affects the flavour, aroma and colour of the tea. The fermentation process of optimization and AI help with the optimization are given below,

5.1. TEA LEAF FERMENTATION PROCESS

The fermentation process involves:

Plucking and Initial Processing

- Plucking: Fresh tea leaves are picked from the tea plants.
- Withering: Leaves are spread out and left to wither under controlled temperature and humidity.

Rolling or Crushing

- After withering, the leaves are rolled or crushed to break open the cells, release the enzymes and juice that react with oxygen during fermentation. This step also helps in shaping the leaves.

Fermentation (Oxidation)

- The rolled leaves are left in a controlled environment for fermentation [64]. The main biochemical change during fermentation is the oxidation of polyphenolic compounds like catechins.
- Oxidation Mechanism: The enzyme polyphenol oxidase (PPO) catalyses the oxidation of catechins into theaflavins and thearubigins which contribute to the colour, flavour and aroma of the tea [65].
- Black tea is fully fermented so that is darker and stronger with more flavour.
- Oolong tea is partially fermented between black and green tea.

Drying

- Once the desired level of oxidation is reached the tea is dried to stop the fermentation and preserve the flavour and aroma. The drying process is done by hot air or pan firing [66].

5.2. OPTIMIZATION IN TEA PROCESSING

Fermenting the tea result in better tea with more flavour, aroma and colour. There are many factors that affect the fermentation process and optimization is to control these factors for consistency [67].

Factors to Optimize

- **Temperature:** The temperature of the fermentation room is key to controlling the enzymatic oxidation. 25°C to 30°C is ideal for fermentation.
- **Humidity:** Humidity also affects the fermentation process. High humidity means unwanted microbe growth, low humidity means slow oxidation.
- **Time:** The length of the fermentation process is another factor. Longer fermentation means stronger flavour and darker colour, shorter fermentation means more of the fresh floral character of the tea.
- **Leaf Quality:** The quality of the plucked leaves, size, maturity and integrity affects the fermentation process. Larger mature leaves oxidise slower [68].
- **Enzyme Activity:** The polyphenol oxidase enzyme is the key to the fermentation process. Enzyme activity is affected by leaf bruising, rolling and overall tea leaf quality [69].

Optimization Techniques

Traditional methods such as trial and error are used to optimize these factors. But modern technology offers a more accurate and efficient approach.

• **Data-driven approach:** By monitoring temperature, humidity and enzyme activity throughout the fermentation process. Operators adjust the environment in real time to maintain optimum conditions.

• **Advanced sensors and automation:** Sensors installed in the fermentation chamber monitor key parameters such as temperature, humidity, and oxygen levels. Automated systems

adjust these variables to maintain desired conditions [71].

5.3. ARTIFICIAL INTELLIGENCE (AI) IN TEA PROCESSING OPTIMIZATION

AI increase the efficiency of tea fermentation by using advanced algorithms and machine learning techniques to monitor, predict, and optimize the fermentation process.

Application of AI in tea fermentation

• **Predictive Modelling:** AI uses historical data and real-time sensor inputs to build predictive models that predict optimal fermentation times, temperatures, and humidity levels. This model helps operators achieve consistent products with minimal trial and error [73].

• **Machine Learning for Quality Control:** AI algorithms that analyse chemical composition, colour changes, and sensory data to predict the final quality of tea before drying. These insights help adjust the process during fermentation to ensure that tea meets the desired specifications [74].

• **Automation control system:** AI integrates with automation systems in tea factories to automatically adjust environmental conditions (e.g. temperature, humidity) during fermentation based on real-time data. This reduces human error and ensures that the fermentation process is as efficient and consistent as possible [75].

• **Pattern recognition:** AI analyses patterns in fermentation data using machine learning models. To find out the relationship between environmental factors and the final quality of tea. This increases process efficiency without the need for extensive intervention [76].

• **AI-powered sensory analysis:** AI is used to analyse sensory data such as taste, smell, and texture. By training a machine learning algorithm with a large dataset of tea properties, the AI learned to predict the sensory properties of tea based on fermentation conditions [77].

Table 4: Research gap for the optimization techniques

Research Gap	Solution
Inadequate knowledge of the ideal fermentation environment.	Optimize humidity, temperature, and fermenting time for quality consistency with real-time sensory information and AI-based forecasting.
Absence of accurate and timely fermentation factor monitoring.	During fermentation, use sophisticated sensors and automated systems to continuously check and modify important parameters including temperature, humidity, and oxygen levels.
Predicting the ultimate level of tea according to fermenting circumstances is challenging.	To forecast and modify fermentation for the desired tea quality, teach machine learning algorithms to evaluate chemical, visual, and sensory data.
Reliance on iterative techniques to optimize processes.	Utilizing both historical and current data, create data-driven strategies to maximize fermentation conditions with the least amount of physical labour.
Failure to effectively relate sensory characteristics to fermented conditions.	Enhance overall quality control by mapping the conditions of fermentation to sensory characteristics including flavour, fragrance, and texture using AI-driven sensory analysis.

Table 4 lists the main problems with the fermentation process. and offers automation and fixation using artificial intelligence. By using data-driven methods and state-of-the-art sensors These solutions attempt to improve quality control and efficiency by optimizing fermentation conditions. Improved real-time monitoring predict tea quality and reduce reliance on trial and error.

6. COMPARATIVE ANALYSIS

A comparative analysis of tea leaf fermentation methods highlights the pros and cons between manual, biochemical and AI methods, although manual methods depend on skilled sensory discrimination. But biochemical methods are highly accurate but resource intensive, and AI models have better scalability and real-time analysis. Although it requires a lot of computational resources and data quality.

6.1. MANUAL METHOD

Expert operators use the senses of sight, smell, taste, and touch to analyse and ferment hand tea. As tea experts, professionals usually evaluate the fermentation process [78]. The professional's talent and experience have a big impact on the precision of this method. Due to the lack of an automated method is subjective and is likely to vary from operator to operator [79]. For this reason, the computing efficiency is extremely low. Labour-intensive manual procedures are time-consuming and, because of reliance on human labour, have limited scalability. Because of this, production on an industrial scale is not feasible. Manual method is suitable for crafts or small operations [80] in terms of durability. Manual methods are inconsistent due to environmental factors and human fatigue, but experienced operators easily adapt to changes, such as unexpected changes in the appearance of leaves.

6.2. BIOCHEMICAL METHODS

Biochemical analysis uses scientific techniques such as high-performance liquid chromatography (HPLC), gas chromatography (GC) or mass spectrometry to track chemical changes (e.g. oxidation of polyphenols) during tea fermentation. This method provides high accuracy by providing accurate and unbiased chemical measurements. profile and reliable for quality control [81]. However, the computational efficiency is moderate. This is because analytics involves collecting, processing, and interpreting large amounts of data. This requires significant time and specialized equipment [82]. Scalability is suitable for processing into small to medium sized production batches. But there are limitations on costs and resources for continuous management. Real-time monitoring in large-scale operations poses difficulties in the robustness of biochemical methods in controlled laboratory environments that affected by sample contamination. Improper measurement or equipment malfunctioning in an industrial setting.

6.3. MACHINE LEARNING/AI METHODOLOGIES

Machine Learning (ML) and Artificial Intelligence (AI) algorithms to analyse data from sensors among fermentation monitoring parameters such as temperature, humidity, colour, odour, chemical changes, etc. After training a model that combines sensory and biochemical data to predict fermentation results. Computational performance is also excellent. Machine learning make possible to analyse and take the decisions in real time. A key advantage of ML/AI systems is the scalability. This is because multiple fermentation units that are easily monitored simultaneously and adapted to industrial-scale operations. Robustly trained models reliably even under environmental changes. Although it may face challenges on a regular basis in addition to updating training data.

Table 5: Comparison of tea quality assessment methods

Criteria	Manual Method	Biochemical Method	Machine Learning/AI Method
Accuracy	Moderate; depends on practitioner skill and prone to subjectivity.	High; precise measurement of chemical profiles.	Very high; integrates sensory and chemical data with sufficient training.
Computational Efficiency	Very low; time-intensive and labor-dependent.	Moderate; requires time and specialized equipment for processing data.	High; real-time or near-real-time analysis after training.
Scalability	Low; suitable only for small-scale, artisanal production.	Moderate; suited for batch processes but not continuous large-scale operations.	High; suitable for large-scale and industrial production.
Robustness	Low; inconsistent due to environmental factors and human variability.	High in controlled lab environments but sensitive to contamination or errors.	High; adaptable to variability but depends on data quality and regular updates.

Table 5 contrasts three methods manual, biochemical, and machine learning/artificial intelligence based on robustness, scalability, accuracy, and computational economy. It emphasizes machine learning and AI are superior to manual approaches in terms of accuracy, scalability, and flexibility, whereas biochemical processes strike a balance between accuracy and moderate scalability.

Table 6: Research gap for the comparative analysis of fermented tea

Research Gap	Solution
Limited scalability and consistency of manual tea fermentation methods.	Develop AI-based systems to enhance scalability and real-time monitoring while reducing human dependency and variability.
Resource-intensive and slow biochemical analysis for monitoring fermentation.	Integrate AI and sensor-based technologies for efficient, real-time analysis and decision-making.

Lack of robust methods to handle variability in fermentation conditions across scales.	Use ML algorithms trained on diverse datasets to improve adaptability and accuracy in industrial-scale operations.

The main obstacles to tea fermentation are listed in table 6 and include unpredictability between scales, scalability constraints, and inefficiencies in biochemical analysis. To increase scalability, efficiency, and adaptability in manufacturing processes, it suggests AI-based solutions such as machine learning, sensor integration, and real-time monitoring.

7. CHALLENGES IN CURRENT RESEARCH

Current research into tea leaf fermentation faces challenges such as fluctuating environmental conditions and the complexity of real-world variables such as raw material diversity. This complicates process standardization. Including high computational requirements for advanced models and limited access to the resources.

1) **Complexity in Real Situation:** Tea fermentation research faces significant challenges when transitioning from controlled laboratory settings to real-world applications. This is due to dynamic environmental factors such as fluctuating temperatures, humidity, oxygen levels and biochemical changes that affect complex process standardization [83]. Raw material variability Including differences in the composition of tea leaves. Growth, species and growing conditions This makes the development of universal methods or models more complex. This is because the interaction between these parts is difficult to fully capture [84].
2) **Computational resource limitations:** Computational tools used in tea fermentation research such as biochemical modelling and machine learning. This is often hampered by the high computational demands of advanced models such as deep learning. This requires significant computing power and large datasets in real-world situations. Relies on complex sensors and imaging systems Data mining creates enormous amounts of data that exceed the capabilities of traditional computer systems. The high costs associated with high performance computing (HPC), cloud services in developing. This is especially true when computational tasks are not supported by green energy sources. This creates an increased demand for more efficient and sustainable solutions.

Table 7: Research gap for the challenges in current research

Research Gap	Solution
Difficulty in standardizing tea fermentation processes due to fluctuating environmental conditions, raw material diversity, and interdisciplinary complexity.	Develop AI-driven adaptive systems and models that account for dynamic variables and integrate biochemistry, microbiology, and sensory data for real-world applications.
High computational demands and resource limitations for advanced models, hindering scalability and accessibility in developing regions.	Design lightweight, energy-efficient algorithms and promote the use of cost-effective computing infrastructure to enable broader adoption and sustainability.

Table 7 highlights challenges in standardizing tea fermentation due to environmental variability and resource-intensive computational models. It proposes AI-driven adaptive systems and energy-efficient algorithms to improve scalability, accessibility, and sustainability.

8. CONCLUSION

The segmentation, classification, and optimization of fermented tea leaves present a complex yet promising area of research and application. Current challenges, such as variability in raw materials, dynamic environmental conditions, computational resource limitations, and the interdisciplinary nature of fermentation processes, highlight the need for innovative solutions. Advances in technologies such as IoT-enabled monitoring, machine learning, and biochemical analysis provide significant opportunities for relief against these issues in terms of accuracy in control, real-time analysis of data, and models adapting to variability. Region-specific consumer preferences are embedded into optimization processes to improve market conformity and quality of the product. Future attempts should be toward making the algorithms more efficient, capturing data economically using cost-effective systems, and creating conditions that minimize the energy requirements of computations. The collaboration across various scientific disciplines, in addition to access to scalable technologies, that lead to the development of robust, efficient, and universally applicable solutions. With these challenges addressed, the field is well prepared to unlock new possibilities for improving the consistency, quality, and scalability of fermented tea production.

CONFLICT OF INTERESTS

None.

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