A reconfigurable integrated electronic tongue and its use in accelerated analysis of juices and wines

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Abstract—Potentiometric electronic tongues (ETs) leveraging trends in miniaturization and internet of things (IoT) bear promise for facile mobile chemical analysis of complex multi-component liquids, such as beverages. In this work, hand-crafted feature extraction from the transient potentiometric response of an array of low-selective miniaturized polymeric sensors is combined with a data pipeline for deployment of trained machine learning models on a cloud back-end or edge device. The sensor array demonstrated sensitivity to different organic acids and exhibited interesting performance for the fingerprinting of fruit juices and wines, including differentiation of samples through supervised learning based on sensory descriptors and prediction of consumer acceptability of aged juice samples. Product authentication, quality control and support of sensory evaluation are some of the applications that are expected to benefit from integrated electronic tongues that facilitate the characterization of complex properties of multi-component liquids.

Index Terms—E-tongue, machine learning, mobile, sensor array

I. INTRODUCTION

The design of cost-effective and rapid screening sensing systems is key to deliver alternative tools for chemical analysis, and electronic tongues have demonstrated to be potentially disruptive for various applications [1]. In particular, ETs have proven useful to identify food products, quantify their major constituents and possibly predict taste attributes [2]. In this context, potentiometric ETs offer clear advantages, such as facile integration and fast response, that make them suitable candidates in the food industry [3]. Hereinafter, an existing technology platform [4] including a microcontroller-based data acquisition, smartphone interface and cloud computing back-end is combined with a miniaturized array of 16 electrodeposited conductive polymers and a specific training methodology [5] to further extend its capabilities. The present contribution demonstrates how different machine learning models can be deployed to reconfigure the same device to analyze fruit juices and bottled wines, and how discrimination of liquids is achieved based on their chemical and sensory attributes.

II. METHODOLOGY

A. Sensor array and liquid samples

A previously described [5] potentiometric electronic tongue comprising 16 conductive polymeric sensors electropolymorized on a common substrate was used in all experiments (Fig. 1). The array was used to test acetic, citric and lactic acid at five concentrations between $10^{-5} - 10^{-1}$ M. The pH of the solutions was adjusted with NaOH to maintain values between 4.2–4.5. A $10^{-3}$ M solution of the respective acid was used as reference solution in each test. The same array was then used to test nine fruit juices of different flavours (4× orange, orange-passion fruit, pear, peach, apricot and multivitamin), whereby one of the orange juice samples was used as reference liquid for testing. Finally, the sensor array was used to test eleven bottled Italian red wines, using one of the wines (Palazzo della Torre, P.d.T.) as reference liquid.

B. Measurement and data processing

A total of 75 discrete hand-crafted features [5] were extracted from 15 unique differential voltages time-series during transition of the sensor from the respective reference liquid to a test liquid. Tests were repeated in randomized order using an automated sampling system [5]. One orange juice was tested after storage at 40°C for 10, 20, 40 or 50 days and compared to the same juice stored at room temperature or in a refrigerator, whereby the latter was also used as reference liquid during testing. All liquids were tested at room temperature. A group of 12 panelists was asked to taste the same juices and bottled wines, and how discrimination of liquids is achieved based on their chemical and sensory attributes.

III. RESULTS AND DISCUSSION

A. Cross-sensitivity to organic acids

Previous work had demonstrated sensitivity of the electronic tongue to metal ions [5]. In the present contribution, each of

Fig. 1: Portable electronic tongue with integrated sensor array.
the 75 features also exhibited variation with changing organic acid concentration, expressed as the slope of the feature magnitude against the logarithm of the acid concentration (sensitivity slope, Fig. 2). Each group of five features is extracted from the same voltage channel comprising a specific pair of polymeric sensors. The feature response is clearly differentiated across the three acids, demonstrating cross-sensitivity of the sensor array. This result suggests that the E-tongue interacts with organic constituents relevant for many beverage classes, including fruit juices and red wines.

**C. Discrimination capabilities**

Classification models were trained with both data sets and compared to a baseline classifier, which was chosen to be a weighted random predictor taking into account the number of tests available for each class compared to the size of whole data set. Due to the high dimensionality of the available feature space compared to the total number of tests, PCA was used to select the minimum number of components required to explain at least 95% of the total variance. Thus, for the classification of juices and wines, only eight and six predictors were used, respectively. Data sets were split randomly in 10 folds, whereof 9 were used for training of classification algorithms and the left-out fold was used for testing. The procedure was repeated for each of the folds and the mean accuracy across the 10 iterations is reported in the first two rows of Table I along with the corresponding standard error, computed as the ratio between the standard deviation and the square root of fold number. For both fruit juices and bottled wines, the accuracy of each of the three classification algorithms is significantly higher compared to the baseline value, indicating favorable discrimination of samples. The LDA model produced the highest classification accuracy (> 97%) in both cases, while the KNN algorithm was generally the least accurate (~ 90%). High performance of the LDA model suggests that the underlying relationship between PCs and class separation could be easily learned by a linear model, given the reduced amount of available training instances. Furthermore, classification of wines based on their provenance was tested using the Italian region of origin as class label, namely Piedmont, Tuscany, Veneto or Other. Results based on the random 10-folds split are reported in the third row of Table I. The KNN algorithm was able to resolve the origin of wines based on the four-classes separation better (98.2%) compared to the other two models (83.6% for LDA, 93.6% for bagged trees) for this task.

**TABLE I: Classification accuracies**

| Data set            | Baseline | LDA   | KNN      | Bag Trees |
|---------------------|----------|-------|----------|-----------|
| Fruit Juices        | 13.9±3.9 | 97.3±1.9 | 90.4±2.2 | 94.5±3.3  |
| Bottled Wines       | 9.1±2.0  | 99.1±0.3 | 89.1±0.5 | 90.9±0.8  |
| Wine Origin         | 21.8±5.2 | 83.6±2.5 | 98.2±1.2 | 93.6±1.8  |
| Orange Flavor       | 50.6±4.4 | 88.9±9.6 | 76.4±9.2 | 90.3±9.7  |
| Juice Acceptance    | 51.9±7.3 | 92.6±1.9 | 65.1±11.1| 88.4±8.4  |
| Wine Alcohol        | 53.3±5.4 | 80.9±9.7 | 68.2±9.5 | 65.5±13.7 |

**D. Estimation of beverage attributes and sensory perception**

A series of binary classifiers was trained to predict specific properties, such as the orange flavor of a juice, the consumer acceptability of an aged sample or the alcoholic content of a wine. For these tasks, each data set was split into a number of folds equal to the number of samples, such that each fold contained only data for the same liquid. Thus, at each iteration, it was possible to simulate the inference of an attribute of a sample unseen during training. The prediction accuracy based
on mean results across folds was always above the baseline level (rows 4–6 in Table I). High standard errors arise from misclassifications due to a particular class, corresponding to an entire mispredicted fold. LDA and the bagged tree models exhibited comparable accuracy (~90%) for the correct prediction of the orange flavor. The main source of misclassification was the special case of the orange–passion fruit mixed juice, which was erroneously classified as an orange juice by all models. Samples stored at room temperature for more than 40 days or at 40°C for more than 10 days were rejected by the sensory panel. The sensory panel response was used as ground-truth for model training on the sensor array data. The highest classification performances were obtained with the LDA model that could be used to predict the acceptance of an unknown aged juice sample with a 92.6% accuracy. Generally, models correctly predicted the rejection of samples stored at 40°C, while misclassifications occurred for samples stored for more than 40 days at room temperature. A binary classifier was also trained to predict the alcohol level of red wines, whereby each wine was assigned to a group with low (12.5–13.5 vol%) or high (14–16.5 vol%) alcohol content. This classification task was the most challenging, with the best accuracy of 80.9% obtained with the LDA model. This is attributed to the relatively narrow range of alcohol vol% for the wines under test, whereby misclassification mostly occurred for wines with intermediate alcohol content (13-13.5 vol%).

IV. CONCLUSION

A remarkably simple integrated sensor array was found to exhibit cross-sensitivity to a range of analytes, including metal ions as shown in previous work, as well as organic acids as demonstrated in the present contribution. Supervised learning was applied to various classification problems to successfully identify fruit juices by fruit type, including similar juices processed in different packages, and bottled Italian wines by their brand and origin. The electronic tongue was also successfully trained with descriptors from sensory evaluation, such as sensory panel acceptability for purchase. Due to the combination of the integrated electronic tongue with an automated data pipeline configurable via a cloud back-end or edge device such as a smartphone, its capacity to be easily reconfigured makes it attractive for remote analysis of complex liquids for a wide range of potential applications in beverage authentication, quality control and product innovation.

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