A Prototype to Detect Alcohol Content in Local Toddy using an Electronic Nose

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***Abstract*—For the purpose of preserving product quality and guaranteeing regulatory compliance, accurate alcohol detection in alcoholic beverages, particularly in local toddy, is crucial. The goal of this study is to produce a reliable alcohol detection device employing electronic nose (e-nose) technology customized for local toddy. The envisioned device includes a sensor array that can detect and examine volatile substances linked to alcohol in local toddy. The system enables real-time alcohol content readings by gathering and analyzing sensor data, enabling accurate quality control and monitoring. Extreme learning machines, artificial neural networks, and multiple linear regression, and multiple nonlinear regression are used to examine the sensor responses to alcohol-associated volatile chemicals. Performance evaluation of the prototype shows that the Artificial N eural N etwork (ANN) model outperforms other models, achieving a Mean Squared Error (MSE) of 1.0000 across multiple test runs, compared to MSE values of 85.627444 for MLR and MNLR models. The Mean Absolute Error (RAE) for the ANN model is as low as 0.0001 in certain runs, demonstrating its precision. These quantitative findings suggest that the ANN model is best suited for accurate alcohol detection in local toddy, offering a significant improvement over traditional methods. The results demonstrate the potential of machine learning methods for detecting alcohol in alcoholic beverages and shed light on the intricate connection between sensor data and alcohol concentrations. These algorithms provide encouraging ways to improve quality control procedures and guarantee constant product quality.**

***Index Terms*—toddy, alcohol content, calibration, e-nose, machine learning**

I. Introduction

Worldwide, civilizations, social circumstances, and industries all depend on alcoholic beverages. For the sake of quality control, regulatory compliance, and consumer safety, alcohol concentration must be measured accurately. Traditional procedures are intrusive and time-consuming [1] , thus a non-destructive solution is required for figuring out how much alcohol is in local toddy, a distinctive fermented beverage.

The goal of this study is to create a toddy analysis prototype that uses an electronic nose. The electronic nose uses gas sensors to detect volatile compounds while simulating the human olfactory system [2]. It allows for quick and effortless alcohol content monitoring while also detecting other volatile substances that may be contributing factors [3]. The variations in the toddy's composition and alcohol level can be properly assessed by utilizing the electronic nose's sensitivity and data analysis techniques, improving quality control in its manufacture.

This study has implications for Sri Lanka's toddy industry since the beverage is important from both an economic and cultural standpoint [4]. The improvement of quality control, consumer confidence, and increased competitiveness of locally produced toddy in both domestic [5] and international markets [6] [7] [8] is supported by the development of the prototype. Ultimately, by offering a precise method of assessing alcohol levels, this research helps the toddy sector flourish and thrive.

II. Related work

Studies that employ classification methods and studies that use regression techniques make up the majority of pertinent studies in the field of alcohol content detection.

In the classification category, The work by G.-J. Jong, Hendrick, Z.-H. Wang, K.-S. Hsieh, and G.-J. Horng [2019] [9] developed a unique feature extraction approach for the olfactory categorization of alcoholic beverages utilizing an electronic nose. Deep learning techniques were used in the study to evaluate patterns in the sensor signals, and they produced encouraging outcomes. Images of correlation coefficients and standard deviations that were obtained from the e-Nose sensors' processed signals were used to generate a dataset. The dataset was used to create two patterns, one based on standard deviations and the other using correlation coefficients that were trained and converted into 3D heat maps. This study highlights the potential of deep learning approaches in accurately detecting the scents of alcoholic beverages and proposes a novel way to feature extraction for fragrance classification utilizing an e-Nose.

The study by P. Tyagi, R. Semwal, A. Sharma, U. S. Tiwary, and P. Varadwaj [10]. describes a low-cost Electronic Nose (E-nose)-based fruit ripeness monitoring system. The E-nose system efficiently tracks odor fingerprints as diverse

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fruits ripen using metal oxide semiconductor gas sensors. To categorize fruits into various stages of ripeness, the study uses an Artificial Neural Network (ANN) model, and its effectiveness is assessed using statistical and graphical measures. This study advances the field of fruit maturity monitoring and provides a useful literature reference for my thesis on utilizing an E-nose prototype to detect the presence of alcohol in local toddy.

On the other hand, regression approaches have been used for some of these studies. In 2019, a study by H. G. J. Voss, J. J. A. Mendes Junior, M. E. Farinelli, and S. L. Stevan [11] contributed to the field of alcohol content detection in beers by developing a prototype using an electronic nose with gas sensors. The equipment was tested on several varieties of beers after being trained on a collection of samples with known alcohol concentrations. This study demonstrates the potential of electronic noses for precise and effective analysis of alcohol levels in the beer sector.

An electronic olfactory system was created in a 2017 study [12] by M. Aleixandre, E. Montero, T. Arroyo, J. Cabellos, and C. Horrillo to quantitatively analyze wine combinations. For forecasting mixture ratios, two techniques—Partial Least Squares Regression (PLS) and Artificial Neural Network(ANN)-were used. ANN performed better than PLS in quantifying white wine combinations, which showed limited accuracy. Both PLS and ANN were successful in quantifying red wine combinations. The study brought attention to how challenging it is to identify flowery scents in white wines using resistive sensors.

A 2020 study [13] by Claudia Gonzalez Viejo concentrated on evaluating beer quality using low-cost techniques, such as an electronic nose, robotics, and machine learning (ML). A nine-sensor e-nose was used in the study to analyze 20 distinct beer samples from diverse fermentation processes. The findings demonstrated a strong link between the e-nose sensors and the beers' carbonation and bitterness, demonstrating the e-nose's capacity to record pertinent fragrance characteristics. This study highlights the promise of using reasonably priced sensor networks and AI-based methods for evaluating beer quality, particularly with respect to qualities of carbonation and bitterness.

III. Methodology

Fig. 1 shows the four-stage workflow that was used to develop and test the prototype for using an electronic nose to determine the alcohol content of local toddy.

A. Device Construction

The construction of the alcohol detection device required the assembly of the sensor matrix and the creation of a homogeneous testing environment. The MQ series of Metal Oxide Semiconductor (MOS) gas sensors, chosen for their low cost and wide availability, made up the sensor matrix.

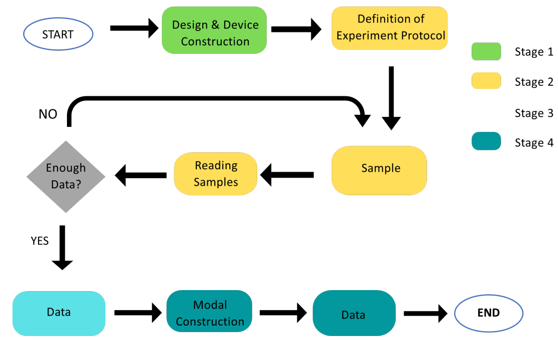


Fig. 1: Workflow for the methodology

The sensors used in the study were chosen based on their Hanwei® datasheets. Table I shows the cases:

TABLE I: Used sensors and their sensitivity gases

Sensor	Sensitivity Gases
MQ-2	H_2, $i-butane$, LPG, CH_4, CO, $ethanol$, $propane$
MQ-3	$ethanol$, small sensitivity to $benzene$
MQ-4	CH_4, H_2, CO, LNG, $ethanol$
MQ-6	LPG, $iso-butane$, $propane$, $ethanol$
MQ-7	H_2, CO, $ethanol$
MQ-8	H_2, $ethanol$, CO, LPG
MQ-9	CH_4, CO, LPG, $ethanol$
MQ-135	NH_3, NOx, $ethanol$, $Benzene$, CO_2

By monitoring changes in the electrical resistance of a heated metal oxide substance, these sensors can identify the presence of particular gases. A DHT11 sensor was also used to track temperature and humidity levels.

In comparison to employing a single sensor, the sensor matrix's mix of many gas sensors increased the system's sensitivity, accuracy, and dependability. The simultaneous monitoring and analysis of environmental variables made possible by the DHT11 sensor allowed for an evaluation of how temperature and humidity impact gas concentrations and system behavior. Sensor data was processed and evaluated using an Arduino Mega 2560 board and breadboards before being transferred to a computer for additional examination and storage.

In the experimental setting, a 20-liter glass chamber was used to establish a regulated environment. This chamber made sure that the environment was predictable and low-interfering, which minimized the influence of unimportant factors and improved the accuracy and dependability of the data that was obtained. With enough air volume for analysis, the chamber's capacity allowed for precise replication of real-world conditions. The alcohol concentration of the acquired air samples was then determined, along with any potential emission sources.

Overall, the experimental setting shows in figure 2 and device's design allowed for precise and reliable alcohol detection, complete data processing, and controlled ambient conditions.

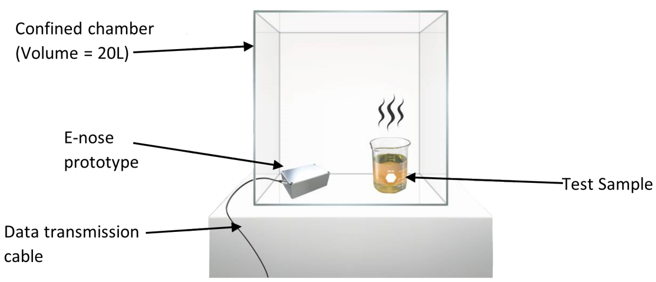


Fig. 2: Experimental setup

B. Experimental Protocol

The obtained samples were meticulously measured, and 100 mL from each sample was used for analysis in order to guarantee the precision and correctness of the results. To avoid contamination or interference and to preserve accurate results, the 20-liter glass experiment chamber was properly cleaned and dried before use. In order to reduce error sources and provide trustworthy data for analysis, the experiment's chamber was sealed to minimize air exchange with the surrounding environment.

To maximize the e-nose's performance and reduce error sources, various processes were done. To stabilize sensor readings and remove transient effects brought on by temperature or ambient changes, the e-nose's sensor system was warmed for 48 hours prior to initial use and again for 10 minutes before each measurement. These carefully monitored preheating procedures offered a steady and reliable working environment for precise readings.

By establishing a relationship between the sensor's output and alcohol content in subsequent tests, the calibration procedure ensured the dependability and accuracy of the e-nose sensor data.

C. Sample Production and Reading Samples

For the calibration process, commercially available alcoholic beverages with predetermined alcohol percentages were used. Base samples with alcohol concentrations of 40%, 8.8%, and 4.8% v/v were used, and additional samples (10%, 12%, 16%, 20%, 24%) were prepared by diluting or concentrating the base samples with water to cover a wide range of alcohol concentrations.During the calibration, 600 data recordings were collected for each sample over a 20-minute period.

Table II shows the details of the calibration dataset when experimented.

As a calibration measure after alignment, the estimation of two different toddy samples—coconut toddy and kithul toddy—was performed using the e-nose.

TABLE II: Details about calibration samples

Alcohol Content	Temperature	Relative Humidity
40%	30.8	47 - 49
24%	33.3	64 - 66
20%	32.8	70
16%	31.3	76 - 77
12%	34.7	60 - 62
10%	32.8	76 - 77
8.8%	31.3	61 - 63
4.8%	30.2	46 - 49

During the calibration, 600 data recordings were collected for each sample over a 20-minute period.

Each example was approximated at several time points after selection to illustrate the typical change in alcohol concentration that occurs over time in drink tests. The intervals between sample collection and measurement were carefully selected to encompass a range of potential alcohol concentrations that the toddy may exhibit throughout time.

A conventional ebulliometer was also used to determine the alcohol percentage of the toddy samples for every measurement session. Measurements were restricted to the first 60 seconds following device exposure because the conventional method only offers a static measurement of alcohol percentage within a short time frame and does not capture the dynamic changes over time. This strategy was chosen to justify the traditional method's employment solely at the times when it is most accurate and to guarantee consistency with its usual application.

D. Data Preprocessing, Data Analysis, and Predictions

The simple moving average (SMA) statistical method, which involved calculating unweighted averages of subsets of n elements in a given dataset, was chosen with some modifications as the data preprocessing method. In SMA the average is calculated as follows for k number of elements [14],

$$SMA_1 = \frac{a_1 + a_2 + a_3 + a_4}{k} \quad (1)$$

$$SMA_2 = \frac{a_2 + a_3 + a_4 + a_5}{k} \quad (2)$$

and so on.

The method was changed to only allow mean moving values with a maximum variation from the mean of three times the standard deviation to be included in the equation for the moving average, as shown by the inequality $|p_i - \mu| \geq 3\sigma$. where p_i is an individual data point, μ is the mean of the dataset, and σ is the standard deviation.

The initial values of the modified moving average could be incorrect until the simple moving average has "settled in" with the data. To resolve this issue, the simple moving average was given a larger initial window size (size of 200) until it stabilized, at which point the fixed window size of 40 elements could be used on the remaining data.

According to the research, regression models are more suited for detecting alcohol content since they can predict the continuous amount of alcohol in each sample. In contrast, discrete classes are more suited for classification models. When detecting alcohol, it is necessary to estimate the precise concentration, which falls within a continuous range. The benefit of supplying accurate quantitative data with one or more decimal places is a feature of regression models. In contrast, classification models would need a wider range of classes that had labels and would present the forecast as probabilities for various class labels. Regression models are therefore more suitable in these applications for precisely predicting alcohol content.

Four regression methods including two statistical regression methods were used: Multiple Linear Regression (MLR) [15] [16], Multiple Non-Linear Regression (MNLR), Extreme Learning Machine (ELM) [17], and an Artificial Neural Network (ANN) model [18].

Additionally, k-fold cross-validation was used to ensure the dependability and generalizability of the statistical models. The dataset in this investigation was separated into ten folds, or subsets, of equal size, as indicated by the value of k, which was 10 [19].

For MLR and MLNR models 70% of the dataset was used as training data and the rest 30% used as testing data. The MLNR models used two separate equations: a polynomial equation and a logarithmic equation. A polynomial equation of the form:

$$y = \beta_1 * e^{\beta_2 * x_1} + \beta_3 * \log(\beta_4 * x_2) \tag{3}$$

A logarithmic equation of the form:

$$y = \beta_1 + \beta_2 * \log(\beta_3 * x_1) + \beta_4 * \log(\beta_5 * x_2) \tag{4}$$

where, y represents the dependent variable x_1 and x_2 are the independent variables β_1,β_2,β_3,β_4,β_5 are the coefficients to be estimated.

In order to make predictions, an ELM (Extreme Learning Machine) model was built. The hidden layer of the model has 100 nodes, and three different activation functions—*sigmoid, hardlim*, and *sin* were tried.

Since ANNs may learn intricate nonlinear patterns in the data, including more conventional architectures like multi-layer perceptrons. Due to ANNs' well-known ability to recognize complicated correlations and patterns, they are well-suited for regression tasks involving intricate interactions between the input variables and the target variable. As a result, ANNs can generate precise predictions.

IV. Results and Discussion

Several performance indicators were used to assess the models. The models' overall performance was measured using the Mean Squared Error (MSE), where smaller values corresponded to more accuracy. Furthermore, the Mean Adjusted R-squared was applied; this metric ranges from 0 to 1, with higher values indicating a better fit to the data.

Table III and IV show the obtained values for performance metrics by MLR and MNLR models on the calibration dataset.

TABLE III: Performance metrics for MLR

Metric	Value
Mean squared error (MSE)	85.627444
Mean adjusted R-squared	0.321334
Mean absolute error(RAE)	7.067744
Root mean squared error(RMSE)	9.247058

TABLE IV: Performance metrics for MLNR

Metric	Value	
	polynomial eq.	***logarithmic eq.***
Mean squared error (MSE)	85.627444	Inf
Mean adjusted R-squared	0.321334	-Inf
Mean absolute error(RAE)	7.067744	1.35004968e+155
Root mean squared error(RMSE)	9.247058	Inf

Based on those findings, it seems to be difficult for both MLR and MNLR models to faithfully reflect the data if the connection between the variables is extremely complicated or deviates from a predetermined functional form.

Table V shows the utilized ELM model training performance results when utilizing three different activation functions,

TABLE V: Performance metrics for ELM

Activation Function	Metric	Value
Sigmoid	Mean squared error (MSE)	96.316769
	Mean adjusted R-squared	0.238357
Hardlim	Mean squared error (MSE)	99.512055
	Mean adjusted R-squared	0.210675
Sin	Mean squared error (MSE)	341.957327
	Mean adjusted R-squared	0.011984

Even with the addition of several activation functions, the ELM model's performance on the calibration dataset was determined to be unsatisfactory. The model was unable to accurately reflect the underlying patterns and relationships in the data, despite the varied representation capabilities of the selected activation functions.

Based on the evaluation of the neural network model using various performance metrics as shown in the table VI, it can be concluded that the model performs effectively and accurately in all cases.

Given that the MLR, MNLR, and ELM models did not perform well on the calibration dataset, it is appropriate to

TABLE VI: Performance metrics for ANN

Metric	Value		
	1^{st} ***run***	2^{nd} ***run***	3^{rd} ***run***
Mean squared error (MSE)	1.0000	1.0000	1.0000
Mean adjusted R-squared	0.0000	0.0000	0.0000
Mean absolute error(RAE)	0.0001	0.0040	0.0004
Root mean squared error(RMSE)	0.0000	0.0023	0.0001

stop using them going forward in the forecasts.

Table VII shows the details about the prediction samples.

TABLE VII: Details about the Toddy samples

Sample	Type	Time (after taken from the tree)
Sample 1	Coconut	after 4 hours
Sample 2	Coconut	after 12 hours
Sample 3	Kithul	after 4 hours
Sample 4	Kithul	after 4 hour
Sample 5	Kithul	after 14 hours
Sample 6	Kithul	after 10 hours
Sample 7	Kithul	after 2 hours

Predictability was determined to be best served by the Artificial Neural Network (ANN) model due to its higher performance with the calibration data.

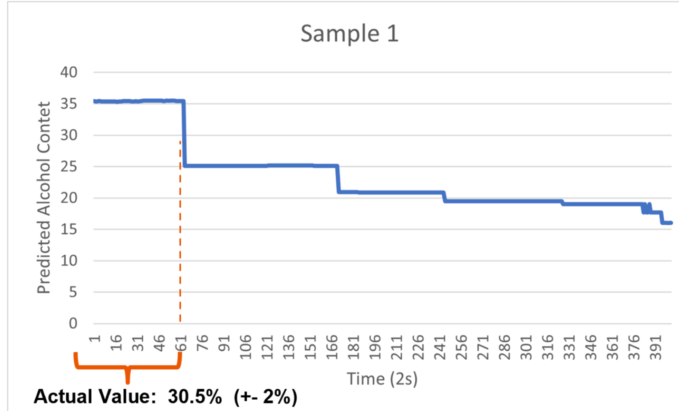
The traditional ebulliometer method is constrained by its ability to measure alcohol content only within a specific time frame. Typically, this method provides measurements of alcohol concentration during the initial 60 seconds of each sample test. Thus, the alcohol percentage for each sample during these initial 60 seconds is as in the table VIII

TABLE VIII: Alcohol percentage of the Toddy samples with ebulliometer

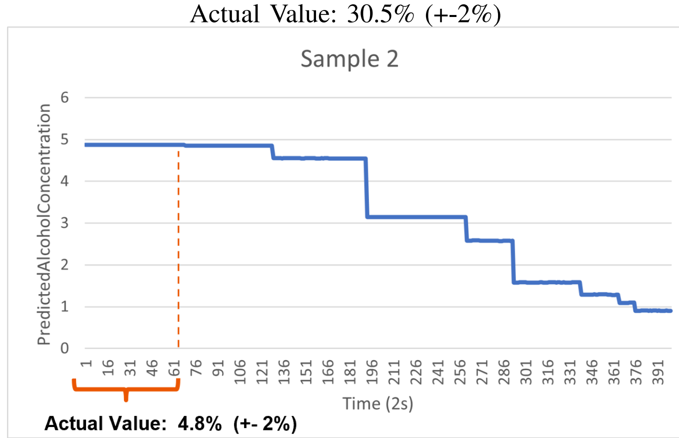
Sample	Alcohol Content (+-2%)
Sample 1	30.5%
Sample 2	4.8%
Sample 3	48%
Sample 4	69%
Sample 5	5%
Sample 6	16%
Sample 7	23%

Figures 4 show the obtained results for predictions with the NN model along with the actual values of the samples taken from ebulliometer measurements.

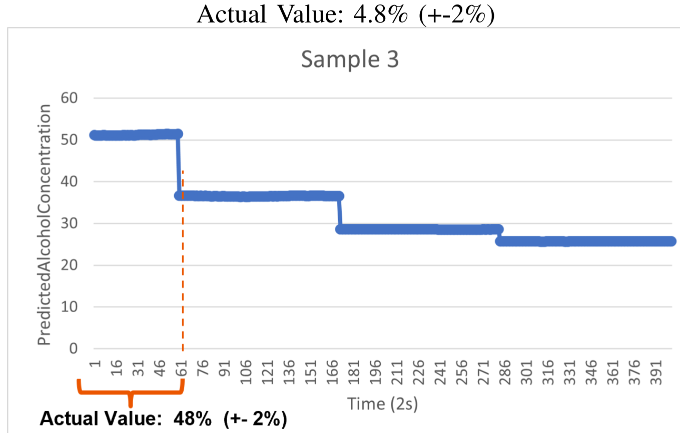
Traditional technologies [20], which are unable to provide continuous monitoring, could only assess the alcohol concentrations at the beginning of each sample test.Consequently, the data obtained from the ebulliometer reflects the alcohol content solely within this limited time window, which may not capture the full dynamic range of alcohol concentration changes over the entire fermentation process. This limitation highlights the need for continuous monitoring solutions to provide a more comprehensive assessment of alcohol content over time. The inability of traditional methods to offer continuous monitoring serves as a significant barrier, hindering the accurate and dynamic assessment of alcohol concentration and resulting in static, rather than dynamically representative, values.



(a) Sample 1
Actual Value: 30.5% (+-2%)

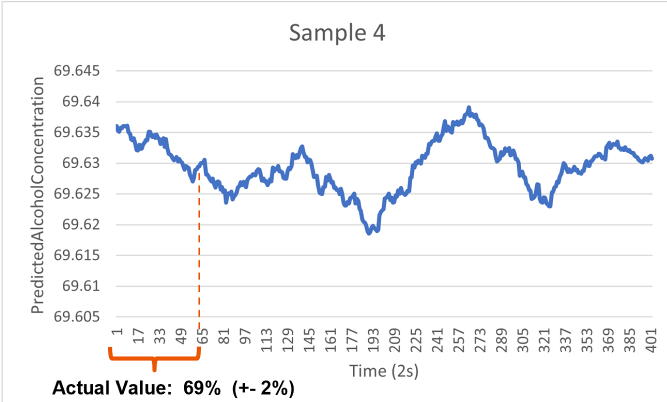


(b) Sample 2
Actual Value: 4.8% (+-2%)

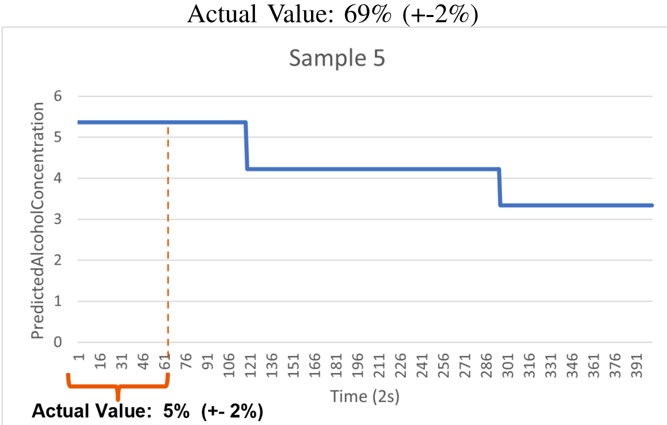


(c) Sample 3
Actual Value: 48% (+-2%)

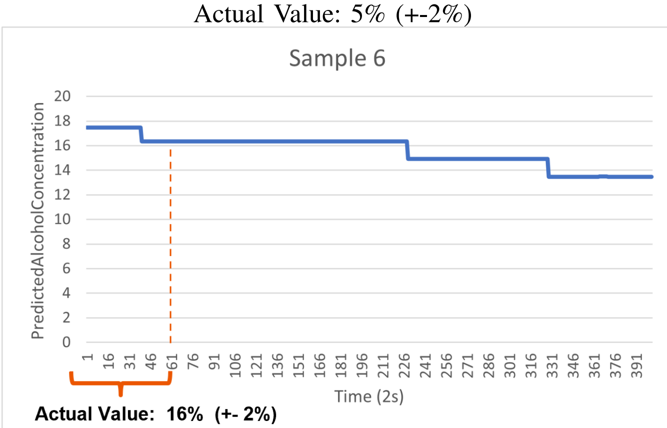
However, the prototype's measured results over a long period of time, were in line with the expected range, proving its accuracy. With this feature, it is possible to monitor processes in real-time and gain a deeper understanding of how alcohol concentration changes as fermentation proceeds. The prototype differs from conventional techniques in that it can offer continuous measurements, underscoring its usefulness for quality control and fermentation process



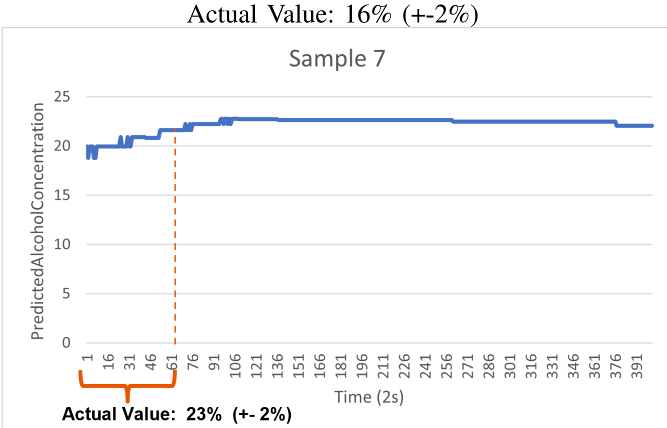
(a) Sample 4
Actual Value: 69% (+-2%)



(b) Sample 5
Actual Value: 5% (+-2%)



(c) Sample 6
Actual Value: 16% (+-2%)



(d) Sample 7
Actual Value: 23% (+-2%)

Fig. 4: Prediction results with NN model

monitoring in the toddy business.

V. Conclusion

The developed prototype shows substantial benefits over conventional approaches, utilizing an electronic nose (e-nose) to measure the alcohol concentration in local toddy. This prototype provides long-term, continuous alcohol concentration monitoring that captures variations in the toddy's alcohol content while it ferments. The prototype performs better when a neural network (NN) model is added since it can better represent complex interactions and outperforms multivariate linear and nonlinear regression models in terms of alcohol concentration estimation.

The e-nose is distinctive in that it is affordable, portable, and capable of real-time monitoring. Small-scale toddy producers do not need to invest in costly infrastructure because the e-nose is accessible to them, unlike traditional approaches requiring for specialized laboratory equipment. Because of its portability, testing may be done right there, minimizing the risk of sample contamination or deterioration during transit and cutting down on turnaround time. The e-nose's real-time monitoring capability allows for prompt quality control and process modifications by providing insights into the dynamic variations in alcohol concentration throughout fermentation.

Furthermore, by eliminating the need for laborious sample preparation, optimizing workflows, and enhancing testing efficacy, the e-nose streamlines the testing procedure. This work has consequences that go beyond the toddy industry [21]. It has potential applications in a number of sectors that require alcohol detection and fermentation monitoring. The prototype's disruptive potential is highlighted by its ability to monitor in real time and its applicability to various beverage sectors. The prototype's efficiency in monitoring alcohol levels across many businesses will be further enhanced by ongoing research and development in alcohol detection technologies.

Future research will focus on sensor development, model optimization, real-time monitoring and data analysis, field testing, integration with quality control systems, and cost optimization to enhance the prototype's ability to identify alcohol in toddy. Exploring novel sensor technologies helps with sensor development's goal of improving sensitivity and stability. Model optimization is the process of enhancing prediction models using cutting-edge machine learning methods. For continuous monitoring, real-time monitoring and data analysis techniques should be created. Performance and applicability will be evaluated with the use of user feedback and field testing. Cost reduction for commercialization and integration with quality control systems are other significant areas of study. The capabilities of the prototype will be improved by these research areas, enabling real-world use in the toddy sector.

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