Rapid Method for Faults Detection in Beer Using a Low-Cost Electronic Nose and Machine Learning Modelling

Claudia Gonzalez Viejo [1]*, Sigfredo Fuentes [1], Carmen Hernandez-Brenes[2]

[1] Digital Agriculture Food and Wine Group, School of Agriculture and Food; Faculty of Veterinary and Agricultural Sciences, The University of Melbourne, Parkville, VIC 3010, Australia
[2] Tecnologico de Monterrey, Escuela de Ingeniería y Ciencias, Ave. Eugenio Garza Sada 2501, Monterrey, N.L., México
*Corresponding author: cgonzalez2@unimelb.edu.au

Introduction

Beer is susceptible to develop different faults (off-flavours/off-aromas) due to the nature of its main ingredients and the variability in the conditions within the production stages and storage; this is especially challenging for craft breweries. Therefore, it is important to develop novel, rapid and non-destructive methods for detection of beer faults. This study proposed an integrated artificial intelligence (AI) system to detect faults in beer using a low-cost and portable electronic nose (e-nose) coupled with machine learning modelling.

Methods

A commercial dry lager beer (Asahi Super Dry, Asahi Breweries, Sumida City, Tokyo, Japan) in 500 mL cans was used as the base for this study. All beers were analysed in triplicates. Samples were spiked with 18 different faults (off-flavours/off-aromas) commonly found in beer at two concentrations (low and high), along with a control (original non-spiked sample). A low-cost and portable e-nose (DAFW; University of Melbourne, Australia) was used to assess the volatile compounds in all samples. Data were analysed for significant correlations ($p < 0.05$) using Matlab® (Mathworks, Inc., Natick, MA, USA) and presented in a matrix.
Outputs from the e-nose were used as inputs to develop three machine learning models based on artificial neural networks (ANN) using Bayesian Regularisation training algorithm to (i) classify samples into control, low and high concentration (Model 1), (ii) predict the fault present in the low concentration samples (Model 2) and (iii) predict the fault present in the high concentration samples (Model 3; Figure 1).

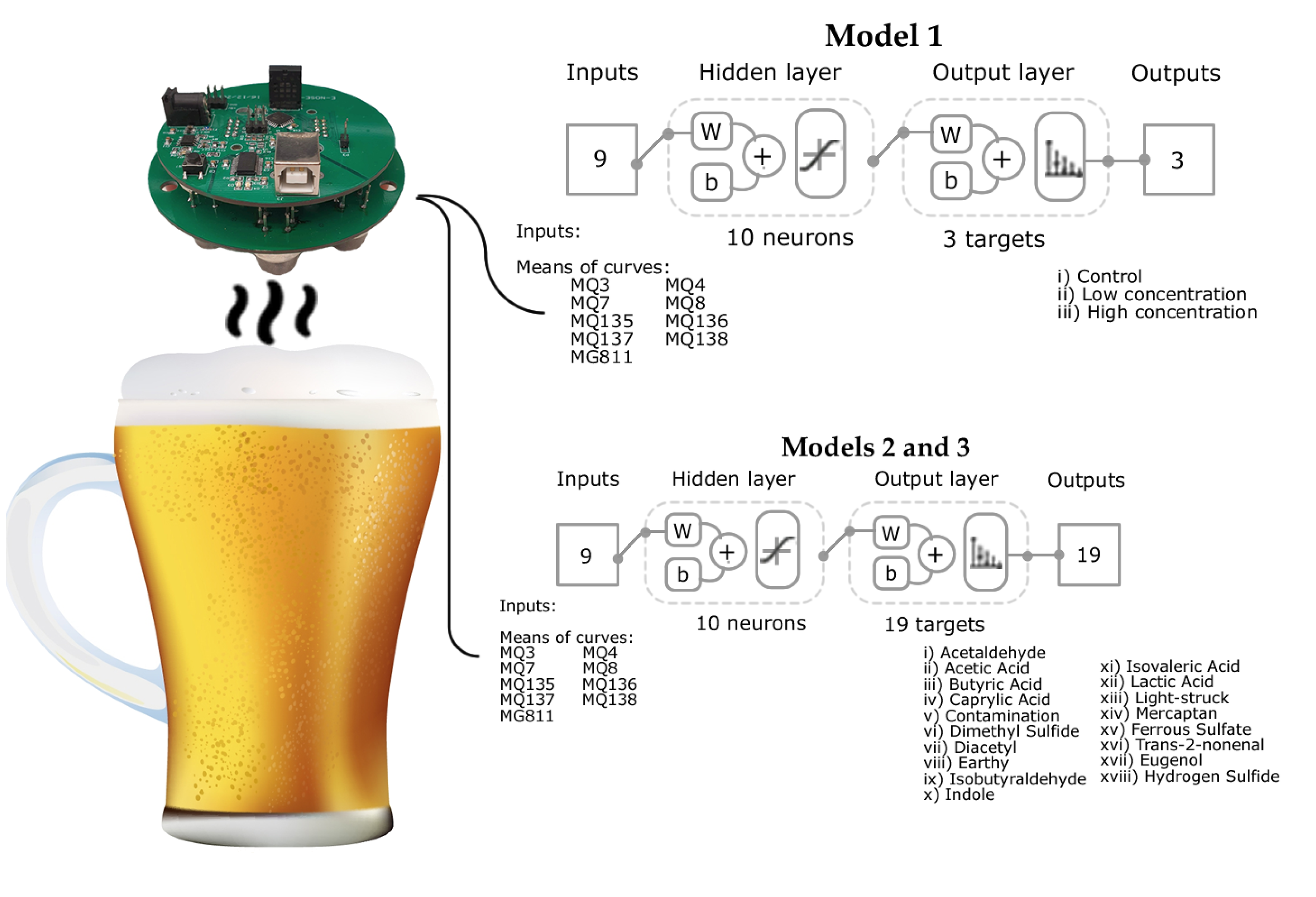

Figure 1. Diagram depicting the analysis of beer volatile compounds using the electronic nose and how these outputs were used as inputs to construct machine learning models. Abbreviations: W: weights; b: bias.

Results

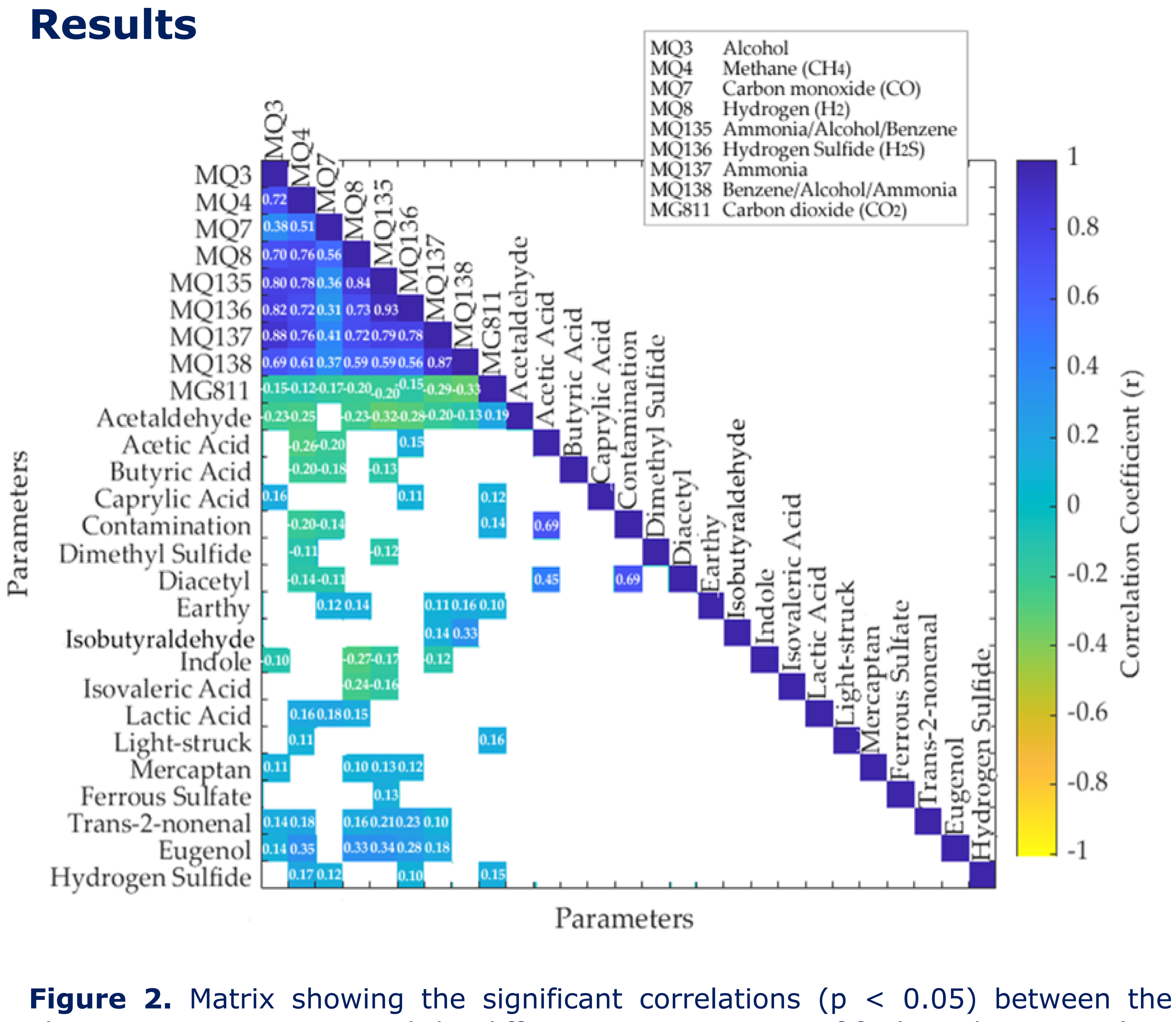

Figure 2. Matrix showing the significant correlations ($p < 0.05$) between the electronic nose outputs and the different concentrations of faults in beer samples.

Figure 2 shows significant ($p < 0.05$) and positive correlations between MQ3 sensor (alcohol) and caprylic acid ($r = 0.16$), trans-2-nonenal and Eugenol ($r = 0.14$) and mercaptan ($r = 0.11$). The hydrogen sulfide sensor (MQ136) presented positive correlations with trans-2-nonenal ($r = 0.23$), Eugenol ($r = 0.28$) and hydrogen sulfide ($r = 0.10$) samples.

Table 3 shows that the three models were highly accurate to predict faults using the e-nose outputs as inputs. Model 1 had 95% overall accuracy to predict the concentration level of faults present in beer. On the other hand, Models 2 and 3 presented 97% and 96% accuracy, respectively. From the performance of the three models, it can be observed that there were no signs of overfitting.

Table 1. Statistical data from the machine learning models showing accuracies and performance based on means squared error (MSE)

Stage	Samples	Accuracy	Error	Performance (MSE)
Model 1: Classification (Low, Medium, High Concentration)				
Training	239	98.5%	1.5%	0.01
Testing	103	87.7%	12.3%	0.08
Overall	342	95.3%	4.7%	-
Model 2: Prediction Low Concentration Faults				
Training	420	99.8%	0.2%	<0.001
Testing	180	90.0%	10.0%	0.009
Overall	600	96.8%	3.2%	-
Model 3: Prediction High Concentration Faults				
Training	420	100%	0.0%	<0.001
Testing	180	87.2%	12.8%	0.011
Overall	600	96.2%	3.8%	-

Conclusion

The proposed method showed to be rapid, reliable, objective and effective apart from low-cost to assess beer quality based on development of faults. The e-noses may be installed at different stages of beer production for early detection of faults, which may allow applying any corrective actions before obtaining the final product.

References

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Acknowledgement

This research was funded by the Mexican Beer and Health Council (Consejo de Investigación sobre Salud y Cerveza de México).