Fuzzy Logic-Based Classification and Authentication of Beverages

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INTRODUCTION

Tea can be considered as one of the most extensively consumed and cherished drinks in the world because of its health, dietetic and therapeutic benefits (Chen et al., 2020; da Silva Pinto, 2013). Conventionally, professional tea testers assessed the quality of a tea brand on the basis of its color, texture, aroma, and taste (Ren et al., 2021). However, this type of judgment conjectured with human perception may be subjective in nature and prone to suffer from inconsistency and fickleness (Yang et al., 2021). Similarly, several mineral water brands are commercially available, and a few of them are sold with fake labels or no labels on them. Famous mineral water brands don't have an appreciable distinction in their ionic compositions. This makes the assessment of water quality and subsequent monitoring complicated but interesting. These factors compel designing a robust classifier and authenticator for the beverages (tea and water). By applying the techniques of Sammon's Nonlinear Mapping (NLM) and entropy-based fuzzy clustering method on the characteristic signatures of different tea and water brands obtained from electronic tongue (e-tongue), a particle swarm optimization (PSO)-tuned fuzzy logic-based expert system was designed for classification and subsequent authentication of beverages. Some commonly used dimension reduction techniques and clustering techniques were also briefly discussed.

BACKGROUND

Previously, a number of research had assessed the quality of beverages using various analytical techniques, such as high-performance liquid chromatography (HPLC), gas chromatography-mass spectrometry (GC-MS), capillary electrophoresis (CE) etc. (Ren et al., 2013; Yang et al., 2020; Zhou et al., 2022). However, all of the above-mentioned techniques are relatively time-consuming, complex, and expensive, which limits their practical applicability. Recently, electronic tongue (e-tongue)-based automated beverage and food quality monitoring has become quite prevalent (Banerjee et al., 2019; Calvini & Pigani, 2022; Garcia-Breijo et al., 2011; Hu et al., 2022; Moreno et al., 2006; Rifna et al., 2022; Sipos et al., 2012; Wang et al., 2019; Wu et al., 2022; Zeng et al., 2022).

An e-tongue consists of some non-specific solid-state ion sensors, different types of transducers, data collectors, and machine learning algorithms for data analysis aiming characterization of liquid samples (Al-Dayyeni et al., 2021; Apetrei & Apetrei, 2013; Escuder-Gilabert & Peris, 2010; Kirsanov et al., 2013; Marx et al., 2021; Ribeiro et al., 2021; Riul Jr. et al., 2010; Tahara & Toko, 2013). Various electrochemical methods, such as pulse voltammetry, potentiometry, amperometry, and stripping

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voltammetry were deployed in e-tongue to generate characteristic signatures (like current signatures due to pulse voltammetry) of the liquid sample to be analyzed. An e-tongue is not a taste sensor; the result of characterization is not necessarily correlated with human taste perception or compared with panelists. In dynamic interfacial techniques, it is not humanly possible to classify just by executing a visual inspection of the waveforms obtained as an output from an e-tongue. Cross selectivity (partial overlapping selectivity) of sensors employed and non-stationarities in the corresponding signals were the reasons, which demand the deployment of machine learning algorithms to formulate automated/computer-based systems for authentication purposes (Ciosek & Wróblewski, 2007; Vlasov et al., 2005). It might be appropriate to refer to a few research contributions regarding the applications of multivariate statistical, neural network-based, and fuzzy logic-based machine learning components practiced in e-tongue devices dedicated to quality monitoring.

Mineral water samples commercially available in the Indian market were utilized to generate e-tongue signatures and developed classifiers using different machine learning algorithms like Slantlet-transform (ST)-based neural networks, Cross correlation-based Sammon's non-linear mapping (NLM), PLS, and PCA (Kundu et al., 2011a, 2011b; Kundu & Kundu, 2013). Sammon's NLM-based tea classifier/authenticator was developed using e-tongue signatures of commercially available tea brands in the Indian market (Kundu & Kundu, 2012). RPCA-based commercial tea classifier was also reported (Kundu et al., 2017). Recently, a correlation coefficient and cluster analysis-based tea aroma detection technique (Wang et al., 2021) and a tea quality identification system based on semi-supervised learning of generative adversarial network (Zhang et al., 2022) were proposed. A convolutional neural network-based feature extraction approach was also utilized in e-tongue system for tea classification (Zhong et al., 2019). A neuro-fuzzy approach for classifying and assessing the aroma, flavor, and taste of black tea using e-tongue and electronic nose (e-nose) signals was also proposed (Mondal et al., 2017). Several studies on utilizing e-tongue and/or e-nose signals to develop classifiers of black tea quality evaluation using the principle of fuzzy logic were previously reported (Roy et al., 2013; Tudu et al., 2009, 2015).

FOCUS OF THE ARTICLE

In the aforesaid backdrop, present research effort is dedicated to designing a beverage classification and authentication device using Sammon's NLM, entropy-based fuzzy clustering method, and subsequent PSO-tuned fuzzy logic-based expert system design. The performance of the developed techniques has been tested on two data sets, as mentioned below.

Data Collection

A data set consisting of six numbers of water brands (Aquafina, Bisleri, Kingfisher, Oasis, Dolphin, and McDowell) certified by ISI were considered for data generation using platinum working electrode in the e-tongue (Kundu, 2015). Each of the brands possessing 3 numbers of samples and each of the samples containing 4402 numbers of features (current signatures from e-tongue due to pulse voltammetric experimentation) were considered to create training database (18×4402). One more replicate; 4th sample time series data were created/simulated for each of the brands under consideration by appending random noise to any of the three training samples, and later those were used for testing the developed algorithms.

E-tongue signals related to tea (using silver as working electrode and six different ISI certified grades of tea; namely Brookbond, Double-diamond, Godrej, Lipton, Lipton-Darjeeling, Marvel), each having