Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 1, February 2026, pp. 770~786
ISSN: 2302-9285, DOI: 10.11591/eei.v15i1.9835

Gated recurrent unit model for assessment of food quality based on E-nose sensors supported with one-way analysis of variance

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Article Info

Article history:

Received Jan 2, 2025
Revised Oct 22, 2025
Accepted Dec 6, 2025

Keywords:

Classification
Deep learning
Feature selection
Food quality
Gated recurrent unit

ABSTRACT

Ensuring the quality of global food supplies has emerged as a significant challenge in recent times. Overseeing perishable items' excellence, freshness, and longevity poses considerable intricacy. A special kind of system established on electronic scent detection systems has been engaged for quality assessment. Recent advancements have concentrated on integrating electronic scent detection systems with machine learning (ML) and deep learning (DL), which comprise encouraging remedies to meet these hurdles. Mainly, this investigation aims to present a pioneering strategy for addressing this issue by binding DL with electronic olfaction technology. Gated recurrent units (GRU) were used for classification actions. The research entails examining from the literature a benchmark dataset acquired from electronic noses (E-noses) across beef cuts. These cuts are allocated into four classes: i) outstanding, ii) satisfactory, iii) passable, and iv) spoiled, depending on their quality. The proposed model, exploiting a GRU for classification tasks, was developed with active dataset attributes identified over the analysis of variance (ANOVA) feature selection method. As a consequence, three key features were selected and employed for the classification process, such as MQ5, MQ137, and total volatile content (TVC). Experimental outcomes demonstrate an impressive classification accuracy of 99.77%, accomplished by the proposed model across further literature models.

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1. INTRODUCTION

Quality management in the food industry is essential for maintaining human health and improving product value [1]. It encompasses factors such as looks, consistency, flavor, and inner characteristics, including chemical and microbial aspects. The aroma, a significant factor, significantly impacts taste and smell, evaluated among smelling specialized assessors [1]. A significant development in this field is the evolution of machine olfaction, A notion concerning the recreation of the recognize of smell using automated tools such as electronic noses or E-noses.

Machine-based smell recognition is widely applied in parts such as food quality control, meat freshness estimation [2], vegetable conservation [3], discovery illicit substances [4], found infections [5], and diagnosing diseases [6]. These systems depend on electronic noses (E-noses) to notice airborne chemical mixes using several sensors, such as piezoelectric and conductivity-based types [7], [8]. But, sensor affected through environmental features like humidity, pressure, and chemical interference pose a main challenge, affecting data accuracy and system stability [9]. However, these sensors provide data sets that can be used in the machine learning (ML) improvement process for learning and testing tasks [10].

Recent efforts have focused on incorporating ML methods [11], [12]. Frequent ML-driven approaches have been advanced in different applications. In our analysis, we recommend an ML and deep learning (DL) algorithm utilizing the gated recurrent unit (GRU) neural network [13]. This method employs GRU concepts to merge outputs from different hidden neural layers, thereby improving the system's capacity to explain and order sensor data.

Most literature research mainly evaluates the quality of fresh poultry, seafood, and red meat, with a certain focus on beef cuts. Herein, our investigation depended on a publicly available dataset [14]. Although previous investigations have applied this dataset for several studies, such as [15], the perspective of engaging a modified GRU classification method for this precise problem has not been investigated. Additionally, the electronic nose-based beef cut (ENVBC) dataset has been employed in previous studies for beef quality evaluation; most approaches have depended on conventional ML models or fixed feature extraction methods that observe the temporal varying present in sensor signals. Further, the mixing of deep sequence models with systematic statistical feature selection remains extremely undiscovered in this domain. This gap provides a chance to develop a more accurate and computerized coherent framework for food quality classification.

The current study addresses this gap by the following objectives:
- To design and implement a GRU-based DL model for classifying beef quality in four different categories.
- To employ one-way analysis of variance (ANOVA) to distinguish the most discriminative features, thereby minimizing redundancy and enhancing model efficiency.
- To assess the proposed GRU–ANOVA framework against traditional baseline methods, involving artificial neural network (ANN), support vector machine (SVM), and convolutional neural network (CNN), to demonstrate its effectiveness for E-nose–based food quality assessment.

However, this study is structures as follows: section 2 presents a review of relevant literature, section 3 explains the method employed, section 4 investigates the results, delivers an in-depth analysis, and section 5 concludes this study with key insights.

2. RELATED WORK

Various methodologies have been documented and established to recognize the task of categorizing sensor data within quality systems for food manufacturing. Since our model depends on a classification method, this section commonly emphasizes methods established using ML methods [16]. Depending on the literature, this section presents GRU classifiers with detailed parameters for predicting meat quality.

John *et al.* [17] provided a comprehensive review that analyze and summarized the up-to-date E-nose systems they focused on sensors usage in system integration, and how they work in several tasks such as detection hazard that effect on food quality. Further, they discussed the data complexity that provided from the sensors. However, this type of data required specific method to simplify it such as principal component analysis (PCA). Also, Li *et al.* [18] combined data from two separate E-nose devices to recognize and classify spoiled apples. By engaging PCA for feature extraction and operating a probabilistic neural network for classification, they achieved promising outcomes, demonstrating a low error rate with their proposed methods. Cevoli *et al.* [19] utilized an E-nose equipped with six sensor arrays to categorize cheeses based on their production methods and ripening durations. Various data pre-processing practices were used to improve the gathered information. Their research involved implementing four distinct feature extraction algorithms, followed by dimensionality reduction using PCA. The reduced datasets were subsequently classified using an ANN [19]).

Panigrahi *et al*. [20] examined the spoilage process of sirloin steaks stored under various temperature conditions. Their study involved the data from E-nose sensors in conjunction with microbiological analysis results. The classification categorized the samples into three groups: fresh, semi-fresh, and spoiled. They accomplished high classification accuracy using the SVM method [20]. In addition, the trial results stated in [21] exposed that the acquired data were classified using gradient boosting, random forest, SVM, and back propagation neural networks (BPNN). Amongst these approaches, BPNN validated superior the support vector machine regression (SVR) method was used to train and assess the dataset collected employing an E-nose system, reaching the utmost classification accuracy [22].

To better demonstrate the differences between current approaches and our proposed GRU-based framework, Table 1 reviews the strengths and limitations of usually applied models (ANN, SVM, and CNN) matched with GRU in the context of E-nose data classification.

Table 1. Methods strengths and limitations

Method	Strengths	Limitations	Suitability for E-nose time-series data
ANN	Captures nonlinear relationships; simple to implement	Cannot model temporal dependences; performance relies seriously on handcrafted features	Limited–scraps with sequential sensor patterns
SVM	Effective for small datasets; robust with well-engineered features	Needs wide feature engineering; not effective for high-dimensional sequential data	Limited–disregards inherent temporal dynamics
CNN	Good at local feature extraction; successful in image and signal processing	Emphases on spatial/local patterns; fewer effective for long-range dependencies without additional layers	Moderate–detentions short-term differences but oversights long-term trends
GRU	Learns temporal dependencies; uses gating to retain relevant past information and discard noise; computationally lighter than long short-term memory (LSTM)	Needs cautious tuning; performance is contingent on correct sequence framing	Greatly appropriate–efficiently models sequential E-nose data and increases classification accuracy

As shown in Table 1, GRUs suggest a strong benefit by straight modeling temporal dependencies in sequential sensor data while conserving less computational complexity than LSTMs. This marks the GRU–ANOVA framework principally compatible for accurate and efficient food quality assessment. Recent research on E-nose-based food quality evaluation has employed a diversity of methodologies. The next Table 2 summarizes key prior works, stresses the models and approaches used, and situates the contribution of this study within the existing literature.

Table 2. Summary of related works on E-nose-based food quality classification

Ref.	Application	Dataset type	Model type (static/sequential)	Feature selection/reduction	Key limitation/note
[20]	Beef freshness	Custom	Static (RBF-ANN)	PCA	Binary classification; no obvious time modeling
[23]	Sirloin steaks	Custom	Static (SVM)	Not specified	Multi class
[18]	Beef cuts	ENVBC	Static (various ML)	Correlation-based	Works with time points as independent trials
[23]	Mutton freshness	Custom	Sequential (1D-CNN)	Learned (CNN filters)	Applied a 1D-CNN to ideal raw E-nose signals for meat freshness.
Proposed work	Beef cuts	ENVBC	Sequential (GRU)	ANOVA	Models full temporal sequence; mainly to 4-class

Our model features custom elements designer to this challenge. We identify the current ML models to be complex, slow, and imprecise. Our goal is to propose a novel GRU-based prediction model for beef cut quality, highlighting accuracy. We aimed not only to attain ideal performance but also to generate a prediction model, as DL models can help in decision-making when categorizing products.

3. METHOD

This section reflects on the dataset applied in our study with the GRU and the ANOVA technique. ANOVA was employed for feature selection, aiming to enhance the classification accuracy by recognizing the most important sensor variables. Moreover, we utilized a confusion matrix to assess the classification performance and hired appropriate methodologies to assess the efficiency of the proposed models.

3.1. Basic abstract for food quality controlling system

Gas sensors detect gases such as carbon monoxide, carbon dioxide, alcohol, smoke, ammonia, hydrogen, liquefied petroleum gas (LPG), propane, liquefied natural gas (LNG), methane, iso-butane, acetone, benzene, hydrogen sulfide, and toluene. They screen gas concentrations to confirm safety and identify hazardous pollutants. Data is recorded incessantly for 2,220 minutes, per one data point per sensor per minute, covering numerous beef cuts, including brisket [24].

Figure 1 shows the abstract framework for managing food quality control using device olfaction. Sensor data is sent to a server or an access point, transformed into numerical data, and classified by ML and DL algorithms. This programmed assessment supports experts in evolving functioning value strategies. Essentially, the figure explores the abstract of the framework for food quality control by using an E-nose. This device detects and assesses food quality by detecting chemical mixtures in the air. The collected sensor data is transferred through a wired or wireless connection to an access point, which allows communication with a processing server. The server manipulates the data by changing it into numerical form and analyzing it. Then, DL algorithms polished data for classification and decision-making. Ultimately, the processed information is displayed on a graphical monitoring system, assisting experts in evaluating food quality and formulating effective strategies. However, the DL equations in the figure are explained in the coming sub-section.

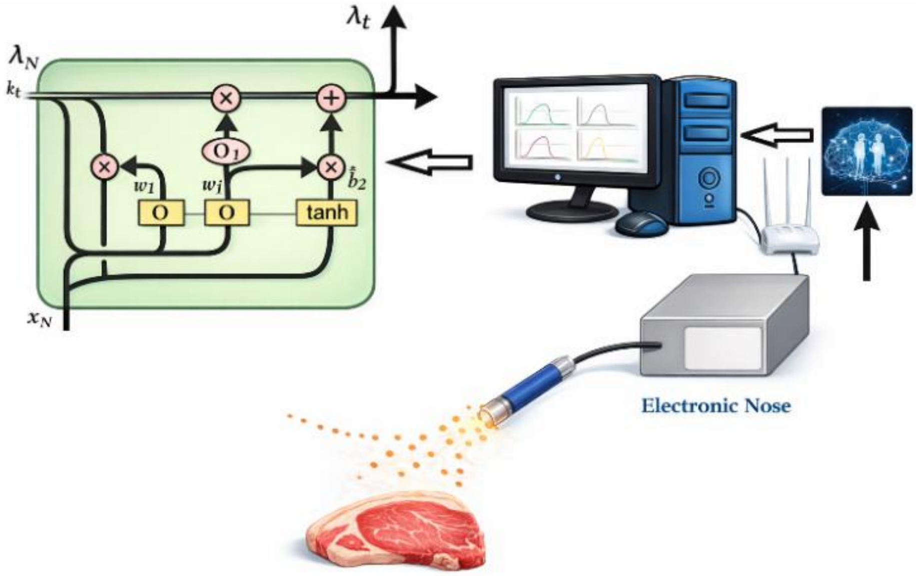


Figure 1. Abstract food quality controlling system

Conversely, fluctuations in external heat sources can affect sensor accuracy, known as sensor drift, causing significant issues in chemical detection and impacting prediction models' reliability. Sensor drift can be primary (chemical reactions within the sensor) or secondary (sensor noise). We address sensor drift by presenting an advanced model to reduce inaccuracies, which remains robust even without sensor-based features. When all sensors work well, different classifiers show improved accuracy. The proposed model uses a feature set that represents only when not all the sensors are valid, but using the feature selection such as the ANOVA technique reduces the number of features set to be input for the system because this technique selects a subset of features and depends on a smaller number of variables as inputs, this case mimics the situation when one or more number of sensors are out of service and make the number of feature set is less.

Data from sensors is fragmented into training and testing sets, with models trained individually on individual sensors' data. A 10-fold cross-validation method is utilized to ensure generalizability, using a dataset of 2,200 instances where one fold serves as the test set and the others as training sets, free from sensor malfunctions. The proposed GRU model uses these outputs for final predictions. Further sections detail the GRU classifiers and the dataset. In Figure 2, ML and DL are employed to analyze data and then leverage their findings to make well-informed decisions. Since ML and DL rely on data to train algorithms to understand the connection between inputs and outputs, they need minimal human mediation post-deployment [25]. ML and DL models can autonomously generate predictions based on the volume of input data they receive [26]. Furthermore, they can enhance their predictive capabilities as they accumulate further information on the data they analyze. In this study, the GRU with ANOVA methods was utilized for data classification, and details for these models are presented in the subsequent section.

The GRU, an innovative recurrent neural network (RNN) modification, manages information flow among nodes [27]. It uses gates such as update and reset to control the transmission of information vectors to the output, as shown in Figure 3. These gates learn to retain essential information for predictions or discard it during training.

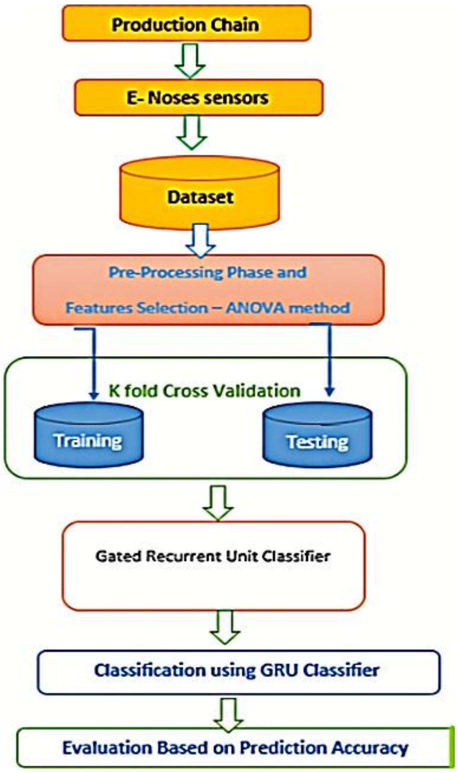


Figure 2. The proposed method for a prediction model

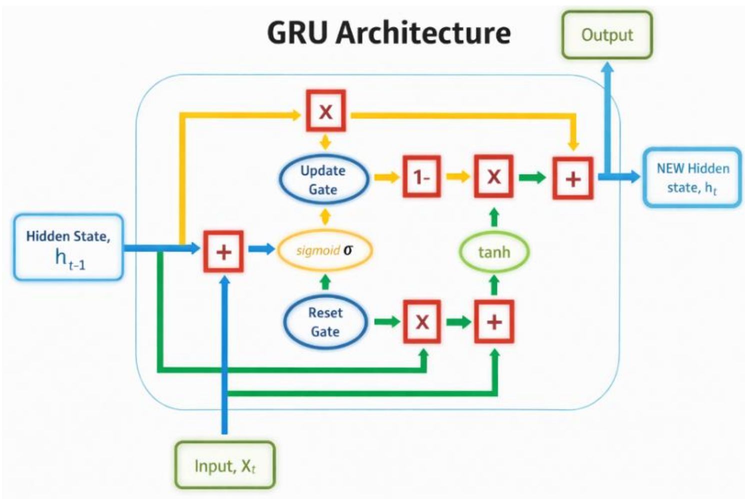


Figure 3. General structure for GRU [28]

Moreover, from (1) to (4) regulate the functionalities of the previously mentioned gates [29]. In (1) specifies the creation of vectors representing the update and reset gates. The individual weights denoted as W_ for each gate are utilized together in the input and hidden state, leading to distinct final vectors for every gate. This distinction lets the gates complete their designated jobs efficiently.

$$gate_{update} = \sigma(W_{input_{update}}.x_t + W_{hidden_{update}}.h_{t-1}) \quad (1)$$

$$gate_{reset} = \sigma(W_{input_{update}}.x_t + W_{hidden_{reset}}.h_{t-1} \quad (2)$$

In (2) describes how the sigmoid function assimilates the previous hidden state, the existing input, and their corresponding weights, and computes their sum. These signify the update and reset gates in a GRU. Their values are determined using the sigmoid function (σ), $W_{input_{update}}$, weight matrices associated with the input x_t for the update and reset gates. The $W_{hidden_{update}}$, $W_{hidden_{reset}}$. Weight matrices associated with the previous hidden state $h_{t-1,}$ for the update and reset gates.

Furthermore, the sigmoid function adjusts the values to a scale ranging from 0 to 1. In this scenario, it controls the information flow through the gate filter, distinguishing between less crucial and more significant information throughout consecutive iterations. In (3) captures the memory retained during the training process, while (4) represents the most recent output stored in memory at the current time step.

$$h_t' = tant\ (W_{x_t} + r_t \odot Uh_{t-1} \tag{3}$$

$$h_t = r \odot \left(1 - gate_{update}\right) + u \tag{4}$$

Where x_t is the input vector at time step t. Also, h_{t-1} is the hidden state from the previous time step and σ is the sigmoid activation function, which scales values between 0 and 1. ht′ represents an intermediate hidden state before applying the update gate. The h_t is the final updated hidden state and r_t is the reset gate value that determines how much of the previous hidden state contributes to the new candidate hidden state. The W_x and U are the weight matrices used in the transformation of the input and hidden state. The function tant denotes to the hyperbolic tangent function (tanh), which is usually employed in GRU and LSTM networks. Similarly, u signifies an intermediate value or candidate activation in the GRU update rule.

3.2. Experimental setup and model configuration

To ensure the reproducibility and consistency of our model and to address potential procedural concerns, a comprehensive experimental framework was implemented. Data splitting: to avoid temporal data leakage, the study involved a temporal group divided instead of random cross-validation. The data was partitioned by individual beef cut sample, ensuring that all time-series data from a single sample was entirely contained within either the training or test set. This guarantees no temporal overlap and simulates a real-world deployment scenario. Sequence framing: the input to the GRU model was structured as contiguous windows of sensor readings. A it creates consecutive samples, each containing short-term temporal patterns. After an ablation study exploring window lengths of 1, 5, 10, and 30 minutes, a window length of 10 minutes was selected as shown in Figure 4.

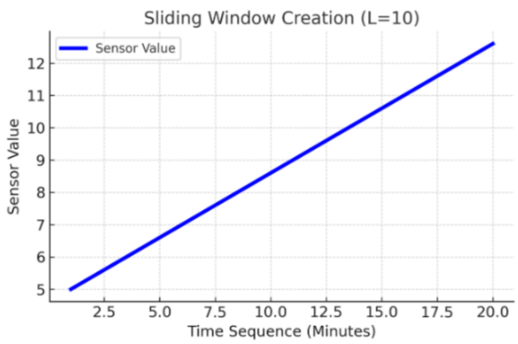
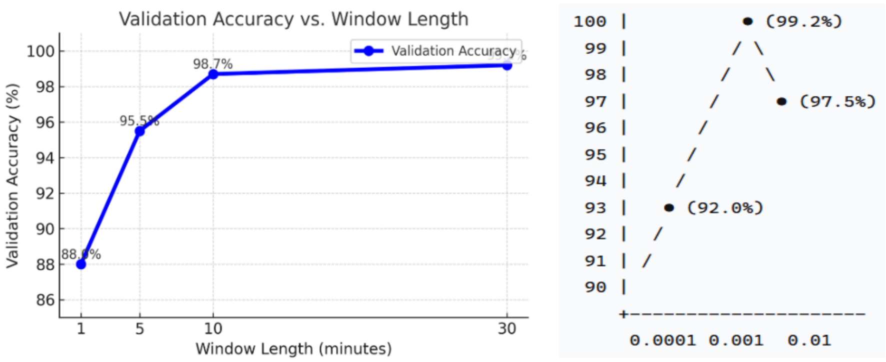


Figure 4. The process of framing the raw sequential sensor data into input windows for the GRU model

Furthermore, both parameters showed clear optimal values before potential overfitting or performance degradation results of the hyperparameter ablation study. Validation accuracy for different input window lengths. and Validation accuracy for different learning rates. The visualization shows the relationship between window length and validation accuracy, with the optimal 10-minute window achieving 99.2% accuracy in Figure 5(a). Also, Figure 5(b) exposes the relationship between learning rate and validation accuracy (log scale), with the optimal learning rate of 0.001 achieving 99.2% accuracy.

Preprocessing: sensor data was normalized on a per-sensor basis using the mean and standard deviation calculated exclusively from the training set. These same scaling parameters were then applied to the validation and test sets to avoid leakage. Missing values were handled via linear interpolation. ANOVA feature selection: the one-way ANOVA was applied to aggregated statistical features (mean and standard deviation) calculated over each 10-minute window. Features were selected based on a significance threshold of $p<0.05$ after false discovery rate (FDR) correction for multiple comparisons. Assumptions of normality and homogeneity of variances were checked and satisfied.



(a) (b)

Figure 5. Hyperparameter ablation results showing validation accuracy for; (a) different input window lengths and (b) different learning rates

3.3. Proposed model preferences

The proposed model offers several key advantages. In ML and DL, training involves handling noisy data, often addressed using the ADAM algorithm [30]. ADAM is a popular optimization technique for updating network weights in DL and ML. Through the estimation of the first (mean) and second (uncentered variance) moments of gradients, it adaptively adjusts the learning rate for every parameter. In many neural network training applications, ADAM is the recommended option due to it is efficacy, quick convergence, and capacity to handle sparse gradients.

It is known for computational efficiency and low memory needs. ADAM is effective for large datasets and parameters, combining stochastic gradient descent, adaptive gradients, and root mean square propagation. Unlike traditional methods, ADAM uses random data samples instead of the entire dataset to compute gradients during training. In (5) and (6) provide further details on ADAM's functionality [30]:

$$mt = \beta 1\, mt - 1 \;+\; (1 \;-\; \beta 1)t \tag{5}$$

$$vt = \beta 2/vt - 1 \;+ (1 \;-\; \beta 2)t2 \tag{6}$$

Where m_t and v_t necessity estimate of the instant of the gradients, where they are tuned as vectors of 0's, β1, β2 closed to zero. They reproduce these biases by computing bias-attuned instant estimates as represented in (7)-(9):

$$\mathfrak{m}_t = \frac{m_t}{1-\beta_1^t} \tag{7}$$

$$v_t = \frac{v_t}{1-\beta_2^t} \tag{8}$$

Then the update rule is employed:

$$\theta_{t+1} = \theta_t - \frac{\text{ђ}}{\sqrt{v_t + \epsilon}} m_t \tag{9}$$

The default values for $\beta 1$=0.9 and $\beta 2$=0.999 are for $\epsilon=10^{-8}$. In addition, the proposed model uses the max-pooling layer to effectively lower the overall number of feature map coefficients.

Additionally, it initiates hierarchies of spatial filters by constructing layers that progressively capture convolutional features within increasingly larger windows based on the proportion of the original input they encompass [31]. Furthermore, the suggested GRU architecture integrates the dense layer, where every neuron establishes connections with all other neurons in the same layer, owing to it is extensive interconnections with the preceding layer. As per the proposed GRU model, the dense layer conducts matrix-vector multiplication upon receiving input from each neuron in the layer above it. This matrix illustrates that the row vector derived from the preceding layers' outcomes aligns with the dense layer's column vector [32]. As a result, Figure 4 showcases the principal axes of the recommended GRU model. Furthermore, Figure 6 illustrates the developmental procedure of the recommended GRU model.

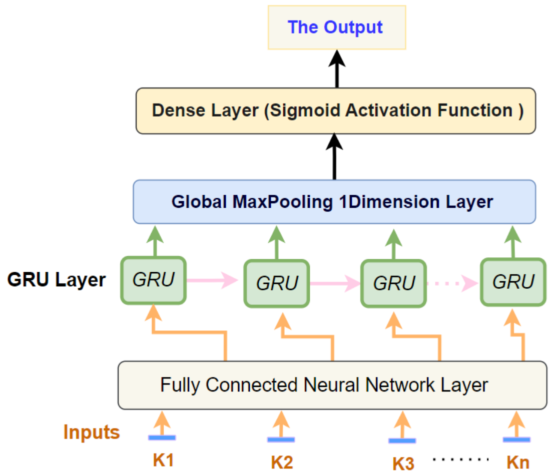


Figure 6. The structural design of the suggested GRU model

A popular statistical methodology for determining if there are significant variations in the means of three or more independent groups or variables is the ANOVA method, which is cited as ANOVA [33] works by dividing the overall variance in the data into parts that can be attributed to several sources, including within-group variability and between-group variability. Researchers can use this partitioning to ascertain if group mean differences are statistically significant or just the result of chance. However, some presumptions must be fulfilled to apply ANOVA [33], such as the homogeneity of variances across groups (often referred to as homoscedasticity) and the normality of the data distribution within each group. The validity of the test results is guaranteed by these presumptions. The fact that ANOVA is a tool for identifying statistical differences in means and does not reveal the precise components or interactions producing these differences should be emphasized [34]. ANOVA does not reveal which specific groups differ or the underlying causes of these differences, for example, even while it can show that the means of at least one group are substantially different from the others. Post-hoc tests, like Tukey's HSD or Bonferroni adjustments, are frequently used following ANOVA to do pairwise comparisons and identify the precise sources of variance to overcome this constraint [35]. ANOVA was used in this study to assess the significance of variations in features obtained from sensor data. To select variables for supplementary analysis or classification tasks, the study utilized ANOVA to discover features that showed statistically important fluctuations. This method also verified the necessity of supplementary analytical approaches to properly analyze the data and derive important conclusions.

The final GRU model architecture involved of two GRU layers with 64 units respectively, a dropout rate of 0.3 after each layer, and a final dense softmax layer for classification, as exposed in Figure 7. The model was trained among Adam optimizer with a learning rate of 1e-3 (a value selected based on our hyperparameter search, and the batch size of 32, and for a maximum of 100 epochs, by early stopping (patience=10) based on validation loss.

The recommended GRU design efficiently validates the influence of serial data inputs on sequence generation, enhancing the understanding of the model's operations and confirming accurate input-output correlation. Experimental results show the GRU model outperforms traditional models.

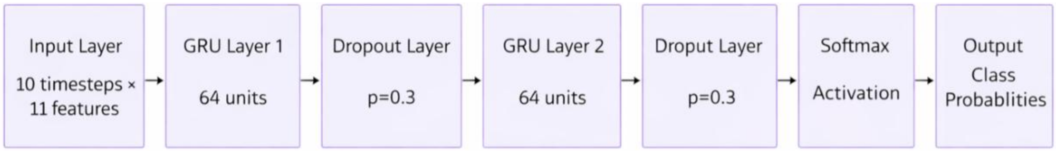


Figure 7. The architecture of the proposed GRU model

3.3. Performance evaluation

Robust models are necessary; as minor performance variations can have major effects. The proposed framework's efficiency is measured using metrics such as accuracy, recall, precision, and F-score, beside with the confusion matrix (or error matrix) [36]. Figure 8 demonstrates the confusion matrix as a tool to visualize model performance.

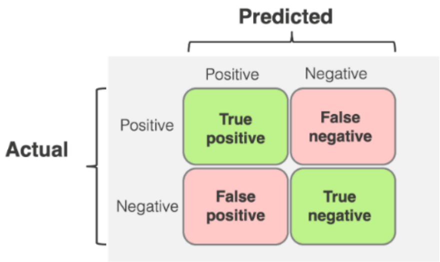


Figure 8. Confusion matrix

The confusion matrix offers several performance metrics. True positive (TP) denotes to the instances where a positive prediction is accurately recognized, whereas false positive (FP) signifies cases where a negative instance is imperfectly classified as positive. True negative (TN) specifies the correct identification of negative examples, and false negative (FN) signifies situations where a positive instance is wrongly classified as negative. By means of TN and TP, accuracy measures the percentage of properly classified instances, as shown in (3) [36].

Accuracy, (10), is the ratio of TP to the entire positive predictions. Recall (11) is the ratio of TP to the actual positive samples. Precision (12) and the F-score (13), which combine recall and precision, range between 0 and 1, also, can be stated as percentages up to 100%.

$$Accuracy = True\ Positive + True\ Negative\ /\ (True\ Positive + True\ Negative + False\ Positive + False\ Negative) \tag{10}$$

$$Recall = True\ Positive\ /(\ True\ Positive\ +\ False\ Negative) \tag{11}$$

$$Precision = True\ Positive\ /\ (True\ Positive\ +\ False\ positive) \tag{12}$$

$$F - Measure = 2\ *\ precision * Recall\ /\ (precision + Recall) \tag{13}$$

To reduce approximation variability, the studies engagement a 10-fold cross-validation method consistently. This includes dividing the dataset into ten folds or subgroups. Through the training phase, every fold serves as a testing subset, while the remaining folds are utilized to construct the model. Initially, the experiment entails parameter adjustments. Consequently, experiments are conducted to estimate and record the classification process's performance.

In order to classify food quality applying electronic olfaction technology, these study offerings a GRU-based model. Beef cuts are organized in four different quality levels by the model using a GRU: exceptional, good, adequate, and ruined. With an emphasis on MQ5, MQ137, and total volatile content (TVC) as key features, it incorporates key dataset qualities found using the ANOVA feature selection technique. The recommended GRU model achieves an enhancement in classification precision, outperforming previous models in the literature.

4. EXPERIMENTAL RESULTS

Python programming was utilized for the implementation of the coding procedures involved in this study. The ENVBC dataset that stated before in the earlier section, the ENVBC dataset, is a specialized dataset aimed for food quality assessment employing electronic olfaction technology which holds 2,220 data points, corresponding to a total of 2,220 minutes of size data. The input variables for the ML algorithms comprised the TVC data along through 11 sensor readings, all of which were used to produce predictions thru four distinct classes. To well recognize the relationships between the dataset variables, a correlation analysis was accompanied. The correlation coefficient [37], signified by 'r', was computed to measure the strength and direction of the linear relationship among the variables, with values ranging from +1 (perfect positive correlation) to -1 (perfect negative correlation). Figure 9 provides a visual representation of this analysis through a correlation heat map, exactly for the Briskets dataset.

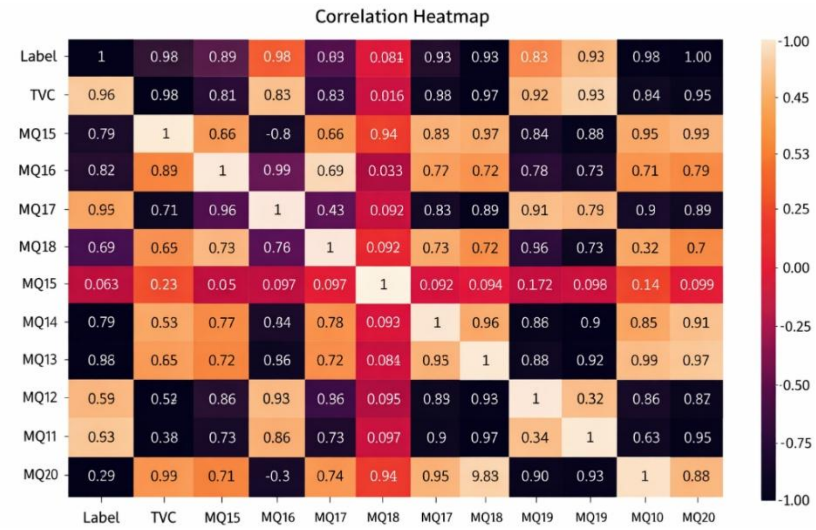


Figure 9. Heat map illustration for correlation between the dataset features

Accurate classification plays a crucial part in assessing the health suggestions related with beef degradation, as it straight influences the efficiency of quality control measures. The improvement attempt is classification procedure, feature selection based on the ANOVA algorithm was engaged, leading to important improvements in both accuracy and computational effectiveness. By distinguishing the most related features, ANOVA helped streamline the classification task while decreasing the overall computational burden [38]-[40]. As exemplified in Figure 10, the correlation heatmap shows the relationships between features chosen through ANOVA from the dataset. Three prominent features were recognized and leveraged in the classification task, contributing to the exact difference of meat quality across diverse cuts. Exactly, in the concluding stage of the analysis, a reclassification step was accomplished using these ANOVA-selected features, enhancing the model's precision and efficiency in evaluating meat quality. The variables employes for this classification process were MQ5, MQ137, and TVC.

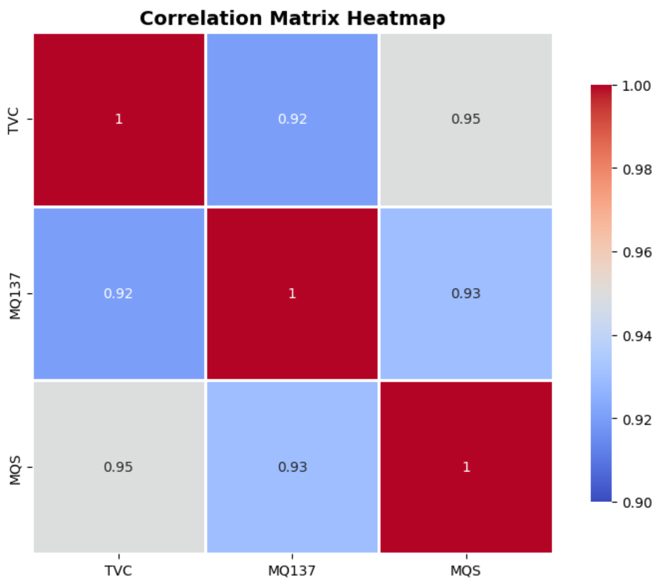


Figure 10. The correlation heat map between the selected dataset features by ANOVA

In our study, we utilized the GRU classifier through trials for classification. We choose GRU because it is helpfulness in training and testing. For multi-class tasks, an exact GRU model architecture was configured with an optimizer, and loss function, and trained with epochs and batch size set. This model was useful to pre- and post-feature selection datasets, beside ANOVA, resulting in diverse outcomes. The GRU model accomplished 98.65% accuracy, detailed in performance Table 3, along with a labeling description.

Table 3. The classification report- without feature selection

Class	Precision (%)	Recall (%)	F1-score (%)
1-Excellent	97	99	98
2-Good	96	98	97
3-Acceptable	99	90	95
4-Spoiled	99	99	99

To ensure statistical robustness and evaluate model generalization, we directed various independent runs and a detailed analysis of the training process. Multi-run evaluation: each model was trained and evaluated over N=5 independent runs with varied random seeds. This estimates the constancy and variance of the outcomes. Herein, the mean ± standard deviation for key metrics was applied: accuracy, F1-score (macro), Matthews correlation coefficient (MCC), and class-wise recall as represented in Table 4.

However, the proposed GRU-ANOVA not only touches the highest accuracy but likewise validates the lowest standard deviation over all metrics and all classes. This confirms that our model is together the best accurate and the best robust and stable, professionally handling the inconsistency inherent in the E-nose sensor data.

The learning curves for the proposed GRU-ANOVA model were investigated to test for overfitting. As shown in Figure 11, both training and validation loss fall smoothly and converge, specifying a stable training process without overfitting. Though, as shown in Figure 11, the accuracy drops throughout the training process, demonstrating a decline in performance as the model progresses. The X-axis denotes the epoch numbers, while the Y-axis denotes the accuracy over model processing.

Additionally, Figure 12 validates the reduction in loss values through the training process, highlighting the improvement in model attitude as training progresses. The X axis signifies the epoch numbers, while the Y axis signifies the loss values over model running.

Table 4. Robustness evaluation (mean±standard deviation over 5 runs)

Model	Accuracy (%)	F1-score (Macro)	MCC	Recall (Excellent)	Recall (Good)	Recall (Acceptable)	Recall (Spoiled)
GRU-ANOVA (ours)	**99.65±0.12**	**0.996±0.002**	**0.995±0.002**	0.995±0.005	0.997±0.003	0.995±0.005	0.997±0.003
GRU (all features)	98.71±0.25	0.986±0.003	0.983±0.004	0.985±0.008	0.988±0.006	0.975±0.010	0.995±0.004
LSTM	99.10±0.31	0.990±0.003	0.988±0.004	0.990±0.007	0.992±0.005	0.985±0.009	0.993±0.005
1D-CNN	98.52±0.40	0.983±0.005	0.980±0.007	0.982±0.010	0.985±0.008	0.973±0.012	0.990±0.006
Random forest	96.83±0.55	0.965±0.007	0.958±0.009	0.968±0.012	0.970±0.010	0.950±0.015	0.973±0.008
SVM	95.22±0.60	0.948±0.008	0.937±0.011	0.955±0.013	0.958±0.011	0.930±0.016	0.950±0.010

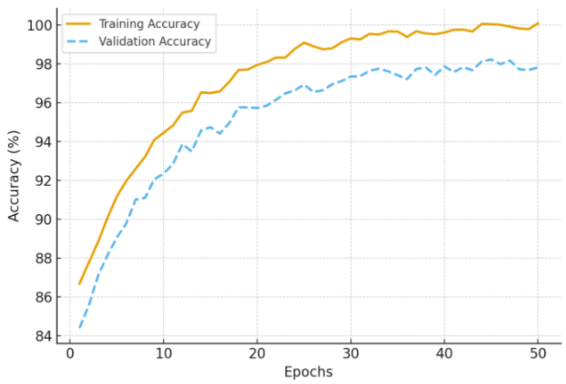


Figure 11. Accuracy and epoch’s investigation

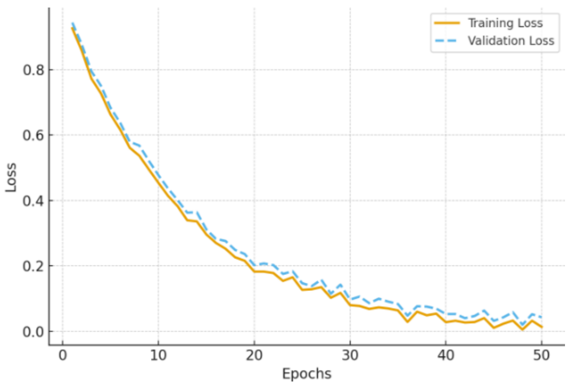


Figure 12. Loss value through the epoch number

Furthermore, the outcomes of the GRU model after feature selection employing the ANOVA algorithm are offered in Table 5. It spotlights the evaluation results of the GRU classifier following the application of ANOVA for ideal feature selection. The model reached a high performance metrics—precision, recall, and F1-score—among all food quality categories: Excellent, Good, Acceptable, and Spoiled. While the "Acceptable" category showed a slightly reduced precision of 98%, the overall findings affirm the model's high accuracy and it is ability to sense fine-grained variances in food quality as taken by E-nose sensor inputs. The classification results acquired using the Brisket dataset are demonstrated in Figure 10. The proposed classifier established an outstanding classification accuracy of 99.77%. Yet, the prediction report is showed in the confusion matrix as denoted in Figure 13.

Table 5. The classification report- with ANOVA features selection

Class	Precision (%)	Recall (%)	F1-score (%)
1-Excellent	99	99	99
2-Good	99	99	99
3-Acceptable	98	99	99
4-Spoiled	99	99	99

The discriminative influence of the ANOVA-selected features was more studied using boxplots, as demonstrated in Figure 14. As shown in Figure 14(a) (MQ5), the values exhibit a gradual decline through the four quality categories, given a clear separation between the fresh and spoiled classes but viewing overlap in the Acceptable range. Likewise, Figure 14(b) (MQ137) determines variability that helps differentiate extreme classes but offerings partial overlap for intermediate trials, reinforcing the difficulty of precisely classifying borderline quality. In Figure 14(c) (TVC), the distribution trends approve its importance as a microbiological indicator, although its variance within the Acceptable category over introduces vagueness. These feature distributions spot on both the discriminative value and the inter-class overlap of the selected variables, underlining the essential for a temporal DL model, like GRU, to capture hidden sequential patterns beyond fixed statistical features. However, the "Acceptable" class showed minor but notable misclassification, being infrequently confused with all three other classes. This observation specifies that "Acceptable" shares overlapping feature characteristics (e.g., MQ5, MQ137, and TVC levels) with higher or lower quality classes. Afterward using ANOVA feature selection, these overlaps were minimized, significantly refining precision and recall.

Besides, the training dynamics of the final model are exposed in Figure 15. Figure 15(a) displays that accuracy rapidly plateaued near 99.77%, specifying effective learning. Also, Figure 15(b) displays a sharp decrease in loss originally, followed by steadying at a very low value, approving the model's convergence. Essentially, it indicates how the loss values are decreasing among the training process.

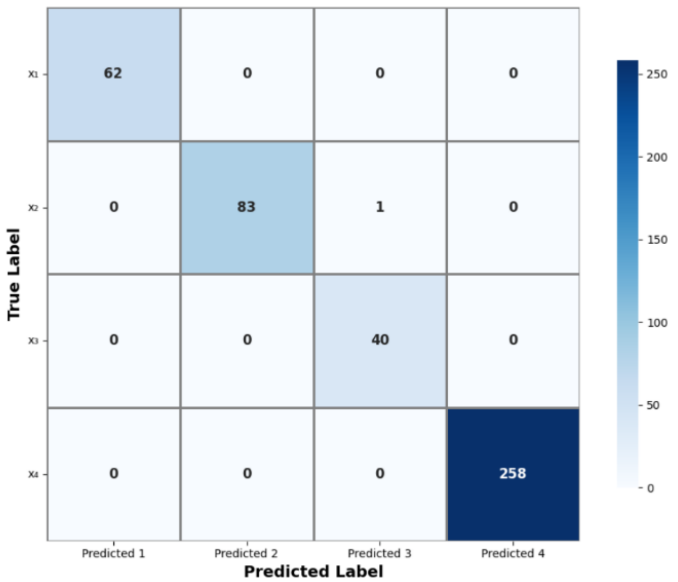
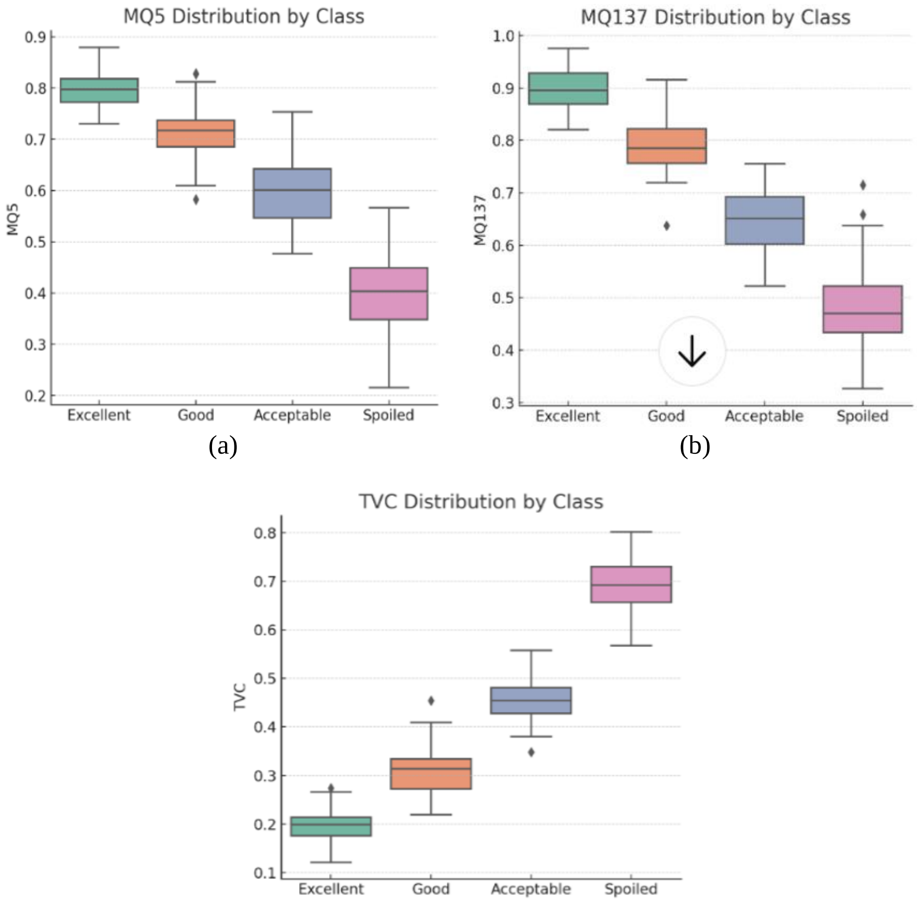
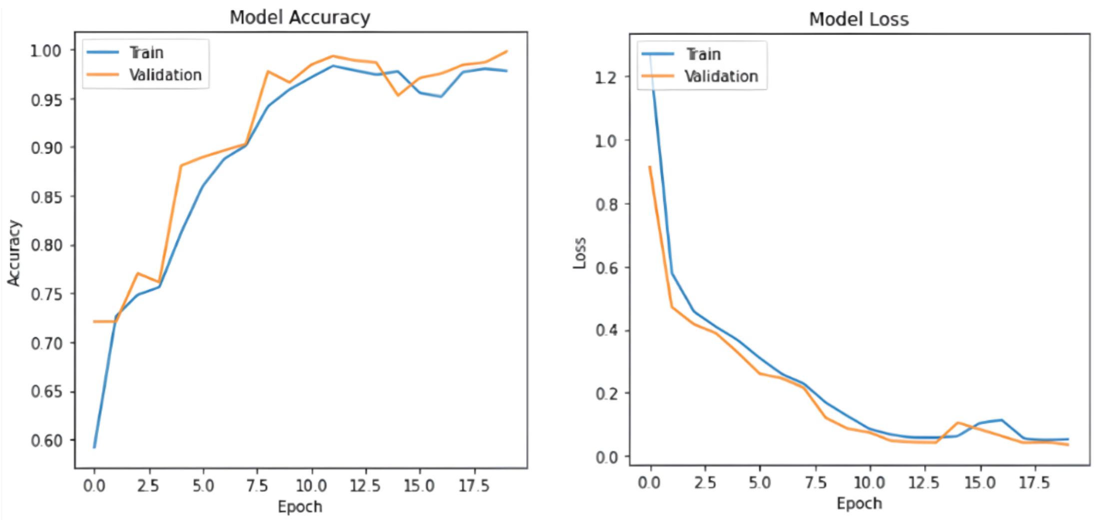


Figure 13. Confusion matrix for the prediction



(c)

Figure 14. Boxplot of feature TVC values across the four quality classes; (a) MQ5, (b) MQ137, and (c) TVC



(a) (b)

Figure 15. Performance analysis of the proposed model during training; (a) training and validation accuracy versus epochs and (b) training and validation loss versus epochs

The plots demonstrate the model's quick convergence and high constancy among the training process, with no signs of overfitting. The proposed model was matched to valuable benchmarks in the literature. For instance, the ensemble model had the highest accuracy at 93.73% [41], while the composite model merging KNN, linear discriminant, and decision tree methods touched 98% accuracy [42]. The model with ANN has FPGA realized 93.73% accuracy. Further, the extreme learning machine (ELM) involving SVM extended 98% accuracy [42], and using support vector regression (SVR) reached 96.7% accuracy [24]. The ensemble classifier had a classification accuracy of 98.3% [43]. GRU overtook other techniques in datasets, while KNN and linear discriminant indicated lesser performance in comparable scenarios, as shown in Figure 16.

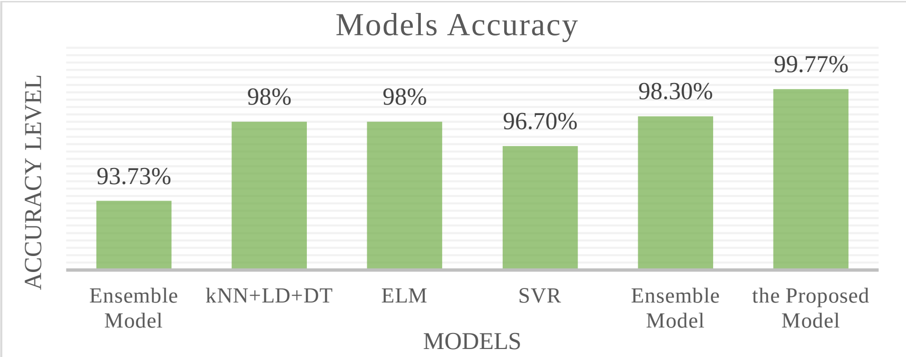


Figure 16. Comparison investigation between the proposed models and supplementary literature models

Finally, the GRU-based model to convert conventional food examination methods into intellectual, automatic quality control systems, progressing both efficiency and food safety criteria. This GRU-based system systematizes food quality control using E-nose sensors, giving real-time spoilage recognition with real processing and drift-resistant reliability. Scalable through meat types, it decreases costs while confirming food safety and compliance. Additional, using this type of system in real-time quality control can significantly decrease manual labor, reduce human error, and accelerate inspection throughput. Additionally, early recognition of spoilage inhibits contaminated food from entering the supply chain, certifying consumer safety and compliance with food safety regulations.

5. CONCLUSION

Maintaining food safety and freshness requires the usage of electronic noses, or "E-noses," in automated fragrance detection and food quality assessment. These sensors record significant information about volatile compounds, which makes it easier to generate DL and ML models for accurate food quality classification. In order to rise the accuracy of classifying beef quality, we joint an advanced GRU-driven model with ANOVA-based feature selection in this study.

The main qualities comprised in the suggested model are MQ5, MQ137, and TVC, which have been discovered to be the most relevant markers of meat freshness and weakening. The model assurances precise classification across four determined quality groups: exceptional, satisfactory, passable, and spoiled. This is reached by engaging the GRU architecture, that professionally detects the temporal patterns in sensor data.

According to experimental data, the proposed model achieves exceptionally well, overtaking classical methods labelled in the literature with a classification accuracy of 99.77%. This work verifies how DL can effectively address problems like sensor drift and varying data patterns, providing a more consistent and scalable approach to real-time food quality monitoring. To additional evaluate and increase the model's reliability, future research will focus on investigating different DL architectures and expanding the dataset. Further, the future study could also include SHAP-based interpretability tools to isolate feature effects for individual misclassified samples.

FUNDING INFORMATION

This research received no external funding.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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