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A Review on Electronic Nose: Coherent Taxonomy, Classification, Motivations, Challenges, Recommendations and Datasets

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ABSTRACT **Context:** Quality Control (QC) has been constantly an essential concern in many fields like food industry production, medical drugs, environmental protection, and so on. An odor or flavor, as a global fingerprint, can be implemented as a non-invasive mechanism for quality assurance. This computer-based approach can assure accurate detection and precise identification of the product quality or manufactured goods. **Objective:** This paper aims to achieve a systematic review about e-nose by introducing the achievements made by researchers in this area, to summarize their findings, to provide motivations and challenges to new researchers in the field of e-nose. **Methods:** The articles that were being utilized in the e-nose field were systematically achieved using three search engines: The online library of IEEE Explore, Web of Science and Science Direct for time span of 7 years (from 2013 to 2020). Both medical literature reviews and technical reviews were considered in the criteria of the research for wider understanding in the field of e-nose. The articles were categorized according to the objective of the research and projected into four classes. Upon completion of screening process 333 research papers using the exclusion and inclusion conditions, as the final set 54 articles were selected. **Results:** The taxonomy of this research was classified into four categories. The first one included the suggested methods that introduced the utilization of the e-nose for classification purposes (9/54 papers). The second category comprises the methods related to the development of e-nose (24/54 papers). The third one included the review studies about the e-nose (8/54 papers). The fourth group comprises comparative studies and evaluation (13/54 papers). **Discussion:** This systematic review contributes for a clearer understanding and a full insight in the e- nose research field by surveying and categorizing pertinent research efforts. **Conclusion:** This review paper will help to address the up-to-date research opportunities, challenges, problems, motivations and recommendations related to the utilization of e-nose in all fields of sciences and industries.

INDEX TERMS Artificial olfaction, electronic nose, feature classification, food quality, machine learning, pattern recognition.

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I. INTRODUCTION

The electronic nose (e-nose), as a device, consists of a chemical sensing unit and a pattern recognition part. The e-nose systems are intended to be utilized for detecting and identifying odors. It is usually done by utilizing chemical sensing units with signal processing and pattern recognition system [1]. Note that the e-nose device can imitate the human's olfactory system for vapor detection of many volatile compounds. It is indeed one the essential tool especially for the Food Industry and can provide numerous advantages to consumers as well [2]. The e-nose techniques or also known as machine olfaction could be used replacement for the usual techniques used in food authentication or other fields [3]. In addition, an e-nose or electronic sensing is a gas sensing unit comprising sensor arrays along with pattern recognition system. E-nose technique has been broadly utilized in various fields recently. Over the last two decades, numerous progress and improvement of artificial olfaction systems has been developed in many aspects that includes data processing, sensor array, and pattern recognition algorithms [4]–[6].

Conversely, the electronic olfactory unit is normally formed together with the nose model to mimic the biological olfactory mechanism of the human. This was proposed as early as 1982 and it was based on two vital assumptions of the human olfactory system. The first one is that no necessity for the odor-particular transducers. The second assumption is that signals of the odor from the transducers can be further analyzed. The odorant detectors, which are the neurons, are the most important characteristic of the model. This detector can respond to several types of chemicals. Gardner and Bartlett, in 1994, introduced a novel description for an artificial olfactory system: "An electronic nose (e-nose) is an instrument, which comprises of an array of chemical sensors with partial specificity along with an appropriate pattern recognition system, capable of recognizing simple or complex odors" [7]–[10].

The application of E-nose has been increasing in many research areas. More attention is focused specifically on process monitoring as well as the food industries quality control. For instance, the e-nose system has been effectively utilized for analysis of food process that include black tea quality assessment and classification purpose, monitoring postharvest processing of grapes, saffron, for pears quality evaluation and ripeness status, coffee, oranges, mangos, apples, pineapples, apricots, peaches, brewery, meat quality assessment, fish freshness, rice wine, quality status of mandarin and many others that have been reported. Moreover, several reviews articles related to e-nose technology can be found in different fields as well. These review articles comprised of e-nose systems applications in pharmaceutical, food industries, agriculture, biomimetic/biotechnology, computational techniques for the analysis of the e-nose data, and pattern recognition methods [11]–[14]. Therefore, this paper aimed to show the accomplishments of researchers and to summarize the previous findings of the research articles in which the e-nose technology is used. Also, to establish assessment methods and measures, and to suggest a taxonomy of literature of this field of study. This research is systematized as follows: Section 1 introduces the field of the study; Section 2 defines the review protocol; Section 3 discusses the method part; Section 4 displays the motivations; Section 5 presents the challenges; Section 6 discusses the recommendations obtained from the reviewed articles; Section 7 summarizes the datasets of the reviewed papers, and Section 8 presents the conclusion for this paper.

II. THE REVIEW PROTOCOL

A. DATA SOURCES

Searching for the e-nose articles were performed by exploring the three search engines: IEEE Xplore digital library, ScienceDirect (SD) and Web of Science (WOS) for the period of 7 years, from March 2013 until May 2020. The search query includes numerous journals and conference articles in electrical engineering, software engineering, computer science, biomedical engineering, and medical field only in English language articles were accepted. Consequently, both technical and medical literature reviews were considered in the search criteria providing the reader a full understanding of the field of this study.

B. STUDY SELECTION

The selection was made through an intensive search of the related publications. The procedure for the selection of the related work depended on two steps. The first step was to scan the titles and skim the abstracts of the selected article to eliminate the duplicated and the unrelated studies. After a full reading of the selected articles from the first stage, the researchers organized the articles according to the proposed section in this study as the second step.

C. SEARCH QUERY

The search query of this study on the IEEE, SD, and WOS databases ran on 6 May 2020. The keywords used in the search query in all databases were ("e-nose" OR "E-nose" OR "E nose" OR "Electronic nose" OR "Electronic-nose" OR "machine olfaction" OR "artificial olfaction" OR "e-sniffer" OR "artificial nose") AND (Detect OR sniff OR classify OR extract) AND (authentication OR "Halal food Authentication") to focus our scope of the search into electronic nose cases. The advanced search option was applied to select the journals and conference articles only. The books and other forms of documents were excluded. The articles that were involved in the scientific research of the e-nose field were considered. Fig.1 depicts a schematic description for the search query and Table 1 shows the search query settings.

D. DATA COLLECTION PROCESS

The selected articles collected from various sources were organized with the related initial classifications. The authors completed a full-text reading of the selected papers and highlighted the important parts needed for this study. The important findings were emphasized, summarized, and tabulated for further use in this research. The Excel and word programs were used to save the highlighted information as well as the surveyed papers list, summary tables, source indices, review sources, purposes, evaluation criteria, used datasets, validation techniques, classification methods, and related figures.

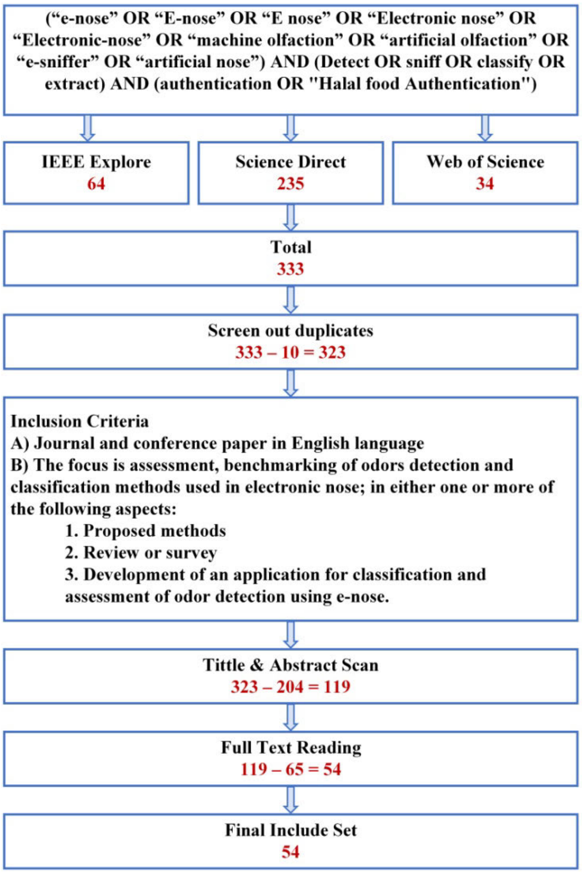

FIGURE 1. Study selection, search query, and inclusion criteria.

TABLE 1. Search query settings.

Online Library	IEEE	Science Direct	Web of Science
Years	2013 – 2020	2013 – 2020	2013 – 2020
Language	Only English	Only English	Only English
Run on	Full Text	Full Text	Full Text
Subject areas	All Available	All Available	All Available
Date of search	06/05/2020	06/05/2020	06/05/2020

III. METHODS

As shown in Fig. 2, in this review the categorization of the e-nose methodology is projected into four classes. The first comprises the suggested methods that introduced the use of the e-nose for classification purposes (9/54 papers). Secondly are the methods related to the development of e-nose systems (24/54 papers). The third one covers the review studies about the e-nose (8/54 papers). The fourth group contains evaluation and comparative studies (13/54 papers).

A. CLASSIFICATION

This category summarizes the methods of classification of the included research articles. The overall context of all papers under this class is (9/54). First, [1] showed that linear discriminant analysis (LDA) was utilized for e-nose data processing and recognition. The results presented that the e-nose was magnificently classified aroma of various kinds of vegetable oil. Second, in [3], this study intended to distinguish between non-alcoholic and alcoholic beer by utilizing a MOS-based electronic nose unit. Backpropagation (BP) and radial basis function (RBF) revealed excellent findings based on binary discrimination between two beer categories with classification accuracy of 100 % based on training and testing data sets used. Third, multi-feature kernel semi-supervised (MFKS) proposed in [4] and aimed to introduce a unified learning framework. The experimental results of MFKS in classification on two artificial olfaction datasets outperformed the super victor machine (SVM) and extreme learning machine (ELM) classifiers.

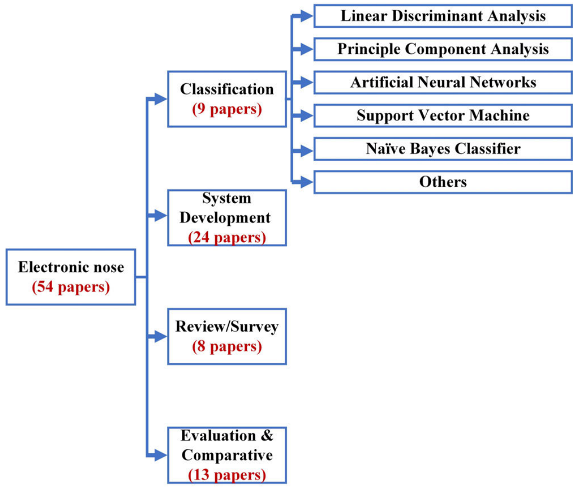

FIGURE 2. Taxonomy of the research literature on electronic nose.

Further as reported in [6], Naïve Bayes (NB) was utilized as classifier along with min-max magnitude scaling for classifying fresh beef and fresh pork. The results attained 75% of classification accuracy for the proposed system using k-fold cross validation for the classification. Fifth, Domain adaptation extreme learning machine (DAELM) was utilized in [15]. The results showed that the DAELM outperforms the current drift compensation techniques. Sixth, Drift correction autoencoder (DCAE) was presented in [16]. The results showed that the DCAE outperforms the conventional drift correction algorithms. Seventh, transfer-sample-based multitask learning (TMTL) in [17] used to highlight the drift setback specifically on machine olfaction. Tests on three data sets confirmed the proposed method was indeed effective based on the good accuracy achieved. Eighth, transfer sample-based coupled task learning (TCTL), was introduced in [18] that were indeed suitable for several regression models and classifications. The accuracy of the proposed algorithms outperformed the existing techniques using less auxiliary samples. Ninth, e-nose along with k-nearest neighbors (K-NN) classifier was presented in [19] in discriminating Agarwood oils as either pure or otherwise. The proposed model enhanced the accuracy from 90% to 100% compared to the standard measures.

B. SYSTEM DEVELOPMENT

This category shows the research papers that introduced methods or proposals to develop systems in e-nose. The general context of all papers under this class is (24/54). In [2], A portable e-nose prototype was developed by the International Islamic University Malaysia (HUM) for rapid detection of ethanol (EtOH) compounds in beverages. This device can display the EtOH concentration in beverages on the LCD screen. The developed device showed high accuracy and reliability because it was able to detect EtOH content in various beverages sold in Malaysia with a concentration as low as 0.1 % (v/v). In [5], this work was intended to introduce a new technique for temperature modulation of the gas sensors to attain fast, accurate, and low-cost detection. Experiments on three indoor air contaminants, which are formaldehyde (HCHO), nitrogen dioxide (NO2) and carbon monoxide (CO), were conducted for performance analysis and data acquisition and. Machine learning methods such as back-propagation artificial neural network (BP-ANN), support vector machine/regression (SVM/SVR) and ELM were applied for concentration and recognition prediction. For Indoor Air Quality (IAQ) monitoring, the result demonstrated that it is useful to use the temperature self-modulation method in the e-nose system. Moreover, the results and the comparisons of the experiments for system cost, gas classification accuracy, power consumption, and concentration prediction error showed high efficacy and precision of the proposed e-nose system. In [7], it was aimed to present effective techniques to handle and solve three challenges of e-nose: signal discreteness, systematical drift issue and nontarget disturbances. A global affine transformation (GAT) approach was introduced for reproducibility enhancement and discreteness reduction. A very simple and effective unsupervised feature adaptation (UFA) model was proposed to improve the drift tolerance of e-nose systems. A novel targets-to-targets self-representation classifier (T3SRC) method was suggested for fast nontargets detection. The experiments demonstrated that the proposed approaches are efficient and effective to solve the three issues mentioned before for e-nose systems. In [9], it was intended to show the benefits of applying data fusion using artificial sensing devices (e-tongue, e-nose, and computer vision system (CVS)) in the characterization of Sicilian honey. By linking e-tongue and CVS combined with multivariate statistical analysis, a powerful tool has emerged in the identification of the botanical source of unidentified honey samples. This technique demonstrated to be simple, fast, and inexpensive with a satisfying recognizing percentage. In [11], this study was aimed to improve the performance of e-nose for odor recognition by using a nonlinear kernel based Renyi entropy component analysis technique. A kernel entropy component analysis (KECA) was introduced and KECA–SVM framework was proposed as a system with feature extraction and recognition for e-nose application. The experimental results on six common indoor air contaminants showed that the KECA–SVM technique outperforms other approaches in classification performance of e-nose. In [12], it was sought to improve the transfer ability of e-noses prediction models. It was implemented by applying windowed piecewise direct standardization (WPDS) algorithm based on generalized ridge regression to transform the variables from the slave device to match the corresponding master one. The master device data were utilized to develop prediction models with a novel strategy known as standardization error-based model improvement (SEMI). In the last step, the standardized slave data can be predicted by the models with an improved accuracy result. Three e-noses were utilized to measure seven groups of gas samples to evaluate the algorithms. The experiments showed that WPDS can outperform the prior techniques in the sense of prediction accuracy and standardization error; SEMI consistently improves the precision of the master model. In [20], this work introduced maximum independence domain adaptation (MIDA) and semi-supervised MIDA (SMIDA) to reduce the interdomain discrepancy. It was done by maximizing the independence between the domain features and the learned features of the samples. experiments on synthetic datasets and four real ones were made to evaluate the effectiveness of the proposed models. They were fast, flexible and can improve the capability of sensor systems. In [21], This work proposed the SVM recursive feature elimination incorporating the correlation bias reduction (SVM-RFE + CBR) to decrease the correlation bias in the linear and nonlinear SVM-RFE. This method was suggested to enhance the stability of the feature selection. To evaluate these algorithms, a synthetic dataset and two breath analysis datasets were utilized for this purpose. The results showed that the nonlinear SVM-RFE + CBR is an effective method. It was able to outperform the standard SVM-RFE and other algorithms. In [22], This study was aimed to present a rapid, innovative, and non-destructive method for discriminating three types of Tropea red onion from each other and the normal red onion. A canonical discriminant function analysis pattern recognition method was used to process the signals from the sensor array. The discriminant function analysis on the onion samples demonstrated a very high classification rate and a strong separation among the four onion groups. In [23], this work was aimed to develop a rapid method that is able to classify licorice roots according to their geographical areas using e-nose based on (MOS). To check the e-nose capability in assigning licorice roots samples to a particular geographical region, discriminant function analysis was applied. The results showed that the e-nose system can be utilized as a tool for an effective, quick, and non-destructive authentication of licorice roots. In [24], the study was aimed to use the e-nose equipped with an array of MOX gas sensors based on thin films as well as nanowires to monitor various roasting processes of the coffee. This work showed that combining temperature and time parameters will save cost and energy for the industry. The results also revealed that the e-nose is a good tool to be used for the roasting process control. In [25], this work was aimed to use the e-nose combined with chemometrics analysis to discriminate a popular alcoholic beverage in China called Chinese Tongshan kaoliang spirit (CTKS) from various geographical origins. The classification models developed by PCA and DFA. The results showed that the proposed model can be used as an efficient way for the authentication of the original CTKS. In [26], this study was aimed to investigate the effectiveness of flash gas chromatography electronic nose (FGC e-nose) and multivariate data analysis to achieve fast screening of extra virgin olive oils that is commercially available and characterized by a various geographical source. PCA, LDA and hierarchical clustering analysis (HCA) were utilized as exploratory tools. To demonstrate the discriminating power of FGC e-nose, a comparison with SPME/GC–MS was implemented. The results for the geographic discrimination showed that the FGC e-nose was comparable with SPME/GC–MS. In addition, by using the same dataset for comparison, the two techniques were not significantly different. In [27], this work was aimed to use the fusion of the e-nose and e-tongue coupled with chemometric multivariate analysis to differentiating seven Chinese robusta coffee cultivars samples with 3 different roasting degrees. The idea of using data fusion strategies was to improve the performance of models comparing to that of a specific technique. To perform the classification, pattern recognition techniques, principal component analysis (PCA), the K-nearest neighbor (KNN), PLS-DA, and BP-ANN were applied. The results confirmed that this fusion strategy was a powerful and effective technique for distinguishing roasted robust coffee beans. In [28], this study was aimed to use the e-nose and the computer vision system in conjunction with multivariate data analysis for the detection of saffron adulteration based on their color and aroma characterization. Also, to show that the combination of different techniques can offer more information about the food and the quality indices will be more reliable and accurate. To show the discrimination ability of the proposed system, PCA, Hierarchical Cluster Analysis (HCA), and SVMs were used to process the extracted variables. For saffron aroma and color strength prediction, two multilayer artificial neural network (ANN-MLP) models were also utilized. The results of the PCA, SVMs, and ANN-MLPs analysis in detecting saffron adulteration showed that the aroma characteristic variables are a little more effective than the color variables. In [29], this work was intended to test the ability of an array of ZnO thin film to discriminate between agave liquor and authentic Tequila. To discriminate between the and Agave liquor and real Tequila and in the recognition of Tequila brands, LDA and the multilayer perceptron neural network were applied. The results were promising to develop a low-cost and inexpensive analysis tool for automatic assessment of fraud in spirits. In [30], this study was aimed to use dynamic headspace sampling (DHS) coupled with gas chromatography–mass spectrometry (GC/MS) and e-nose to determine the characteristic volatile profile of propolis with the aim of identifying the geographical area of propolis. To differentiate the regions of the propolis samples, PCA based on the data of the DHS–GC–MS and e-nose was applied to investigate and get the essential volatile compounds for that. The results showed that the GC/MS and e-nose combining with PCA could effectively differentiate the twelve propolis samples from four various geographical areas in China. In [31], this work was aimed to present a web-based application that is able to identify the best machine learning approach for comparing data from different analytical methods, to provide the best prediction accuracy of various kinds of microorganisms responsible for meat spoilage. The web-based application was named ''MeatReg'' and it was made to be available online for free to enhance the food safety management system. To predict bacterial counts for Lactobacilli, Pseudomonads, B. thermosphacta and Enterobacteriaceae, and for the total viable count, seven machine learning methods: Stepwise Linear regression (SL-R), Ordinary Least Squares Regression (OLS-R), Partial Least Squares Regression (PLS-R), Principal Component regression (PC-R), Random Forests Regression (RF-R), Support Vector Regression (SVM-R), and k-Nearest Neighbours' Regression (kNN-R) were utilized. Five different analytical and imaging tools were used to collect metabolomics data from minced beef samples and used to test the platform (MeatReg). In [32], this study was aimed to discuss that the data fusion of different methods such as e-tongue, e-nose, computer vision system, and IR spectroscopy coupled with advanced chemo metric tools could perform a crucial role in the automation of saffron quality assessment. Also, this work was aimed to provide an overview of the current and possible innovative systems for saffron quality characterization and their future perspectives. In [33], this study was aimed to use the headspace solid-phase micro extraction gas chromatography–mass spectrometry (HS-SPME/GC-qMS) and e-nose coupled with principal component analysis to classify and characterize cocoa bean shell (CBS) collected from different geographical areas and obtained from cocoa beans of diverse cultivars. Nevertheless, in this study, the authors stated that their findings were incomplete, and they need to consider a larger number of samples for a further exhaustive investigation. In [34], this work was intended to explore the possibility of increasing the shelf life of rice germ by decreasing water activity and considering the storage atmosphere packaging. A portable e-nose and a Fourier-transform NIR (FT-NIR) spectrometer were used to assess the quality of this by-product during the storage. In [35], this study was aimed to develop a novel technique for comprehensive and accurate identification of the original locations of Hou Po. Also, to predict the contents of the relevant chemical elements. A colorimeter and an e-nose were used to determine the color and odor characteristics, respectively. To distinguish the original location of the Hou Po samples and predict the contents of the relevant chemical elements, different discriminant models were applied. The results showed that the colorimeter and the e-nose are promising techniques for qualitative and quantitative quality check of Chinese herbal medicines. In [36], this study was aimed to use the e-nose coupled with data analysis for sausage authenticity assessment, checking the amount of soy protein in sausage composition to avoid several types of fraud, and test the adulteration levels. Two methodologies for data analysis in this study were used for investigation and comparison. In this first one, odor pattern recognition with the utilization of geometric parameters algorithm was applied. In the second one, e-nose features coupling with multivariate analysis techniques was used. The results showed that the e-nose system can be used as a robust analytical method for sausage authentication and sample adulterated detection at various soy protein levels. In [37], this work was aimed to examine the ability of e-nose, e-eye, and e-tongue to characterize edible olive oils (extra virgin, olive, and pomace). Also, for the assessment of the quality decay of extra-virgin olive oil and olive oil. mid-level data fusion technique was applied to extract related data from various analytical sources. The results showed that the combination of the e-nose, e-eye, and e-tongue with the data processing approach can characterize different categories of edible olive oils based on their sensorial properties. Also, can evaluate the quality decay of oils.

C. REVIEW/SURVEY

This class contains the review papers that intended to explain the recent progress in the e-nose. The general context of all papers under this class is (8/54). In the first work of [8], the purpose of it was to review the recent developments in the artificial sensor for instance tongue, nose and eye application field considering the most significant contributions over the past five years, in the assessment of animal food products. Secondly [10] presented the recent enhancements in existing techniques for detection and treatment of specific foods by ionizing radiations. Also, new methods based on Nuclear Magnetic Resonance (NMR) and Near Infrared (NIR) spectroscopy combined with multivariate data analyses and sensors like biosensors along with electronic nose are discussed. Thirdly in the review paper of [13], it aimed to cover the e-nose system application in ensuring both quality and safety in particular medicinal plant products that are commercially available. Also, this paper included the e-nose systems benefits along with the limitations. Fourthly, [14] showed that data fusion strategy, which means combining data from several sensors that include combining of e-nose, e-tongue, computer vision system, and spectroscopy data that resulted as a system out-perform the typical systems as compared to individual techniques. The new method led to develop a technique with comprehensive and complementary information related to analysis of food. The fifth, [38] provided an overview about the fusion of data techniques for quality assessment along with beverages and food authentication. Different levels applications of data fusion were listed and described for a selection of products. Sixthly, [39] presented several vital aspects to motivate e-nose usage in the quality assessment of bakery product. Also, challenging problems, applications, future trends, and perspectives are considered. Seventhly, [40] reviewed the most important contributions of both e-tongues and e-noses methods related to food authenticity assessment and adulteration control on a time span of ten years. Eighthly, [41] discussed data mining obtained from food evaluations applying non-destructive /non-invasive/ analytical methods to check the quality, safety, and authenticity by using computer science techniques.

D. EVALUATION AND COMPARATIVE STUDY

This category displays the methods of evaluation and comparison of several e-nose research groups. The general context of all papers under this class is (13/54). In the first paper [42], which is about identifying different plants from Asteraceae family, 11 different multiple mathematical algorithms (PCA along with partial least squares (PLS) as well as a total of nine Artificial Neural Networks (ANN) classifiers were utilized for analyzing signal of the e-nose based on Asteraceae family selected plants, and comparison were done too. In the second paper [43] machine learning approaches that include classifiers such as NB, K-NN, LDA, decision tree (DT), ANN, and support vector machine (SVM) were utilized to analyze the raw data mixture of the fruit juice–alcohol. In the third paper [44] which is about discrimination of various indoor odors, various classifier techniques like PCA, SVM, LDA, and Naïve Bayes classifier (NBC) were utilized. In the fourth paper [45] PLS, multiple linear regression (MLR), and backpropagation neural network (BPNN) were used for pork content prediction in minced mutton. In the fifth paper [46] which is about classification of the freshness of the squeezed cherry tomatoes, four supervised approaches namely quadratic discriminant analysis, LDA, SVM and BPNN along with one semi-supervised approach specifically Cluster-then-Label were used. In the sixth paper [47] which is about distinguishing between alcoholic and non-alcoholic beer, LDA, PCA along with soft independent modeling of class analogy (SIMCA) was utilized. In addition, SVM as well as partial least square discriminant analysis (PLS-DA) were utilized too. As for the seventh paper [48] specifically on identification and classification of red wines, two times types of distance analysis namely Euclidean and Mahalanobis distance along with correlation analysis and LDA were utilized. Further, in the eighth paper [49] which is about identifying the status of adulteration specifically for mutton along with low-quality duck meat, linear regression was used to compute both qualitative and quantitative analysis in this study as well as fisher LDA (FLDA), and classification using multilayer perceptron NN (MPPN). In the ninth paper [50] which is about characterizing and discriminating geographical origin, age, and drying of 35 saffron samples, two analytical techniques specifically solid-phase microextraction gas chromatography mass spectrometric (SPME-GC-MS) and Conventional Isotope-ratio mass spectrometry (IRMS) were applied. In the tenth paper [51] which is about classifying the oranges samples of three geographical regions, three multivariate statistical approaches that were PCA-LDA, SELECT-LDA and partial least squares-discriminant analysis (PLS-DA) were used. In the eleventh paper [52] which is about characterizing

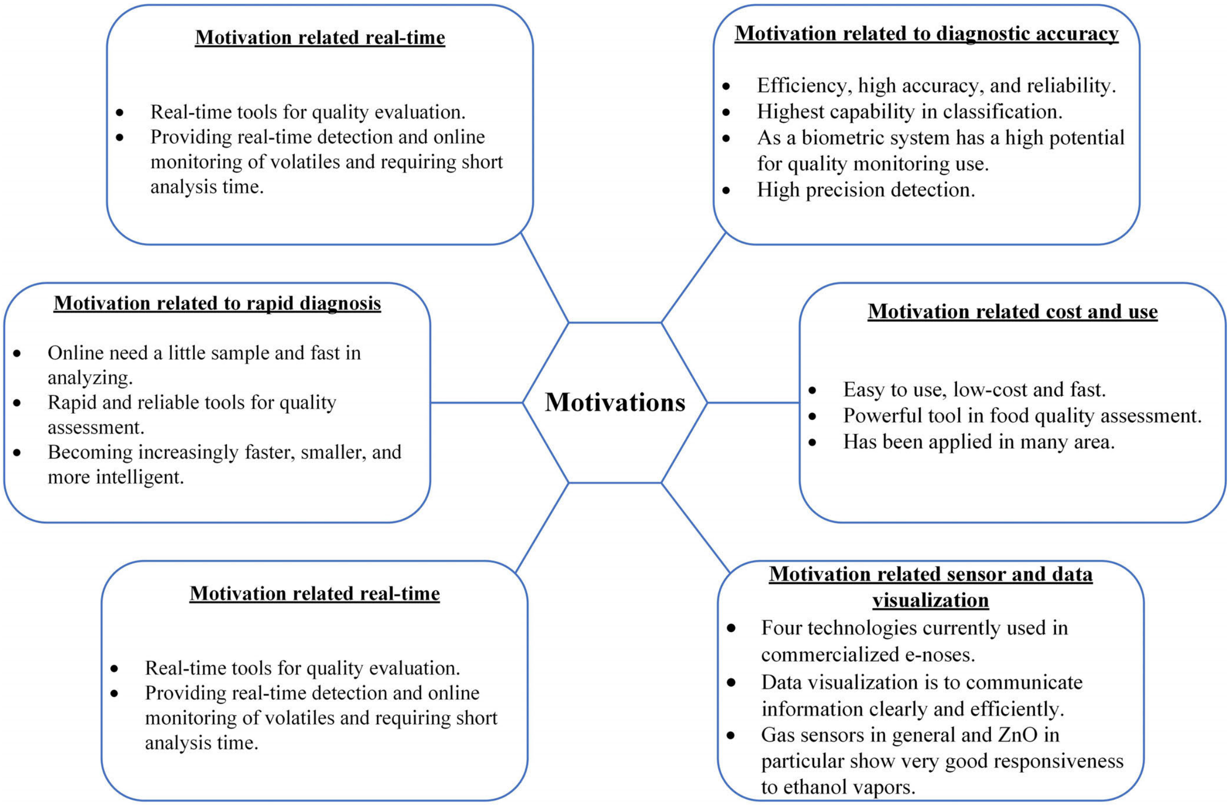

FIGURE 3. Categories of motivations for detection, authentication, and classification of Electronic Nose.

and differentiating boiled pork from three types of breeds, PCA, agglomerative hierarchical clustering (AHC), PLS-DA, and LDA was applied. In the twelfth paper [53] classification results of Indian black tea based on various grades using several classifiers namely K-NN, clustering nature (PCA plot) along with KNN using 10-fold cross-validation approach, PLS-DA, and Sammon's projection were reported. In the thirteenth paper [54] which is about analyzing characteristic sensors based on the data extracted, targeting to establish flavor and fresh/moldy apples information prediction model using LDA, SVM, BPNN, along with and radial basis function NN (RBFNN) were discussed.

IV. MOTIVATIONS

This section describes the improvements reviewed in the literature, organized as groups of related advantages containing the reference for additional discussion. Fig. 3 demonstrates the brief review of the motivations for using the e-nose.

A. MOTIVATION RELATED DIAGNOSTIC ACCURACY

The e-noses devices have several benefits comparing to traditional methods for evaluating aroma of food that include high sensitivity, simplicity, speed, requirement of smaller samples, and excellent correlation based on data attained from assessments of sensory. The e-nose techniques have been demonstrated to be a valuable assessment and authentication approach for meat adulteration detection because of the high accuracy and efficiency of this method [36]–[49]. Also, in the discrimination of oranges according to their geographical origins [51], recognizing the origin locations of the Hou Po samples [35], and detecting and recognizing fresh and moldy apples [54]. In [3], e-nose systems with high ability in classification can be helpful in off flavor detection. Subsequently, beer monitoring in brewery will be more accurate and reliable, where EtOH content could detect as low as 0.1 % (v/v) [2]. An e-nose system can be used as model for prediction purpose based on training samples group and as an essential part for odors recognition. The model should be able to perform based on different conditions as well [18]. In the work of [39], Artificial nose with inspiration source as a biomimetic system from human nose is high suitable for checking of quality related to bakery products. Moreover, in [5], high precision of detection with a low-cost system with an optimal temperature modulation method of gas sensors.

B. MOTIVATION RELATED COST AND USE

The e-nose system has been utilized in numerous important fields, such as medical diagnosis, food analysis, environmental monitoring, and quality identification [7], [43]. In [6] and [16], the e-nose technique has demonstrated to be an efficient instrument in food quality monitoring such as odor of tea, beef spoilage, tempeh, herbal drinks and many more. Moreover, some of the advantages are flexibility, reliable, fast, economical, ease of usage, and apposite for analysis during online checking.

C. MOTIVATION RELATED SENSOR AND DATA VISUALIZATION

Nowadays, gas sensors are available in several types, but just four kinds of e-nose are used in marketed system. The techniques include Crystal Microbalance (QCM), Metal Oxide Semiconductor (MOS), Quartz, Metal Oxide Semiconductor Field-Effect Transistor (MOSFET), and Bulk acoustic wave (BAW) sensors. MOS and MOSFET are used mainly in the hybrid e-nose system. However, MOS, MOSFET, and QCM are being used in different ways by the commercial systems as well. In this type of e-nose system, the main advantage it is that incorporates the benefits based on various types of transducers. Also, it will give an option for which chemical sensors can be utilized at the same time [14], [50]. According to [29], ZnO in particular and overall metal oxide gas sensors show excellent responsiveness to ethanol vapors. In [41], Raman spectroscopy and Infrared sensors have numerous applications in analysis of quality specifically industries related to food. In the data visualization [31], the main aim is to convey clear and efficient information to the users. This can be done through information graphics like charts and tables. This will help the users in analyzing and interpreting the data and make it more accessible, understandable, and usable.

D. MOTIVATION RELATED REAL-TIME

The e-nose system has the possibility to utilize as a real-time monitoring technique [6]. In [13], the advantages of using e-nose was that it incorporated good data correlation and high sensitivity which is based on the sensory panels by human targeted for definite applications for instance ease of built, food monitoring control, capable for detection in real-time, cost-effective, volatiles monitoring via online mode, non-destructive techniques, and lesser time required for analysis. The IR spectroscopy and the e-nose could be combined for system related to real-time to be used for aroma, taste quality assessment, and saffron color. Moreover, with benefits such as faster development, cost optimization, and enhance accuracy methods for saffron quality evaluation, industries that include medicinal and other associated aromatic can gain advantage from these features [32].

E. MOTIVATION RELATED RAPID DIAGNOSIS

The e-nose techniques showed better regular laboratory analysis due to its simplicity and ease of handling on a daily routine. The e-nose offers a non-destructive and quick replacement in sensing aroma. previously, the e-nose system has been effectively used in various fields like the food industry [48]. Electronic nose aimed to artificially perceive appearance and flavor. It has been increasing significantly as a reliable tool especially for quality assessment and monitoring in the food industries [8]. The e-nose has a great benefit for meat evaluation against the overall count of bacteria, sensory panel, gas chromatography, and TVB-N [6], and with its rapidity and reliability can be used for extra virgin olive oil adulteration detection as reported in [40]. In the research by [47], the use of e-nose is more demanded in the brewery due to system reliability specifically speed of analysis.

F. MOTIVATION RELATED METHODS AND TECHNIQUE

In this section, Table 2 tabulated the motivations based on the methods and techniques of classification extracted from the articles being reviewed.

V. CHALLENGES

In recent years, the need for the utilization of the e-nose for detection and classification has risen. However, there are many challenges in various essential aspects. Such challenges are the low sample size of the dataset, calibration, and others. The Details for the challenges can be seen in the complete discussion in Table 3.

A. CHALLENGES RELATED TO COLLECTED DATA

Nowadays, the gained data distribution in many different steps due to the rising of big data, with some changes in experimental and analysis conditions for instance domains diversity and changings. e-nose data labeled and data collection are tedious and labor intensive, however using small number of labeled data during classification for training and testing lead to poor simplification and an unreliable model, precisely for bulky scale applications [15]. Other challenges faced by researchers was the drift correction algorithms using samples in target domains are not appropriate in solving this problem, due to the difficulties in data collection from different sources [12], [16], [17].

B. CHALLENGES RELATED SAMPLE SIZE

The process of sensing gas samples by changing the electrical resistance value of metal oxide semiconductors. The change in the resistance value as a result of combustion reactions that take place with the surface of the metal oxide particles filled with oxygen species. Classifier training using few labeled samples (target domain) is very interesting and meaningful deprived of neglecting the recognized inoperable old data (source domain), and understand well-organized and effective of knowledge transfer for instance drift compensation specifically from the source domain to multiple target domains [15]. It can be seen that the breath samples have greater SE (standardization error) than the chemical samples [12]. In the case of small sample sizes and small differences between class covariance matrices, it will effect on supervised classification method [46]. In addition, actual dataset, size, samples, or possible stratification distribution along with the background information may contribute to variation in validation strategy. For instance, a model with small samples or number is indeed very sensitive to random results [41].

C. CHALLENGES RELATED TO FEATURES

Feature extraction is the key step in e-nose systems, which plans the high-dimensional data against an appropriate

TABLE 2. Motivations for the techniques and methods based on classifications established.

No	Methods	Motivation
1	Linear Discriminant Analysis (LDA)	Using LDA, the accuracy attained for the training datasets was 100% followed by 93.6% and 85.4% for testing and validation dataset accordingly [1] ; Feature extraction using Step-LDA was reported to be the most apt as proven by [45] ; 100% accuracy were attained for both training and testing datasets using LDA with minimal two variables in establishing the two models specifically CP2eCP4 and CP3eCP4 [47]; One of the most well-known classification technique is indeed LDA specifically the linear discriminant functions and thus LDA have successfully used in numerous applications [48]
2	Extreme learning machines (ELMs)	(ELMs) is proven to be efficient and effective for both regression and pattern recognition as well [15]; Due to its efficiency and effectiveness in various areas involving regression and pattern recognition, ELM was highly recommended for solving a single-layer feed-forward network (SLFN) [5].
3	Support Vector machine (SVM)	SVM outperformed as the best classifier based on both training and testing dataset as reported in [44]; SVM successfully achieved perfect accuracy for classification of beer based on the training and testing datasets utilized [47]; SVM is proven suitable to solve problems related to both regression and classification [38] ; SVM is a widespread algorithm for partial classification due to its good generalization ability and high accuracy, hence it has been effectively applied in numerous e-nose applications [21]
4	Naïve Bayes	Naïve Bayes is indeed well known for its performance as classifiers especially its speed ability to handle large dataset [6]
5	Logistic Regression and ridge regression	Both logistic and ridge regression are also well known for their ability in the area of regression and classification [18].
6	The Dynamic Headspace (DHS)	DHS are popular in terms of low sample manipulation along with low limits detection and contributed to high sensitivity [30].
7	Gas chromatography–mass spectrometry (GC-MS)	GC-MS is one of the most well-known methods in food volatiles analysis due to its high reproducibility [30].
8	Artificial Neural Networks (ANNs)	ANNs have proven capable to produce high accuracy based on g non-linear behavior dataset. ANNs are known to mimic the biological system by bringing together followed by transmitting the signals to the central of the nervous system. Next is data processing along with decision making depending on the objects being identified. Data fusion that include BPNN along with the modified versions for instance RBF and probabilistic neural networks (PNN) are the most widely used along with another popular feed-forward multilayer network specifically the BPNN [38].
9	Principal Component Analysis (PCA)	PCA is considered as one of the well-known unsupervised techniques for exploratory purposes based on the rule of thumbs of PCA for the experimental data. This is to confirm the trend of the data as well as to determine for any outliers. With the given dataset, PCA can be used for model optimization via correlation within samples identification [31, 33].
10	LabView based e-noses (LVB)	The benefits of (LVB) are high efficiency low-cost and heuristic for lab usage [7].

chosen subspace low dimensional data while preserving the highlighted structure of data and improving the discriminative capability of features [4]–[7]. Deep learning methods has been tested as feature extraction from unlabeled gas samples and tackle sensor drift implicitly as reported in [17]. In this case, finding the optimal combination of extracted features and preprocessing that further detail the significant of the instrumental responses variation as well as providing the most optimum model is indeed challenging [38]. However, e-nose data was incompletely and was not fully explored due to the techniques of feature extraction used in previous studies. At the moment, only one steady response is extracted as feature from each sensor prior to standardization[12]. It was found that e-nose could not fully mimic the human biological features specifically identifying elusive analyses in complicated mixtures although with the technology advancements and proven findings as reported by previous studies[8].

D. CHALLENGES RELATED TO TECHNICAL CHALLENGES

E-nose sensor array comprised of wide and partially overlapping selectivity for compound volatile measurement in the headspace of the sample, combined with data tools of statistical computerized multivariate to give an odor fingerprint of the samples [45]. The propolis volatile consistency is extremely dependent based on the geographical region. One of the most vital quality that are used to determine the propolis organoleptic feature is the volatile fraction and this feature contributed to high consumers acceptance as well. Note that the propolis composition is indeed complex due to several different volatile compounds of classes for instance alcohols, esters, aldehydes, ketones, acids and terpenes presented in the chemical pattern of the propolis [30]. The correlation between temperature of sensors and heating voltage has been studied in this research. The voltage of heating is exponentially proportion to the heating temperature sensors. The sensor array modulation can lead to ironic gases patterns than the same array without modulation because the modulation of temperature is able to vary the gas sensors resistance sensitivity. e-nose performance is highly affected by temperature modulation. Temperature modulation is very important and necessary to improve e-noses performance. It is very important to know that in the modulation mechanism, there is a minor difference between the modulation of temperature (static) and self-modulation temperature (dynamical) [5].

TABLE 3. Categories of challenges for electronic nose classification and detection.

Challenge related to data collected	○ Condition, precision, and reliable.
	○ Result of the subject data must be able to represent supporting data for the expert
	○ Alternatives, non-standardization, and subjective reports
Challenge related to low sample size	○ Acquisition and signal processing data takes a lot of time
	○ E-nose can be applied on several field which is needed calibration from real data
	○ The main challenge involving samples per subject is due to the gas data sets is low whilst a total subject is high.
Challenge related to features	○ The main problem faced by classification method is prediction to be done using small samples size.
	○ Determined all chemical content from something is difficult.
Challenge related to technical challenges	○ There are several volatile chemicals.
	○ Temperature is also an external factor that can affect performance
	○ Classifier performance may be decreasing caused by irrelevant features
	○ Challenge of vary chemicals scattered in the air
	○ Sensor drift is a serious issue in performance of devices
	○ Chemicals have different characteristics
Challenge related to technical noise	○ Differences among sensor sensitivity led to different content detection that can make different analysis and conclusion.
	○ Differences in work procedures such as devices, data acquisition and properties of objects
	○ Drift noise is main issue in application of e-nose which cannot be avoided
	○ The accuracy is not only the goal of evaluation.
	○ The accuracy of transudative confidence machine agree with the error rate of the classifier
	○ Nonconformity measure value is affected by different parameter settings
Challenge related to Evaluation	○ The classification costs are neglected.
	○ Real time e-nose application still difficult to set.
	○ Time consuming on calculation complexity.
Reliability and predictions	○ An abundance of contents causes an increase in the time needed
Challenge related to time consuming	○ Difficulty in obtaining a satisfactory classification result compare with real environmental data
	○ Unrelated and redundant genes can cause over-fitting
Challenge related to over-fitting	○ Study correlation between the biomedical, environmental, and electronics levels is difficult
	○ There is no superior classification method in several fields
Challenges related to classification methods	○ Data fusion is not usually enhanced individual results and, in some situation, reduced the classification rate.

E. CHALLENGES RELATED TO TECHNICAL NOISE

When samples transfer contains outliers and noise then the process is worth noting, which precisely are not reflecting the appropriateness of the selected data distribution and hence will lower the accuracy if more information are transferred to them. One of the method to spot the outliers are based on tacit and previous knowledge [17]. For instance, transfer samples that contained noise will influence the improvement of process and lessen the accuracy [16]. Normally, data from single techniques are preprocessed followed by properly scale along with removal of uninformative systematic variations and reduction in noise, due to the scale dependent of multivariate analysis [38]. Several methods for preprocessing prior to data analysis were proposed due to noise issues and at times occurrence of scatter effects as well [41].

F. CHALLENGES RELATED TO EVALUATION

E-nose technology is utilized to determine the presence of fingerprint of volatile compounds in the food sample headspace based on semi-selective sensors array; therefore, reliable and fast methods for evaluating organoleptic features are highly demanded such as flavor and aroma [3], [47]. Besides sensory evaluation, analysis of both physical and chemical along with analysis of quality are the approach used for evaluation of fermented liquor product, however these factors are subjective since it is highly depended on human specifically the evaluators condition that comprised of the evaluator mental state, physical condition, that could affect the evaluation performance or accuracy [25]. Ideally, classification performance as well as quality of products to be evaluated could be enhanced through combination of several artificial sensing systems, however the development of this category of system is still in its infant stage and more studies need to be conducted in this field in ensuring the combined system will be apt to be used in the stated applications [8].

G. CHALLENGES RELATED TO RELIABILITY AND PREDICTIONS

Sensor array, is able to convert chemical changes into electrical signal indication, measurement and control systems that equipped with all needed electronics circuits for measuring signals output by the sensors that include A/D converters, signal conditioning, interface circuits and techniques used for recognizing different patterns in order to perform a prediction or classification [3]. However, all these parameters can differ with respect to time, for instance the sensors sensitivity characteristics, the signal source and the condition of operation. Hence, the performance of the prediction models could degrade during testing although the performance during training were excellent and this was due to time-varying shift and variation in instruments [16]. In addition, during training or learning stage was about mapping in a predictive manner between both the input and output, in other words the output state can be foreseen or predicted based on the future input and the learning function utilized [44].

H. CHALLENGES RELATED TO TIME CONSUMING

Some of the conventional approach drawbacks evaluating quality parameters by these trained expert panels include time consuming, high budget required to pay the expert services as well as the possibility of inconsistency in the evaluation process as a result of fatigue, stress or maybe due to the online tool measurements being used were not fully understood by these expert panels [14]. Volatile analyses in all industries such as food, cosmetics and drugs depend on two traditional techniques: quality sensory panel analysis and conventional GC-MS. However, these two methods are indeed labor dependable and too costly for application in quality control of routine food category and time consuming as well [3]. Most of the techniques to pre-process are really time intense and involving complicated pre-processing for spirit. Hence, a new approach with less complexity, convenient and speedy is needed in determining the spirit authenticity [25].

I. CHALLENGES RELATED TO OVER-FITTING

Some of the setbacks related to over-fitting were due to numerous variables that were highly dependable on the techniques used. This could be overcome by identifying the most significant variables or parameters that further acted as the main inputs for data analysis and computational purpose [3]. In addition, the transfer samples cannot be allied well in case transfer sample is too small, Meanwhile, excessively emphasis on the transfer samples will lead to overfitting [17]. In recent year, the main purpose of classification is to be able to categorize the unlabeled unseen or testing data upon successfully producing a good training model that this may also contributed to over-fitting in ensuring superior accuracy during testing stage [46].

J. CHALLENGES RELATED TO CLASSIFICATION

Sensors and instruments that are utilized for signals measurement might be a factor that caused drift in posterior distribution of the testing samples versus the training samples and this further invalidated the regression or classification models that were trained earlier due to sensor life span, environmental change and instrumental variation [17]. To overcome this issue, a more reliable classification method that consists of several stage classifiers is required for classifying the mixture meat. Moreover, the signal processing technique to be used with the e-nose should be more robust in nature that will be able to combat all the drawbacks or limitation [6]. The classification was seriously deteriorating [7] even though too much effort has been made on different algorithms, sensor drift still occurred due to unknown dynamic processes like aging, poisoning and many more. However, some findings proven that feasibility study is needed for relatively small samples to be handled during generalization in the case of propolis database. It was found that this led a possibility of being wrongly classified [22].

VI. RECOMMENDATIONS

This section introduces important recommendations to the researchers in this field. Fig. 4 depicts the categories of recommendations for the researchers and the users of the e-nose.

A. RECOMMENDATIONS BASED ON CLASSIFICATION ACCURACY (FOR RESEARCHERS)

Several recommendations can be considered for improving classification accuracy as reported by several researches. Precision recommendations focus on classification model, informative features, and small number of features. In summary [47], LDA was proven capable to be used for classification purpose by excluding the use of SVM which is more complex as compared to LDA and in [6] NB showed excellent performance in classification stage based on training accuracy attained using small dataset. In the work of [23], good data mining approach is required that could process and perform classification accordingly based on the sensors output data and this will further contributed to a more reliable e-nose system. As reported in [42] for evaluation of the proposed models, in order to overcome over-fitting as well as ensuring good accuracy performance during classification, a cross-validation method based on 10-fold was applied. Conversely, in improving sensitivity along with ease of detection as well as semi-volatiles extraction, pre-concentration systems was proposed in ensuring identification of these features [13]. In addition, as discussed in [39], the measurement of instrumental field changed drastically because of increasing multivariate data analysis which is also known as chemometrics. Another significant finding was volatile substances analysis based on PCA that was used as data selection in discriminating samples between both hazelnut oil versus virgin olive oil (VOO) and this method proven effective using the three fast procedures utilized [40]. Finally, the extraction features as discussed in [38] showed suitable in handling dimensionality reduction and sustaining the relevant information due to large data volume which further include feature selection process. As for findings as discussed in [49], in order to ensure that the proposed method was indeed reliable and robust, additional samples of meat from several other regions need to be utilized during training and testing in supporting the findings that the proposed system was indeed apt to be used.

B. RECOMMENDATIONS BASED ON CLASSIFICATION PERFORMANCE (FOR RESEARCHERS)

The following recommendations must be taken in consideration in enhancing the e-nose performance of classification:

Feature selection is one of the stages in any pattern recognition. During feature selection, redundant, irrelevant

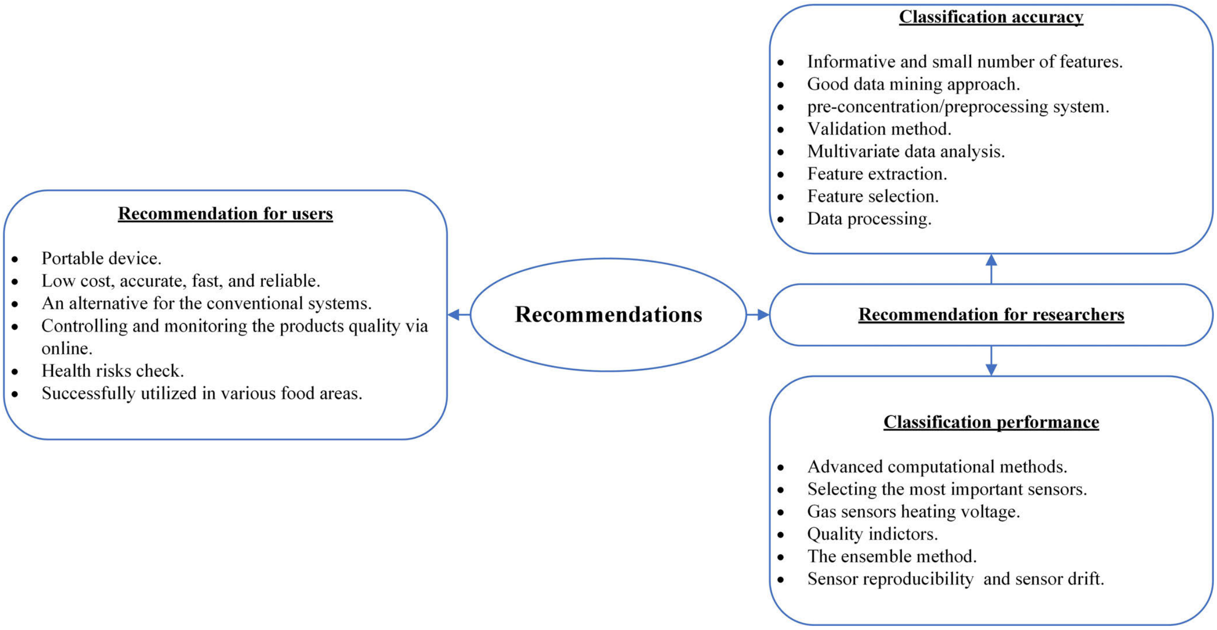

FIGURE 4. Categories of recommendations for the electronic nose.

and noisy features were removed from the original space of features and thus reduced the possibility of over-fitting and further enhanced the model performance and at the same time optimizing both space and time of the learning or training algorithm [21]. As reported in [3], one of the keys in enhancing the e-nose capability for the case of brewery is based on ANN as an advanced computational tool in order to select the most vital sensors that significantly contributed in discriminating between the groups of beers under classification with the sensors transient state being considered while eliminating the steady state condition [3]. Next is the findings as reported in [4] specifically in selecting virtuous features generated by the sensors and further produced an enhance odor patterns for the e-nose classifier to be able to increase the performance in discriminating the odors for further classification or categorization. As for the results discussed in [5], the classification performance of e-nose during recognition stage was highly dependable on the value of the gas sensors heating voltage. In the case of SVM, two parameters that contributed to accuracy performances are the most optimum values of generalization parameter c and the parameter of the kernel namely gamma as reported in [46]. Furthermore, in order to be able to discriminate accordingly the beers under categorization as either alcoholic or non-alcoholic [47], once again the classification stage utilized SVM that resulted in perfect accuracy during classification. Odor sensors in the e-nose system are considered as the most sophisticated section since numerous gas sensors are made possible. However, the five most regular sensors techniques as described in [13] were Bulk Acoustic Wave (BAW), Conducting Polymer micro-sensors (CP), Optical sensors, Metal-Oxides Sensors, and Metal Oxide Semiconductor Field Effect Transistors (FET). Additionally, amongst these five sensors type, the most being utilized in e-nose system for commercialization purpose were the CP and MOS. This is due to the robustness owned by these two types of sensors and were able to detect all the quality parameters required which include taste, color as well as aroma along with possibility of combining different methods for real-time application in monitoring the product quality [13]. Moreover, as discussed in [21], both parameters of a sensor specifically drift and reproducibility are the most vital characteristics in determining the performance of the system. Note that reproducibility of a sensor is indeed essential in preserving the performance of the system due to any faulty sensor(s) upon being replaced. As reported in [29], since fabrication of sensor is considered straightforward specifically involving physical deposition of Zn along with simple step in oxidation process, hence it was possible to sustain the device reproducibility for the case of gas-sensitive films being used in this research.

C. RECOMMENDATIONS BASED ON IMPORTANCE (FOR USERS)

A recommendation for researchers and users like the consumer or food engineer is presented in this section.

These recommendations aim to show the importance of using the e-nose for classification and automatic detection. Nowadays, the e-nose technology has been successfully utilized in various food areas [30]. One example is the e-nose developed by [2] that was used for testing the content of ethanol (EtOH) in beverages and at the same time can be benefited by the consumer since it was designed to be portable for mobility purpose. It is indeed desire to have

TABLE 4. Datasets used in the reviewed articles.

#	Ref.	Datasets	Type	Source
1	[4, 15-17]	Gas Sensor Array Drift	13,910 measurements of samples under observation that consist of six (6) categories specifically gases acetone, ethanol, acetaldehyde, ammonia methylene, and tuluene	**UCI Machine Learning Repository**http://archive.ict.uci.edu/mt/datasets
2	[46]	USDA (United States Department of Agriculture)	150 that comprised of 25 samples with six (6) different storage time (ST)) of juice samples.	**United States Department of Agriculture**http://www.ams.usda.gov/AMSv1.0/getfile?dDocName=STELPRDC5050331.
3	[5]	Temperature self-modulated gas sensing system	HCHO, 100 samples NO2, 113 samples CO, 96 samples	**Provided by**: Yin, X., et al. (2016). "Temperature modulated gas sensing e-nose System for low-cost and fast detection." **16**(2): 464-474.
4	[7]	Publicly Available. Gas Sensor Array Drift	Six types different gases: formaldehyde (188), carbon monoxide (58), benzene (72), ammonia (60), toluene (66), and nitrogen dioxide (38); 13,910 measurements of samples under observation that consist of six (6) categories specifically gases acetone, ethanol, acetaldehyde, ammonia methylene, and tuluene	**Provided By:** L. Zhang *et al.*, "A novel background interferences elimination method in e-nose using pattern recognition," *Sens. Actuators A Phys.*, vol. 201, pp. 254–263, Oct. 2013. **UCI Machine Learning Repository** http://archive.ics.uci.edu/ml/datasets/Gas+Sensor+Array+Drift+Ttaset+an+Different+Concentration
5	[20]	Gas Sensor Array Drift; Breath Analysis Dataset; Corn Dataset	13,910 measurements of samples under observation that consist of six (6) categories specifically gases acetone, ethanol, acetaldehyde, ammonia methylene, and toluene; Six classes of subjects specifically healthy (125), chronic kidney disease (340), diabetes (431), cardiopathy (97), breast cancer (215) and lung cancer (156); 80 Corn samples of moisture specifically protein, starch and oil.	**UCI Machine Learning Repository** http://archive.ics.uci.edu/ml/datasets/Gas+Senser+Array+Drift+Dtaset+al+Different+Concentration **Provided by:** K. Yan, D. Zhang, D. Wu, H. Wei, and G. Lu, "Design of a breath analysis system for diabetes screening and blood glucose level prediction," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 11, pp. 2787–2795, Nov. 2014. **Corn Dataset** http://www.eigenvector.com/data/Corn/
6	[22]	Generated Database Plant	Three (3) samples of each category of Red onion namely Tropea Ecotype "Mezza Campana", Tropea Ecotype ''Tonda'', and Tropea Ecotype ''Allungata''	**Provided by:** Russo, M., et al. (2013). "Non-destructive flavor evaluation of red onion (Allium cepa L.) Ecotypes: An electronic-nose-based approach." **141**(2): 896-899.
7	[21]	Sensor Array (Commercially Available)	Carbon dioxide sensor Temperature humidity sensor 9 metal oxide semiconductor (MOS) sensors.	**Provided by:** K. Yan, D. Zhang, D. Wu, H. Wei, G. Lu, IEEE Trans. Biomed. Eng. 61 (2014) 2787–2795.
8	[12]	Generated Database	3 e-Noses devices with exhaled breath - Acetone - Hydrogen - Ammonia	**Provided by:** Yan, K., et al. (2015). "Improving the transfer ability of prediction models for electronic noses." **220**: 115-124.
9	[28]	Generated Database Color Aroma	13 samples tested that include authentic saffron, ACS, ACYSS, along with ten (10) adulterated samples based on UV–visible spectroscopy	**Provided by:** Kiani, S., et al. (2017). "Integration of computer vision and electronic nose as non-destructive systems for saffron adulteration detection." **141**: 46-53.
10	[33]	Generated Database cocoa bean	44 samples from various geographical regions in 19 countries and 4 cultivars	**Provided by:** L. Barbosa-Pereira, O. Rojo-Poveda, I. Ferrocino, M. Giordano, and G. Zeppa, "Assessment of volatile fingerprint by HS-SPME/GC-qMS and e-nose for the classification of cocoa bean shells using chemometrics," *Food research international,* vol. 123, pp. 684-696, 2019.
11	[50]	Generated Database saffron	35 samples from different origin	**Provided by:** R. Rocchi *et al.*, "Comparison of IRMS, GC-MS and e-nose data for the discrimination of saffron samples with different origin, process and age," *Food Control,* vol. 106, p. 106736, 2019.

an affordable system specifically low cost, accurate, fast, reliable as well as robust in its performance for authentication and predicting accurately the flavor and coffee qualities [27]. Conversely, a system with good accuracy and economical is also needed to distinguish between the meat of pork versus beef based on a more suitable pattern recognition approach to be coupled with the e-nose system [6]. Furthermore, as reported in [42], e-nose was highlighted as highly potential to be used for identifying both quantitative and qualitative values of herbal plants based on the signals produced using e-nose technology related to the chemical constituents of these types of plants. Moreover, during the operations of medicinal plant that include fermentation and drying, the aroma can be distorted, altered, or destroyed. Therefore it is indeed vital to efficiently monitored and controlled the aromatic characteristics of these materials during processing stage [13]. Besides that, as reported in [39], in order to fulfill the preference according to consumers requirement specifically the bakery products quality evaluation, the overall information namely flavor, taste, color and sound related to the product quality prior to consumption is essential. In addition, as for food engineers, several other vital aspects in the bakery industry were controlling and monitoring via online since the quality of the products were established between processes. Therefore, the e-nose is really suitable to be installed in the bakery production lines especially during fermentation in order to monitor the process of the working conditions [39]. Also, it was found that it is important to determine the organoleptic adulterations since this could contribute to the consumers' health risks caused by processed tomato that can be affected easily via microbial contamination. Hence, a reliable and speed method for detecting spoilage using the e-nose is crucial in ensuring safety of the food being produced [40].

VII. DATASETS

The details about the available datasets such as size, type, and source in the selected articles in this study were summarized in Table 4. These datasets are useful to test the classifiers and the pattern recognition techniques. Also, they can be used for comparison purposes in e-nose studies. Moreover, the summarized datasets in this table can save the searching time and effort for new researchers in the e-nose field.

VIII. CONCLUSION

The utilization of the e-nose system in several fields for classification and detection is one of the promising technologies nowadays. Research efforts in the e-nose field are continuing in improving and ongoing. However, several aspects are still ambiguous. This review is intended to contribute to the e-nose field by providing insights and understanding through surveying and classifying the related research efforts in this area. The review in this area of study can provide a significant path for the researchers in their research and learning path. The information in this research was obtained through intensive searching, surveying, and reading of the research papers in this field.

The search query of this study was done on three websites (IEEE, SD, and WOS) over a time span of 7 years, from March 2013 until May 2020. After refining the articles from the search query, 54 articles were selected in the final set for this review paper out of 333. In this systematic review paper, the research efforts on e-nose were projected into four classes. The first class, classification, comprises the suggested methods that introduced the use of the e-nose for classification purposes (9/54 papers). Secondly, system development, covers the methods related to the development of e-nose systems (24/54 papers). The third one, review/survey, includes the review studies about the e-nose (8/54 papers). The fourth class, evaluation and comparative, comprises evaluation and comparative studies (13/54 papers).

In this review, the major contributions in the e-nose technology in several fields were outlined, for example, aromatic plants, medical drugs, food industries, etc. It has been shown that the e-nose system has a potential for use as a fast, low-cost, accurate, reliable, and non-destructive technique for classification, monitoring of storage conditions, detection of contamination, spoilage, adulteration, identification of volatile compounds…etc. in addition to the advantages of the e-nose system shown in this review, the fusion approach using e-tongue and CVS coupling with e-nose revealed a powerful tool in the identification with a satisfying recognizing percentage. This methodology of the combination of multi-way techniques like e-nose, e- tongue, and CVS offers an interesting and effective approach for evaluation.

Also, this review article included important sections for the researchers, and to remain up to date, such as the challenges, motivations, recommendations, and data sets used in the e-nose field. By highlighting the challenges and presenting several recommendations to overcome the current questions in this field of study, this review can help to be used as a roadmap for future work for the researchers in this field.

In the near future, e-nose technology can be seen in many sectors such as the food and beverages industry, healthcare, security, environmental monitoring, and others. The e-nose industry is at the stage to design a less expensive, smaller, and more specialized device to produce results that can be interpreted by the user easily. However, the final step left to be completed nowadays is to develop an e-nose device that can use for a wide range of applications using a limited number of sensors. Once this task is completed, the e-nose device can accelerate the diagnosis process. Also, it can replace the conventional time-consuming methods in many industries.

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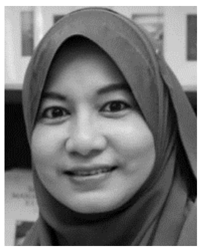

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