IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received May 13, 2021, accepted May 29, 2021, date of publication June 3, 2021, date of current version June 15, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3086038

Artificial Perception of the Beverages: An In-Depth Review of the Tea Sample

AMRUTA BAJIRAO PATIL, MRINAL RAHUL BACHUTE, AND KETAN KOTECHA
Electronics and Telecommunication Engineering Department, Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University) (SIU), Pune 412115, India

Corresponding authors: Mrinal Rahul Bachute (mrinal.bachute@sitpune.edu.in) and Ketan Kotecha (director@sitpune.edu.in)

ABSTRACT India is the second-largest tea producer and consumer in the world after China. In 2017, the Indian tea market size accounted for 130 billion Indian rupees. An estimated global tea market size was at USD 13.31 billion in 2019, and the expected compound annual growth rate is 5.5% up to the year 2025. India can grab the worth tea market size globally by making market strategies with AI and ML-based demonstrations for the unique identity of tea flavor. Conventional instruments available are not handy, time-consuming and require a skilled person to operate. The tea attributes should be digitally recognizable before purchase from the consumer's perspective, significantly enlarging the tea market circle. In the paper, a comprehensive review about an artificial perception of tea has been discussed. Three major attributes of the tea sample, its taste, smell, and color, are under consideration. With the help of various sensors, the attributes of liquefied tea samples had got converted into their digital signature. By analyzing the correlation of them with the pattern recognition, their classification had been done. The electronic feature fusion of tea liquor attributes may cause handling issues with the formation of redundant data. So this paper explains the method and guidelines of applying specific filters which remove the redundant data. The constructive sample data can establish the decision matrix for correlation. With the established decision matrix, précised test prediction can be achieved for the tea sample based on correlation and regression. The limitations and glitches of the conventional instruments for an artificial perception have been discussed in-depth for possible improvement. The paper ends with a bibliometric analysis of the topic "artificial taste perception of tea," which had derived from the standard repository of Web of Science. The bibliometric analysis is very useful to showcase the current research trends in the artificial taste perception of tea.

INDEX TERMS Artificial intelligence (AI), machine learning (ML), pattern recognition, e-tongue, e-nose, principal component analysis (PCA), artificial neural network (ANN), peak signal to noise ratio (PSNR), bibliometric analysis.

I. INTRODUCTION

Due to long and fast working hours, people use ready-made food and drink products of various brands. Assurance of quality, safety, and taste uniformity of such food and drink products are essential as such products, can directly affect human health and safety when they get contaminated. The problems like contamination with beverages had found frequently, which were triggered by economical benefits. An urge for human health awareness and its safety leads to early warning for such contamination cases, and it is possible with artificial intelligence. The property of the tongue to analyze and segregate various taste patterns can be artificially formed using sensors and programming. The programmed hardware discriminates various tastes and the taste patterns of a single sample with different concentrations. Artificial intelligence is very much helpful; to get early intimation about food-drink products; before its sale and consumption, with various types of monitoring such as - whether the beverage is alcoholic or non-alcoholic, pure or impure, aging flavor analysis of beverages, and also measures the effect of process control variables for establishing devotion to government standards.

Worldwide, water, milk and tea are the widely consumed traditional drinks with various health benefits. Initially, water exists in nature in pure form, but now with the increment in demand due to the day by day increase in population and

The associate editor coordinating the review of this manuscript and approving it for publication was Charith Abhayaratne.

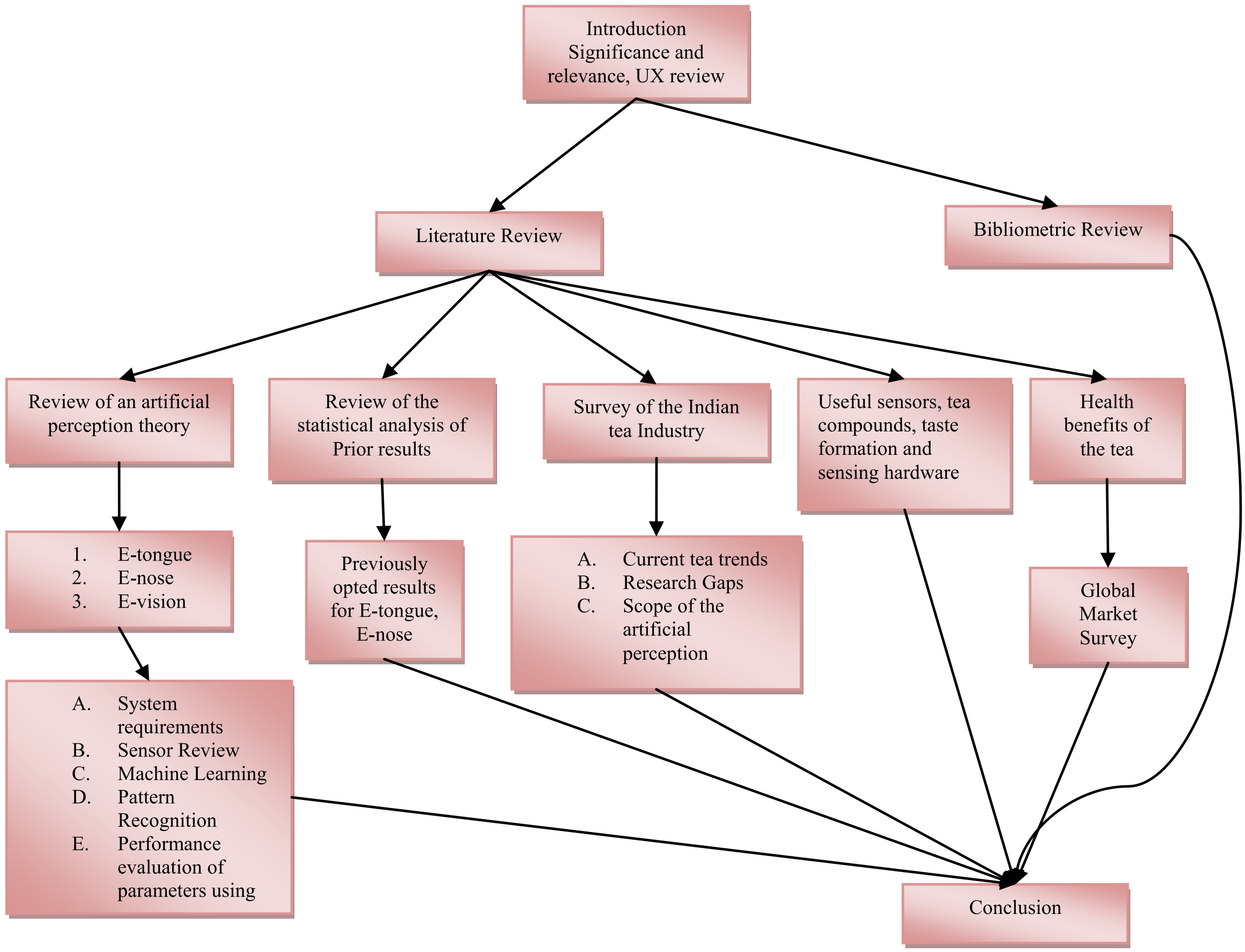


FIGURE 1. Outline of the paper.

added pollution, the water supply becomes narrow and gets contaminated. The government and municipal corporations have formed water storage, filtering and processing units. The government needs and forms water resource quality monitoring and assures its safety for people with national revenue.

Due to abundant nutrients, milk is supreme food for human beings. In the milk industry- supply chain, to get more profit; some common malpractices and frauds are extensively and gradually spreading; such as additions of water, sugar, milk from other species, harmful chemicals, and detergents-soaps to increase its quantity, weight and fat percentage. Also, preservatives have been used to increase the shelf life of food and beverage products. Detection of such malpractices and overdose of preservatives with artificial perception is very much required; as in metro cities, infants are dependent on packet milk. State and central government food agencies have regularly keep watch on food and drink industries. After safety tests, these agencies provide certification to the food and drink products; without proper government certification, these products must not be sold into the market.

Tea is the worldwide most popular hot beverage. Today cultivation of tea has spread everywhere in the world. It is a strong economical asset of an agricultural commodity like China, India. As India is the second-largest producer, exporter and consumer of tea, tea is the national agro-economical asset of India and its national drink. To knob huge tea production, automation and artificial intelligence are obligatory at various tea processing stages.

With the digitization and pattern recognition of main attributes of water, milk and tea or any other beverage, the artificial monitoring and grading can be unified and personalize as per the health history and requirement of human being, which turns into a reduction of their malpractices, economically triggered adulterations and dependency on manual test methods.

The outline of the paper is shown in figure 1.

User experience evaluation (UX) is the study to know customer's interest in any particular tea brand and get the motivation behind that interest. This kind of study is specifically carried out by monitoring and observing the targeted market for the tea sale. This kind of analysis is preferable to plan market strategies [125]. For any startup and business, some primary data is required as follows:

1) **Who are the customers?**
To know your customers is the most important and urgent need before the start of any business. This kind of survey set the target market and collects the customer data like their age range, interest in particular tea brand, motivations behind interest, like health consciousness, belly fat reduction, diabetic patient, routine diet, gender, product cost, availability, tea attributes like flavor, color, fragrance.
2) **Which kind of customers are there?**
Online customers and offline customers are available for tea.
Online customers are dependent on online reviews, offers, service time and experience of online purchase. Sometimes they are not aware of the options and buy the products already known to them. They do not think about trial of the new product as the purchase is online. The other types of customers are offline, they enjoy the trial of variety, but if they are specific in motivation, they fix the tea brand with a little trial.

In India, 80% of the tea produced is consumed within the country, as per the annual report of the Tea board of India. The customer age range is specifically from 18 to 60 years. Tea is more familiar and popular in India than Coffee.

The Executive summary of the study on domestic consumption of tea in India explains the domestic consumption evaluation had done in two phases-The pilots and Pan-India Survey.

1. For Pilot testing-Questionnaires had prepared by the Tea board of India concerning industry bodies, tea associates, and major stakeholders in the tea industry. This method is used to collect the response from consumers, Institutions and trade channel partners.

2. For Pan-India survey- This testing attentive to the sample household across urban and rural India and socio-cultural regions and classes. The survey was carried out with dedicated questions to capture the key trends, patterns, and purchase behavior.

3. Direct Interviews were planned with focus group discussion to gain qualitative insights from users and associates.

4. Findings from the survey- The Tea consumption In India is skewed towards North and West India. North states ∼32% whereas in West ∼31% tea consumption had accounted. According to the report, relatively low consumption had occurred at North East ∼19% while at south region it was ∼18%.

5. Consumption pattern-64% Population in India is a tea-drinking population. Over 80% population drinks tea before breakfast with milk and sugar. Population ∼80% preferred packet tea as it brands quality. More than 70% population purchases tea from stores.

II. REVIEW OF ARTIFICIAL PERCEPTION- E-TONGUE, E-NOSE, E-VISION AND FEATURE FUSION OF ATTRIBUTES

A few decades back, the two problems were very general in food-drink industries, first was low objectivity of taste, and the second was its low reproducibility in processed food [17], [18], [22]–[27]. Initial taste sensors were designed for these objectives. The human tongue cannot identify the chemical substance present in the food; rather, it identifies the set of similar tastes. The human brain understands and restores that response as a discrete experience gained against the received taste senses. Likewise, the artificial sense is about a group of similar taste responses created due to chemical substances lies in the same group. For example, sweet taste identifies by the presence of sugar, which can be glucose, sucrose, fructose or a combination of those, and umami comes from amino acid glutamate [16]–[21], [28] etc.

Kiyoshi Toko, Professor at Kyushu University in Fukuoka, Japan, has made e-tongue from polymer membrane consisting of specific lipids and reacts to specific elements that create food tastes. The different lipid membranes had mounted on the plastic hose and connected to electrodes; plastic hose drowned into liquid under test, which generated the countable potential difference and was observed due to reaction between liquid molecules and membrane. This response is further used to create pattern characteristics for the specific taste under analysis.

Physicist Seunghun Hong of Seoul National University in South Korea had created carbon nano-tubes transistors coated with the protein found in human taste receptors for the detection of bitterness. This taste device is extremely wise to electrical changes causes due to bitterness and reacts exactly like the human tongue. Kenneth Suslick, a chemist and materials scientist at the University of Illinois at Urbana-Champaign, had developed the taste sensing system on the color-changing property of chemicals. Some of the chemicals had changed the color due to reaction with specific pigments of liquids; on that basis, they identified the taste. Chemist Eric Anslyn of the University of Texas at Austin and his colleague at the University of California, Davis, Anslyn had developed a taste sensing system to detect the toxic drug in the wine. The toxic drug may get created in wine due to the addition of different juice or due to aging of some elements in wine, or due to high concentration of some elements. The test system is based on nuclear magnetic resonance (NMR) spectroscopy [13].

In one more experiment, the taste sensor used was a sensor array of six different metallic electrodes; it was sensing specific elements from the sample and limited to electrical detection of the sample. These taste sensors were not optimum and global as their prediction was variable and dependent on the presence of specific elements [1]. The expanded requirement of taste perception; to overall response sensitivity, which does remain to the specific element of the sample, and another need was; data received from the sensory mechanism should correctly analyze with indeed statistical implication. With that vision, the electronic tongue was designed based on Alpha Mos taste sensors, using principal component analysis (PCA) and artificial neural network (ANN). E-tongue was now capable enough to discriminate basic five tastes of the liquid sample, and accordingly, it can classify the beverage with the commercial taste sensor TS-5000Z. The objective decided and achieved with E-tongue was consistent taste response. A threshold of an artificial taste perceived by an e-tongue and the human tongue should have matched; a correctly defined unit of information from the sensor to an electrical signal and sensor must sense continuous interaction between taste substances. The portable E-tongue using a microprocessor and signal conditioning unit with five electrodes had been described with many practical applications [1].

The electronic tongue is the analytical instrument consisting of an array of chemical sensors which are low selective, highly stable and high cross-sensitive to another element of the sample with specific pattern recognition or multivariate calibration for data processing. The physical, chemical and biological properties of test samples had converted into electrical data, and suitable data processing was applied to grade the sample's taste. A wide variety of sensors for E-tongue had been discussed like electrochemical-voltammetric, impedimetric, amperometric through gravimetric to optical sensors such as absorbance, luminescence, reflectance etc. Sensors were applied with different environments for a liquid sample and gaseous sample of the same drink; with a fusion of the data, the grading would be done. As data redundancy problem occurs with PCA, which may create misclassification; so, the PCA method was not applied everywhere. Instead, one-to-one sensor plot results in matrix form had drawn; when the three out of four sensors were having the same response, it confirmed the grade based on that analysis. There are few commercial solutions available for taste perception, such as the TS-5000Z taste sensing system, Intelligent Sensor Technology Inc., Jap, Astree II (Alpha MOS, Toulouse, France, Multiarray Chemical Sensor(McScience Inc., Suwon, Korea), and Sensor System (St. Petersburg, Russia). Several sample applications were discussed with their major attributes and attempted artificial taste perception systems. With the limited availability of non-invasive chemical sensors and biosensors, the creativity and innovation in E-tongue are also limited. Still, the analytics or information can be possible to derive several ways that can create variation in probabilities of solution [8], [14].

Water is the natural resource, universal solvent and crucial need for a human being. It always gets contaminated with impurities, of which some are due to natural causes and some of due to human-made pollution. Artificial impurities are hazardous for human lives as they cause various health issues and sometimes become so critical and put human lives into chaos. The system had established to detect impurities in water based on E-tongue 36-37] and E-nose [38], [39] with additive wavelet transform and homomorphism image processing. This electronic sensor system could extract the required information from a water sample. An image enhancement technique is very useful to advance the visual quality of an image. Detection of water impurity said above had used the infrared image processing. Infrared image processing was consists of large black areas and small details. An additive wavelet transform is used as a decomposition algorithm to separate these small image information details into several frequency sub-bands. In addition, homomorphic enhancement algorithms had used for transforming these small details to illumination, and reflectance components and then reflectance components are amplified, showing the details correctly. With this at the end, infrared image reconstruction was performed using MATLAB tool, Peak Signal to Noise Ratio (PSNR) was determined. For Pure water, PSNR is very high (62.59dB), and in the water, with increasing % impurities, PSNR became lower down [6], [122].

In developing and underdeveloped countries, malpractices like milk adulterations are going on because of financial greediness and insufficient supply for the rising population. On a primary basis, the impurities in milk were detected by chemical, tests but milk's chemical properties had changed. Only one kind of milk impurity could detect with a single chemical test; it means separate tests were required for other impurities with separate milk samples. A combination of chemical tests for two or more impurities is not possible. These common techniques were not always convenient and accessible. The fraud rant practices are exponentially rising in diverse ways. To solve this issue, the scientific communities and regulatory authorities must bring a transparent and automated adulteration monitoring system [7].

The sense of smell is the inspiration of electronic-nose (E-nose). Automatic detection, identification, and classification of smell are complicated tasks as smells are created naturally by air and the surrounding environment. With the combination of substances; sometimes new odor may get created which is stronger than initial odors of discrete substances in the mixture, sometimes due to counter-reaction of the substances new odor may get created which is having different concentration, Sometimes masking of one pleasant odor had done by an unpleasant odor. Capturing various odors by an array of the sensor, digitalizing the extracted data information, and applying pattern recognition or machine learning (ML) algorithm the quality analysis of odor is possible. Description of E-nose seems analogical to the human nose, a neural system of body and decision-making ability of the human brain. The hardware must be implemented for odor sensation, its digitization, and software for its identification and classification. In the E-nose, the hardware part consists of a sensor array, signal conditioning unit, and software part containing the necessary processor with associated processing – storage unit and programming software for the odor classification.

A. SYSTEM REQUIREMENTS FOR ARTIFICIAL TASTE/ODOR/COLOR PERCEPTION

The three major attributes of beverages are their flavors, smells, and colors [41]–[43]. The flavors, smells and colors of

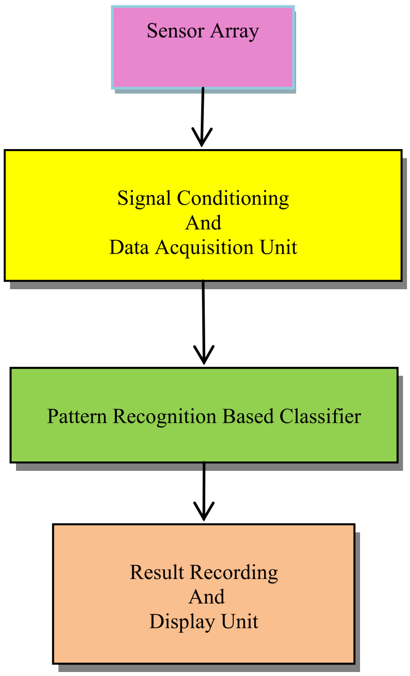


FIGURE 2. System requirements for artificial taste/odor/color perception.

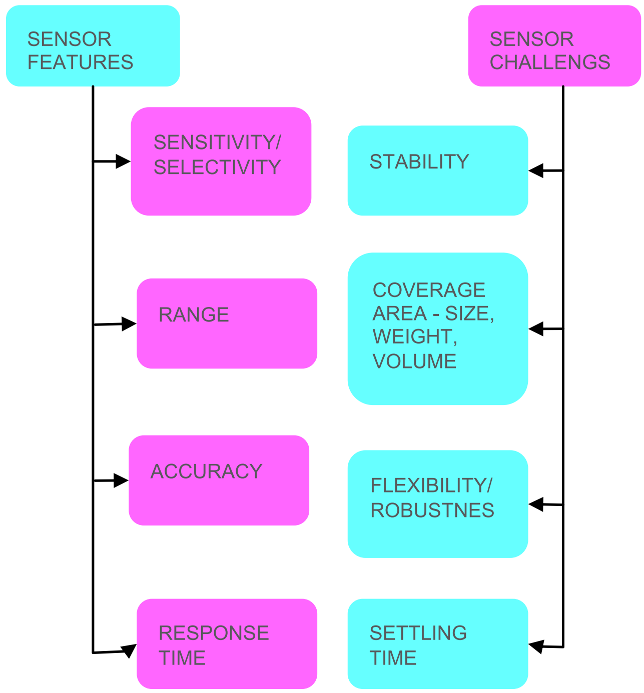


FIGURE 3. Sensors features and challenges.

beverages are created due to biochemical compounds present in their liquor, and they vary according to the proportion of compounds. For flavor detection, biochemical electrode sensors are useful, whereas gas sensors are required for odor detection. For color detection, color sensors based on the RGB principle, digital cameras with image processing techniques have reported satisfactory.

For a complete analysis of any beverage, it is necessary to correlate all the above-said attributes with a statistical model. The design of such a statistical model is the most challenging task as the sensor's sensitivity, repeatability, and stability are the most critical features to control properly. Some common problems that have been reported in beverage industries are liquor impurities; shelf an artificial perception is required to maintain the quality process, as shown in figure 2.

B. SENSOR REVIEW

Sensor systems detect specific taste, aroma and color only after relies on the chemical. Initially, the digital dataset of various attributes has to be created for their libraries. The sensor used in E-tongue, E-nose and E-vision should possess the general properties such as–

1) high selectivity and sensitivity with less response time to a specific attribute

2) high stability for the result measurement

3) high resistance to other aromas to distinguish other aromas

4) insensitive to temperature and humidity

5) small in size, cheaper, reusable.

Metal oxide sensors (MOS), conducting polymer sensors (CP), quartz crystal microbalance (QCM) sensor, acoustic wave sensors (AW), electrochemical (EC) sensors, catalytic bed sensor (CB), optical sensors, photoionization detector (PID) these many sensors are useful to identify the odors in various applications; of which MOS is commonly used sensor, suitable for variety of gases, operated with maximum value of temperature and requires maximum power consumption and present with two types n-mos and p-mos. The reaction between oxygen molecules of air and the surface of the n-mos sensor results in free electrons are trapped creates potential barriers between grains that inhibit the carrier mobility that generates large resistance areas. P-mos sensors create holes by the oxidation process.MOS detection sensor range is 5 to 500ppm, and it is mainly used for indoor-outdoor beverage monitoring. Conducting polymer sensors are used mainly in medical and pharmaceutical applications. Resistance of the polymer sensor changes with the detection of specific odor when the reaction happens with the chemical. QCM sensor determines small surface variations by measuring frequency changes.

Acoustic sensors work like QCM. In electrochemical sensors quantity of gas is measured by the flow of current due to reaction. Optical sensors detect odor based on fluorescent colors emitted by various gases. Due to the ionization of gases using ultraviolet light, formed ions create an electric current detected by the PID sensor [11]. Figure 3 is about features and challenges of sensors.

C. MACHINE LEARNING

Machine learning is a device's capability to learn independently from experience to make accurate predictions for upcoming events of similar types. It is suitable for classification problems like character or attributes recognition, feature

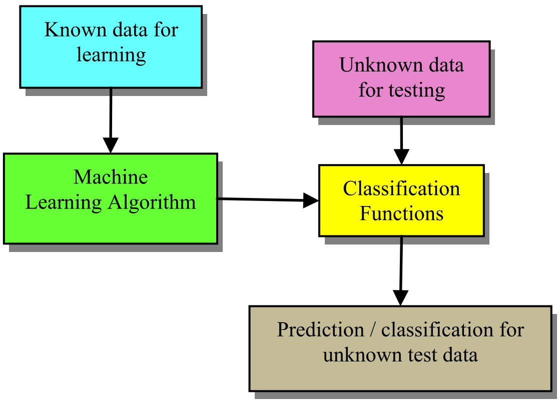


FIGURE 4. The common perception of machine learning.

detection, text categorization, bioinformatics, and business analysis. It is a software program to search outcome expected from the hypothesis.

Figure 4 is about the conceptual understanding of machine learning. In 1st step, training data was available to machine learning programs as input with classification functions. In the 2nd step, the unknown data for testing is given to the classifier. Now classifier classifies the unknown test data based on its experience gained by the training data model. Machine learning (ML) is the application of artificial intelligence that enables the system to learn and improve from experience without being explicitly programmed. There are four groups of ML algorithm as described in figure 5,

1) **Supervised Learning**
2) **Semi-supervised Learning**
3) **Unsupervised Learning**
4) **Reinforcement Learning.**

The dataset in supervised learning is consists of known inputs and known outputs provided to the ML algorithm, with that robust mapping model is obtained.

This model is useful to classify new upcoming data. Grading using regression model and prediction can be easily done with the help of supervised learning, as described in figure 6.

The semi-supervised model contains both known and unknown data; with the help of known data, the unknown can be classified; this is basically to handle large unknown data. Model is useful for the reduction of the computational issues that rescue time. Unsupervised learning has only inputs, based on a given dataset, the pattern is recognized. Unsupervised learning can handle clustering, association, and dimensionality reduction problems. Reinforcement learning is the flexible approach that learns from previous knowledge and routinely implies the performance of upcoming data [11]. Machine learning is a technique that allows the computer to learn through various designing algorithms.

The branch streamed from performance, and computational analysis of machine learning algorithm is known as a computational learning theory. For the training of neural networks and decision trees, supervised learning algorithms are very useful. Network classification error estimation and expert opinion to decide the most informative data features are the two basic requirements in supervised learning. If these requirements are not available or not applicable for such cases, all relevant features have been measured to check impact. Then the most impactful features get isolated in the form of result. This method of feature isolation is called "brute force," but with this method, the risk factor is very high and is generated due to missing feature values, gaps and noises [123].

Overfitting function occurs in machine learning algorithms because of special cases. Overfitting functions create huge complexity, data memorizing and are less impactful for most general cases. The penalty sometimes is very high with data overfitting. It is better to avoid such special cases, which may lead to over-fitting of data function, and it is only possible with intuition and expertly data handling.

The supervised and semi-supervised learning approaches were suitable in the proposed algorithm design and, hence, discussed in-depth.

Unsupervised learning is much complicated. The categorization and rules have not been discussed and provided to the process agents directly by offering rewards and giving additional benefit to make a decision framework suitable to a problem is acquired and implemented. Possible challenges involved in model selection discussed in figure 7.

Table 1 is about the list of acronyms and their meanings that are used throughout this paper.

D. PATTERN RECOGNITION

Pattern recognition is required to identify the specific pattern generated by the dataset acquired. Principle component analysis (PCA) is a widely used unsupervised learning tool required to reduce dataset dimensionality linearly. The high dimension data is converted into low-dimension data, spanned by principal components of the largest variance in the original variables using PCA. Linear discriminant analysis (LDA) is a widely used supervised learning tool for linear dimensionality reduction. Support vector machine (SVM) is a supervised learning tool used for linear and nonlinear binary classification. It determines the best fitting function used for classification. Artificial neural network (ANN) is used with the machine learning framework. Cross-sensitivity is the interference of an unwanted smell or taste to desired smell or taste, which has to be detected as sometimes the unwanted features mislead the classification [11].

E. PERFORMANCE EVALUATION OF PARAMETERS IN MACHINE LEARNING

The confusion matrix is essential to put for evaluation parameters to find a system performance evaluation matrix. Figure 8 indicates the general confusion matrix in machine learning. The parameters like accuracy, sensitivity, precision and specificity have to be calculated for the prediction result based on True positive (TP), False positive (FP), False negative (FN) and True negative (TN) values.

Accuracy is the ratio of the number of correct test predictions to the total number of test input samples as shown in (1).

FIGURE 5. Machine learning approaches.

The idle accuracy value is 100%, which indicates no error in the predicted outcome.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{1}$$

Precision is the ratio of correct positive predictions to the total number of positive test input samples (2).It lies between 1.0 (for full precision) to 0.0 (for no precision).

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{2}$$

Sensitivity is the correctly determined actual positives test predictions as given in (3). The model that results in more than 90% sensitivity and specificity is the better practical model with good diagnostic ability

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{3}$$

Specificity is the correctly classified actual negatives test predictions as given in (4).

$$\text{Sensitivity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{4}$$

F1 score is the practical, useful measure in uneven class distribution, which balances precision and recall. The F1 score is the weighted average of both precision and recall. The F1 score should be one for idle performance.

$$\text{F1-score} = \frac{2^*(\text{Precision})^*(\text{sensitivity})}{(\text{Precision} + \text{Sensitivity})} \tag{5}$$

These statistical evaluation parameters are derived from the confusion matrix and are essential to assess the system model performance for the proposed objective. This analysis is very useful to re-correct and redirects the system for the said task for better performance.

III. REVIEW OF STATISTICAL ANALYSIS OF PRIOR RESULTS FOR TEA SAMPLE

The fusion of E-nose and E-tongue is established for tea quality estimation using the fuzzy neural network (FNN). The human tea tester grades the tea sample based on its attributes-taste, briskness, and astringency. Those grades are considered a standard reference, and the digitization of these graded samples has been used to form a known dataset to train

TABLE 1. Summary of important acronyms.

Acronyms	Meaning
E-tongue	Electronic Tongue
E-nose	Electronic Nose
PCA	Principal Component Analysis
ANN	Artificial Neural Network
Abd	Advanced biosensors for detection
PSNR	Peak Signal to Noise Ratio
ML	Machine Learning
MLR	Multiple Linear Regression
PLSR	Partial Least Square Regression
BPNN	Back Propagation Neural Network
NMR	Nuclear Magnetic Resonance
MOS	Metal Oxide Semiconductor Sensors
QCM	Quartz Crystal Microbalance Sensor
EC	Electrochemical Sensor
CB	Catalytic Bed Sensor
PID	Photo Ionization Detector
CP	Conducting Polymer Sensors
AW	Acoustic Wave Sensors
n-mos	N-channel metal oxide semiconductor
p-mos	P-channel metal oxide semiconductor
PID	Proportional Integral Derivative Control
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
FNN	Fuzzy Neural Network
LMBP	Levenberg-Marquardt Back Propagation training algorithm
RBF	Radial Basis Function neural network
MSE	Mean Squared Normalized Error
TQI	Tea Quality Index
pH	Power of hydrogen
GC	Gas Chromatography
HPLC	High-Performance Liquid Chromatography
ICP-MS/MS	Inductively Coupled Plasma Mass Spectrometry measures
FOM	Fractional Order Model
GUI	Graphic User Interface
SAPV	Small Amplitude Pulse Voltammetry
LAPV	Large Amplitude Pulse Voltammetry
DWT	Discrete Wavelet Transform
PN	Probabilistic Neural Network
FOTF	Fractional Order Transfer Functions
ARMA	Auto-Regressive Moving Average
CPE	Constant Phase Elements
WE	Working Electrodes
RE	Reference Electrode
CE	Counter Electrode
OFT	Optimum Fermentation Time
CHD	Coronary Heart Disease
QCL	Quality Control Laboratory
NABL	National Accreditation Board for testing and calibration Laboratories
ILAC	International Laboratory Accreditation Cooperation

the model. Fuzzy classifiers use fuzzy logic in the course of their training. The three classifiers are established to classify black tea

1) **E-nose**

2) **E-tongue**

3) **Fusion of E-tongue and E-nose,** and had applied on four grades of Indian tea. The 48 samples with four different grades had tested five times each for three individual classifiers, generated 240 sample measurements. E-nose had established with five MOS sensors from Figaro, and E-tongue had used with voltammetric electrodes [2].Medical health benefits of green tea are well known, so classification based on bitterness [29]–[35] and astringency had to be carried out with E-tongue, E-nose and classifier algorithms same described as previous, only with the difference is in classification algorithms. The three models are applied for

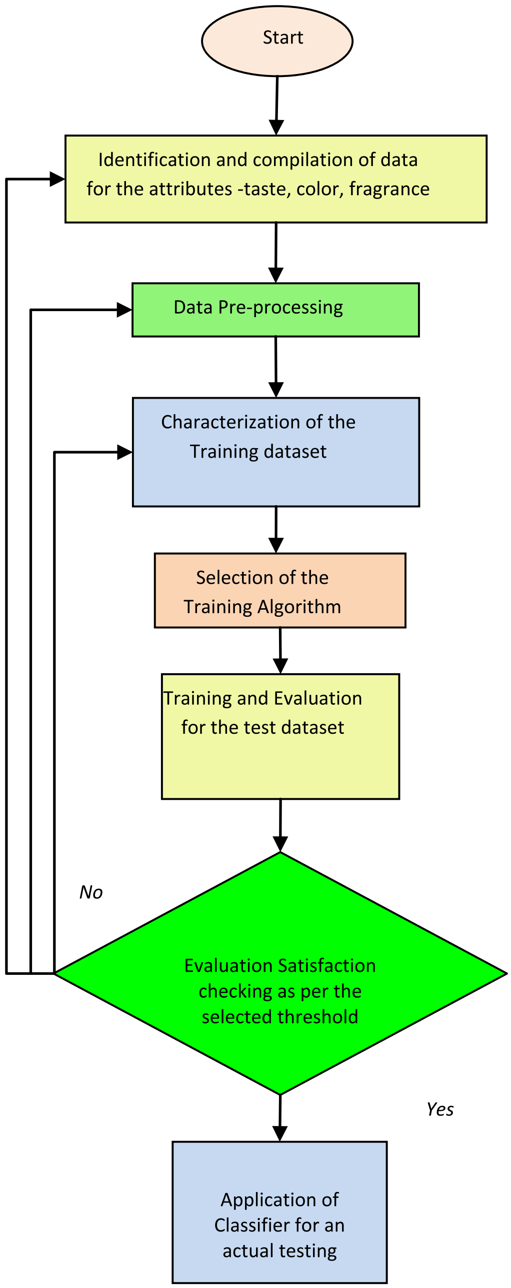


FIGURE 6. Supervised machine learning algorithm.

green tea classification – Multiple linear regression (MLR) [118]–[121], Partial least square regression (PLSR) and Back-propagation neural network (BPNN). BPNN is most effective and better, both in the training and testing phase [3].

It has high correlation coefficient (R); R = 0.98 for bitterness and R = 0.96 for astringency [3].

Tea quality prediction by Sparse modeling with E-tongue is established with sparse decomposition method. E-tongue hardware is moreover the same as we had discussed in previous cases. Still, the Sparse model is developed for signal matrix and resulting feature vector coefficients of the sparse model are treated as characteristic attributes of tea sample and used in both training and testing phase [4].

E-tongue and ANN do identification of fake green tea. The response is compared for two techniques of ANN

1) Back-propagation neural network with the Levenberg-Marquardt training algorithm (LMBP)

2) Radial Basis Function neural network (RBF) with mean squared normalized error (MSE) [122].

Both algorithms have a full identification rate in the training set, but in the testing data set, the RBF is more efficient than LMBP [9]. Machine vision system for tea quality index (TQI) is established for the fermentation process to check the size and color of tea grains. Manually the uniform testing is impossible and non-uniform. The digital camera is used to capture both RGB pictures and gray pictures. With the application of image processing techniques and size and color estimation algorithms, the TQI is determined. TQI and tea quality is having an inverse relation with the specified algorithms [10]. The fermentation process of black tea had automated with the e-nose and LabVIEW simulation software [12].

IV. INDIAN TEA INDUSTRY

Tea is broadly classified into three types' black tea, oolong tea and green tea. In India, the cultivation of black tea is very high, green tea cultivation is in the second position, and oolong tea is rarely cultivated. Black tea has antioxidant properties due to polyphenol, which reduces chronic disease and improves health immunity. Some flavonoids in black tea improve heart health, decrease the peril of high blood pressure, reduce high cholesterol, reduce blood sugar, reduce chances of stroke and cancer, reduce stress, and maintain overall health. An Oolong tea is good for digestion, drinks after a heavy meal, and prepared without milk and sugar. Green tea is good for increasing metabolism and improves brain function; it also offers all the health benefits of black tea and oolong tea.

With processing, tea is classified into CTC, orthodox, leg-cut, green and instant tea. The CTC and orthodox tea are of high-demand grades. In India, the Indian tea board decides the grades of manufactured tea and marketing strategies. As tea is an economical crop cultivated worldwide and in India, artificial intelligence may boost marketing strategy and export of tea.

A. CURRENT TEA MARKET TRENDS

Nowadays, people are more aware of the health benefits of herbal and green tea, which may increase the demand for tea types, but the cost of tea types- depends on additional health ingredients and tea taste.

B. RESEARCH GAPS OCCURRED IN INDIAN TEA SECTOR

The following issues have occurred in the Indian tea sector; some are related to hardware, and some are related to software.

1) The taste sensing response should be consistent enough to make firm decisions and develop pattern recognition for the given tea sample. The existing taste sensing hardware is

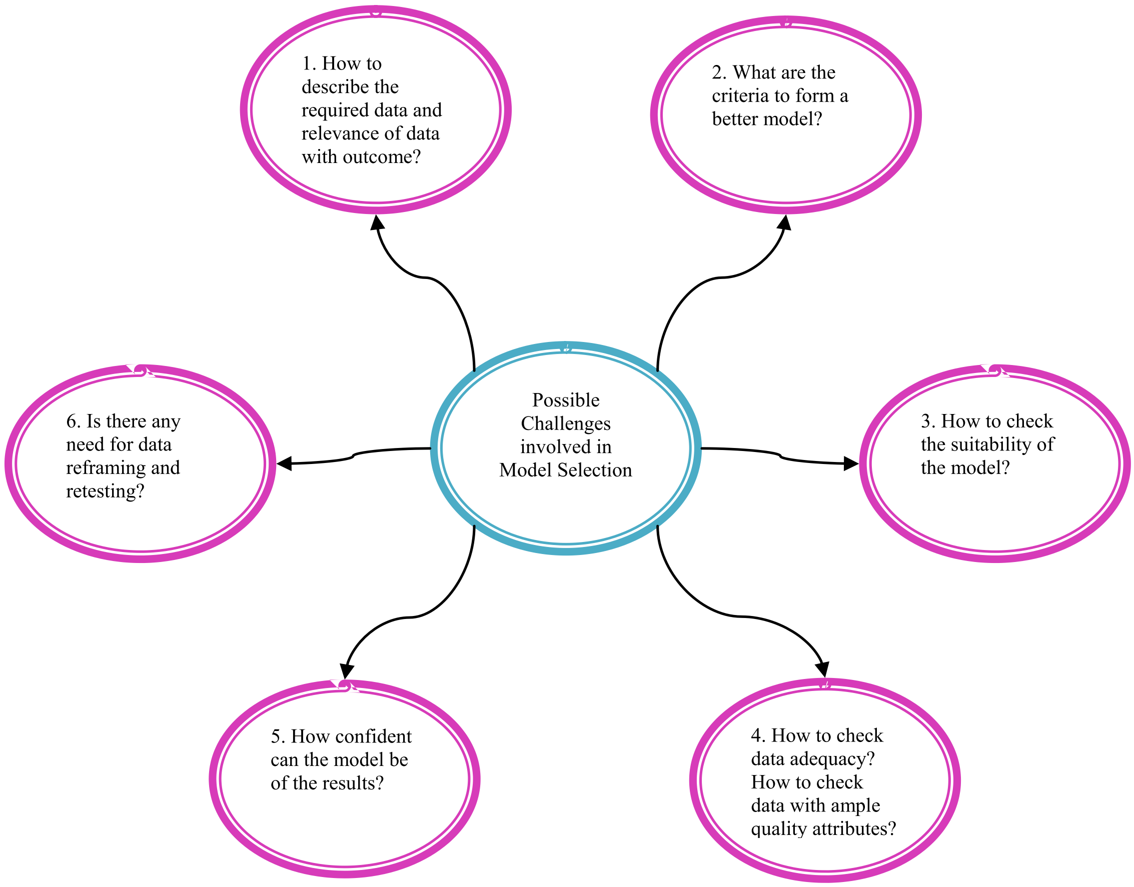


FIGURE 7. Possible challenges involved in model selection.

not consistent enough and having poor stability in response generation.

2) All the three attributes of tea species – its color, flavor and odor are not tested simultaneously with the help of technology. Only fusion of odor and flavor is done with the help of an artificial neural network and biochemical sensors by Alpha MOS, Headquartered in Toulouse, France.

3) In India, E-nose was developed for black tea classification by CDAC in collaboration with the Jadhavpur University of Kolkata. It is under test and observation, still not open for market and public utilization.

4) The average classification rate and accuracy of tea grading should increase with the help of various machine learning algorithms.

5) The human taste threshold should match with the artificial taste perception threshold for the correct classification of taste.

6) The Human tea tasters are also required for confirmation of tea attributes in India. So the dependency is always there on Human tea tasters. Automation and technology can tolerate the decision dependency on human tea testers.

7) The technology for determining the age of tea leaf is not yet developed; it approximates estimation according to the human tea tasters. The development of the AI tool to determine the age of tea leaf, also useful to find the storage time for particular tea species. The stock can then be open for the market before the expiry date.

		True condition	
		True Condition Positive	**True Condition negative**
Prediction condition	**Predicted Condition positive**	True Positive	False Positive
	Predicted Condition negative	False Negative	True Negative

FIGURE 8. Confusion matrix in machine learning.

C. SCOPE OF THE ARTIFICIAL TASTE PERCEPTION IN TEA INDUSTRY

Tea is the most popular beverage worldwide, and it is the economical backbones of tea-producing countries like India, China, Sri Lanka, Kenya etc. Indian tea is famous globally, especially Darjeeling tea, famous for its unique flavor and taste. As India is the second-largest Tea producer, with automation and technology, bulk production can be easily categorized in various grades for its brick color, odor and taste. With the help of a market survey and its analysis, it is easy to find people's interest in particular species of tea. For the separation of that particular tea species and showcase the attributes of that tea species, an experimental demonstration is required, which further leads to marketing strategies of tea branding.

V. USEFUL SENSORS, TEA COMPOUNDS, TASTE FORMATION AND SENSING HARDWARE REVIEW

For artificial taste perception of tea samples, two types of sensors are very useful; of which the first is the pH sensor and the other is astringency sensor. Both sensors define the acidity level of the tea liquid sample.

A. pH SENSOR

pH is the potential of hydrogen or the power of hydrogen in any liquid sample. Liquid containing more $H+$ ions remains acidic, and if it contains more OH- ions remains alkaline. The power of hydrogen (pH) value varies from 1 to 14. Liquid with pH value 7 is neutral, liquid containing pH below 7 is acidic, and when pH is above 7, fluid is alkaline. With the help of pH electrode and reference electrode, the potential difference is measured for a given liquid sample.

$$V = VpH - Vref \tag{6}$$

Equation (6) is to find a potential difference where VpH is the voltage of the pH electrode concerning ground and $Vref$ is reference electrode voltage for ground.

Now with the help of the Nernst equation, pH is calculated

$$V = -kTpH \tag{7}$$

where k is Boltzmann's constant and T is temperature.

By using "(6)" and "(7)," the pH of the given tea liquid sample is given with the help of a software algorithm.

B. ASTRINGENCY SENSOR

For astringency and bitterness measurement, potentiometric and voltammetric sensors are very useful [13]–[16]. The signal is measured as the potential difference between the working electrode and the reference electrode, and accordingly, the value of bitterness is defined [15].

Evaluation of tea sample is difficult because several compounds contribute to the taste formation of tea. Due to this, the taste prediction of the tea sample is not followed with instruments in lots of tea producer countries. Normally, in the tea industry, the person having experience in tea testing is recruited for taste assessment [45]. The tea tasters generally evaluate tea in a range of 1 to 10 individually for its odor, color and flavor. But as the flavor evaluation is human-dependent, it generates individual inconsistent given by them, which can be altered by various parameters like fatigue, work or mental pressure and states, de-sensitivity due to long working experience [45].

TABLE 2. Biochemical compound contributes to tea taste formation.

Compound Name	Taste formation
Polyphenol	Astringent
Amino acids	Brothy
Caffeine	Bitter
Theaflavins	Astringent
Thearubigin	Ashy and slight astringent

(SOURCE: PAPER [63])

Multivariate calibration methods are explained in the paper [46]; some chemical methods of testing are also available for tea quality evaluation like gas chromatography (GC), high-performance liquid chromatography (HPLC) [47], and capillary electrophoresis [48]. All these methods are dependent on the skilled person, can be done in the laboratory, time-consuming, manual and expensive again. It isn't easy to correlate the subjective score given by tea tasters with the result obtained by chemical testing. The chemical tests describe the compound contribution in the tea sample, which are more objective types [49].

The compounds enlisted in table 1 are responsible for major taste contribution [50]. The objective of tea quality testing is not to detect the percentage of chemical compounds present in tea liquor but to get the overall response of tea taste similar to the human tongue [51].

The black tea classification using voltammetric sensors was done with the help of an array of five working electrodes with one reference electrode and counter. This tea testing is formed on the principle of pulse voltammetry analysis.

For the categorization of wine [52], fat content of milk [53], beverages [54]–[56], water [57] and tomatoes [58], the measurement techniques like voltammetry, potentiometric and conductometry sensing principles have been successfully utilized. An amperometric electronic tongue has been formed to quantify the astringency of the tea sample [59]. Self-polishing e-tongue for tea [60] and potentiometric electronic tongue for Korean green tea [61] have been developed successfully. Voltammetric e-tongue is very simple, robust, multipurpose and highly sensitive for taste perception [62].

In voltammetric e-tongue, the test result has been continuously monitored throughout the test duration since input was applied to the test system. It is not in chemical processing where results are obtained at the end of laboratory tests and not instant action. The e-tongue described in paper [57] where low-cost data acquisition card has used instead of the expensive potentiometer for the voltage pattern detection with the help of current generation. The samples were of black tea, collected from Kanan Devan Hill plantation of south India [63]. The measurements of this e tongue had been correlated with the scale given by tea testers to form the

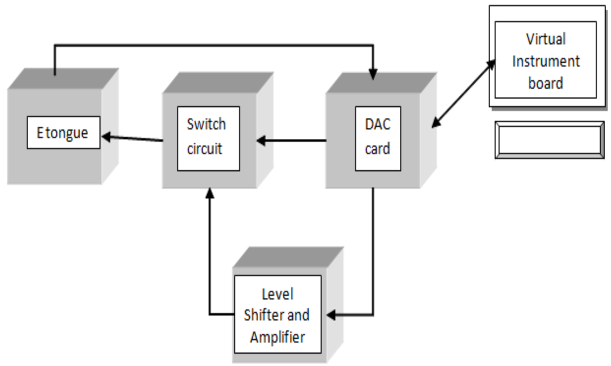


FIGURE 9. Voltametric e-tongue block diagram.

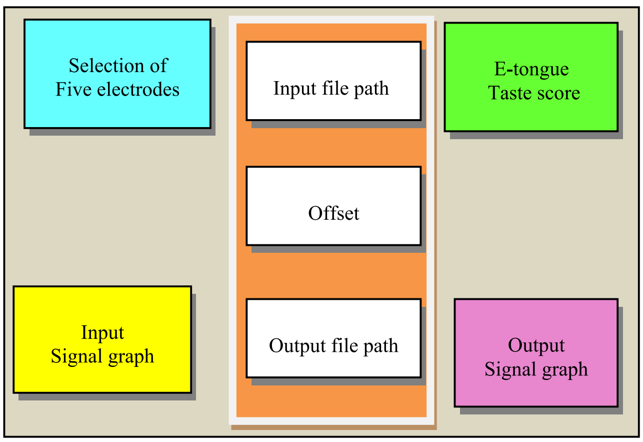


FIGURE 10. Graphic user interface (GUI) for E-tongue.

computational model for the prediction of unknown tea samples. Figure 9 shows a block schematic of the voltammetric e-tongue.

E tongue is formed with five working electrodes of different metals like gold, platinum, iridium, rhodium, palladium and platinum counter electrode with Ag/Agcl reference electrode for tea quality testing. Signal generation and data acquisition are under computer control with switch circuit, level shifter and amplifier. LabVIEW software is used as a computational unit for voltage pattern recognition with cheaper data acquisition card USB6008 of national instruments. For the correlation of result attributes obtained by electrodes with the human tea tester scale, customized software is developed. This software controls signal generation, signals, user interface, and computing modules [63].

Voltammetric e-tongue with Fractional Order Model is also available and shown in figure 11. The sensing hardware is the same as mentioned in figure 9. Only the model's objective given in figure 11 is a more accurate prediction with a fractional-order model (FOM).

The front panel using a graphic user interface for e tongue is given in figure10, which is designed using LabVIEW software. The user can select working electrodes out of five electrodes and check the input signal graph, output signal graph with the e-tongue score. A middle section for input file path, output file path and offset are the settings for the data acquisition card. Neural network and statistical methods are used for correlation and classification analysis. The tea liquor without milk has been assessed for its taste and correlated with the manual score given by tea testers [63].

The virtual instrument board is made up of fuzzy logic, and the neural networks provide the intelligent system that classifies the tea attributes for quality evaluation. The classifier is the algorithm which generates class label to verified object according to its description.

The tea liquor for the test sample is made ready by boiling 150ml of distilled water and pouring 750mg black tea sample for 5minutes. Tea leaves are filtered by filter paper; the filtered liquid is permitted to cool at room temperature for 20minutes, then it can be used as a sample for measurements. After each measurement, the electrodes have washed with distilled water. The user can select small amplitude pulse voltammetry (SAPV), large-amplitude pulse voltammetry (LAPV) and staircase waveforms. As huge data is generated with the measurements mentioned above and has to handle, the neural network is not feasible, so discrete wavelet transform (DWT) is selected to classify tea samples [63].

For continuous signal analysis, the wavelet transform is useful because it provides time and frequency information. Mallat's pyramidal algorithm is used to form DWT. In DWT, the signal is decomposed with the help of digitalized filters; the high pass filter outcome is stored as a coefficient, and the low pass filter outcome is used to form a compressed vector. Unique repetitive compression is required for the reduction of the data set. The classification accuracy is best with six-level of compression. According to the mean square error between original data and reconstructed data, the mother wavelet has to be selected. The various DWT algorithms are available of which HAAR wavelet is more suitable for the data compression technique as it has the least mean square error [63].

The neural network classifiers like BP-MLP, RBF and PNN are compared to evaluate which PNN is proved a more accurate classifier with a high classification rate and low misclassified patterns. Five tea grades have been tested, but the samples are from a single tea garden, so the e-tongue is evaluated for limited scope. The advantage of this design is the low-cost solution, portable as well [63].

To improve the voltammetric sensor fractional-order model (FOM) is developed and described in paper [64]. It describes the correct behavior of the electrochemical process by analyzing the current generated in the voltammetric sensor for the black tea liquor taste analysis. Here, the research methodology adopted selects the best fractional-order transfer functions (FOTF), which estimate the model's optimistic parameters and decompose the FOTF into its equivalent circuits. The study's objective is to find the effect of tea sample concentration on the model parameters and potential discrimination by electrodes. The common issues generally occurred with e-tongue are discussed. The standards are not universal and fixed, so the unavailability of such sensor array, wide calibration of the sensor measurement

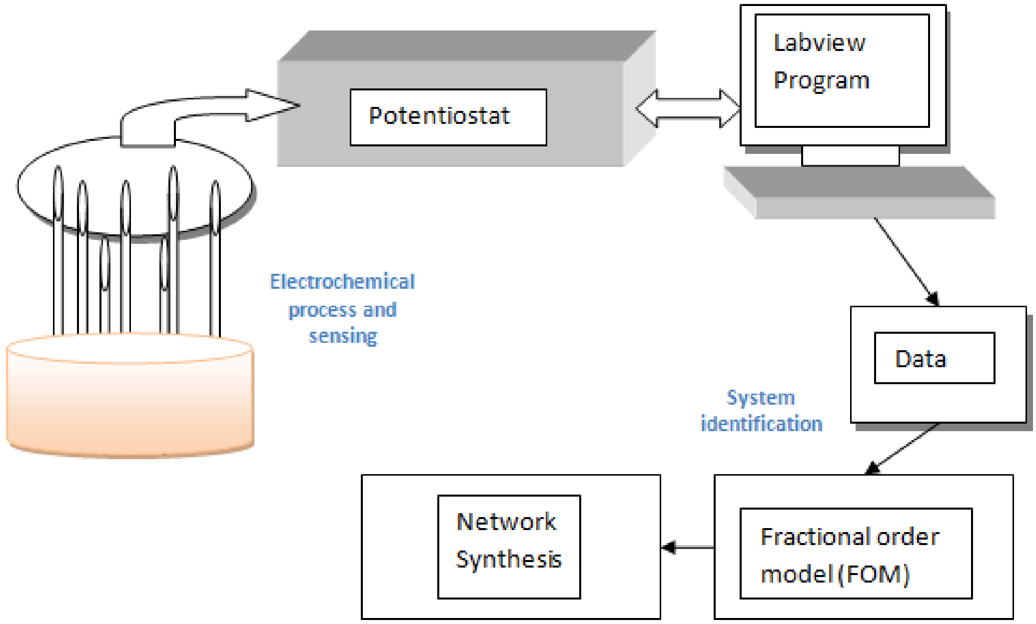


FIGURE 11. Voltammetric e-tongue with fractional order model.

system is required, test sample preparation uncertainty, and sometimes portability of system [65].

As numerous chemical compounds are present in the test, liquor and electrodes are also of variety, and parameter modeling becomes challenging. The selection of FOM structure from available models for the optimum multi-electrode tea taste system requires in-depth investigation [67]–[75].

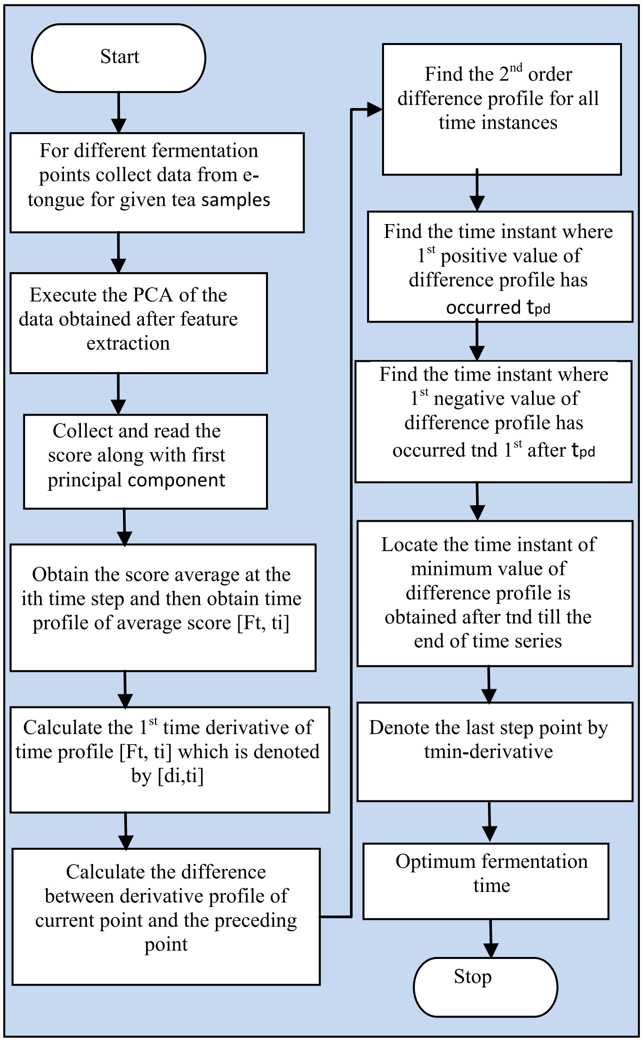
Randles equivalent circuit is used to model electrochemical system [67], [76], [77]. Randles equivalent circuit is enhanced further for a technique of system recognition using e-tongue signals [78]. In other experiment [79] for impedance analysis of taste sensors, the auto-regressive moving average (ARMA) model has utilized. The voltammetric e-tongue development is so far based on ideal circuit consideration. Still, the behavior of electrochemical processes had not been configured ideally, and many times, the response stray from ideal considerations. It causes due to practical limitations of circuit elements such as double-layer capacitor with nonideal charge transfer impedance. Due to such practical issues to model, the e-tongue fractional entities like Warburg elements and constant phase elements (CPE) are to be used compulsory [67]. In-circuit FOM modeling is very much required to balance such competencies early.

The fractional elements such as CPE and Warburg elements are also known as fractance. They are generally used to model the electrochemical processes using electrode-electrolyte interactions. The conventional passive elements like resistors, capacitors and inductors are also used to form the fractional circuits. So the main force of study is to find optimum design model for the electrode sensors of the e-tongue using fractional elements to balance in-competencies of conventional passive elements [64].

1) SYSTEM HARDWARE AND FUNCTIONING

The system block diagram is given in figure 11, which consists of working electrodes (WE) along with a standard Ag/AgCl reference electrode (RE) and a stainless steel (SS316) counter electrode (CE). A set of five WE's of metals like gold, iridium, palladium, platinum and rhodium is used for electrochemical synthesis. Multi-channel laboratory potentiostat is used to apply voltage pulses to all the WE's sequentially concerning the RE [78]. A sampler with a sampling rate of 1000 samples per second is used to sample response current. For the user interface, the system is designed in LabVIEW. Metal wires with 1 mm diameter have been chosen as electrodes, and they are electrochemically stable, react less with the natural environment, and have low maintenance. Sensor electrodes were wrapped separately in Teflonsleeves. These WE's were arranged in a circular manner around RE in the same 1.2cm radius to keep the solution resistance the same for each WE; this also assurers the minute effect of geometry on response current obtained by sensor electrodes. So, mainly the response is dependent on the test solution and electrode material. Metal electrodes were uncovered 2mm inside the test liquor. This electrode assembly is 7cm long and of 6.58cm radius.

For the experiment, five black tea samples (S1 to S5) were tested. The test solution had prepared by mixing 100ml boiling ultrapure water into a flask containing 1.2g of black tea, and after 10 minutes rest period, it was filtered. A sample of 20ml was used for the test analysis. After each test, electrodes were rinsed properly in ultrapure water and with zero-grade emery paper. The CTC tea samples tested are S1 and S5 of grade dryer mouth (DM), while S2 is broken pekoe (BP), S3 is pekoe fanning (PF), and S4 is dust (D). With the application



(SOURCE: PAPER [80])

FIGURE 12. Correlation using PCA.

of large amplitude pulse voltammetry (LAPV) signal as input to WE, the quality of tea samples was estimated [66].

Tea aroma has seven sensory properties like fresh floral, sweet floral, citrus, sweet fruity, fresh green, resinous and roasted. All these seven properties were measured by the gas chromatography method [46].

The major contribution of paper [64] is the introduction of the fractional element in the voltammetric e-tongue [39]–[44] with the variance analysis for each metal electrode type.

Table 3 is about Electrode ratings per tea sample for fractional impedance, and the root means square error.

Voltammetric e-tongue is used to obtain the optimum fermentation time of curl black tea [80]. The principal component analysis (PCA) correlates the e-tongue response with the biochemical changes during tea's fermentation process. The detailed flowchart is given below in figure 10 for the optimum fermentation point. Calculate the difference between the derivative profile of the current point and the preceding point. The algorithm is given in figure 12.

After the optimum fermentation instant, the charge activity at the working electrode is found with the maximum drop rate. The current response of e-tongue retains useful information about fermentation. Different tea samples produce different fermentation profiles according to the leaf composition and attributes. The feature values of E-tongue gain required information to permit the detection of OFT for all samples at a correlation of 0.97 with the reference estimations of the same. The standard deviation of error was below 2 min, while the maximum deviation from actual values was ±5 min.

The algorithm is easily incorporated for real-time operation as it does not require future values to detect OFT. It was notified that only 1st principal component score was used in the methodology of detection. All other attributes tied by applying sophisticated data processing methods such as neural networks may be used to detain the temporal patterns of difference among the attributes. It allows precise and vigorous exposure of optimum fermentation duration for many samples [80].In another paper [3], the taste detection analysis had done for the bitterness and astringency of green tea.

The three types of green tea samples have analyzed by using e-nose and e-tongue. With the help of correlation analysis, the sensor array was optimized. The optimized signal obtained by sensor array was correlated with bitterness and astringency of green tea by using multiple linear regressions (MLR), partial least squares regression (PLSR), and back-propagation neural network (BPNN). The compounds like Caffeine, polyphenols, amino acids, and some other organic compounds cause bitter and astringent tea taste. The main alkaloid in tea is Caffeine, and it is 2%-5% of the dry weight of tea which causes mainly the bitter taste of tea, whereas catechins are the major source of astringency. In paper [3], the development of both e-nose and e-tongue for green tea taste had explained in detail with correlation analysis [3].

2) ELECTRONIC NOSE

The hardware used for e-nose is the same as mentioned in figure 1; specifically named as the portable electronic nose (PEN3) from Win Muster Airsense (WMA) Analytics Inc. Ten MOS sensors have used to form a sensor array that operates at 350-500 C °. The sensor obtains the response in the format G/G0 where G is the conductivity of volatile gas, whereas G0 is the conductivity of the gas filtered by standard activated carbon [3]. The software used to analyze data is WinMuster software.

3) ELECTRONIC TONGUE

In figure 1 general hardware block schematic required to form an e-tongue is given the same system is used in paper [3].The taste sensing equipment SA402B, produced by Intelligent Sensor Technology Co. Ltd. in Japan, is used as an e-tongue. The sensor array is composed of taste sensors for bitterness and astringency measurement with Ag/AgCl reference electrodes. The artificial ester film having a thickness few hundred micrometers is used for ion exchange. The Ag/AgCl

TABLE 3. Electrode ratings per tea sample for fractional impedance and root mean square error.

Tea grades	Electrode									
	Au		Ir		Pd		Pt		Rh	
	RFRA	ERROR	RFRA	ERROR	RFRA	ERROR	RFRA	ERROR	RFRA	ERROR
S1	296KΩ	0.90%	669KΩ	13.74%	49KΩ	2.35%	70KΩ	2.20%	184KΩ	3.02%
S2	220KΩ	0.75%	162KΩ	12.35%	42KΩ	2.76%	49KΩ	0.41%	68KΩ	1.91%
S3	228KΩ	0.85%	97KΩ	0.82%	56KΩ	0.84%	60KΩ	1.95%	51KΩ	1.63%
S4	238KΩ	0.78%	91KΩ	1.51%	55KΩ	1.98%	58KΩ	1.36%	50KΩ	1.80%
S5	132KΩ	1.02%	282KΩ	6.90%	43KΩ	1.42%	41KΩ	1.02%	75KΩ	2.32%

(SOURCE: PAPER [64])

reference electrodes sense change in the membrane potential after electrochemical reaction in mV. The software used with e-tongue converts the measured potential into a taste value.

Data and statistical analysis of e-nose and e-tongue were done based on regression coefficient- and root means square error of the models, and it was performed using MATLAB 2012a software [3]. As the original data matrix was derived from 15 successive tests for each sample of green tea, the matrix size is very large for the machine learning algorithm. Therefore to reduce the size of the original data matrix, a feature extraction technique had used. The sensor electrode requires a stabilization time of around 30sec; the data extracted after it was considered characteristic value [3]. It was observed that the polyphenols and caffeine both are positively correlated with the taste and aroma of the green tea sample. The caffeine content was found less in high-grade tea samples near it was 1st and 2nd-grade samples. The volatility of flavor compounds was dependent on polyphenols [81].

Paper [82] had shown that the chemical effect between caffeine and flavor compounds could form a complex molecular structure. Some studies [83] found that the flavor and aroma of the tea sample had changed significantly with the addition of exogenous amino acids. With this, it was also proved that the bitterness is proportional to astringent value. Bitterness in the top grade green tea sample was moderate, whereas, in 2nd grade, it was highest [3].

In the paper [3], three different models have analyzed MLR, PLSR and BPNN. The statistical model MLR is used to study the linear relationship between multiple **i**ndependent variables to dependent variables. MLR is comparatively fast, covers all independent variables and suitable too. In the MLR model, the response from all seven sensors of e-nose

TABLE 4. Taste analysis with the chemical composition of Xinyang Maojian tea.

Green tea sample	Top grade tea	1st-grade tea	2nd-grade tea
Mass fraction of polyphenols/%	21.02%	19.58%	18.81%
Mass fraction of caffeine/%	3.78%	3.72%	3.52%
Bitterness value	5.63	4.50	6.24
Astringency value	26.05	25.20	27.50

((SOURCE: PAPER [81])

had considered as independent variables, and bitterness and astringency values generated by e-tongue had considered as dependent variables. A total of fifteen tests per tea grade sample took, of which randomly ten test results were used for calibration, and the remaining five results were used for the prediction set. So a total of 30 results were used for model calibration, and 15 results were used to test model prediction [3].

PLSR is a fixed linear regression model which extracts the linear relation among all the data entries to reduce the data set. PLSR is based on MLR, PCA and canonical correlation analysis and can generate a more effective model [3].

BPNN builds the input-output mapping without any mathematical equation. BPNN model uses sensor output of e-nose as input whereas bitterness and astringency response of e-tongue as target values [84]. In BPNN, 70% of input data entries are considered calibration sets, 15% data entries as the validation set, and the remaining 15% data entries are the prediction set.

TABLE 5. Prediction result of bitterness.

Statistical model	MLR	PLSR	BPNN
Regression coefficient of calibrationSet	0.833	0.815	0.981
Regression coefficient of predictionSet	0.558	0.58	0.923
Root mean square error of calibrationSet	0.309	0.326	0.255
Root mean square error of predictionSet	0.643	0.61	0.34

(SOURCE: PAPER [81])

TABLE 6. Prediction result of astringency.

Statistical model	MLR	PLSR	BPNN
Regression coefficient of calibration set	0.77	0.718	0.961
Regression coefficient of prediction Set	0.542	0.386	0.866
Root mean square error of calibration set	0.618	0.686	0.318
Root mean square error of prediction set	0.73	0.868	0.547

(SOURCE: PAPER [81])

It was proved by above table 5 and table 6 that the BPNN model is more accurate for the prediction of bitterness and astringency test of the green tea samples. For both the bitterness and astringency test, the regression coefficient of the calibration set is greater than 0.95%, and the regression coefficient of the prediction set is greater than 0.85%.Root mean square error in both cases for calibration and prediction is comparatively low [3].

BPNN has other advantages like nonlinear mapping, generalized adaptive self-learning and fault tolerance is also good [3].

VI. HEALTH BENEFITS OF TEA

The scientific name of the tea plant is Camellia sinensis. Tea is nothing but the processed leaves of Camellia sinensis. According to processes, the tea types had decided, such as Black tea (fermented), Green tea (non-fermented), and Oolong tea (partly fermented). The highest demand for black tea is in United States, India and Western countries. Black tea liquor is dark brown with a sweet fragrance. The taste of black tea is stronger than Green and Oolong tea. The pure black tea liquor without additives and sweeteners contains low calories, fat, protein and sodium [86]. Tea is a very useful drink for mental and physical health balance.

Black tea reduces cholesterol, the risk for cancer, heart disease, type 2 diabetes and also useful for weight loss and mental alertness [85]. Paper studies [87]–[89] explained the antimicrobial property of black tea. Another study [90] exposed the anti-inflammatory, anti-allergic, antiviral, and anti-carcinogenic features of black tea. In papers [90]–[92], it implied that black tea has phytonutrient that wants to be consumed daily for healthy living as part of the diet.

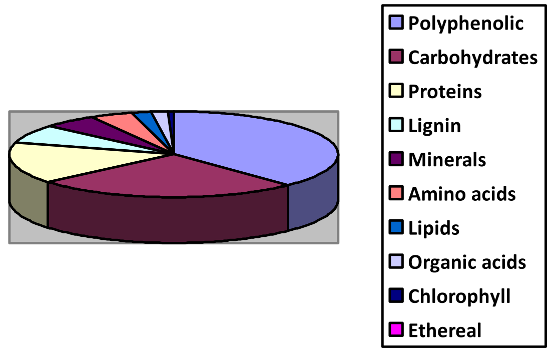


FIGURE 13. Compound compositions in fresh tea leaves.

The composition of fresh tea leaves is as shown in figure 13: 36% polyphenolic compounds, 25% carbohydrates, 15% proteins, 6.5% lignin, 5% minerals and trace elements,4% amino acids, 2% lipids, 1.5% organic acids, 0.5% chlorophyll as well as carotenoids and etherealsubstances below 0.1%, vitamins (B, C, E). The contains of tea like Catechins, and other polyphenols have antioxidant properties [93].

The two main processes involved in tea manufacturing are withering and fermentation. Both these processes affect the flavor and quality of tea. The process starts with the collection and cleaning of leaves. Withering involves partial drying of the tea leaves. This process creates some chemical changes.

In the withering process, air whisks through the leaves to reduce the moisture contents of the leaves. It is very important to maintain ambient temperature as over and under heating causes the variation in a chemical reaction, which leads to different flavors and qualities of tea. This is followed by leaf maceration, in which the leaf is cut into small pieces and fermentation where the polyphenols are oxidized to form the characteristic compounds of Black tea [85]. After fermentation, the moist leaves are dried to seize the oxidation process. In the end, various grades of tea have been sorted according to their sizes like whole leaf, broken, fanning's and dust [94]. The solid extract of Black tea contains polyphenolic compounds, including catechins;other flavonoids; amino acids;methylxanthines, carbohydrates, proteins, and minerals [93]. Black tea is also considered a dietary source of antioxidant nutrients and certain phytochemical compounds. These compounds improve the health benefits of the consumption of Black tea. In India, coronary heart disease (CHD) is rapidly increasing due to high saturated fats, low exercise, table work and a fast-food lifestyle.

Paper [95] explores the consumption of Black tea associated with the deterrence of atherosclerosis and heart disease. Paper [96] showed that Green tea enriched with Black tea theaflavin proved useful in reducing LDL cholesterol. Study [97]is based on black tea's influence on antioxidant capacity plasma, which reduces hypertension.

Disorder Type II diabetes causes inadequate insulin secretion by pancreatic β-cells. In a paper study [24]y, PCA's correlation between black tea consumption and Diabetes was evaluated by confirmed the negative correlation between them. This research explained how polyphenols act as preventive agents for lipid and glucosemetabolism disorders associated with Type II diabetes.

Obesity is a common health issue nowadays. Obesity causes due to more intake of calories than burning calories.

Pharmacological actions in cells were influenced by Theaflavins, which improves the metabolic rate of the body. Black tea contains catechins that possess anti-obesity and

Hypolipidemic effects [98]. Polyphenols present in Black tea stimulates lipolysis in the adipose tissue that was somewhat responsible forweight loss. Gallic acid present in Black tea suppresses food intake [85].

Abnormal food intake and food habits may cause a risk of developing cancer. The research investigations have explored that a diet full of flavonoids has lower incidences of cancer. Black tea is a flavonoid-rich beverage, so it is the main agent in cancer prevention that has to include in regular diet consumption.

In periodontal disease, the gums and bones which hold teeth become seriously get affected. Tea is the natural remedy to cure such diseases [101]. Study [99] shows that the presence of polyphenols in tea reduces bacterial growth and mouth infections.

Paper [100] reveals that the regular consumption of black tea reduces the chances of neurodegenerative diseases.

Chronic diseases like rheumatoid arthritis, asthma, stroke, Allergic reactions caused due to foreign protein such as to cause coughing, breathing difficulties, clogged sinuses, skin eruptions had lower down by boosting of immune response with consumption of black tea as it is an antioxidant, antiviral, antibacterial and anti-inflammatory responses.

Molecular compounds like Methylxanthines are present in Black tea, which reduces cardiac stimulants, diuretics, and smooth muscle relaxants [85]. The general observation about Methyl xanthines is that it reduces fluid content and causes dehydration. Another survey by Maughan and Griffin46 implicated that the tea consumption did not cause diuretic upshot if the consumption is less than 300mg of Caffeine at one sitting 9approximately six to seven cups of tea). The caffeine compound present in black tea directly affects the central nervous system, causes wakefulness, and removing the sensation of fatigue. The very common form of methylxanthenes is Caffeine. Theophylline is another compound found in tea that reduces problems related to the respiratory system. l-Theanine is the compound found in tea, including almost 50% of its amino acid content and responsible for its exclusive ''brothy'' taste. Tea consumption causes a change in Alpha waves, occurs in the brain and ultimately

TABLE 7. Tea worldwide production.

Country	2015	2016	2017	2018	2019
China	2249.00	2404.95	2496.41	2610.39	2799.38
India	1208.66	1267.36	1321.76	1338.63	1390.08
Kenya	399.21	473.01	439.86	493.00	458.85
Sri Lanka	328.96	292.57	307.72	304.01	300.13
Vietnam	170.00	180.00	175.00	185.00	190.00
Indonesia	132.62	137.02	134.00	131.00	128.80
Others	796.43	838.83	843.64	904.18	882.84
Total	5284.88	5593.74	5718.39	5966.21	6150.08

(Qty in M.Kg)
(Source: ITC Annual Bulletin of Statistics, 2020)

TABLE 8. Tea worldwide export.

Country	2015	2016	2017	2018	2019
Kenya	443.46	480.33	415.72	474.86	496.76
China	324.96	328.69	355.26	364.71	366.55
Sri Lanka	301.32	280.87	278.20	271.78	289.59
India	228.66	222.45	251.91	256.06	252.15
Vietnam	133.5	142.00	140.00	130.00	136.00
Indonesia	61.92	51.46	54.19	49.03	43.11
Others	303.57	300.70	301.73	316.69	319.51
Total	**1797.38**	**1806.50**	**1797.01**	**1863.13**	**1903.67**

(Qty in M.Kg)
(Source: ITC Annual Bulletin of Statistics, 2020)

leads to relaxation. It is important for neuroprotective effects and improves cognition properties, handles brain functioning.

Study [85] concludes with the elements present in Black tea causes lots of preventive health benefits and uses for a regular healthy diet plan.

Table 7 shows the worldwide production of tea. According to it, China is in 1st position in Tea production, and India is in 2nd position worldwide [5].

The below-given table 8 explores the export of tea worldwide. According to it, Kenya is in 1st position in tea export; China and Sri Lanka are on 2nd and 3rd position respectively. Worldwide, India is in 4th position in tea export. It means Kenya is the country where tea consumption within the country is less, and in India, the tea consumption within the country is high.

Table 9 indicates the worldwide demand and supply of tea. It shows the production is slightly or cut to cut larger than

TABLE 9. World demand and supply of tea.

Year	World Production	Apparent Global Consumption	(+) or (-)
2015	5285	5035	250
2016	5594	5307	287
2017	5718	5520	198
2018	5966	5722	244
2019	6150	5859	291

(Qty in M.Kg)
(Source: ITC Annual Bulletin of Statistics, 2020)

TABLE 10. World auction prices of tea.

Year	World Auction Prices in US$/Kg					
	India	Sri Lanka	Kenya	Indonesia	Malawi	Bangladesh
2015	1.94	3.01	2.73	1.56	1.56	2.41
2016	2.00	3.20	2.29	0.00	1.55	2.55
2017	2.04	4.06	2.81	0.00	1.84	2.45
2018	2.03	3.58	2.43	0.00	1.84	3.11
2019	2.00	3.05	2.04	0.00	1.46	2.31

(Qty in M.Kg)
(Source: ITC Annual Bulletin of Statistics, 2020)

consumption. The demand for tea completely satisfies by tea production worldwide.

Table 10 specifies the worldwide auction price. Actions in the countries Sri Lanka and Kenya have been reasonably competent in price detection. These countries are working hard to improve their auction system. On the other hand, India is below Bangladesh in getting worldwide auction prices. It shows India needs immediate attention to build an appropriate auction system on an international level. As tea is a national asset of India, the marketing strategies have to be improved further.

The tea board of India had developed the central quality control laboratory (QCL) at Tea Park, Siliguri, with exclusive tea testing facilities. This is a well-equipped lab with skilled and technical manpower support. The international standards of tea quality have been maintained following the ISO/IEC 17025:2005.

The objective of this laboratory is to assist the Indian Tea industry in the confirmation of national and international quality standards in the production of high-quality tea. For quality control of laboratories National Accreditation Board for testing and calibration Laboratories (NABL) is the governing body in India. NABL is associated with International Laboratory Accreditation Cooperation (ILAC) for international market mutual recognition arrangement [107]. QCL at Siliguri has under the accreditation of NABL for various tea tests like biochemical parameters, pesticide residue, heavy metal and microscopic examination of tea samples.

TABLE 11. Selection of keywords on tea industry analysis.

Primary keyword	-	"Artificial intelligence"
Secondary keywords	Using and	"tea"
	Using or	-

Some of the important types of equipment available in QCL at Siliguri are Liquid Chromatography-Mass spectrometry measures (LC-MS/MS), Gas Chromatography-Mass Spectrometry measures (GC-MS/MS), Inductively Coupled Plasma Mass Spectrometry measures (ICP-MS/MS), Laminar flow, Autoclave, Spectrophotometer, Microscope, High-Performance Liquid Chromatography (HPLC). Qualified scientists with experience in analytical areas, biochemistry, microbiology are generally appointed as in-charge for QCL [107].

VII. BIBLIOMETRIC ANALYSIS OF ARTIFICIAL TASTE PERCEPTION OF TEA

The bibliometric analysis is the statistical study of recent research trends in a particular research area [102]–[106]. To avoid repetitive research, it is essential to know the historical and current happenings in the selected research area. The major contribution of the research is reported through research articles, research reports and thesis, journal papers, book chapters, conference proceedings [117]. The above said publications are available in two types of repositories, of which one is based on subscription, and the other is open-access type. For the subscription-based research publications, the fees have to pay by the researcher or organization to access data. Still, non-subscription or open access is freely available online articles with standard databases like Web of Science, Google Scholar, Scopus, Research gate, Jgate. Educational organizations, research and development departments of scientific organizations and industries make available the related research material with subscription policy and government grants through the library portal. This kind of primary data discovery is required to know the scope and limitations of the research topic. Research gaps and research scope can be easily identified by the bibliometric analysis [117].

The Web of science is a standard knowledge hub selected for bibliometric analysis. In this paper online tool named clarivate analytics by Web of science has been used for bibliometric review [117].

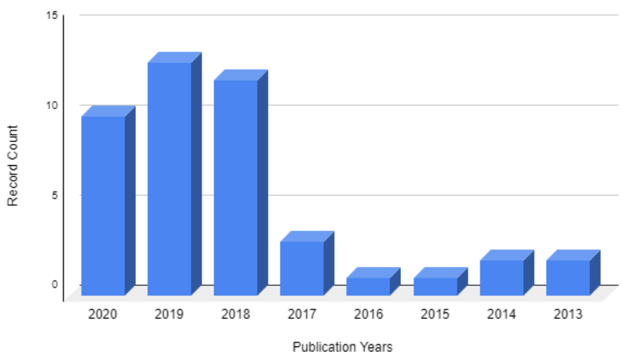
The keywords are the important topics related to the research area. Those are classified into primary and secondary types. The primary keyword defines the major contribution, whereas the secondary keyword generates related subtopics and application areas.

The query used to search in Web of science is "artificial intelligence" and "tea" as shown in Table 11. Yearly publishing trends for the selected keywords are given in Table 12.

TABLE 12. Yearly publishing trends.

YEAR	PUBLICATION COUNT
2020	10
2019	13
2018	12
2017	3
2016	1
2015	1
2014	2
2013	2
TOTAL	44

Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)



Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 14. Artificial intelligence and tea - years per publication count Data access information.

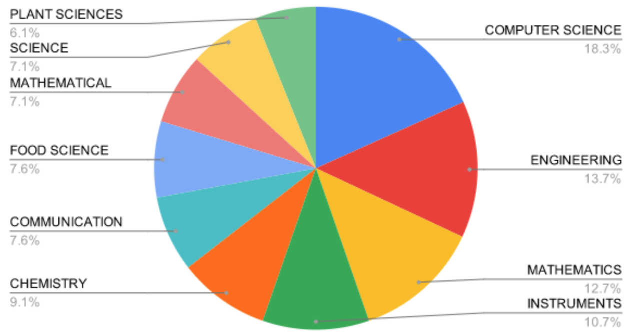
The search query was generated for the last decade and only limited to articles in the English language.

This paper explains the graphs and tables for the domain - artificial intelligence and tea; with the help of Web of Science bibliometric analysis.

Many filters are available in the Web of Science database, such as open access category, keyword search, Duration, Languages, Country/Territory, Author search, Document type.

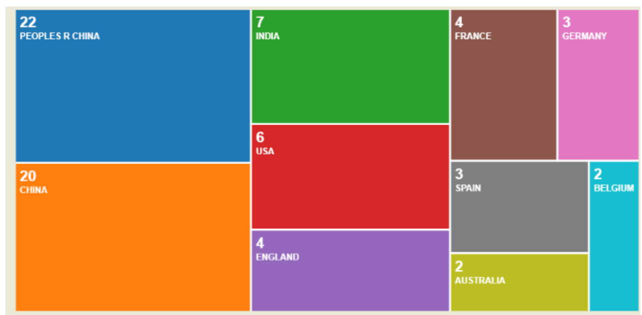
The Clarivate analytics of Web of Science shows interesting facts given in figure 14 for the publications on Artificial intelligence and tea. Suddenly after 2017, in 2018, an extreme rise in publications had occurred. In 2019 it was at its peak, and in 2020 a slight decrement in publications, but still, it is comparatively higher than publications before 2017.

It proves that the research area of artificial intelligence and tea has strong potential for advancement. In the future, this domain helps the agricultural commodity of the tea sector.



Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 15. Artificial intelligence and tea –research area per publications Data access information.



Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 16. Artificial intelligence and tea – top ten countries per research publications Data access information.

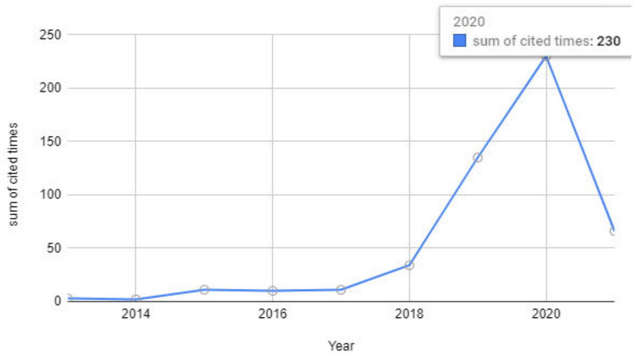
TABLE 13. Type of publication documents on artificial intelligence and tea.

DOCUMENT TYPE	NUMBER OF DOCUMENTS	RESULT IN PERCENTAGE
ARTICLE	43	81.13%
OTHER	05	9.43%
REVIEW	02	3.77%
EDITORIAL	02	3.77%
DATA PAPER	01	1.89%
TOTAL	53	100%

Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

Figure 15 indicates the report generated by the Web of Science clarivate analytics in the research area artificial intelligence and tea, which shows all the related fields with their utilization percentage. Computer science, mathematics, engineering, and instruments publications are higher compared to other fields.

Figure 16 is the heat map of the top 10 countries most active in artificial intelligence and tea. India is in 3rd position in research publications on artificial intelligence and tea.

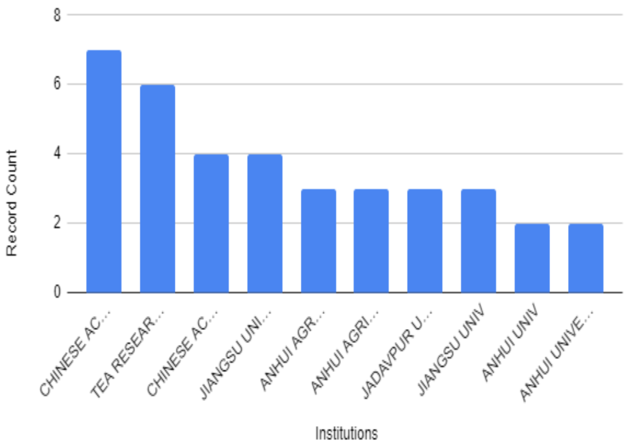


Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 17. Artificial intelligence and tea –additive citations per year Data access information.

TABLE 14. Database survey for artificial intelligence and tea.

Standard database	Records found
WOS	44
KJD	02
SCIELO	02
Total Records	48



Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 18. Artificial intelligence and tea –top 10 Institutions per record count Data access information.

Tea is the national drink of India, and India is the 2nd largest tea producer globally; 80% of produced tea is consumed within the country only. So, advancement in the artificial intelligence technique in the tea sector improves the marketing strategies of tea abroad and be an asset for the tea-producing countries.

Figure 16 proves that in comparison with China, India is lagged in tea research. In terms of percentage research proportion, India is exactly lagged by 50% of China, and with the help of engineering and technology, the improvement is possible.

Table 13 indicates that 81.13% of articles were published on artificial intelligence and tea, and 3.77% of reviews are available among all document types. The average citation per item is 11.41, with an h-index is 14. The h-index signifies the individual's (authors) scientific research outcome regarding scientific productivity and research impact. The citation report for 44 results shows that there search article cited without self-citation is 207 for the selected keyword.

TABLE 15. Analysis of the top ten publications based on citation in artificial intelligence and tea.

Sr.No.	Publication Year	Total Citations	Average per Year	Referances
1	2018	68	17	[108]
2	2019	33	11	[109]
3	2019	29	9	[110]
4	2018	26	6.5	[111]
5	2018	25	6.25	[112]
6	2014	24	3	[113]
7	2018	23	5.75	[114]
8	2014	22	2.75	[115]
9	2019	18	6	[116]
10	2018	18	4.5	[117]

Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

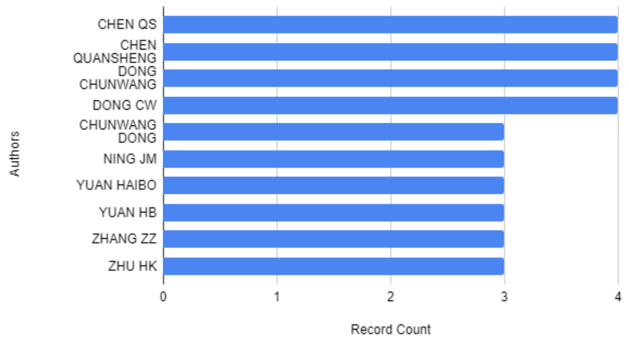
The graph of figure 17 is the trend line progressively; each year sum of citation count is also increasing. It means the scope of research is increasing day by day. In the year 2020, the sum of citations is at the peak.

With the web of science, two more databases are available and surveyed for "artificial intelligence" and "tea," namely KJD (Korean Journal Database) and SCIELO (SciELO citation index) given in Table 14.

The below graph of figure 18 depicts institutions per publication record count, by which it can see that more publications are from Chinese institutions. Jadavpur University from India had published three records.

Database with a maximum number of citations so far is given in Table 15. An observation informs that the article "Never-Ending Learning" has a maximum citation number among all publications.

The above graph, figure 19, indicates the top 10 authors in the domain of artificial intelligence and tea. It is very useful information for new researchers in the domain; they can find



Data access information source: https://mjl.clarivate.com/search-results (accessed on March.23, 2021)

FIGURE 19. Artificial intelligence and tea –Top 10Authors per record count Data access information.

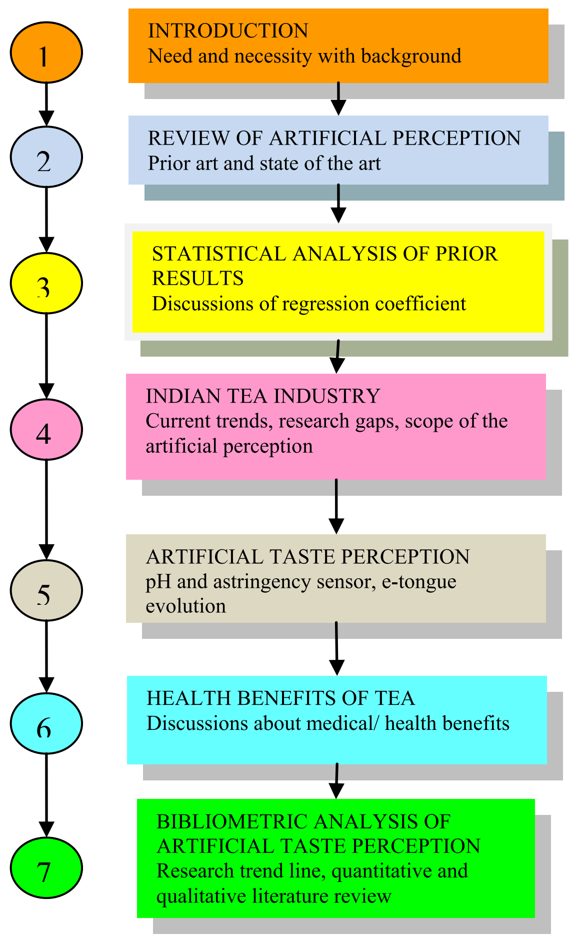


FIGURE 20. Summary of the paper.

publications by author search, collaborate, and get further research guidance.

VIII. CONCLUSION

For the enhancement of the global tea market, artificial perception of tea is very much required. As tea is an agro-economical asset of India, to boost the tea export, the digital attribute sampling of various tea species may create its own identity based on flavor. This identity can create with the help of artificial intelligence and machine learning, and it can catch the global tea market to broaden the scope of the sale.

Another aspect is -health assurance. Nowadays, it is the most urgent concern which needs extra attention. Due to increased population and pollution, drink products; become narrow and contaminated day by day. Fast and long working hours cause the ready-made food and drink habits for, e.g., tea consumption. The contamination in food and drink products causes due to human-made preparation methods or natural pollution. Sometimes, it generates intentional adulteration for economic benefits or created due to the aging of products.

It is essential to capture the tea taste artificially before consumption, personalize health prescription of diet according to the health history of human beings, and control the excessive tea drink habits with a description of tea sample.

India is the 2nd largest tea producer, consumer and exporter in the world. To detect the grade quality of tea, India is still dependent on human tea testers. Sometimes due to the personal inability of the tea testers, the decision may lead to wrong results. The chemical test types of equipment are available in Indian laboratories, but they quantify particular biochemical compounds in tea liquid. The taste of tea and the presence of biochemical compounds are manually mapped, and accordingly, the grades have been decided by a person skilled in the art.

The mapping of test score obtained from human tea testers and chemical methods fallowed in laboratories are difficult to correlate. With the help of a machine learning algorithm, it is possible to obtain a personalized result score for a specific health diet.

With a sensor array of E-nose, E-tongue and E-vision, it is possible to establish the monitoring system that assigns grades of the tea samples, detects impure samples, and sets uniformity and stops fraud. Machine learning, image processing, fuzzy logic with neural network-these are the current ongoing technologies that are useful to map attributes in artificial perception.

ACKNOWLEDGMENT

For a good literature survey, the role of the library is very important. Symbiosis International University (SIU) has a sophisticated library web portal. SIU library is always trying to build resources and make them available to research scholars on time. SIU organizes seminars, webinars on various topics like literature review, Paper writing, Publications to make researchers aware in-depth. The authors would like to thank both SIU and SIU library heads for their supreme support, timely communication, and guidance.

REFERENCES

[1] Y. Tahara and K. Toko, "Electronic tongues—A review," *IEEE Sensors J.*, vol. 13, no. 8, pp. 3001–3011, Aug. 2013.

[2] R. B. Roy, A. Modak, S. Mondal, B. Tudu, R. Bandyopadhyay, and N. Bhattacharyya, "Fusion of electronic nose and tongue response using fuzzy based approach for black tea classification," *Procedia Technol.*, vol. 10, pp. 615–622, Jan. 2013.

[3] G. Zou, Y. Xiao, M. Wang, and H. Zhang, "Detection of bitterness and astringency of green tea with different taste by electronic nose and tongue," *PLoS ONE*, vol. 13, no. 12, Dec. 2018, Art. no. e0206517.
[4] P. Saha, S. Ghorai, B. Tudu, R. Bandyopadhyay, and N. Bhattacharyya, "Tea quality prediction by sparse modeling of electronic tongue signals," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 9, pp. 3046–3053, Sep. 2019.
[5] (Dec. 2020). [Online]. Available: http://www.teaboard.gov.in/TEABOARDPAGE/MjlwNQ==
[6] S. A. Nagtode and D. N. Choudhari, "Identification of impurity level in liquids using electronic sensor based system," *Int. J. Innov. Res. Elect., Electron., Instrum. Control Eng.*, vol. 3, no. 6, pp. 77–82, 2015.
[7] T. Azad and S. Ahmed, "Common milk adulteration and their detection techniques," *Int. J. Food Contamination*, vol. 3, no. 1, pp. 1–9, Dec. 2016.
[8] M. Podrażka, E. Bączyńska, M. Kundys, P. Jeleń, and E. W. Nery, "Electronic tongue—A tool for all tastes?" *Biosensors*, vol. 8, no. 1, p. 3, Dec. 2017.
[9] Y. Li, J. Lei, and D. Liang, "Identification of fake green tea by sensory assessment and electronic tongue," *Food Sci. Technol. Res.*, vol. 21, no. 2, pp. 207–212, 2015.
[10] G. Singh, "Machine vision system for tea quality determination–tea quality index (TQI)," *IOSR J. Eng.*, vol. 3, no. 7, pp. 46–50, Jul. 2013.
[11] D. Karakaya, O. Ulucan, and M. Turkan, "Electronic nose and its applications: A survey," *Int. J. Automat. Comput.*, vol. 17, no. 2, pp. 179–209, 2020.
[12] B. H. Tozlu and H. İ. Okumuş, "A new approach to automation of black tea fermentation process with electronic nose," *Automatika*, vol. 59, nos. 3–4, pp. 373–381, Oct. 2018.
[13] M. R. Bajec and G. J. Pickering, "Astringency: Mechanisms and perception," *Crit. Rev. Food Sci. Nutrition*, vol. 48, no. 9, pp. 858–875, Sep. 2008.
[14] M. Habara, H. Ikezaki, and K. Toko, "Study of sweet taste evaluation using taste sensor with lipid/polymer membranes," *Biosens. Bioelectron.*, vol. 19, no. 12, pp. 1559–1563, Jul. 2004.
[15] N. Hayashi, R. Chen, H. Ikezaki, T. Ujihara, H. Kitajima, and Y. Mizukami, "Evaluation of the astringency of black tea by a taste sensor system: Scope and limitation," *Biosci., Biotechnol., Biochem.*, vol. 71, no. 2, pp. 587–589, Feb. 2007.
[16] N. Hayashi, R. Chen, H. Ikezaki, and T. Ujihara, "Evaluation of the umami taste intensity of green tea by a taste sensor," *J. Agricult. Food Chem.*, vol. 56, no. 16, pp. 7384–7387, Aug. 2008.
[17] Y. Mizota, H. Matsui, M. Ikeda, N. Ichihashi, K. Iwatsuki, and K. Toko, "Falvor evaluation using taste sensor for UHT processed milk stored in cartons having different light permeabilities," *Milchwissenschaft*, vol. 64, no. 2, pp. 143–146, 2009.
[18] T. Uyen Tran, K. Suzuki, H. Okadome, S. Homma, and K. Ohtsubo, "Analysis of the tastes of brown rice and milled rice with different milling yields using a taste sensing system," *Food Chem.*, vol. 88, no. 4, pp. 557–566, Dec. 2004.
[19] K. Sasaki, F. Tani, K. Sato, H. Ikezaki, A. Taniguchi, and T. Emori, "Analysis of pork extracts by taste sensing system and the relationship between Umami substances and sensor output," *Sens. Mater.*, vol. 17, no. 7, pp. 397–404, 2005.
[20] R. Chen, I. Hidekazu, and K. Toko, "Development of sensor with high selectivity for saltiness and its application in taste evaluation of table salt," *Sens. Mater.*, vol. 22, no. 6, pp. 313–325, 2010.
[21] S. Cui, J. Wang, L. Geng, Z. Wei, and X. Tian, "Determination of ginseng with different ages using a taste-sensing system," *Sens. Mater.*, vol. 25, no. 4, pp. 241–255, 2013.
[22] (Feb. 25, 2013). *Fukushima Prefecture*. Japan. [Online]. Available: http://wwwcms.pref.fukushima.jp/download/1/nougyou.tikusan_20sanko- 6.pdf
[23] Y. Ueda, M. Yonemitsu, T. Tsubuku, M. Sakaguchi, and R. Miyajima, "Flavor characteristics of glutathione in raw and cooked foodstuffs," *Biosci., Biotechnol., Biochem.*, vol. 61, no. 12, pp. 1977–1980, Jan. 1997.
[24] T. Ohsu, Y. Amino, H. Nagasaki, T. Yamanaka, S. Takeshita, T. Hatanaka, Y. Maruyama, N. Miyamura, and Y. Eto, "Involvement of the calcium-sensing receptor in human taste perception," *J. Biol. Chem.*, vol. 285, no. 2, pp. 1016–1022, Jan. 2010.
[25] H. Ikezaki, "Masking technology in foods," in *Taste Modification Technology of Food and Medicine*, K. Toko and T. Uchida, Eds. San Francisco, CA, USA: CMC Publishing, 2007, pp. 131–141.
[26] K. Toyota, H. Cui, K. Abe, M. Habara, K. Toko, and H. Ikezaki, "Sweetness sensor with lipid/polymer membranes: Response to various sugars," *Sens. Mater.*, vol. 23, no. 8, pp. 475–482, 2011.
[27] K. Toyota, H. Cui, K. Abe, M. Habara, K. Toko, and H. Ikezaki, "Sweetness sensor with lipid/polymer membranes: Sweet-responsive substances," *Sens. Mater.*, vol. 23, no. 8, pp. 465–474, 2011.
[28] H. Akitomi, Y. Tahara, M. Yasuura, Y. Kobayashi, H. Ikezaki, and K. Toko, "Quantification of tastes of amino acids using taste sensors," *Sens. Actuators B, Chem.*, vol. 179, pp. 276–281, Mar. 2013.
[29] T. Harada, T. Uchida, M. Yoshida, Y. Kobayashi, R. Narazaki, and T. Ohwaki, "A new method for evaluating the bitterness of medicines in development using a taste sensor and a disintegration testing apparatus," *Chem. Pharmaceutical Bull.*, vol. 58, no. 8, pp. 1009–1014, 2010.
[30] M. Okamoto, H. Sunada, M. Nakano, and R. Nishiyama, "Bitterness evaluation of orally disintegrating famotidine tablets using a taste sensor," *Asian J. Pharmaceutical Sci.*, vol. 4, no. 1, pp. 1–7, 2009.
[31] M. Ito, K. Wada, M. Yoshida, K. Wada, and T. Uchida, "Quantitative evaluation of bitterness of H1-receptor antagonists and masking effect of acesulfame potassium, an artificial sweetener, using a taste sensor," *Sens. Mater.*, vol. 25, no. 1, pp. 17–30, 2013.
[32] N. Ono, Y. Miyamoto, T. Ishiguro, K. Motoyama, F. Hirayama, D. Iohara, H. Seo, S. Tsuruta, H. Arima, and K. Uekama, "Reduction of bitterness of antihistaminic drugs by complexation with β-cyclodextrins," *J. Pharmaceutical Sci.*, vol. 100, no. 5, pp. 1935–1943, May 2011.
[33] M. Kitamura, "Development concept and formulation design of cetirizine hydrochloride OD tablet," *Pharmaceutical Technol. Jpn.*, vol. 27, no. 4, pp. 699–706, 2011.
[34] S. Takagi, K. Toko, K. Wada, and T. Ohki, "Quantification of suppression of bitterness using an electronic tongue," *J. Pharmaceutical Sci.*, vol. 90, no. 12, pp. 2042–2048, Dec. 2001.
[35] T. Fukagawa, Y. Tahara, and M. Yasuura, "Relationship between taste sensor response and amount of quinine adsorbed on lipid/polymer membrane," *J. Innov. Electr. Commu.*, vol. 2, no. 1, pp. 1–6, 2012.
[36] Y. Tahara, A. Ikeda, Y. Maehara, M. Habara, and K. Toko, "Development and evaluation of a miniaturized taste sensor chip," *Sensors*, vol. 11, no. 10, pp. 9878–9886, Oct. 2011.
[37] Y. Tahara, K. Nakashi, K. Ji, A. Ikeda, and K. Toko, "Development of a portable taste sensor with a lipid/polymer membrane," *Sensors*, vol. 13, no. 1, pp. 1076–1084, Jan. 2013.
[38] Q. Liu, W. Ye, L. Xiao, L. Du, N. Hu, and P. Wang, "Extracellular potentials recording in intact olfactory epithelium by microelectrode array for a bioelectronic nose," *Biosens. Bioelectron.*, vol. 25, no. 10, pp. 2212–2217, Jun. 2010.
[39] P. Chen, X.-D. Liu, B. Wang, G. Cheng, and P. Wang, "A biomimetic taste receptor cell-based biosensor for electrophysiology recording and acidic sensation," *Sens. Actuators B, Chem.*, vol. 139, no. 2, pp. 576–583, Jun. 2009.
[40] Q. Liu, F. Zhang, D. Zhang, N. Hu, H. Wang, K. J. Hsia, and P. Wang, "Bioelectronic tongue of taste buds on microelectrode array for salt sensing," *Biosens. Bioelectron.*, vol. 40, no. 1, pp. 115–120, Feb. 2013.
[41] C. Zhang and K. S. Suslick, "A colorimetric sensor array for organics in water," *J. Amer. Chem. Soc.*, vol. 127, no. 33, pp. 11548–11549, Aug. 2005.
[42] C. Zhang, D. P. Bailey, and K. S. Suslick, "Colorimetric sensor arrays for the analysis of beers: A feasibility study," *J. Agricult. Food Chem.*, vol. 54, no. 14, pp. 4925–4931, Jul. 2006.
[43] C. Zhang and K. S. Suslick, "Colorimetric sensor array for soft drink analysis," *J. Agricult. Food Chem.*, vol. 55, no. 2, pp. 237–242, Jan. 2007.
[44] K. Umino, M. Habara, and K. Toko, "Simple screening method for pesticide residues by detecting coexistent adjuvants using potentiometric measurement," *Sens. Mater.*, vol. 24, no. 1, pp. 1–11, 2012.
[45] N. Bhattacharyya, R. Bandyopadhyay, M. Bhuyan, B. Tudu, D. Ghosh, and A. Jana, "Electronic nose for black tea classification and correlation of measurements with 'tea taster' marks," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 7, pp. 1313–1321, Jul. 2008.
[46] N. Togari, A. Kobayashi, and T. Aishima, "Relating sensory properties of tea aroma to gas chromatographic data by chemometric calibration methods," *Food Res. Int.*, vol. 28, no. 5, pp. 485–493, Jan. 1995.
[47] Y. Zuo, "Simultaneous determination of catechins, caffeine and gallic acids in green, oolong, black and pu-erh teas using HPLC with a photodiode array detector," *Talanta*, vol. 57, no. 2, pp. 307–316, May 2002.
[48] H. Horie, T. Mukai, and K. Kohata, "Simultaneous determination of qualitatively important components in green tea infusions using capillary electrophoresis," *J. Chromatography A*, vol. 758, no. 2, pp. 332–335, Jan. 1997.
[49] B. Banerjee, *Tea Production and Processing*. New Delhi, India: Oxford & IBH Publishing Co., 1993.

[50] Tocklai Tea Research Association. (Jan. 2021). [Online]. Available: https://www.tocklai.net

[51] P. Ivarsson, S. Holmin, N.-E. Höjer, C. Krantz-Rülcker, and F. Winquist, "Discrimination of tea by means of a voltammetric electronic tongue and different applied waveforms," *Sens. Actuators B, Chem.*, vol. 76, nos. 1–3, pp. 449–454, Jun. 2001.

[52] V. Parra, Á. A. Arrieta, J. A. Fernández-Escudero, H. García, C. Apetrei, M. L. Rodríguez-Méndez, and J. A. D. Saja, "E-tongue based on a hybrid array of voltammetric sensors based on phthalocyanines, perylene derivatives and conducting polymers: Discrimination capability towards red wines elaborated with different varieties of grapes," *Sens. Actuators B, Chem.*, vol. 115, no. 1, pp. 54–61, May 2006.

[53] B. A. Lawton and R. Pethig, "Determining the fat content of milk and cream using AC conductivity measurements," *Meas. Sci. Technol.*, vol. 4, no. 1, pp. 38–41, Jan. 1993.

[54] A. Legin, A. Rudnitskaya, Y. Vlasov, C. Di Natale, F. Davide, and A. D'Amico, "Tasting of beverages using an electronic tongue," *Sens. Actuators B, Chem.*, vol. 44, nos. 1–3, pp. 291–296, Oct. 1997.

[55] Q. Chen, J. Zhao, and S. Vittayapadung, "Identification of the green tea grade level using electronic tongue and pattern recognition," *Food Res. Int.*, vol. 41, no. 5, pp. 500–504, Jan. 2008.

[56] P. Ciosek, Z. Brzózka, and W. Wróblewski, "Electronic tongue for flow-through analysis of beverages," *Sens. Actuators B, Chem.*, vol. 118, nos. 1–2, pp. 454–460, Oct. 2006.

[57] A. Scozzari, N. Acito, and G. Corsini, "A novel method based on voltammetry for the qualitative analysis of water," *IEEE Trans. Instrum. Meas.*, vol. 56, no. 6, pp. 2688–2697, Dec. 2007.

[58] K. Beullens, D. Kirsanov, J. Irudayaraj, A. Rudnitskaya, A. Legin, B. M. Nicolaï, and J. Lammertyn, "The electronic tongue and ATR–FTIR for rapid detection of sugars and acids in tomatoes," *Sens. Actuators B, Chem.*, vol. 116, nos. 1–2, pp. 107–115, Jul. 2006.

[59] M. Scampicchio, S. Benedetti, B. Brunetti, and S. Mannino, "Amperometric electronic tongue for the evaluation of the tea astringency," *Electroanalysis*, vol. 18, no. 17, pp. 1643–1648, Sep. 2006.

[60] J. Olsson, F. Winquist, and I. Lundström, "A self polishing electronic tongue," *Sens. Actuators B, Chem.*, vol. 118, nos. 1–2, pp. 461–465, Oct. 2006.

[61] L. Lvova, A. Legin, Y. Vlasov, G. S. Cha, and H. Nam, "Multicomponent analysis of korean green tea by means of disposable all-solid-state potentiometric electronic tongue microsystem," *Sens. Actuators B, Chem.*, vol. 95, nos. 1–3, pp. 391–399, Oct. 2003.

[62] P. Ivarsson, Y. Kikkawa, F. Winquist, C. Krantz-Rülcker, N.-E. Höjer, K. Hayashi, K. Toko, and I. Lundström, "Comparison of a voltammetric electronic tongue and a lipid membrane taste sensor," *Analytica Chim. Acta*, vol. 449, nos. 1–2, pp. 59–68, Dec. 2001.

[63] M. Palit, B. Tudu, P. K. Dutta, A. Dutta, A. Jana, J. K. Roy, N. Bhattacharyya, R. Bandyopadhyay, and A. Chatterjee, "Classification of black tea taste and correlation with tea taster's mark using voltammetric electronic tongue," *IEEE Trans. Instrum. Meas.*, vol. 59, no. 8, pp. 2230–2239, Aug. 2010.

[64] S. Kumar and A. Ghosh, "An improved fractional-order circuit model for voltammetric taste sensor system with infused tea as analyte," *IEEE Sensors J.*, vol. 20, no. 14, pp. 7792–7800, Jul. 2020.

[65] A. Legin, D. Kirsanov, and M. del Valle, "Avoiding nonsense in electronic taste sensing," *TrAC Trends Anal. Chem.*, vol. 121, Dec. 2019, Art. no. 115675.

[66] A. Ghosh, A. K. Bag, P. Sharma, B. Tudu, S. Sabhapondit, B. D. Baruah, P. Tamuly, N. Bhattacharyya, and R. Bandyopadhyay, "Monitoring the fermentation process and detection of optimum fermentation time of black tea using an electronic tongue," *IEEE Sensors J.*, vol. 15, no. 11, pp. 6255–6262, Nov. 2015.

[67] A. J. Bard and L. R. Faulkner, *Electrochemical Methods: Fundamentals and Applications*, 2nd ed. New York, NY, USA: Wiley, 2001.

[68] T. J. Freeborn, "A survey of fractional-order circuit models for biology and biomedicine," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 3, no. 3, pp. 416–424, Sep. 2013.

[69] T. J. Freeborn, B. Maundy, and A. S. Elwakil, "Extracting the parameters of the double-dispersion cole bioimpedance model from magnitude response measurements," *Med. Biol. Eng. Comput.*, vol. 52, no. 9, pp. 749–758, Sep. 2014.

[70] R. K. H. Galvao, S. Hadjiloucas, K. H. Kienitz, H. M. Paiva, and R. J. M. Afonso, "Fractional order modeling of large three-dimensional RC networks," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 60, no. 3, pp. 624–637, Mar. 2013.

[71] L. A. Jacyntho, M. C. M. Teixeira, E. Assuncao, R. Cardim, R. K. H. Galvao, and S. Hadjiloucas, "Identification of fractional-order transfer functions using a step excitation," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 62, no. 9, pp. 896–900, Sep. 2015.

[72] M. Tiitta and H. Olkkonen, "Electrical impedance spectroscopy device for measurement of moisture gradients in wood," *Rev. Sci. Instrum.*, vol. 73, no. 8, pp. 3093–3100, Aug. 2002.

[73] T. Repo, J. Laukkanen, and R. Silvennoinen, "Measurement of the tree root growth using electrical impedance spectroscopy," *Silva Fennica*, vol. 39, no. 2, pp. 159–166, 2005.

[74] C.-M. Lin, L.-H. Chen, and T.-M. Chen, "The development and application of an electrical impedance spectroscopy measurement system for plant tissues," *Comput. Electron. Agricult.*, vol. 82, pp. 96–99, Mar. 2012.

[75] C. M. Ionescu and R. De Keyser, "Time domain validation of a fractional order model for human respiratory system," in *Proc. MELECON 4th IEEE Medit. Electrotech. Conf.*, May 2008, pp. 89–95.

[76] J. E. Craven, D. S. Kinnamon, and S. Prasad, "Randles circuit analysis toward investigating interfacial effects on microchannel electrodes," *IEEE Sensors Lett.*, vol. 2, no. 1, pp. 1–4, Mar. 2018.

[77] S. M. M. Alavi, A. Mahdi, S. J. Payne, and D. A. Howey, "Identifiability of generalized randles circuit models," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 6, pp. 2112–2120, Nov. 2017.

[78] S. Kumar, A. Ghosh, B. Tudu, and R. Bandyopadhyay, "A circuit model estimation of voltammetric taste measurement system for black tea," *Measurement*, vol. 140, pp. 609–621, Jul. 2019.

[79] A. Bhuyan, B. Tudu, R. Bandyopadhyay, A. Ghosh, and S. Kumar, "ARMAX modeling and impedance analysis of voltammetric E-tongue for evaluation of infused tea," *IEEE Sensors J.*, vol. 19, no. 11, pp. 4098–4105, Jun. 2019.

[80] A. Ghosh, P. Sharma, B. Tudu, S. Sabhapondit, B. D. Baruah, P. Tamuly, N. Bhattacharyya, and R. Bandyopadhyay, "Detection of optimum fermentation time of black CTC tea using a voltammetric electronic tongue," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 10, pp. 2720–2729, Oct. 2015.

[81] A. Y. Yashin, B. V. Nemzer, E. Combet, and Y. I. Yashin, "Determination of the chemical composition of tea by chromatographic methods: A review," *J. Food Res.*, vol. 4, no. 3, pp. 56–88, 2015.

[82] B. M. King and J. Solms, "Interactions of volatile flavor compounds with propyl gallate and other phenols as compared with caffeine," *J. Agricult. Food Chem.*, vol. 30, no. 5, pp. 838–840, Sep. 1982.

[83] X. L. Zhou, A. Zhu, J. Liu, Y.-H. Mei, H. Zhang, and F.-L. Chen, "Effect on the tea by adding amino acids," *Amino Acids Biotic Resour.*, vol. 29, no. 2, pp. 46–48, 2007.

[84] J. Yao and J. Xu, "Research on the BPNN in the prediction of PMV," *Appl. Mech. Mater.*, vol. 29, pp. 2804–2808, 2010.

[85] G. Sen and B. Bera, "Mini review black tea as a part of daily diet: A boon for healthy living," *Int. J. Tea Sci.*, vol. 9, nos. 2-3, pp. 51–59, 2013.

[86] E. J. Gardner, C. H. S. Ruxton, and A. R. Leeds, "Black tea—Helpful or harmful? A review of the evidence," *Eur. J. Clin. Nutrition*, vol. 61, no. 1, pp. 3–18, Jan. 2007.

[87] F.-L. Chung, J. Schwartz, C. R. Herzog, and Y.-M. Yang, "Tea and cancer prevention: Studies in animals and humans," *J. Nutrition*, vol. 133, no. 10, pp. 3268S–3274S, Oct. 2003.

[88] A. Morshedi and M. H. Dashti-Rahmatabadi, "Chronic consumption of Kombucha and black tea prevents weight loss in diabetic rats," *Iranian J. Diabetes Obesity*, vol. 2, no. 2, pp. 23–26, 2010.

[89] A. Deka and J. A. Vita, "Tea and cardiovascular disease," *Pharmacolog. Res.*, vol. 64, no. 2, pp. 136–145, Aug. 2011.

[90] T. MacKenzie, L. Leary, and W. B. Brooks, "The effect of an extract of green and black tea on glucose control in adults with type 2 diabetes mellitus: Double-blind randomized study," *Metabolism*, vol. 56, no. 10, pp. 1340–1344, Oct. 2007.

[91] P. M. Almajano, R. Carbó, L. A. J. Jiménez, and H. M. Gordon, "Antioxidant and antimicrobial activities of tea infusions," *Food Chem*, vol. 108, no. 1, pp. 55–63, 2008.

[92] S. Crouvezier, B. Powell, D. Keir, and P. Yaqoob, "The effects of phenolic components of tea on the production of pro- and anti-inflammatory cytokines by human leukocytes," *Cytokine*, vol. 13, no. 5, pp. 280–286, Mar. 2001.

[93] Y. Shukla and P. Taneja, "Anticarcinogenic effect of black tea on pulmonary tumors in Swiss albino mice," *Cancer Lett.*, vol. 176, no. 2, pp. 137–141, Feb. 2002.

[94] W. Łuczaj and E. Skrzydlewska, "Antioxidative properties of black tea," *Preventive Med.*, vol. 40, no. 6, pp. 910–918, 2005.

[95] W. Luczaj and E. Skrzydlewska, ''Antioxidative properties of black tea,'' *Preventive Med.*, vol. 40, pp. 910–918, Jun. 2005.

[96] A. M. Baruah and P. K. Mahanta, ''Fermentation characteristics of some assamica clones and process optimization of black tea manufacturing,'' *J. Agricult. Food Chem.*, vol. 51, no. 22, pp. 6578–6588, Oct. 2003.

[97] J. M. Geleijnse, L. J. Launer, A. Hofman, H. A. Pols, and J. C. Witteman, ''Tea flavonoids may protect against atherosclerosis,'' *Arch. Internal Med.* vol. 159, no. 18, pp. 2170–2174, 1999.

[98] J. M. Hodgson and K. D. Croft, ''Dietary flavonoids: Effects on endothelial function and blood pressure,'' *J. Sci. Food Agricult.*, vol. 86, no. 15, pp. 2492–2498, Dec. 2006.

[99] M. A. Vermeer, T. P. J. Mulder, and H. O. F. Molhuizen, ''Theaflavins from black tea, especially Theaflavin-3-gallate, reduce the incorporation of cholesterol into mixed micelles,'' *J. Agricult. Food Chem.*, vol. 56, no. 24, pp. 12031–12036, Dec. 2008.

[100] J.-K. Lin and S.-Y. Lin-Shiau, ''Mechanisms of hypolipidemic and anti-obesity effects of tea and tea polyphenols,'' *Mol. Nutrition Food Res.*, vol. 50, no. 2, pp. 211–217, Feb. 2006.

[101] P. S. Stefano and C. Scully, ''A review—Polyphenols, oral health and disease,'' *J. Dentistry*, vol. 37, no. 6, pp. 413–423, 2009.

[102] S. A. Mandel, T. Amit, O. Weinreb, and M. B. H. Youdim, ''Understanding the broad-spectrum neuroprotective action profile of green tea polyphenols in aging and neurodegenerative diseases,'' *J. Alzheimer's Disease*, vol. 25, no. 2, pp. 187–208, Jul. 2011.

[103] A. Gokhale, P. Mulay, D. Pramod, and R. Kulkarni, ''A bibliometric analysis of digital image forensics,'' *Sci. Technol. Libr.*, vol. 39, no. 1, pp. 96–113, 2020, doi: 10.1080/0194262X.2020.1714529.

[104] N. V. Raju and N. S. Harinarayana, ''Research productivity and citation impact of S.C. Sharma as seen through the scopus database,'' *Library Philosophy Pract. (e-J.)*, Jan./Feb. 2021, Art. no. 4276. [Online]. Available: https://digitalcommons.unl.edu/libphilprac/4276

[105] K. D. Kadam, S. A. Ahirrao, and K. Kotecha, ''Bibliometric analysis of passive image forgery detection and explainable AI,'' *Library Philosophy Pract. (e-J.)*, 2020, Art. no. 3897. [Online]. Available: https://digitalcommons.unl.edu/libphilprac/3897

[106] *(PDF) Application of Author Bibliographic Coupling Analysis and Author Keywords Ranking in Identifying Research Fronts of Indian Neurosciences Research*. Accessed: Oct. 4, 2020. [Online]. Available: https://www.researchgate.net/publication/333104239_Application_of_author_bibliographic_coupling_analysis_and_author_keywords_ranking_in_identifying_research_fronts_of_Indian_Neurosciences_research

[107] R. Patil and S. Kumar, ''Bibliometric survey on diagnosis of plant leaf diseases using artificial intelligence,'' *Int. J. Mod. Agricult.*, vol. 9, no. 3, pp. 1111–1131, 2020.

[108] T. Mitchell, W. Cohen, E. Hruschka, P. Talukdar, B. Yang, J. Betteridge, A. Carlson, B. Dalvi, M. Gardner, B. Kisiel, and J. Krishnamurthy, ''Never-ending learning,'' *Commun. ACM*, vol. 61, no. 5, pp. 103–115, 2018.

[109] L. Li, S. Xie, J. Ning, Q. Chen, and Z. Zhang, ''Evaluating green tea quality based on multisensor data fusion combining hyperspectral imaging and olfactory visualization systems,'' *J. Sci. Food Agricult.*, vol. 99, no. 4, pp. 1787–1794, Mar. 2019.

[110] G. C. Román, R. E. Jackson, R. Gadhia, A. N. Román, and J. Reis, ''Mediterranean diet: The role of long-chain ω-3 fatty acids in fish; polyphenols in fruits, vegetables, cereals, coffee, tea, cacao and wine; probiotics and vitamins in prevention of stroke, age-related cognitive decline, and alzheimer disease,'' *Revue Neurologique*, vol. 175, no. 10, pp. 724–741, Dec. 2019.

[111] J. Sandino, G. Pegg, F. Gonzalez, and G. Smith, ''Aerial mapping of forests affected by pathogens using UAVs, hyperspectral sensors, and artificial intelligence,'' *Sensors*, vol. 18, no. 4, p. 944, Mar. 2018.

[112] Q. Chen, M. Chen, Y. Liu, J. Wu, X. Wang, Q. Ouyang, and X. Chen, ''Application of FT-NIR spectroscopy for simultaneous estimation of taste quality and taste-related compounds content of black tea,'' *J. Food Sci. Technol.*, vol. 55, no. 10, pp. 4363–4368, Oct. 2018.

[113] P. Pławiak and W. Maziarz, ''Classification of tea specimens using novel hybrid artificial intelligence methods,'' *Sens. Actuators B, Chem.*, vol. 192, pp. 117–125, Mar. 2014.

[114] X. Wu, J. Yang, and S. Wang, ''Tea category identification based on optimal wavelet entropy and weighted k-Nearest neighbors algorithm,'' *Multimedia Tools Appl.*, vol. 77, no. 3, pp. 3745–3759, Feb. 2018.

[115] A. Saha, A. Konar, A. Chatterjee, A. Ralescu, and A. K. Nagar, ''EEG analysis for olfactory perceptual-ability measurement using a recurrent neural classifier,'' *IEEE Trans. Human-Mach. Syst.*, vol. 44, no. 6, pp. 717–730, Dec. 2014.

[116] M. Panwar, D. Biswas, H. Bajaj, M. Jobges, R. Turk, K. Maharatna, and A. Acharyya, ''Rehab-Net: Deep learning framework for arm movement classification using wearable sensors for stroke rehabilitation,'' *IEEE Trans. Biomed. Eng.*, vol. 66, no. 11, pp. 3026–3037, Nov. 2019.

[117] C. Dong, J. Li, J. Wang, G. Liang, Y. Jiang, H. Yuan, Y. Yang, and H. Meng, ''Rapid determination by near infrared spectroscopy of theaflavins-to-thearubigins ratio during congou black tea fermentation process,'' *Spectrochim. Acta A, Mol. Biomol. Spectrosc.*, vol. 205, pp. 227–234, Dec. 2018.

[118] Patil, Amruta Bajirao Research Scholar and Bachute, Mrinal Rahul Ph.D Guide and Associate Professor. (2021). *A Bibliometric Analysis of the Tea Quality Evaluation Using Artificial Intelligence*. Library Philosophy and Practice (e-Journal). [Online]. Available: https://digitalcommons.unl.edu/libphilprac/4959

[119] M. R. Bachute and R. D. Kharadkar, ''Performance analysis and comparison of complex LMS, sign LMS and RLS algorithms for speech enhancement application,'' *Asian J. Converg. Technol.*, vol. 3, no. 2, 2017.

[120] M. Bachute and R. D. Kharadkar, ''Analysis and implementation of time-varying least mean square algorithm and modified time-varying LMS for speech enhancement,'' *Int. J. Sci. Res.*, vol. 4, no. 4, pp. 764–768, Apr. 2015.

[121] M. Bachute and R. D. Kharadkar, ''Analysis of least mean square and recursive least squared adaptive filter algorithm for speech enhancement application,'' in *Proc. Int. Conf. Next Gener. Comput. Technol.*, Singapore: Springer, Oct. 2017, pp. 590–604.

[122] T. A. Lonare and M. R. Bachute, ''Noise cancellation using least mean square and wavelet transform for speech enhancement,'' *JournalNX*, vol. 2, no. 6, pp. 13–17, 2016.

[123] M. G. Sv and M. R. Bachute, ''Speech enhancement by a microphone array using various modelling approach,'' *Int. J.*, to be published.

[124] S. Z. Zhang, ''Data preparation for data mining,'' *Appl. Artif. Intell.*, vol. 17, pp. 375–381, Apr. 1999.

[125] L. L. Yu, ''Efficient feature selection via analysis of relevance and redundacy,'' *J. Mach. Learn. Res.*, vol. 5, pp. 1205–1224, Oct. 2004.

[126] J. Lee and S. Kang, ''Consumer-driven usability test of mobile application for tea recommendation service,'' *Appl. Sci.*, vol. 9, no. 19, p. 3961, Sep. 2019.

AMRUTA BAJIRAO PATIL was born in India. She received the B.E. degree in electronics and telecommunication from the Cummins College of Engineering for Women, Pune, in 2009, and the M.Tech. degree in electronics and VLSI technology from the Bharati Vidyapeeth College of Engineering, Pune, in 2014. She is currently pursuing the Ph.D. degree with Symbiosis International University, Pune. Since 2010, she has been teaching with the Department of Electronics and Telecommunication, Bharati Vidyapeeth College of Engineering, where she is currently working as an Assistant Professor. She has published research articles in many well-known journals at the national and international levels. Her research interests include embedded system applications and machine learning.

MRINAL RAHUL BACHUTE was born in India. She received the master's degree in digital electronics and the Ph.D. degree in study and analysis of adaptive filters for speech enhancement applications. She is currently an Associate Professor and an Industry Liaison Officer with the Department of Electronics and Telecommunication Engineering, Symbiosis Institute of Technology, Pune Symbiosis International (Deemed University), Pune, India. She has teaching experience of 20 years and has guided many graduate students for their projects. Her research articles have been published in many reputed journals and conferences at the national and international levels. Her research interests include digital signal processing and adaptive signal processing.

KETAN KOTECHA received the M.Tech. and Ph.D. degrees from IIT Bombay.

He is currently holding the positions as the Head of the Symbiosis Centre for Applied AI (SCAAI), the Director of the Symbiosis Institute of Technology, the CEO of the Symbiosis Centre for Entrepreneurship and Innovation (SCEI), and the Dean of the Faculty of Engineering, Symbiosis International (Deemed University). He has expertise and experience in cutting-edge research and projects in AI and deep learning for the last (more than) 25 years. He has published more than 100 widely in a number of excellent peer-reviewed journals on various topics ranging from cutting-edge AI, education policies, teaching-learning practices, and AI for all. He has published three patents and delivered key note speeches at various national and international forums, including at the Machine Intelligence Laboratory, USA; IIT Bombay under World Bank Project; International Indian Science Festival organized by the Department of Science Technology, Government of India; and many more.

Dr. Kotecha was a recipient of the two SPARC projects worth INR 166 lakhs from the MHRD Government of India in AI in collaboration with Arizona State University, USA, and The University of Queensland, Australia, and also a recipient of numerous prestigious awards like Erasmus+ Faculty Mobility Grant to Poland, the DUO-India Professors Fellowship for research in responsible AI in collaboration with Brunel University, U.K., the LEAP Grant at Cambridge University, U.K., the UKIERI Grant with Aston University, U.K., and a grant from the Royal Academy of Engineering, the U.K., under Newton Bhabha Fund. He is also an Academic Editor of the *Peerj Computer Science* journal and an Associate Editor of IEEE ACCESS journal.