Rapid Detection of Rice Adulteration using a Low-Cost Electronic Nose and Machine Learning Modelling

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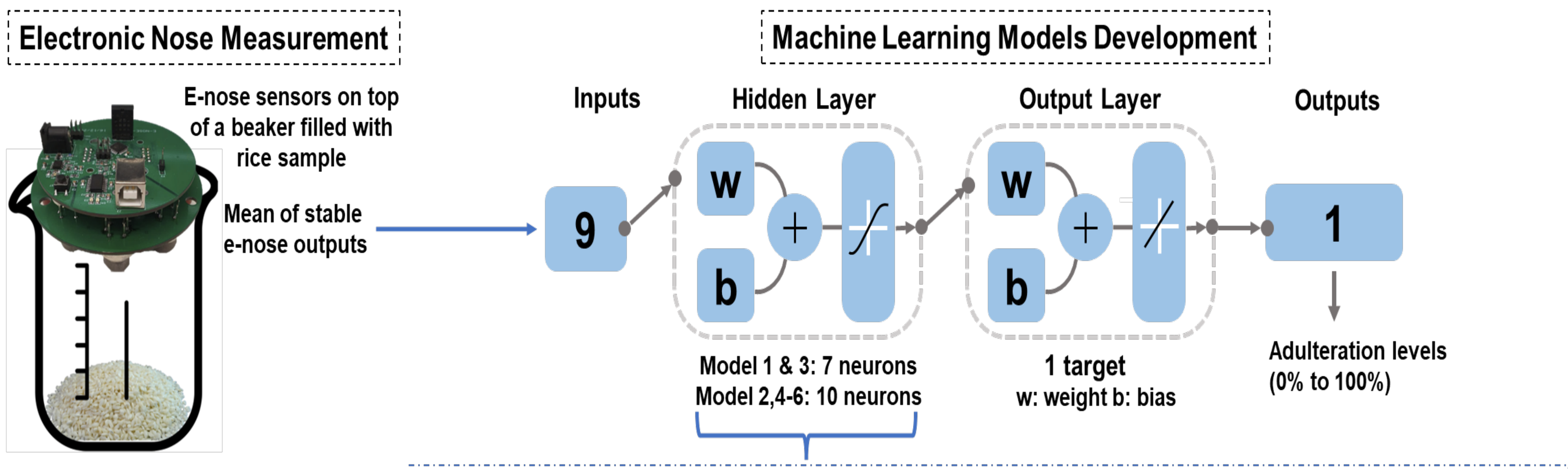
Introduction

Rice adulteration is a common food fraud problem in the rice industry since the adulterants are similar in visual aspects to the authentic rice. Commonly, the lower price/quality adulterant is mixed with the authentic rice to gain more profit (FAO, 2021). However, this has become a serious problem to the industry and tainted consumer perceptions. Current methods used to detect rice adulteration use involve analytical methods that are costly, time-consuming, and tedious with very low replicability. Therefore, this study aimed to develop an alternative method for rapid detection and of high replicability potential of rice adulteration using a low-cost and portable electronic nose (e-nose) coupled with machine learning (ML) modeling techniques.

Material and Methods

Six combinations of adulterated raw rice samples were prepared by mixing the authentic rice with common adulterant (100 g) in proportions from 0% to 100% with 10% increment by weight. The original samples included Basmati and Sushi rice from different origins, premium and regular grade Sushi rice, aromatic (i.e., Basmati and Jasmine rice) and non-aromatic rice (i.e., regular long grain rice), and organic and non-organic rice. A low-cost e-nose (Gonzalez Viejo et al., 2020) developed by the Digital Agriculture, Food and Wine group, The University of Melbourne (DAFW-UoM) was used in this study to obtain the gas exchange readings from rice samples from the headspace of a 500 ml beaker in triplicates. ML regression models of the six rice samples were developed using artificial neural network (ANN) algorithms to predict the rice adulteration levels (targets) based on the mean values of the stable voltage outputs acquired from the e-nose as inputs (Figure 1).



E-nose sensors:
MQ3: Ethanol
MQ4: Methane
MQ7: Carbon monoxide
MQ8: Hydrogen
MQ135: Ammonia/alcohol/benzene
MQ136: Hydrogen sulphide
MQ137: Ammonia
MQ138: Benzene/alcohol/ammonia
MG811: Carbon dioxide

Machine Learning Models	Authentic Rice Samples	Adulterants
Model 1: Rice from different origin	Basmati grown in Pakistan (BSR)	Basmati grown in India (BAW)
Model 2: Rice from different origin	Sushi rice (SRS; grown in Australia)	Sushi rice (PDR; grown in America)
Model 3: Aromatic and non-aromatic rice	Basmati from Pakistan (BSR)	Long grain rice (LGW)
Model 4: Aromatic and non-aromatic rice	Jasmine rice (JAS)	Long grain rice (LGW)
Model 5: Premium and regular rice	Koshihikari rice (KHO)	Sushi rice (SRS)
Model 6: Organic and non-organic rice	Medium grain organic rice (MOR)	Medium grain (MGB)

Figure 1. Diagram of main steps to predict the quantitative levels of rice adulteration using electronic nose sensors as inputs coupled with regression models for the six authentic rice mixed with common adulterant.

Results

Table 1 shows that the ML models had high prediction accuracy with correlation coefficient, R between 0.98 to 0.92. The mean squared error (MSE) values for all ML models confirmed no signs of under-or-overfitting since the training MSE values were lower than the validation and testing stages and similar MSE values were observed for both validation and testing stages. Figure 2 shows the overall R values for all ML models with 95% confidence bounds.

Conclusion

The study showed the successful implementation of a low-cost method to detect rice adulteration level using non-destructive technique. The proposed method may potentially be adopted as an artificial intelligence (AI) tool for rapid adulteration detection during rice inspection to obtain results in real time. These AI tools could secure provenance and rice quality to consumers and reduce adulteration at different stages of the production chain.

Table 1. Machine learning regression models of artificial neural network (ANN) developed to predict quantitative levels of rice adulteration (target) using the low-cost electronic nose readings as inputs. Abbreviations: R: correlation coefficient; MSE: mean squared error.

Stages	Samples (n)	Observations	R	Slope	Performance (MSE)
			Model 1		
Training	230	2530	0.95	0.90	0.90×10^2
Validation	50	550	0.94	0.91	1.16×10^2
Testing	50	550	0.94	0.97	1.33×10^2
Overall	330	3630	0.95	0.91	-
			Model 2		
Training	230	2530	0.95	0.89	0.93×10^2
Validation	50	550	0.91	0.84	1.78×10^2
Testing	50	550	0.84	0.91	3.67×10^2
Overall	330	3630	0.92	0.89	-
			Model 3		
Training	230	2530	0.97	0.94	0.90×10^2
Validation	50	550	0.95	0.91	1.16×10^2
Testing	50	550	0.91	0.84	1.33×10^2
Overall	330	3630	0.96	0.92	-
			Model 4		
Training	230	2530	0.97	0.91	0.63×10^2
Validation	50	550	0.96	0.92	0.88×10^2
Testing	50	550	0.91	0.80	2.01×10^2
Overall	330	3630	0.96	0.89	-
			Model 5		
Training	230	2530	0.99	0.94	0.26×10^2
Validation	50	550	0.98	0.95	0.29×10^2
Testing	50	550	0.98	0.94	0.44×10^2
Overall	330	3630	0.98	0.94	-
			Model 6		
Training	230	2530	0.95	0.88	1.07×10^2
Validation	50	550	0.91	0.88	1.62×10^2
Testing	50	550	0.91	0.88	1.62×10^2
Overall	330	3630	0.94	0.87	-

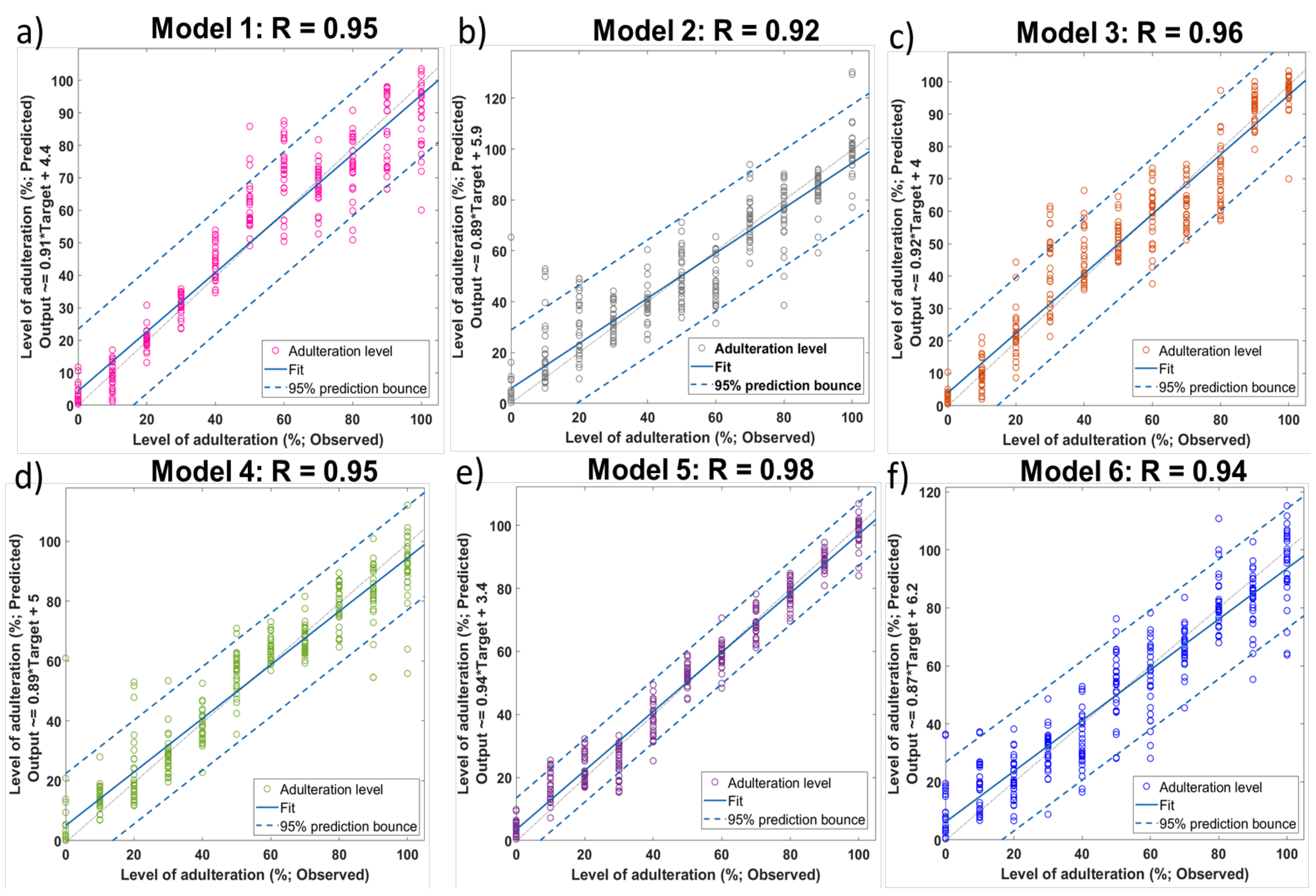


Figure 2. Overall ANN models performance, developed to predict rice adulteration levels (target) using e-nose sensors (inputs) for (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4, (e) Model 5, and (f) Model 6. The description of machine learning models are shown in Figure 1 (Material and Methods).

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