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DISTANCE-BASED FEATURE SELECTION FOR LOW-LEVEL DATA FUSION OF SENSOR DATA

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Low level data fusion offers a mechanism for raw data from different sensor devices to be fused in an attempt to improve classification performance. This scenario creates a challenge for engineers to deal with large number of features over the smaller number of observations, or also known as high dimensional problem. Traditionally, engineers prefer to apply feature extraction in choosing important features for classification task. Unfortunately, the traditional method is bound to certain limitations. Thus, the objective of this study is to propose a feature selection based on unbounded Mahalanobis distance $[0, \infty)$ to replace the feature extraction phase in the low-level data fusion. The average pair-wise distances for the fused features were calculated and filtered from largest to smallest values, and features with the larger distance value are considered important. Classification results using the ranked features in a feature subset selection manner have shown that the proposed distance provides an effective and easy approach in choosing the important features that lead to good classification performance.

***Keywords*:** Feature Selection, Mahalanobis Distance, Classification, Data Fusion

1. Introduction

Nowadays, the application of sensor devices in food and beverage manufacturing industries has become a common setting. Sensor devices are used to replace the trained human panel which may have some drawbacks such as discrepancy due to human fatigue or stress, time consuming, expensive and impossible for on line monitoring, and finally the evaluation perceptions depend on panelists' training. Therefore, complimentary yet reliable artificial sensors that mimic the trained human panel's smell and taste system were proposed to overcome the drawbacks. The application of electronic nose and electronic tongue were introduced to substitute these systems which has begun in the early 1980s and 1990s, respectively. Unfortunately, these sensors work independently. In order to combine the information from the two sensors to increase the classification or identification accuracy, the multi sensor data fusion method was introduced.

One of the multi sensor data fusion frameworks employed in food industries is the Joint Directors of Laboratories (JDL) Data Fusion Framework or sometimes known as JDL process model (Hall, 1992) which consists of low-level data fusion, intermediate-level data fusion and high-level data fusion. A custom phase that involves in all level of data fusion is the feature extraction process where the fusion could occur either at the raw data level (prior to feature extraction), at the feature vector level (prior to identity declaration), or at the decision level (after each sensor has made an independent declaration of identity). Due to some weaknesses of feature extraction method specifically in choosing specified features, this study intends to introduce a simple yet effective method to replace the conventional method. Therefore, the objective of this study is to propose a new approach to replace the feature extraction phase with feature selection method for the low-level data fusion of two sensor devices i.e. electronic nose and electronic tongue. A distance-based feature selection using unbounded Mahalanobis distance criterion is applied for classification of multi-class problem.

2. Review of Literature

Survey of literature was conducted regarding the low-level data fusion, feature extraction and feature selection related to the application of sensor devices in food and beverage industries that may involve the application of electronic nose, electronic tongue and other sensor devices.

2.1 Low Level Data Fusion

The simplest model for multi sensor data fusion is the low-level data fusion as shown in Figure 1. It implies a concatenation of raw data from different sensors from similar or dissimilar sensors (Rudnitskaya et al., 2006). The resulting data matrix as a result from the low-level data fusion contains *n* rows of observations from different classes with *p* columns of features that are obtained from the fused sensors. Basically, this framework combines signals from similar or different sensors to produce new data that is predicted to be more informative for classification.

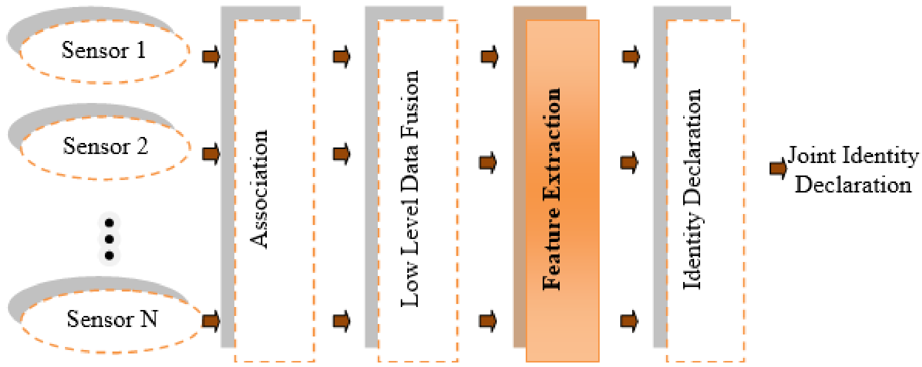

Figure 1: Framework for low level data fusion (Hall, 1997)

Several research that have applied electronic nose and electronic tongue, and/or other sensors include Vera et al. (2011), Zakaria et al. (2011), Zakaria et al. (2010), and Rodriguez-Mendez et al. (2004). The low-level data fusion is preferred due to its ability to fuse raw data i.e. signals from different or similar sensors before feature extraction is imposed towards the fused data matrix. Some researchers presumed this framework as the most efficient compared to the intermediate-level and high-level data fusion because it avoids loss of information since all available raw data from each sensor are employed in the next phase.

2.2 Feature Extraction

Traditionally, feature extraction is employed in the framework of low, intermediate and high-level data fusion. Most previous researchers who applied multi sensor data fusion based on JDL process model were only focused on the use of principal component analysis as the feature extraction approach (Prieto et al., 2011, Vera et al., 2011, and Zakaria et al., 2010). Feature extraction is favorable due to its advantageous to deal with high multicollinearity among the *p* fused features from the applied sensor devices. It also allows visualization most of the information contained in raw data matrix in *p* principal components which are orthogonal to each other. Unfortunately, the resulting linear combinations of the *p* principal components are difficult to interpret especially when specific or subset of features is/are of interest. Furthermore, decision to include certain number of principal components for the next phase in the fusion framework are either based on the average eigenvalue, percentage of variance explained or simply using the scree graph. In this context, the inclusion of all the fused features without considering the relevancy or informative of a single feature is ignored. Thus, studies on feature selection as an alternative to feature extraction i.e. principal component analysis tool in multi sensor data fusion is addressed in this study.

2.3 Feature Selection

Dealing with multi sensor data fusion means more features are being considered for the construction of classifiers especially for low level data fusion. This is due to the nature of this framework that will fuse all the resulting features from the applied sensors which usually lead to the problem of curse of dimensionality. Classification within this condition may be inaccurate and the inclusion of too many features may harm the performance of a sample classifier (Foithong et al., 2012 and McLachlan, 1992). In addition, unlike feature extraction method where all features are included in the analysis, feature selection is able to identify and include only relevant features for the next phase in data fusion framework. Feature selection is a process of identifying the most useful features in describing differences among the possible class (McLachlan, 1992). According to Dernoncourt et al. (2014), feature selection is the process of removing irrelevant features in reducing the dimensionality of data to processed, decreasing the execution time and improving the predictive accuracy of classifier (Chandrashekar and Shahin, 2014).

There are two common evaluation functions for feature selection that are allocation and separation criteria. The general aim of an evaluation function is to measure the discrimination ability of a feature or subset of features to distinguish different class labels. Allocation criterion measures the effectiveness of fused feature in predicting class membership using the overall error rate of the optimal rule formed by the p fused features. Whereas, separation criterion assesses the effectiveness of p fused feature which tends to maximally distinguish or separate the observations to its classes (Masnan et al., 2017). Thus, allocation criterion is appropriate if the objective is to identify feature useful to form a classifier with high accuracy for allocating future observations. Whilst, separation criterion is relevant if the objective is to identify features that are useful to describe separation between classes. Established by the later approach, a method that can be applied is the distance-based feature selection that aims to identify useful features by their discriminating power based on highest distance for separation among classes from the available p fused features. Ray and Turner (1992) have introduced unbounded and bounded Mahalanobis distance-based evaluation criteria for multi class classification problem both in the distribution free and Gaussion distribution cases for the recognition of hand-printed numeric characters. This study applies the unbounded Mahalanobis distance criterion to replace the feature extraction phase in the low-level data fusion framework for multi-class classification problem.

3. Methodology

The proposed methodology in this study is an extension work from Ray and Turner (1992) with regards to the unbounded Mahalanobis distance for feature evaluation, but with some modification so that it can be applied in multi sensor data fusion particularly the low-level data fusion. The calculation of unbounded Mahalanobis distance within the range $[0, \infty)$ in this study is obtained based on the pair-wise distances between multi-class $(\pi > 2)$ classification. This criterion is practical in selecting relevant features since it can provide a measure of similarity between multivariate populations and uses covariance information between features to weight the contribution of all features to the unbounded distance. Furthermore, the unbounded distance gives less weight to features that have high variance and high correlation (Masnan et al., 2017).

Figure 2 illustrates the graphical presentation of the pair-wise distance for multi class classification problem. Suppose the preprocessed data matrix for investigation are $\mathbf{X}_{ip_1}$ with p_1 features are from electronic nose, and $\mathbf{X}_{ip_2}$ with p_2 features from electronic tongue, and the fused features denotes as $\mathbf{X}_{ip} = (\mathbf{X}_{ip_1} + \mathbf{X}_{ip_2})$. All the $\mathbf{X}_{ip}$ observations are partitioned to multi-class (π)

where $i = 1, 2, ..., \pi$, and $k = 1, 2, \ldots, n$, with a total of $p = \left(p_1 + p_2\right)$ fused feature from the electronic nose and electronic tongue, respectively. For this study, even though different sensor devices were applied, the low-level data fusion is successfully implemented by controlling similar number of observations within similar number of classes for each data collected using the electronic nose and electronic tongue.

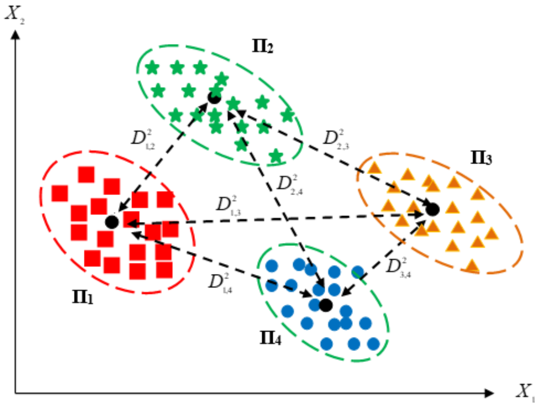

Figure 2: Graphical representation of pair-wise unbounded Mahalanobis distance for multi-class

In order to evaluate the fused features that are useful to describe separation between classes, the univariate unbounded Mahalanobis distances $\left(\Delta^2_{Uij}\right)$ which is estimated by D^2_{Uij} are calculated. These calculations were developed using algorithms that were executed using RStudio which simplifies the calculation of pair-wise distance for every single fused features. Equations (1) to (4) are the calculation for the estimated pair-wise-class (i, j) distances of D^2_{Uij} required for the feature evaluation where $\left(i = 1, 2, ..., \pi; j = i+1, ..., \pi - 1; i \neq j\right)$ and n is the sample size of the respective class. Equation (3) is the simplified calculation of the univariate Mahalanobis distance where the inverse of S_{ij} in (2) is the reciprocal of the respective common variance. The summation of each of the resulting ${}^{\pi}C_2$ pair-wise distances in (3) divided by ${}^{\pi}C_2$ gives the average unbounded Mahalanobis distance of each of the evaluated feature where $D^2_{U_{x(ip)}} \in [0, \infty)$. The process is repeated for each of the p fused feature independently.

$$D^2_{ij} = \left(\bar{X}_i - \bar{X}_j\right)^T S^{-1}_{ij} \left(\bar{X}_i - \bar{X}_j\right) \tag{1}$$

$$S_{ij} = \frac{\sum_{k=1}^{n_1}\left(X_{ik} - \bar{X}_i\right)\left(X_{ik} - \bar{X}_i\right)^T + \sum_{k=1}^{n_2}\left(X_{jk} - \bar{X}_j\right)\left(X_{jk} - \bar{X}_j\right)^T}{n_1 + n_2 - 2} \tag{2}$$

$$D^2_{ij} = \frac{\left(\bar{X}_i - \bar{X}_j\right)^2}{S_{ij}} \tag{3}$$

$$D^2_{U_{x(ip)}} = \frac{1}{{}^{\pi}C_2} \sum_{i=1}^{\pi} \sum_{j=i+1}^{\pi-1} D^2_{ij} \tag{4}$$

The average pair-wise distances for each p fused features will be obtained using (4), and the generated values are ranked from largest to smallest. The largest average pair-wise distance values based on the ranked features is considered as the indicator of good discriminant features to describe separation between classes. The objective of performing univariate unbounded Mahalanobis distance is to select the best subset of features that has been ranked and further selected for best performance of classification. For simplicity of showing the ${}^{\pi}C_{2}$ pairwise-class distances per feature, Table 1 represents the combinations of the resulting distances for a feature x, $D^2_{U_x}$.

Table 1: The generated ${}^{\pi}C_{2}$ pair-wise distances among classes for univariate feature

	π_1	π_1	π_1	π_1	$\cdots$	π
π_1	0	$D^2_{1,2}$	$D^2_{1,3}$	$D^2_{1,4}$	$\cdots$	$D^2_{1\pi}$
π_2	$D^2_{2,1}$	0	$D^2_{2,3}$	$D^2_{2,4}$	$\cdots$	$D^2_{2\pi}$
π_3	$D^2_{3,1}$	$D^2_{3,2}$	0	$D^2_{3,4}$	$\cdots$	$D^2_{3\pi}$
π_4	$D^2_{4,1}$	$D^2_{3,2}$	$D^2_{4,3}$	0	$\cdots$	$D^2_{4\pi}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	0	$\vdots$
π	$D^2_{\pi 1}$	$D^2_{\pi 2}$	$D^2_{\pi 3}$	$D^2_{\pi 4}$	$\cdots$	0

The diagonal elements are the distances of the same centroids while either of the pair-wise distances in the lower or upper diagonal is useful for the required distance measure. In this study, the lower diagonal pair-wise class's distances are used. The algorithm for the unbounded pair-wise Mahalanobis distance (4) for low-level data fusion of electronic nose and electronic tongue is described as follows. Basically, this algorithm can be applied to replace the traditional feature extraction i.e. principal component analysis.

Input : $\mathbf{X}_{ip} = (\mathbf{X}_{ip_1} + \mathbf{X}_{ip_2})$ - matrix of observation for fused feature set

Output : Ranked fused features $\mathscr{F} = \left[\mathbf{D}^2_{U_1} > \mathbf{D}^2_{U_2} > \ldots > \mathbf{D}^2_{U_p}\right]$

Step 1 : **Initialize** $\mathbf{X}_{ip} = \left[X_{i1}, \ldots, X_{ip_1}, \ldots, X_{ip2}, \ldots, X_{ip}\right]$

Step 2 : **For** each feature $\left(X_{ip_1}, X_{ip_2}\right) \in \mathbb{Z}^p$

i. Calculate the unbounded Mahalanobis distance for ${}^{\pi}C_{2}$ pair-wise classes using criterion (3) for each fused feature in $\mathbb{Z}^p$

$$D^2_{ij} = \frac{\left(\bar{X}_i - \bar{X}_j\right)^2}{S_{ij}}, (i = 1, 2, \ldots, \pi; j = i+1, \ldots, \pi - 1; i \neq j)$$

ii. Calculate the average distance for ${}^{\pi}C_{2}$ pair-wise classes using criterion (4) for each fused feature in $X_{ip} \in \mathbb{Z}^p$

$$D^2_{U_{x(ip)}} = \frac{1}{{}^{\pi}C_2} \sum_{i=1}^{\pi} \sum_{j=i+1}^{\pi-1} D^2_{ij}$$

iii. Store $D^2_{U_{x(ip)}}$ into $\mathscr{F} = [\ \ ]$

Step 3 : **End** of **for** loop

Step 4 : **Rank** $D^2_{U_{x(ip)}}$ (from largest to smallest values) where

$$\mathscr{F} = \left[\mathbf{D}^2_{U_1} > \mathbf{D}^2_{U_2} > \ldots > \mathbf{D}^2_{U_p}\right].$$

Step 4 :**Filter** $\mathscr{F}$ for best feature subset evaluation.

The evaluation of the algorithm will be illustrated using four datasets of different honeys for the classification of pure and adulterated honey. The secondary dataset was obtained from the Center of

Excellence for Advanced Sensor Technology (CEASTech), Universiti Malaysia Perlis. In order to evaluate whether the fused features with the highest average pair-wise unbounded Mahalanobis distance is able to separate multi-class problem, the ranked features will be used to perform classification of pure honey from its adulterated concentrations. Linear discriminant analysis classifier will be used to evaluate the performance of the selected subset of features for the four honey datasets namely Agromas, As-Syifa, Syair Timur and Tayyibah. The apparent error rate of the classification will be implemented using the leave-one-out approach which is believed can improved the classification process.

4. Result and Discussion

Table 2 presents the ranking of features based on the output of the algorithm for the unbounded pair-wise Mahalanobis distance for low-level data fusion. There are 32 and 10 array of sensors for electronic nose (*N*) and electronic tongue (*T*), respectively. These array of sensors became the features used for feature evaluation. Features from both devices were numbered based on their total array of sensors attached in both sensors. From the results, obviously each different honey recorded different features' performance which means no specific similar features dominate the highest ranking.

Table 2: Ranked fused features for four types of honeys.

Agromas		As-Syifa		Syair Timur		Tayyibah	
Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance
N23	11,949.06	*N26*	1937.62	*N29*	12593.81	*T7*	84016
N5	11,343.20	*N5*	1872.11	*N5*	6375.09	*T2*	17337.5
N29	10,027.52	*N29*	1815.44	*N23*	6014.23	*N29*	4120.59
N31	4,040.16	*N31*	1116.44	*N31*	5832.96	*N23*	3493.41
N9	3,680.18	*N15*	1086.9	*N26*	5555.79	*N31*	2661.3
N26	3,482.48	*N9*	1058.89	*N9*	4647.56	*N5*	2235.94
N11	3,074.39	*N20*	994.57	*T2*	4354.62	*N6*	2188.87
N6	2,418.34	*N16*	928.61	*N11*	3749.95	*N26*	2043.21
N20	2,300.65	*N23*	917.45	*N6*	3650.01	*N9*	1883.41
N10	1,793.69	*T11*	888.82	*N20*	3259.16	*N20*	1156.73
N17	1,778.24	*N17*	886.27	*N17*	2369.79	*N10*	1097.63
N15	1,407.55	*N13*	832.86	*N28*	2264.82	*N17*	1052.48
N16	1,161.90	*N8*	800.05	*N10**	1997.47	*T11*	1037.43
N28	1,129.29	*N21*	779.23	*N1*	1778.03	*N22*	1029.37
N22	1,124.58	*N11*	755.48	*N8*	1742.91	*N8*	1020.89
N8	1,094.92	*N18*	727.66	*N18*	1742.85	*N28*	1019.52
N18	1,074.86	*N28*	712.29	*N15*	1695.26	*N18*	900.7
N13	869.54	*N7*	626.57	*N16*	1346.31	*N15*	870.4
N12	770.64	*N12*	616.34	*N22*	1207.47	*N16*	802.34
T11	762.64	*N10*	582.97	*N30*	1074.31	*T9*	660.37
N30	741.57	*N1*	580.04	*N3*	913.47	*N11*	657.82
N4	669.04	*N3*	545.42	*T9*	889.88	*N12*	554.35
N7	646.60	*N4*	516.91	*N12*	868.62	*N13*	544
N14	574.10	*N14*	502.47	*N13*	842.9	*N27*	537.6
N21	546.70	*T2*	498.87	*N19*	826.82	*T1*	513.37
N19	536.86	*N2*	436.33	*N4*	818.7	*N19*	475.41
N2	532.30	*N22*	423.87	*N27*	761.42	*N7*	474.97
N1	500.41	*N25*	405.44	*N2*	700.4	*N1*	446.23
N27	459.53	*N19*	385.8	*N7*	687.86	*N21*	440.02
N3	446.28	*N27*	347.33	*N21*	682.05	*N14*	434.49
N24	318.36	*N6*	344.93	*N25*	587.72	*N30*	416.91
N25	317.15	*N24*	337.84	*N24*	569.58	*N25*	321.53

Table 2: Ranked fused features for four types of honeys (continued).

Agromas		As-Syifa		Syair Timur		Tayyibah	
Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance	Ranked Feature	Unbounded Distance
T2	236.18	*T9*	318.68	*T11*	542.8	*N3*	318.65
T3	193.98	*T7*	281.94	*N14*	510.64	*N24*	291.55
T7	180.85	*N30*	261.39	*T1*	341.75	*N2*	274.43
T1	133.79	*T3*	258.33	*T8*	215.54	*N4*	263.23
N32	119.50	*T8*	148.62	*T5*	177.28	*T8*	185.14
T5	96.45	*T1*	132.06	*N32*	142.51	*N32*	143.86
T9	69.64	*T4*	96.43	*T4*	92.6	*T3*	114.05
T8	55.04	*T5*	70.97	*T3*	62.53	*T4*	98.99
T4	42.19	*N32*	67.79	*T7*	60.66	*T5*	90.02
T10	41.37	*T10*	43.47	*T10*	11.09	*T10*	76.1

Based on the results in Table 2, the top-ranked features can be considered random i.e. without any specific pattern of domination from a specific features for all dataset. However, from the observation of the top-ten-ranked features, several similar features appeared in all the dataset without any specific order e.g. *N5*, *N9*, *N20*, *N23*, *N26*, *N29*, and *N31*. The evaluation of the ranked features was made using the generated feature subset based on the inclusion of one feature at a time which begin with the top-ranked to the bottom-ranked. For example, the classification of Agromas honey from several adulterated concentrations, the generated feature subset begun with (subset 1=*N23*), (subset 2=*N23, N5*), (subset 3=*N23, N5, N29*), etc. until the last feature subset that contain all 42 fused features (subset 42=*N23, N5, N29, ..., T10*). The Agromas honey achieved 100% correct classification by using the 21 top-ranked features, and the result remain unchanged even though more features were included, except for the inclusion of feature 34 (*T3*) which affect the accuracy to drop to 99%. Figure 2 describes the behavior of the classification accuracy for each of the generated feature subset for all the datasets involved.

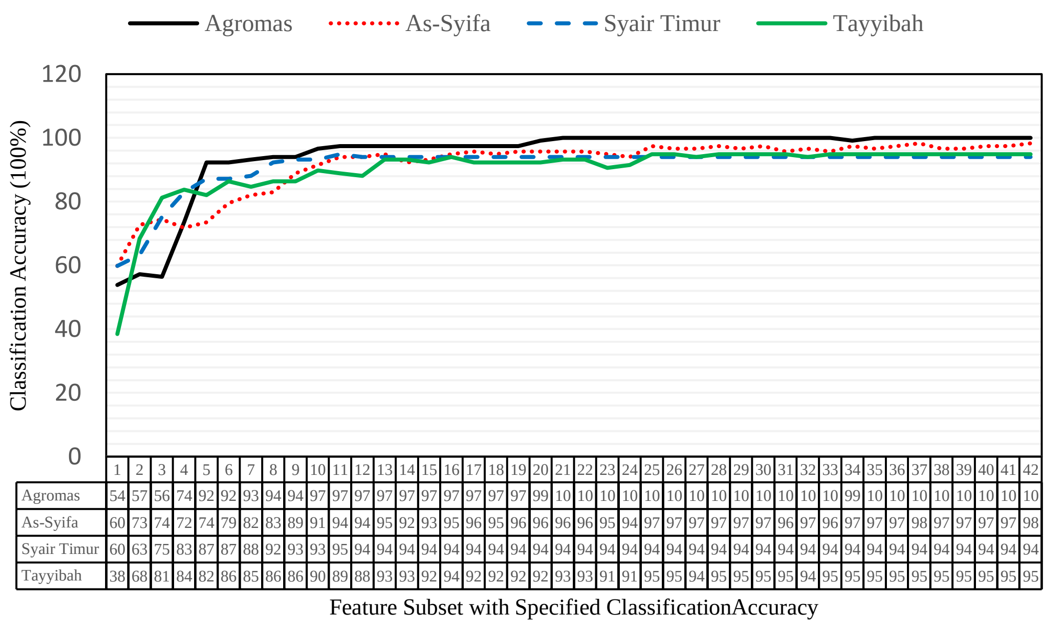

Figure 2: Classification performance of ranked feature subset (inclusion of one ranked-feature)

5. Conclusion

Feature selection based on the evaluation of unbounded Mahalanobis distance can be used to replace the conventional feature extraction for the low-level data fusion involving different sensor devices. The proposed method has shown potential result of classifying pure honey from adulterated honey concentrations by selecting several specific top-ranked features. Unlike feature extraction, distance-based feature selection offers a simple and objective method to identify features that are useful to describe separation between classes which lead to good classification performance. However, the low-level data fusion can be a disadvantage if the features from one of the sensor devices were ranked at the bottom. This can be observed from the electronic tongue where most of

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