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

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Presentation Outline

BACKGROUND OF STUDY & AIM

MATERIAL & METHODS

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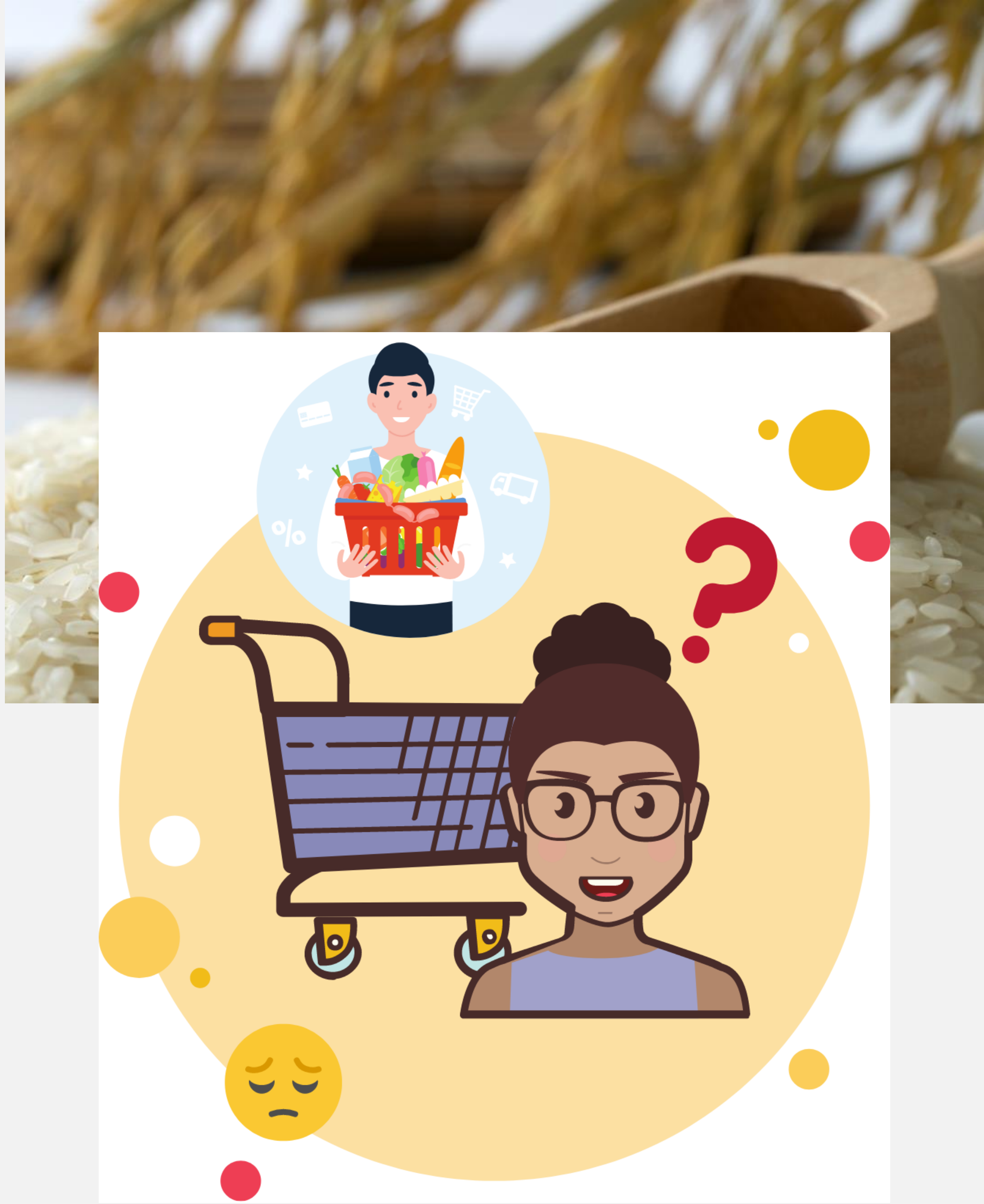
Background of Study

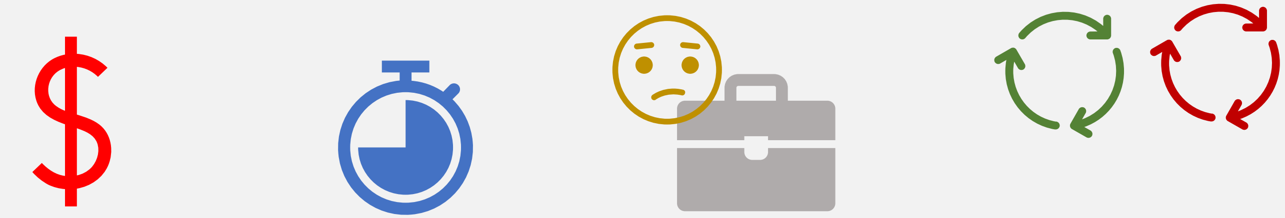
Rice adulteration is a common food fraud problem in the rice industry since the adulterants are similar in visual aspects to the authentic rice.

Commonly, the lower price/quality adulterant is mixed with the authentic rice to gain more profit [1].

However, this has become a serious problem to the industry and tainted consumer perceptions.



Current methods used to detect rice adulteration involve analytical methods.



Costly | Time-consuming | Tedious | Very low replicability

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.

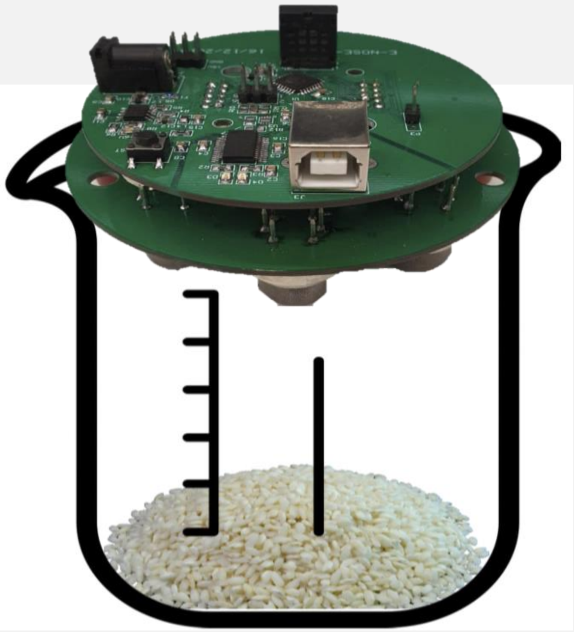
Material & Methods

ML Models

- 1, 2 — Rice from different origin
  - Basmati (BSR; Pakistan) | Basmati (BAW; India)
  - Sushi rice (SRS; Australia) | Sushi rice (PDR; America)
- 3, 4 — Aromatic & non-aromatic rice
  - Basmati (BSR) | Long grain rice (LGW)
  - Jasmine (JAS) | Long grain rice (LGW)
- 5 — Premium & regular rice — Koshihikari (KHO) | Sushi rice (SRS)
- 6 — Organic & non-organic rice — Medium organic rice (MOR) | Medium grain (MGB)

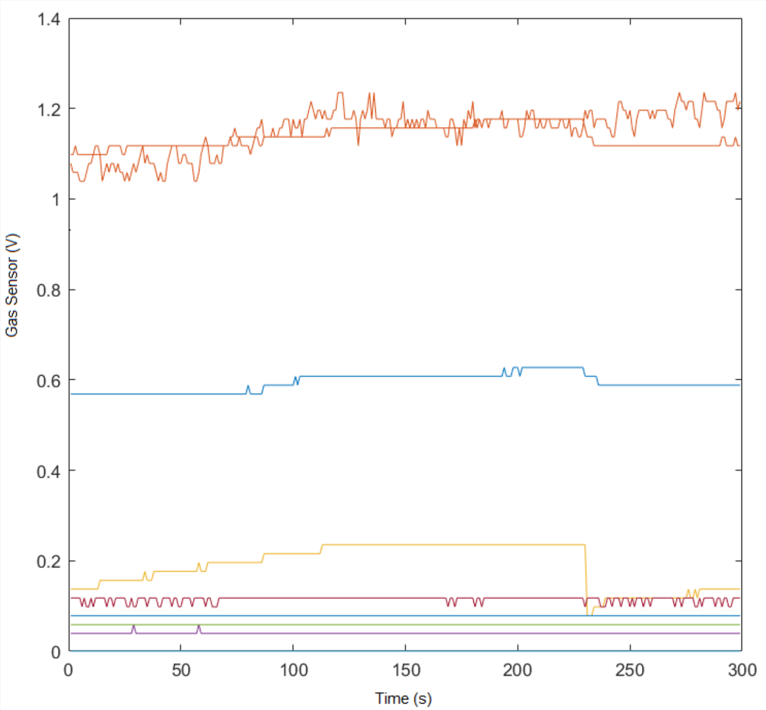
The authentic rice was mixed with common adulterant (100 g) in proportions from 0% to 100% with 10% increment by weight.

Electronic Nose Measurement



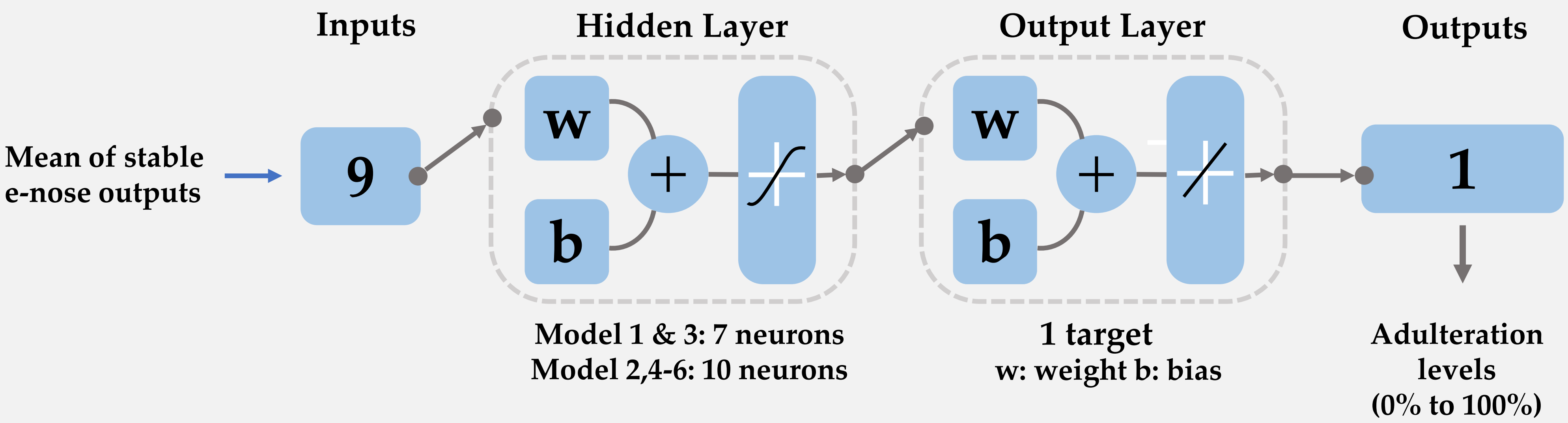
MQ3: Ethanol
MQ4: Methane
MQ7: Carbon monoxide
MQ8: Hydrogen
MQ135: Ammonia/alcohol/benzene
MQ136: Hydrogen sulphide
MQ137: Ammonia
MQ138: Benzene/alcohol/ammonia
MG811: Carbon dioxide

- A glass beaker filled with the rice sample and was shaken five times before the measurement to help the rice release the aroma into the headspace.
- The e-nose measurement was obtained from the top opening of the glass beaker ($D_{e\text{-}nose}$ = 92 mm) [2].



- Exposure time: 60s
- Calibration: 20s (to allow the sensors to reach the baseline reading)
- A supervised code (Matlab 2021a , Mathworks Inc., Natick, MA, USA) was used to extract the output signals by dividing the stable signals into ten equidistance subdivisions to get ten means of voltage output per sensor [3].

Machine Learning Models Development



Regression models developed using electronic nose sensors data (Model 1 - 6) and as inputs to predict rice adulteration levels of six adulterated rice samples.

Results

- ML models had high prediction accuracy with correlation coefficient, R between 0.92 to 0.98.

- The mean squared error (MSE) values for all ML models confirmed no signs of under-or-overfitting.
  - training MSE values were lower than the validation and testing stages
  - similar MSE values for validation and testing stages

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 (BSR:BAW)			
Training	230	230	0.95	0.90	0.90×10^2
Validation	50	50	0.94	0.91	1.16×10^2
Testing	50	50	0.94	0.97	1.33×10^2
Overall	330	330	0.95	0.91	-
		Model 2 (SRS:PDR)			
Training	230	230	0.95	0.89	0.93×10^2
Validation	50	50	0.91	0.84	1.78×10^2
Testing	50	50	0.84	0.91	3.67×10^2
Overall	330	330	0.92	0.89	-
		Model 3 (BSR:LGW)			
Training	230	230	0.97	0.94	0.90×10^2
Validation	50	50	0.95	0.91	1.16×10^2
Testing	50	50	0.91	0.84	1.33×10^2
Overall	330	330	0.96	0.92	-
		Model 4 (JAS:LGW)			
Training	230	230	0.97	0.91	0.63×10^2
Validation	50	50	0.96	0.92	0.88×10^2
Testing	50	50	0.91	0.80	2.01×10^2
Overall	330	330	0.96	0.89	-
		Model 5 (KHO:SRS)			
Training	230	230	0.99	0.94	0.26×10^2
Validation	50	50	0.98	0.95	0.29×10^2
Testing	50	50	0.98	0.94	0.44×10^2
Overall	330	330	0.98	0.94	-
		Model 6 (MOR:MGB)			
Training	230	230	0.95	0.88	1.07×10^2
Validation	50	50	0.91	0.88	1.62×10^2
Testing	50	50	0.91	0.88	1.62×10^2
Overall	330	330	0.94	0.87	-

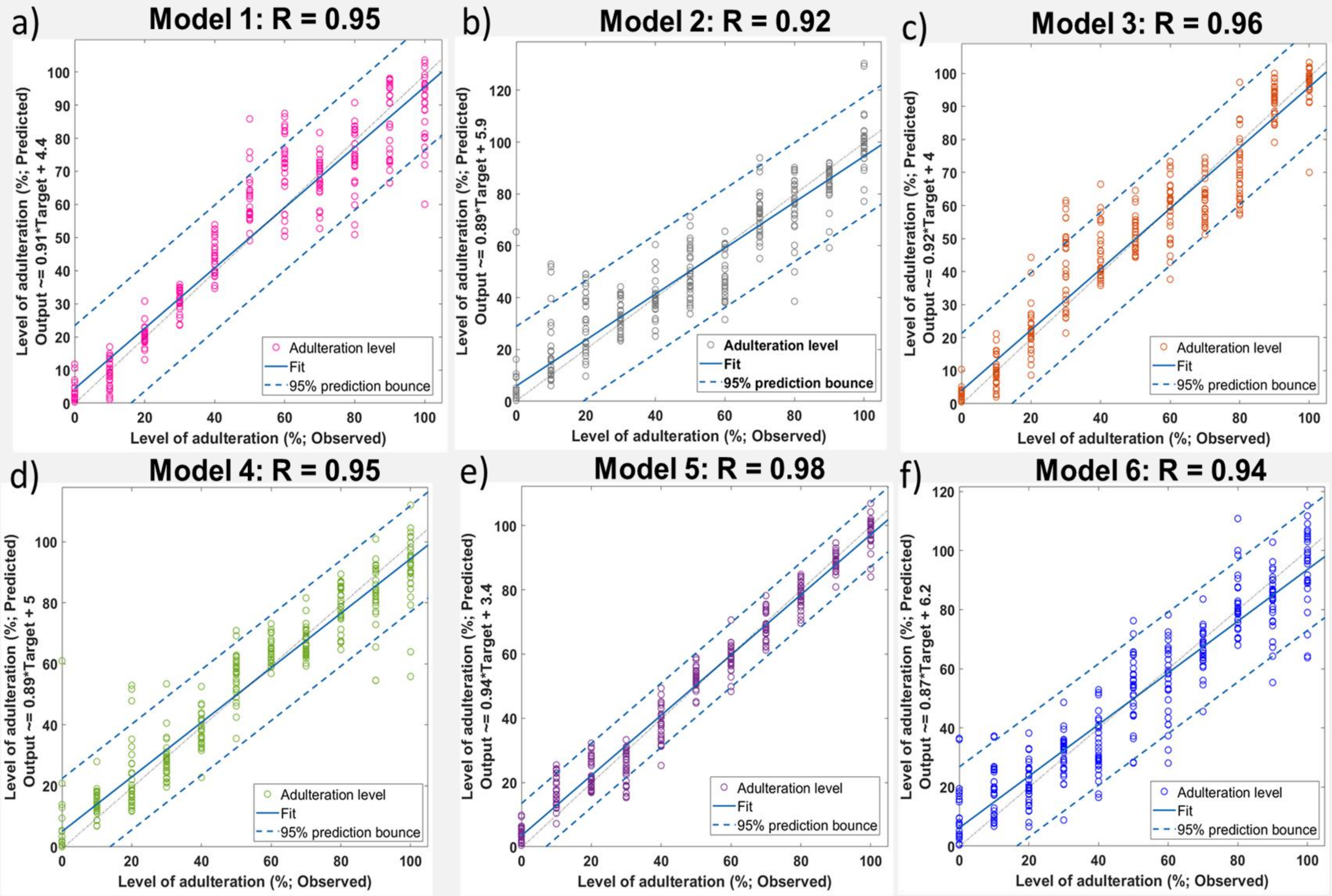


Figure 2. Overall ANN models performance, developed to predict rice adulteration levels (target) using e-nose sensors (inputs) for (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4, (e) Model 5, and (f) Model 6.

Conclusions

The study showed the successful implementation of a **low-cost method** to detect rice adulteration level using **non-destructive technique**.

The method has potential as an AI tool for **rapid detection** of rice adulteration during routine inspection to obtain results in **real time**.

These AI tools could **secure provenance and rice quality** to consumers and **reduce risk of adulteration** at different stages of the production chain.

References

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[3] Gonzalez Viejo, C.; Tongson, E.; Fuentes, S. Integrating a Low-Cost Electronic Nose and Machine Learning Modelling to Assess Coffee Aroma Profile and Intensity. *Sensors (Basel)* **2021**, *21*, doi:10.3390/s21062016.

Thank you for your attention