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ELECTRONIC NOSE TECHNOLOGY FOR RAPID DETECTION OF ADULTERATED CAMEL MILK POWDER

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ABSTRACT

In recent years, owing to popular use and high price of camel milk powder, it is likely to be adulterated, hence needs a quick method of detecting adulteration. This study took camel milk powder as the research object, and added 0%, 1%, 5%, 10%, 20%, 30%, 50% and 100% adulterants, such as goat milk powder, cow milk powder, protein powder and starch for sample preparation. According to the odour characteristics of adulterated camel milk, the electronic nose technology combined with principal component analysis (PCA) and partial least square discriminant analysis (PLS-DA) were used for qualitative discrimination and quantitative analysis. Finally, multiple linear regression analysis (MLR) was used to verify the information of adulterated camel milk powder samples. The results showed that PCA analysis can distinguish different proportions of adulterated camel milk powder; PLS-DA model can effectively distinguish adulterated camel milk powder, and the detection limit of adulteration in camel milk powder was 1%. The correlation coefficients of linear regression analysis were all higher than 85%, and the predicted value and the actual adulteration value showed a certain linear relationship, indicating that the model had good generalisation ability. Therefore, it was feasible to use the electronic nose to realise the rapid detection method of camel milk powder adulteration.

Key words: Adulteration, camel milk powder, electronic nose, qualitative discrimination, quantitative analysis

In many countries, camel milk is popular due to its perceived health-promoting properties. Camel milk contains high amounts of the immune-active proteins, such as lysozyme, lactoferrin, lactoperoxidase, immunoglobulins, as well as vitamin C and insulin, all of which play important roles in disease defense mechanisms (Mal and Pathak, 2010). Furthermore, camel milk has potential beneficial effects, such as anti-carcinogenic, antihypertensive and anti-diabetic ones (Marwa *et al,* 2019). However, camel milk, like any other milk, is extremely perishable, causing losses to both the farm and the market (Haileeyesus *et al,* 2018). Therefore, to preserve its physical, chemical, and nutritional properties, camel milk is usually produced and processed into camel milk powder and to, extend its shelf life, reduce transportation costs, and expand the application range (Thao *et al,* 2019).

Because of its low production, the price of camel milk is ten times that of cow milk, reaching RMB 90-120 per kilogram in China (Zhao *et al,* 2016). With the increasing demand for camel milk, adulteration of camel milk is not uncommon. (Wang *et al,* 2020). In recent years, several adulteration practices have been found in milk and dairy products, such as adding melamine (Lim *et al,* 2016), other animal milk (Liao *et al,* 2017), protein powder and starch (Tatiane *et al,* 2017). Such adulteration creates great concern for the entire production chain. The authenticity of milk powder is a big issue in China.

The existing milk powder adulteration detection technologies include near-infrared spectroscopy (Ning *et al,* 2015), high performance liquid chromatography (Jablonski *et al,* 2014), Raman spectroscopy (Qin *et al,* 2016), polymerase chain reaction (PCR) technology (Wang *et al,* 2020), fluorescence spectroscopy (Serap *et al,* 2017) and nuclear magnetic resonance (NMR) (Qiang *et al,* 2017). These instruments are expensive, and the data analysis requires specialised software and algorithms, making it time-consuming and difficult for ordinary food inspectors to master. Therefore, it is meaningful to need a simple and effective method to detect adulteration of camel milk powder.

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This study used the odour characteristics of camel milk powder through electronic nose technology to explore the lowest detection limit of the adulterated camel milk powder.

Materials and Methods

Materials

The raw camel milk powder (TF) used in this experiment was provided by Inner Mongolia Desert God Biotechnology Co. Ltd. and Zhenmu Whole Goat Milk Powder (YF), Yili Whole Milk Powder (NF), Gusong Potato Starch (DF) and By-Health Soy Protein Isolate Powder (BF) were purchased from a local supermarket.

Sample Preparation

Taking camel milk powder (TF) as the research object, adding C0, C1, C2, C3, C4, C5, C6 and C7 (0%, 1%, 5%, 10%, 20%, 30%, 50% and 100%) cow milk powder (NF), goat milk powder (YF), protein powder (BF) and starch (DF) were tested. Adulterated camel milk powder and purified water at a ratio of 1:7.2 (m/m) were stirred and mixed and then emulsified and homogenised for 15 minutes to obtain adulterated milk samples. The adulterated milk samples were brought to room temperature before being detected by the electronic nose (Ma *et al,* 2014).

For detection of E-nose, the optimised detection procedure was as follows:10mL of the milk sample was placed in a beaker of 100mL at the temperature of 25°C±3°C, and the beaker was sealed by plastic for a headspace generation time of 30 min. The headspace gas was detected by E-nose.

Detection Procedures of Electronic Nose

To collect the odour fingerprint of the adulterated camel milk powder, an E-nose of PEN 3 (Airsense Corporation, Germany) was used. The E-nose system consisted of three parts: the first was the sampling apparatus, the second was the detector unit containing of a sensor array of 10 different metal oxide sensors, and the third was pattern recognition software of Win Muster v.1.6. The nomenclature and characteristics of the 10 metal oxide sensors are listed in Table 1 (Dong *et al,* 2018). It shows that each sensor has a certain degree of affinity towards specific chemical or volatile compounds.

In order to detect adulterated camel milk powder through the electronic nose, the experimental conditions described in our previous study were used (Wu *et al,* 2021), as shown in Table 2. All the adulterated samples were detected at room temperature with 20 duplications.

Data Analysis

The response values of different sensors of the electronic nose were drawn using Origin 2019b software, principal component analysis (PCA) and partial least square discriminant analysis (PLS-DA) were analysed using SIMCA 14.1 software (Umetrics, Sweden), and multiple linear regression analysis (MLR) is used Mnitab 19.0 software analysis.

Results and Discussion

Sensor selection

The electronic nose test was performed on samples with different adulteration ratios, and

Table 1. Sensors used and their main applications in PEN3 electronic nose.

Number in array	Sensor name	General description	Reference
S1	W1C	The main sensitive substances are aromatic compounds	Toluene, 10×10^{-6}
S2	W5S	The main sensitive substance is hydroxide	NO_2, 1×10^{-6}
S3	W3C	The main sensitive substances are ammonia and aromatic compounds	Benzene, 10×10^{-6}
S4	W6S	The main sensitive substance is hydrogen	H_2, 10×10^{-5}
S5	W5C	The main sensitive substances are alkanes, aromatic compounds and weakly polar compounds	Propane, 1×10^{-6}
S6	W1S	The main sensitive substance is methane in the environment	CH_3, 10×10^{-5}
S7	W1W	The main sensitive substances are sulfur-containing organic and inorganic compounds, terpenes and pyrazine compounds	H_2S, 1×10^{-6}
S8	W2S	The main sensitive substances are ethanol and some aromatic compounds	CO, 10×10^{-5}
S9	W2W	The main sensitive substances are aromatic compounds and sulfur-containing organics	H_2S, 1×10^{-6}
S10	W3S	The main sensitive substances are alkanes	CH_3, 10×10^{-5}

Table 2. Parameters of the electronic nose experiment.

Project	Parameter
Zero gas	Clean air, gas filtered with charcoal filter
The amount of sample in the vial	10mL
Vial volume	100mL
Initial injection flow	400 mL/min
Chamber flow	400 mL/min
test temperature	25°C
Presampling time	5s
Measurement time	70s
Sample interval	1s
Zero point trim time	10s
Flush time	60s

finally the response graph of the electronic nose to each sample was obtained. Fig 1A was the electronic nose sensor of unadulterated camel milk powder. The abscissa was the measurement time and the ordinate was the sensor response signal value, G/G0. G and G0 were the values reported by the sensors after exposure to the sample gas and the zero (control) gas, respectively (Xiaobao *et al,* 2018). The sensor array was composed of 10 sensors that are exposed to the headspace of the milk samples. During measurement, data were recorded every second for 70s, for a total of 700 records per sample, to allow the sensors to reach stable signal values. After sampling, the response values of the 10 sensors of the electronic nose gradually deviated from the baseline, and then gradually stabilised and most sensors began to reach a stable state in 60s. Therefore, the average value within 60-64s was selected as the characteristic value for subsequent analysis in this experiment. In addition, different sensors had different responses to camel milk powder. The S2 sensor had the largest response to camel milk powder, mainly detecting hydroxide compounds; followed by S7 and S6, mainly detecting sulfur-containing organic and inorganic compounds and methane.

In order to better compare the response of the electronic nose to camel milk powder (TF), goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF), the response of the sensor was extracted and its radar chart was drwan (see Fig 1B). The radar graph showed that the response results of each sensor from each sample were different, and the response value of S7 and S6 sensors were quite different, followed by S9 and S8 sensors. Therefore, it could be distinguished based on the response difference of the 10 sensors of the electronic nose to different substances.

PCA results

PCA was used to reduce the dimension and for primary evaluation of the similarity of classes (Fardin *et al,* 2018). PCA is a mathematical algorithm that can reduce the dimensionality of the data without significant information loss and calculate the contribution of the principal components (PCs) (Stewart *et al,* 2014). The main idea of PCA is to project the information to some PCs, which can reduce the dimensionality of data while most variances are retained. A few PCs, which replace the original data, can show in a better way the variance distribution among the samples (Fei *et al,* 2017).

In order to better distinguish the adulterated camel milk powder samples, principal component analysis was performed on the electronic nose detection data, as shown in Fig 2. Based on the results of PCA analysis, the adulterated camel milk powder samples mixed with goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF) (as shown in Fig 2A-2D), the two main components of PC1 and PC2 are 74.8% and 16.2%, 70.6% and 17.2%, 76.9% and 11.8%, 73.4% and 19.9%, respectively, the inter-sample variance accounted for 91%, 87.9%, 88.7% and 93.3% of the total data. The results were reliable since the first two principal components together contributed more than 85% to the cumulative variance (Rizelio *et al*. 2012). There were obvious differences between camel milk powder (TF), goat milk powder (YF), milk powder (NF), protein powder (BF), starch (DF) and adulterated camel milk powder in different proportions. Although the 10% and 20% protein powder (BF) adulteration groups partially overlapped, however, these can basically be distinguished.

PLS-DA results

A quantitative model of adulteration in camel milk powder was established by partial least squares (PLS) regression method. Partial least squares-discriminant analysis (PLS-DA) is a versatile algorithm that can be used for predictive and descriptive modelling as well as for discriminative variable selection (Lee *et al,* 2018). The main principle of PLS-DA is to first use PLS to extract the principal component of the sample, and then use the principal component as a new variable to establish a regression model between the independent variable of the

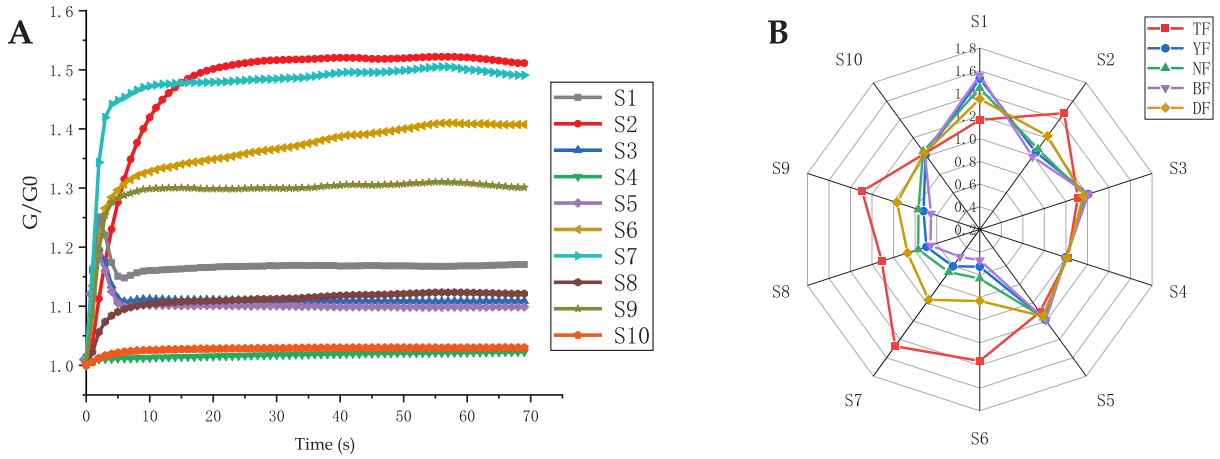

Fig 1. (**A**) Response curve of electronic nose sensor to pure camel milk powder; (**B**) Radar pattern response of electronic nose sensor.

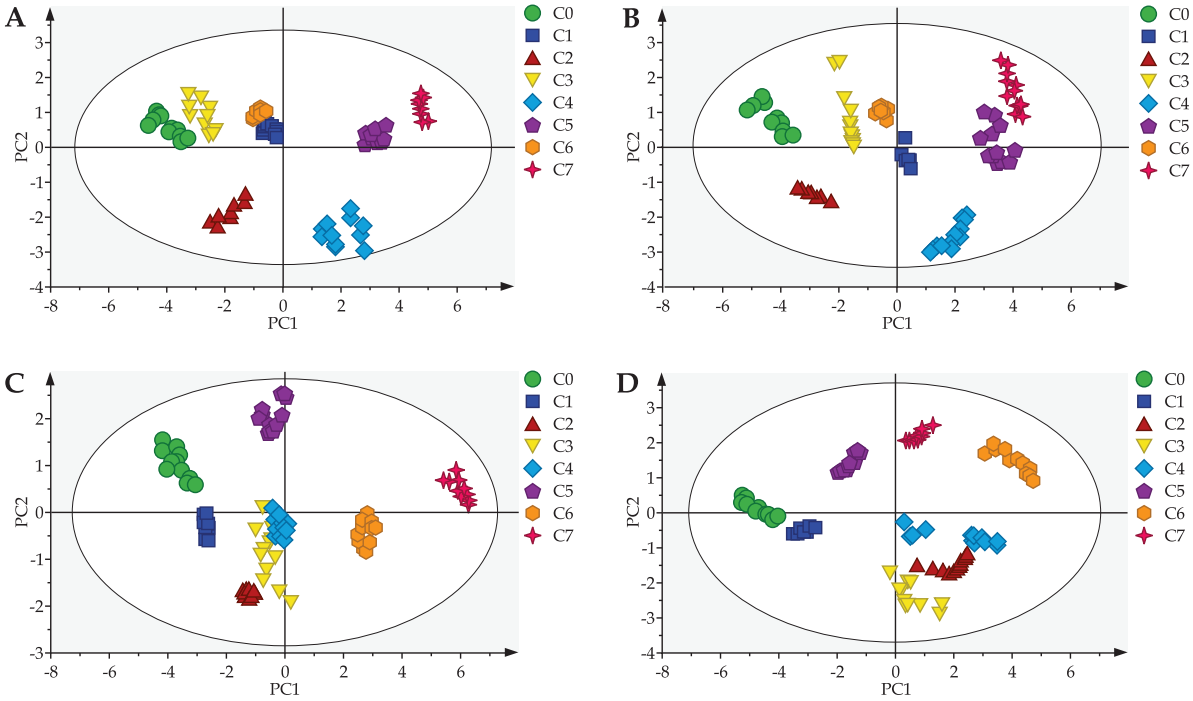

Fig 2. **(A)** PCA score chart of the electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of goat milk powder (YF); **(B)** PCA score chart of the electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of cow milk powder (NF); **(C)** PCA score chart of the electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of protein powder (BF); **(D)** PCA score chart of the electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of starch (DF).

training sample and the categorical variable, and perform discriminant analysis (Huangg, 2021). The data matrix were imported into the SIMCA statistical software and analysed it by PLS-DA (Fig 3). In the adulterated camel milk powder (TF) model was mixed with goat milk powder (YF), R2X (cum) = 0.936, R2Y (cum) = 0.601, Q2 (cum) = 0.599; incorporated into the cow milk powder (NF) model, R2X (cum) = 0.898, R2Y (cum) = 0.589, Q2 (cum) = 0.585; incorporated into the protein powder (BF) model, R2X (cum) = 0.874, R2Y (cum) = 0.975, Q2 (cum) = 0.974; incorporated into the starch (DF) model, R2X (cum) = 0.965, R2Y (cum) = 0.517, Q2 (cum) = 0.515. The value of R2Y and Q2 should be greater than 0.5, indicating that the predictive ability of the PLS-DA model is better (Xi *et al,* 2021), and the results are shown in Fig 3A-3D. The adulteration groups of different concentrations are more clearly distinguished on the PLS-DA score chart, and C0 (0%) and C1 (1%) can be better distinguished. The above

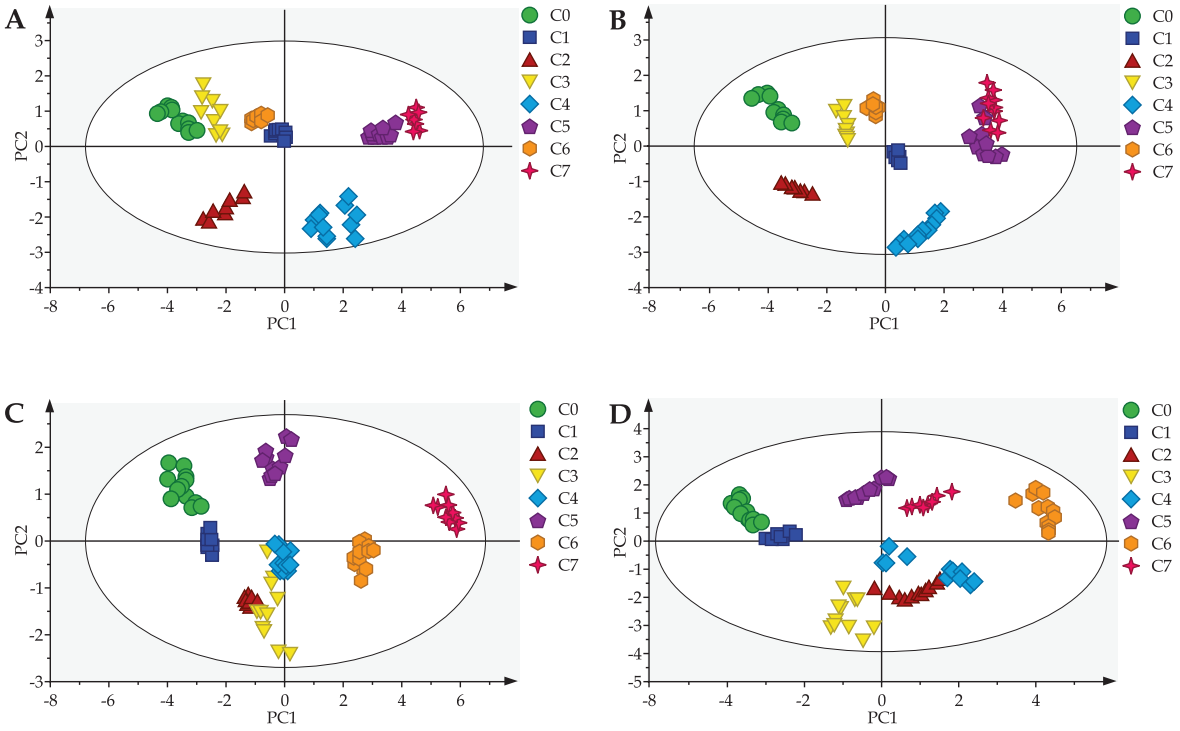

Fig 3. (**A**) PLS-DA score graph of the electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of goat milk powder (YF); (**B**) PLS-DA score graph of electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of cow milk powder (NF); (**C**) PLS-DA score map of electronic nose response value of adulterated camel milk powder (TF) mixed with different concentrations of protein powder (BF); (**D**) PLS-DA score graph of electronic nose response values of adulterated camel milk powder (TF) mixed with different concentrations of starch (DF).

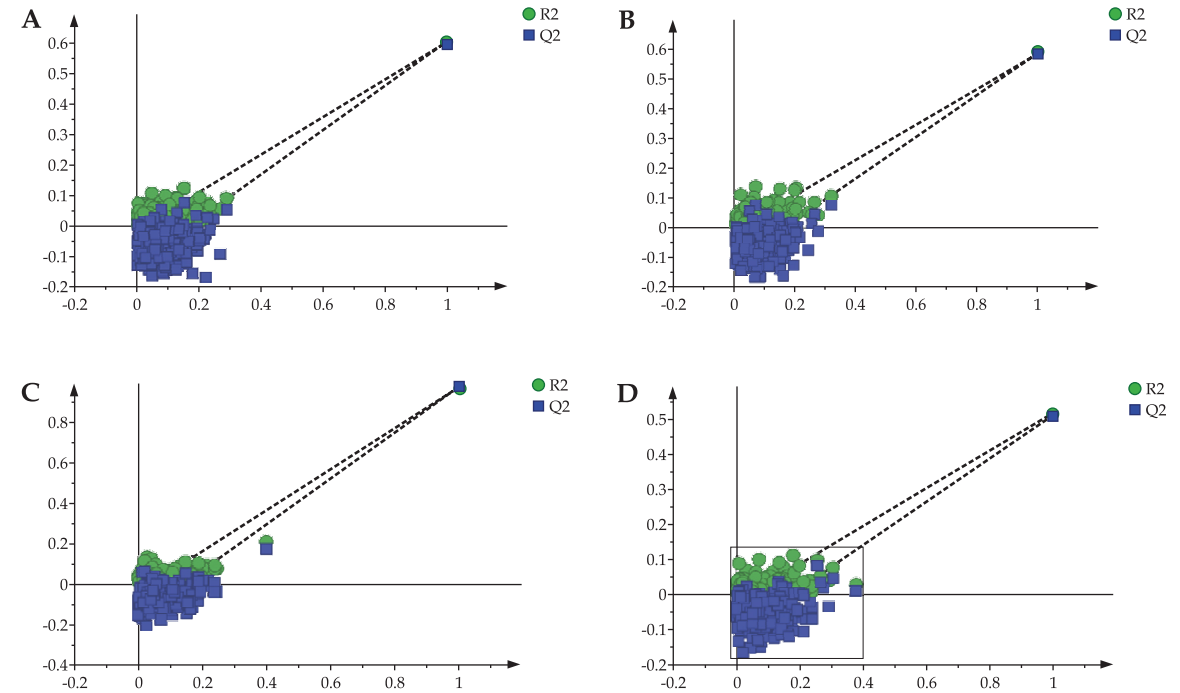

Fig 4. **(A)** The replacement inspection chart of adulterated camel milk powder (TF) mixed with different concentrations of goat milk powder (YF); **(B)** The replacement inspection chart of adulterated camel milk powder (TF) mixed with different concentrations of cow milk powder (NF); **(C)** The replacement inspection chart of adulterated camel milk powder (TF) mixed with different concentrations of protein powder (BF); **(D)** The replacement inspection chart of adulterated camel milk powder (TF) mixed with different concentrations of starch (DF).

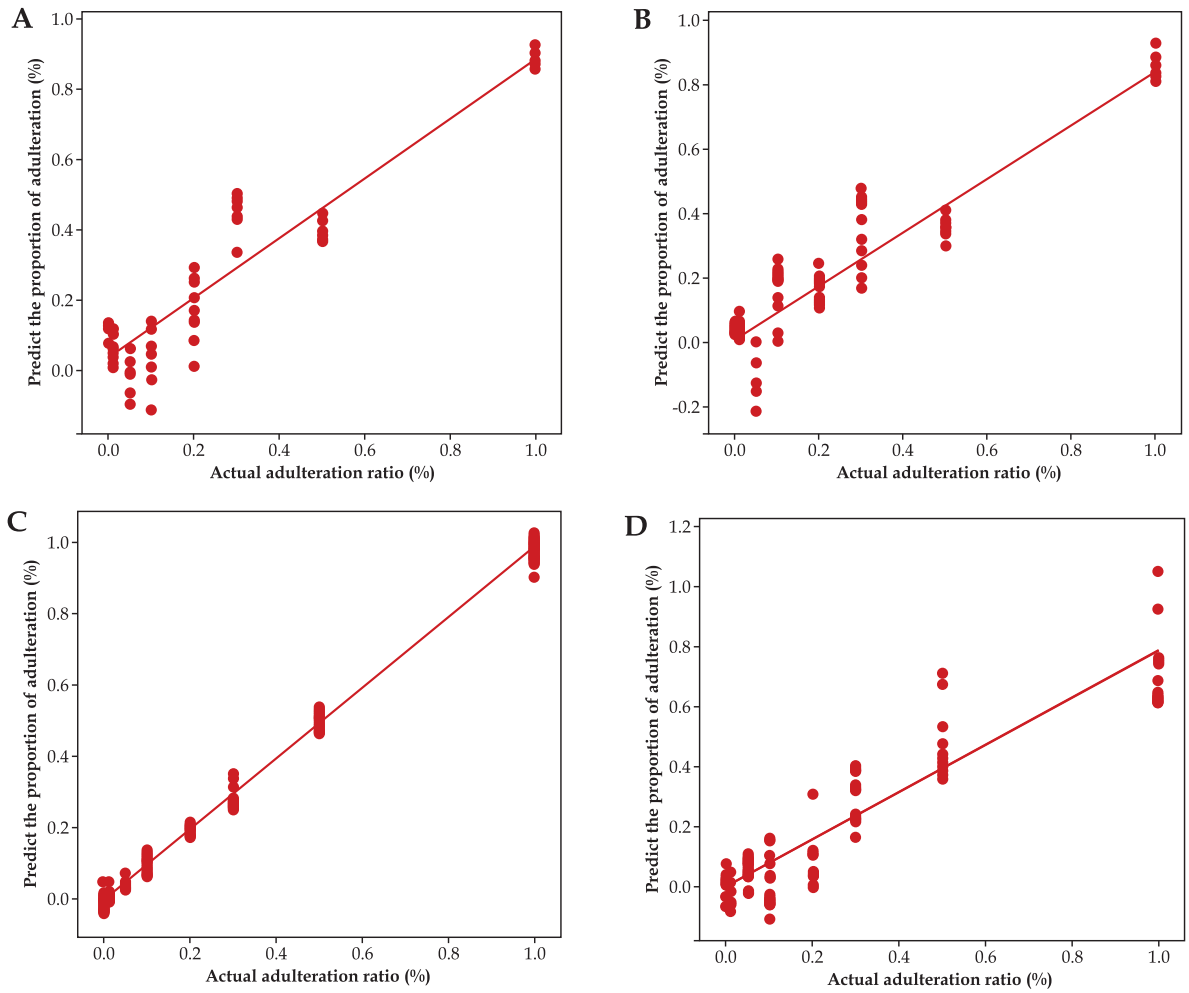

Fig 5. **(A)** MLR analysis diagram of adulterated camel milk powder (TF) mixed with different concentrations of goat milk powder (YF); **(B)** MLR analysis diagram of adulterated camel milk powder (TF) and different concentrations of cow milk powder (NF); **(C)** MLR analysis chart of adulterated camel milk powder (TF) mixed with different concentrations of protein powder (BF); **(D)** MLR analysis chart of adulterated camel milk powder (TF) mixed with different concentrations of starch (DF).

results showed that the detection limit of goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF) in camel milk powder (TF) mixed with electronic nose was 1%, and it can be objectively reflect different adulteration concentrations.

In order to prevent the model from over-fitting, this study was carried out with 200 replacement verifications on the sample data (Wu *et al,* 2020). Fig 4 is a partial least squares discriminant analysis (PLS-DA) model replacement verification diagram. Among them, R2 is the cumulative variance value, and Q2 is the cumulative cross-validity, generally, Q2<0, the model is considered to be reliable, there is no over-fitting phenomenon, and the modeling is successful (Tang and Liao, 2014). The results of adulterated camel milk powder samples mixed with goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF) are shown in Fig 4A-4D, Q2 is -0.115, -0.12, -0.148 and -0.0991, respectively, indicating that the original model does not have over-fitting phenomenon, and the model has good predictive ability.

MLR results

Multiple linear regression analysis is the most commonly applied statistical method of all scientific fields (Show and Gwowen, 2019). MLR is used to determine the relationship between multiple independent predictor variables and a dependent variable (Rebechi *et al,* 2015). At a first step, calibration is performed to build a mathematical model; then, the model is validated in a prediction step (Ragno *et al,* 2004 and Thomas, 1994). In this study, a linear regression fitting model was used for verification and analysis, and the size of the coefficient of determination was used to judge the degree of reliability of the regression equation estimation or the degree of fit of the regression line.

The coefficient of determination of the adulteration model with goat milk powder (YF) was 89.1%. Taking into account the influence of the number of independent variables, the coefficient of determination was corrected, and the adjusted coefficient of determination was 89%; for those with cow milk powder (NF), the coefficient of determination of the adulteration model was 89.7%, and the adjusted coefficient of determination was 89.5%; the coefficient of determination of the adulteration model with protein powder (BF) and the adjusted coefficient of determination were 99.4%; the coefficient of determination with starch (DF), the coefficient of determination of the adulteration model was 86.5%, and the adjusted coefficient of determination was 86.3%; the above results showed that the regression equation was highly reliable in estimation.

The relationship between the actual adulteration ratio of goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF) and the predicted adulteration ratio of the model is shown in Fig 5A-5D. The regression equations established are as follows:

$Y = -23.20 + 2.03X_1 - 0.691X_2 - 5.37X_3 - 19.35X_4 + 28.76X_5 + 1.673X_6 + 0.299X_7 + 2.46X8 - 0.108X_9 + 10.38X_{10}$;

$Y = -53.1 + 4.61X_1 - 0.917X_2 + 0.52X_3 - 11.86X_4 + 35.80X_5 + 0.103X_6 + 2.012X_7 + 8.08X_8 - 1.556X_9 + 10.84X_{10}$;

$Y = -3.52 + 3.682X_1 - 0.2274X_2 - 2.235X_3 - 2.147X_4 - 0.82X_5 + 0.322X_6 + 0.353X_7 + 0.249X_8 - 0.1349X_9 + 3.927X_{10}$;

$Y = -54.81 - 11.32X_1 + 2.087X_2 + 27.05X_3 + 13.37X_4 + 20.7X_5 - 3.546X_6 + 1.24X_7 + 3.91X_8 - 3.409X_9 + 1.60X_{10}$;

where Y is the predicted adulteration ratio, X_1~X_{10} are the response values of 10 sensors.

It can be seen from Fig 5 that the predicted value of the adulteration ratio is relatively close to the true value, indicating that the electronic nose can better predict adulterated goat milk powder (YF), cow milk powder (NF), protein powder (BF), and starch (DF) in camel milk powder (TF). The prediction results of the electronic nose for adulteration quality scores of 0% and 1% are very close, but from the linear fitting situation, the prediction value of the electronic nose for the adulteration concentration of 1% is near the true value, indicating that the electronic nose is against the detection concentration of adulterated goat milk powder (YF), cow milk powder (NF), protein powder (BF) and starch (DF) in camel milk powder (TF) can be accurate to 1%. The MLR results once again proved that the electronic nose can be used for rapid detection and identification of adulterated odour characteristics at different concentrations, which provides a good basis for consumers and various dairy companies.

Conclusion

Based on the unique smell of camel milk powder (TF), this study used an electronic nose technology to study adulterated camel milk powder. Principal component analysis (PCA) and partial least square discriminant analysis (PLS-DA) were used to qualitatively and quantitatively analyse camel milk powder with different amounts of adulteration, and successfully detected the purity and blending of camel milk powder (TF). The result analysis finally determined that the minimum detection limit of goat milk powder (NF), cow milk powder (NF), protein powder (BF) and starch (DF) mixed with camel milk powder (TF) was 1%. On this basis, a linear regression fitting model was established through the multiple linear regression analysis (MLR) method to verify the feasibility of the electronic nose technology for rapid qualitative discrimination and quantitative analysis of adulterated camel milk powder. It will help provide effective reference value for the detection of adulteration of dairy products in the market.

References

Dong F, Zhu X and Zha E (2017). Application of electronic nose in identification of adulterated beef roll. Science and Technology of Food Industry 4:219-227.

Fardin A, Esmaeil MG, Hekmat R and Kobra H (2018). Detection of the adulteration in pure cow ghee by electronic nose method (case study: sunflower oil and cow body fat). International Journal of Food Properties 1:1670-1679.

Fei Z, Yajing Z, Jiyu P, Yirong J, Maiquan L, Yuan J and Baiyi L (2017). Origin Discrimination of Osmanthus fragransvar. thunbergii Flowers using GC–MS and UPLC-PDA Combined with Multivariable Analysis Methods. Phytochemical Analysis 28:305-315.

Haileeyesus H, Michael W and Daniel S (2018). The effect of pretreatment (spray drying) on the yield and selected nutritional components of whole camel milk powder. Journal of Food Science 12:1-9.

Huangg X (2021). HPLC Fingerprint analysis and chemistry pattern recognition of wild and cultivated gentiana. China Pharmacist 2:278-287.

Jablonski JE, Moore JC and Harnly JM (2014). Nontargeted detection of adulteration of skim milk powder with foreign proteins using UHPLC-UV. Journal of Agricultural and Food Chemistry 22:5198-5206.

Lee LC, Liong CY and Jemain AA (2018). Partial least squares-discriminant analysis (PLS-DA) for classification of high-dimensional (HD) data: a review of contemporary

practice strategies and knowledge gaps. The Analyst 15:3526-3539.

Liao J, Liu YF, Ku T, Liu MH and Huang Y (2017). Qualitative and quantitative identification of adulteration of milk powder using DNA extracted with a novel method. Journal of Dairy Science 3:1657-1663.

Lim J, Kim G, Mo C, Kim MS, Chao K, Qin J, Fu X, Beak I and Cho BK (2016). Detection of melamine in milk powders using near-infrared hyperspectral imaging combined with regression coefficient of partial least square regression model. Talanta 151:183-191.

Ma L, Ja R, Yang C and Ding W (2014). Rapid detection of goat milk powder adulterated milk powder based on electronic nose. Dairy Industry 11:47-50.

Mal G and Pathak (2010). Camel milk and milk products. SMVS' Dairy Year Book 97-103.

Marwa MD, Heba HS and Samah ME (2019). The effects of camel milk powder on the stability and quality properties of processed cheese sauce. Acta scientiarum polonorum. Technologia Alimentaria 4:349-359.

Ning-ning W, Bing-hui S, Jian-jun G, Zhong-rui Z, Ye-wei Z, Lu-da Z, Yan-lu Y, Yu-yan Z, Cheng-yu D and Ding-ming K (2015). Detection of adulteration in milk powder with starch near infrared. Guang Pu Xue Yu Guang Pu Fen Xi 8:2141-2146.

Qiang Qiang L, Zunbo Y, Dan Z, Xianghe M, Xiumei P, Yue L, Russell F, He C and Gang C (2017). The Application of NMR-based Milk Metabolite Analysis in Milk Authenticity Identification. John Wiley and Sons, Ltd 9:2875-2882.

Qin J, Kim MS, Chao K, Dhakal S, Lee H, Cho BK and Mo C (2017). Detection and quantification of adulterants in milk powder using a high-throughput Raman chemical imaging technique. Food Additives and Contaminants 2:152-161.

Ragno G, Ioele G and Risoli A (2004). Multivariate calibration techniques applied to the spectrophotometric analysis of one-to-four component systems. Analytica Chimica Acta 512:173-180.

Rebechi S R, Vélez MA, Vaira S and Perotti MC (2015). Adulteration of Argentinean milk fats with animal fats: Detection by fatty acids analysis and multivariate regression techniques. Food Chemistry 192:1-26.

Rizelio VM, Gonzaga LV, Borges GDSC, Maltez HF, Costa ACO and Fett R (2012). Fast determination of cations in honey by capillary electrophoresis: a possible method for geographic origin discrimination. Talanta 99:450-456.

Serap DV, Elif E and Ismail HB (2017). Rapid discrimination between buffalo and cow milk and detection of adulteration of buffalo milk with cow milk using synchronous fluorescence spectroscopy in combination with multivariate methods. Journal of Dairy Research 2:214-219.

Show LJ and Gwowen S (2019). Sample size calculations for model validation in linear regression analysis. BioMed Central 1:1-9.

Stewart S, Ivy MA and Anslyn EV (2014). The use of principal component analysis and discriminant analysis in differential sensing routines. Chemical Society Reviews 43:70-84.

Tang J and Liao X (2014). GC-MS combined with PLS-DA to discriminate the varieties of Xinjiang lavender essential oil. Computers and Applied Chemistry 6:701-704.

Tatiane BC, Laerte DC, Pedro HRC, Helen KS, Juliana BC and Paulo FM (2017). Adulteration identification in raw milk using Fourier transform infrared spectroscopy. Journal of Food Science and Technology 8:2394-2402.

Thao MH, Sophia C, Anya JEY, Ruchitha S, Bhesh RB and Nidhi B (2019). Changes in physicochemical properties of spray-dried camel milk powder over accelerated storage. Food Chemistry 295:224-233.

Thomas E (1994). A primer on multivariate calibration. Analytical Chemistry 15:795-804.

Wang Z, Li T, Yu W, Qiao L, Liu R, Li S, Zhao Y, Yang S and Chen A (2020). Determination of content of camel milk in adulterated milk samples by normalized real-time polymerase chain reaction system based on single-copy nuclear genes. Journal of the Science of Food and Agriculture 8:3465-3470.

Wu D, Qi B, Si R, He J and Jirimutu (2021). Rapid Detection of Adulteration in Camel Milk by Electronic Nose. Science and Technology of Food Industry. pp 1-12.

Wu S, Wr RW and Che XX (2020). Study on the application of human breath on-line detection mass spectrometer to the flavor identification of edible candy. Journal of Food Safety and Quality 20:7213-7219.

Xi J, Zhang Y, Wu M, Zhang W, Xu Z and Xia W (2021). PMP-HPLC Fingerprint of Partial Acid Hydrolysate of Lycium Barbarum Polysaccharides based on the Chemometric Methods. Science and Technology of Food Industry 1-12.

Xiaobao W, Xingfeng S, Yingying W, Lingzhi C, Leiqing P and Kang T (2018). Rapid detection of adulterated peony seed oil by electronic nose. Journal of Food Science and Technology 6:2152-2159.

Zhao RGT, He WNM and Zhitong W (2016). Determination of nutrient composition of camel milk. China Animal Industry 7:51-52.