

Beef spoilage assessment using e-nose and machine learning on unbalanced dataset

Noreddine Kazitani¹, Miloud Chikr-El-Mezouar¹, Elhocine Boutellaa²

¹RCAM Laboratory, Djillali Liabès University, Sidi-belabès, Algeria

²IEEE University of M'Hamed Bougara, Boumerdès, Algeria

Article Info

Article history:

Received Nov 23, 2025

Revised Mar 12, 2026

Accepted May 26, 2026

Keywords:

Beef quality

Data balancing

E-nose

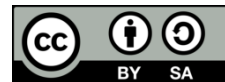
Meat freshness

SMOTE

ABSTRACT

Food quality and freshness especially meat which have short shelf life like beef meat is a real problem in nowadays. This kind of food should be stored at suitable temperature and humidity conditions. For this purpose, a system is created to detect different states of freshness through an open unbalanced dataset. Machine learning models' performance is affected by unbalanced classes, which leads to biased outcomes and poor performance on minority classes, to address this issue this study uses synthetic minority oversampling technique (SMOTE). For this purpose, an open dataset containing 10800 samples, where four classes are distinguished (excellent, good, acceptable and spoiled). In this study, the proposed e-nose is composed of 10 sensors. For classification 6 machine learning methods are used. The best results are obtained from k-nearest neighbors (KNN) model with 99.83% of accuracy, 99.86% of precision, 99.80% of recall and 99.83% of F1-score.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Noreddine Kazitani

RCAM Laboratory, Djillali Liabès University

Sidi-belabès, Algeria

Email: noreddine.kazitani@univ-sba.dz

1. INTRODUCTION

Beef meat, due to its high nutritional content, particularly protein, has seen an increasing consumption over the years, especially in emerging-economy countries [1], and this trend continues to rise. Ensuring quality and freshness of beef meat presents a global challenge for maintaining a healthy nutrition. Proper storage conditions, including appropriate temperature and humidity are crucial, as beef is highly susceptible to microbial contamination. The exposure to open air accelerates its spoilage and promotes bacterial growth, reducing its shelf life to just few hours [2]. In previous decades, microbial activity was the primary indicator used to assess meat quality. According to Wojnowski *et al.* [3], this process typically took 72 hours.

However, recent advancements in technology, such as the use of electronic nose (e-nose), have dramatically reduced the time required for quality assessment, enabling measurements to be completed in as little as a few seconds to one minute. E-nose is a set of chemical or gas sensors that emulates the nose of a human being by measuring the presence and number of particular substances, it is an innovative technology designed to reproduce the human olfactory system [4], first time used in 1994 by Craven [5], e-nose has gained a significant interest in recent years. E-nose systems offer rapid, non-invasive, and precise analysis, providing valuable real-time data about the freshness, quality, and safety of several products, making it an essential tool in industries requiring odor-based detection.

The e-nose consists of multiple sensor types that respond to specific chemical signatures. The sensors generate electronic signals that are processed by algorithms to interpret and classify different odors or

chemical compositions. This technology has a wide range of applications, including food quality monitoring, environmental pollution detection, and medical diagnostics. In our study, we use e-nose technology to assess and quantify the extent of beef spoilage.

The e-nose system incorporates 10 sensors (MQ2, MQ3, MQ4, MQ5, MQ6, MQ8, MQ9, MQ135, MQ136, DHT22) chosen for their high sensitivity to the volatile organic compounds (VOCs) emitted by animal meat at ambient temperatures, these sensors have high sensitivity to VOCs particles, which are organic compounds having a high volatility at ambient temperature, VOCs are produced by animal meat, its composition change while spoilage meat process, as meat spoils, the composition of VOCs undergoes significant changes, which makes them key indicators for monitoring its freshness. Each sensor generates a signal based on the detected changes in VOCs over time. These signals are then analyzed with machine learning algorithms to measure the degree of spoilage. Specifically, the machine learning model is trained to classify the beef into four classes: excellent, good, acceptable and spoiled. A major challenge in developing machine learning models to get an accurate detection of spoilage is the quantity of data required for effective training. Additionally, the available data is unbalanced, which can hinder model performance.

Several recent studies have addressed beef spoilage assessment. Wijaya *et al.* [2] utilized the same database as in this study and applied three classification models: artificial neural networks (ANN), support vector machines (SVM), and k-nearest neighbors (KNN). They compared classification performance for two three and four class scenarios, achieving mean accuracies of 87.29%, 86%, and 85% respectively. In a subsequent study, Wijaya *et al.* [6] further explored this database in 2019, this time filtering the signal from noise using wavelet transformations. They performed 3-class and 4-class classifications, obtaining accuracies of 91.57% and 88.29%, respectively. Abouelmagd [7] employed a hard voting classifier that combined 4 models: linear regression, KNN, decision tree classifier and random forest classifier. They reported an accuracy, recall, precision and F1-score of 99.75%.

Other studies used deep learning like Wijaya *et al.* [2] which used 12 databases for each beef meat cut, they applied a deep learning method named DWTLTSM, it consists to extract signal characteristics using wavelets and a deep learning classification using long short-term memory (LSTM) method, which is a subclass of recurrent neural network (RNN), they obtained an overall average of 94.83%. Hong *et al.* [8] used another deep learning method named Backpropagation Neural Network (BPNN) associating with principal component analysis for feature extraction, they obtained 96.19% of accuracy.

Based on these problems, this paper used an open dataset made by Wijaya *et al.* [9]. In order to achieve sustainable development, the subsequent sections of this study are structured as follows. In the second section, the presented approach is described in details. The third and fourth section presents the results of this approach and discuss them. Conclusion and future work are found in the fifth Section.

2. METHOD

In this section, the methodology adopted in this study is described. The proposed approach integrates data collection process, preprocessing steps, machine learning algorithms, followed by model evaluation, The overall workflow of the proposed framework is illustrated in Figure 1.

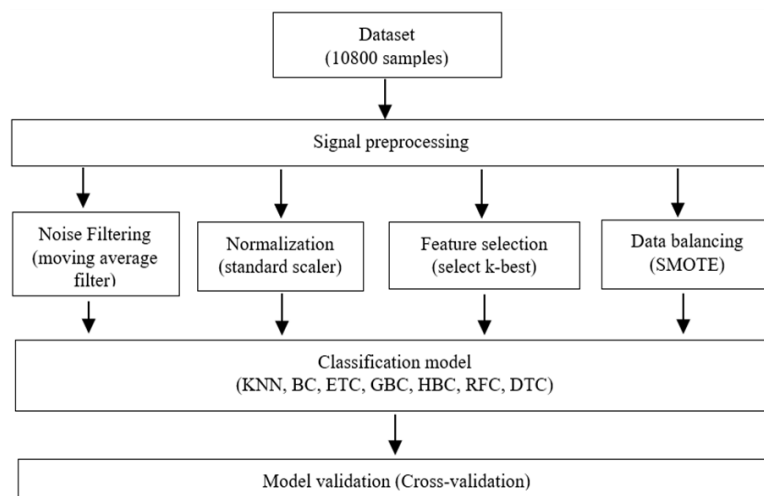


Figure 1. Case study development process

2.1. Electronic nose description

The e-nose utilized for our work is developed by Wijaya *et al.* [9]. It consists of 10 MOS sensors (metal oxide semiconductor). Table 1. Denotes MQ gas sensors manufactured by Zhengzhou Winsen Electronics Technology Co., Ltd.

Table 1. Specification of the electronic nose sensors

sensor	Sensing for air compound
MQ2	Propane, methane, butane, alcohol, hydrogen
MQ3	Methane (CH ₄), hexane, propane, CO, alcohol,
MQ4	Benzene, buthane
MQ5	Propane, butane, methane, CO ₂
MQ6	Butane, propane
MQ8	Hydrogen (H ₂)
MQ9	Propane, methane, CO
MQ135	Ammonia (NH ₃), Carbon dioxide (CO ₂), NO _x ,
MQ136	Smoke, alcohol, benzene
DHT22	Temperature, humidity

2.2. Data collection

The database is made by Wijaya *et al.* [9], in order to collect data for the experiments, 500 grams of fresh extra-lean beef was tested using the e-nose in uncontrolled environment condition. This process consists in taking e-nose measurements on a beef sample every minute during 36 hours. Thus, in total 2160 measurements were taken. This experiment was repeated on 5 different dates: 12 May 2016, 8 October 2018, 11 October 2018, 13 October 2018, and 15 October 2018.

The data collection process yields a total of 10,800 samples. This data was then analyzed by specialized scientists to assess its freshness. The meat quality has been categorized into four classes depending on bacterial activity measured using the total viable count (TVC) which gives an estimate of the concentration of the bacteria in a given sample it is generally expressed in colony-forming units per gram (CFU/g), as defined in Table 2. Four identified classes are excellent, good, acceptable and spoiled. The data distribution over the four classes is provided by Table 3.

Table 2. TVC of each beef meat quality

Class	TVC (log ₁₀ CFU/g)
Excellent	< 3
Good	3-4
Acceptable	4-5
Spoiled	>5

Table 3. Data distribution over classes

Class	Number of samples
Excellent	1200
Good	3300
Acceptable	1500
Spoiled	4200

2.3. Signal noise reduction

Signals collected from sensors are contaminated with noises such as semiconductor noise and thermo-noise [10]. For this purpose, a moving average filter (MAF) is implemented; it consists to smooth signals by averaging data points within a fixed-size moving window, each value is replaced by the mean of its neighboring data points.

$$x[n] = \sum_{i=0}^M \frac{1}{M+1} x[n-i] \quad (1)$$

where "n" represented the length of the signal, x[n] represents the sensor measurements, and "M" is the order of the filter, if this parameter is increased, a smoother signal is obtained, but at the cost of losing fine details. In this study, a filter order of 4 is used.

2.4. Normalization

After the sample collection is done, normalization is the first step in data preprocessing, it transforms features with different scales to a common scale, this allows to reduce the influence of the outliers of the data [11]. For this purpose, standard scaler (also known as Zero-Mean normalizer) technique is applied. The resulting data is zero-center and its standard deviation equal to 1. The (2) reminds the standardization formula [12].

$$z = (x - \mu) / \sigma \quad (2)$$

"z" is the normalized data sample, "x" is the original value, "μ" is the data mean and σ is the data standard.

2.5. Feature selection

In machine learning process, Feature selection is crucial; it consists to reduce feature arrays and choose only relevant features and omit irrelevant and redundant features which are non-informative [13]. To both minimize the computational cost of modelling and increase the performance of the model, for this purpose we used a method named select kbest. This technique depends on a variance analysis test "chi square", this test is used to measure the statistical dependence between every feature and the target variable. the features are kept only if highest score is obtained, more details description can be found in Fan *et al.* [14]. The five features are considered as relevant by 'select kbest' (MQ3, MQ4, MQ8, MQ9, MQ135).

2.6. Dataset split

The dataset is divided into 2 sets; a train set with 8424 samples which represents 78% of the dataset and a test set with 2326 samples (22 % of the dataset).

2.7. Data balancing

Unbalanced datasets present a significant challenge in classification tasks, as learning algorithms tend to be biased toward majority classes resulting poor learning performance. Therefore, class balancing is a crucial step to improve model reliability and performance. To this end, we use the synthetic minority oversampling technique (SMOTE), which is the most dominate technique used in data balancing [15], in contrast to other techniques, SMOTE generates new synthetic samples rather than duplicating existing ones, it consists to generate samples of a minority class by connecting each data point with its k nearest neighbors [16], this technique is used to increase the number of samples in the minorities classes, by balancing it with the majority class "excellent", in our study we set k=5. After applying SMOTE, the size of the train set from 8,424 to 13,120 samples, with 3,280 samples in each class and the test-set remains unchanged with 2326 samples. The dataset size increase from 10,800 to 15,446 samples.

2.8. Machine learning algorithms

After dataset preparation and preprocessing, several machine learning algorithms are used to classify data and predict various classes. Machine learning algorithms analyze data and use the insights gained to make informed decisions. To determine the most suitable algorithm for beef spoilage and enhance data handling efficiency.

2.8.1. K-nearest neighbors (KNN)

Widely used for classification tasks, KNN is a non-parametric algorithm that operates as a lazy learner, meaning it does not build an explicit model. Instead, it detects the K nearest data points to a given input by measuring Euclidean distance. Due to its simplicity, KNN is highly adaptable to datasets of varying sizes [17].

2.8.2. Extra trees (ET)

Extra trees classifier is an ensemble method, which consists to fit a large number randomized decision trees on different data points, it relies on a massive number of decision trees to reduce the risk of overfitting [18]. These decisions of the trees are aggregated to generate the final prediction by voting [19], which helps reduce variance and improve robustness.

2.8.3. Gradient boosting classifier (GBC)

Gradient boosting classifier generates an ensemble of weak learners, typically decision trees, where each successive tree corrects the errors of the previous one. This iterative learning process fits new models to improve the accuracy of the prediction [20].

2.8.4. Hist gradient boosting classifier (HGBC)

Hist gradient boosting classifier is an optimized version of Gradient Boosting, designed to be faster and particularly effective for high-dimensional and imbalanced datasets.

2.8.5. Random forest classifier (RFC)

Similar to extra trees, random forest classifier creates a group of decision trees during training. The output is determined by the majority vote across trees. This classifier works by selecting random subsets of features and constructing decision trees from bootstrapped training samples. RFC's performance is very similar to support vector machines (SVMs) in terms of accuracy, training time, and hyperparameters [21].

2.8.6. Decision tree classifier (DT)

It used for both classification and regression tasks, decision tree classifier consist to dividing the data based on attribute values. During node selection, information gain is used to determine the best feature to split on, ultimately maximizing the separation of the dataset into distinct subgroups [22], [23].

2.9. Hyperparameter setting

All hyperparameters of the models were optimized using GridSearchCV. This guarantees that each model was evaluated under its optimal configuration, enhancing the robustness and comparability of the results. The hyperparameters used in this study are shown in Table 4.

Table 4. Hyperparameters setting for machine learning algorithms used in this study

Algorithms	Hyperparameters
KNN	k=5, leaf_size=40, algorithm="brute", p=1, weights='distance' n_estimators=250, criterion='entropy',
ET	min_samples_leaf=1, max_depth=20, min_samples_split=4 max_features='sqrt',
GBC	min_samples_leaf=2, min_samples_split=10
RF	n_estimators=50
HGBC	max_iter=200, learning_rate=0.2
DT	Default hyperparameters

2.10. Model validation

To validate the created models, cross-validation is a resampling method used to estimate prediction error, with bootstrap methods being the most commonly employed alternative [24]. The cross-validation technique is used to assess classification performance of the developed models. This approach enables a thorough assessment of the model's performance. The dataset was divided into 5 equal parts, with 4 parts used for training and 1 part for testing. The training and testing process was repeated for a total of 5 cycles, corresponding to the number of subsets, the classification metrics were then calculated by averaging the results obtained across all repetitions.

3. RESULTS

To measure the machine learning models performance, accuracy, precision, recall, and F1-score metrics. The corresponding formulas for these metrics are provided in (3), (4), (5) and (6).

$$\text{accuracy} = (\Sigma TP + TN) / \text{all predictions} \quad (3)$$

$$\text{precision} = \Sigma TP / (\Sigma TP + \Sigma FP) \quad (4)$$

$$\text{sensitivity (recall)} = \Sigma TP / (\Sigma TP + \Sigma FN) \quad (5)$$

$$\begin{aligned} \text{F1-score} &= (2 * \Sigma TP) / (2 * \Sigma TP + \Sigma FP + \Sigma FN) \\ &= 2 * ((\text{sensitivity} * \text{precision}) / (\text{sensitivity} + \text{precision})) \end{aligned} \quad (6)$$

where TP (true positive) is the correct prediction of the model for a positive sample, TN (true negative) is the correct prediction of the machine learning model for a negative sample, FP (false positive) is the incorrect prediction of the model for a negative sample (predicted positive), and FN (false negative) is the incorrect prediction of the model for a positive sample (predicted negative).

Once preprocessing of the dataset done, we proceed to train the machine learning models, the classification was performed using the original train size of the dataset, which consists of 10,800 samples, as shown in Table 5. KNN, ET, GBC, RF and HGBC models, achieved accuracies exceeding 99%, recording 99.3%, 99.02%, 99.07% and 99.12% respectively. The results indicate that ET is the most effective model with 99.3% of accuracy, 99.43% of precision, 99.16 % of recall, and 99.29% of F1-score, on the other hand DT model achieved the lowest performance with 98.7% of accuracy, 98.71% of precision, 98.60 % of recall, and 98.65% of F1-score.

Table 5. Performances of different machine learning algorithm without SMOTE

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
KNN	98.98	99.12	98.74	98.92
ET	99.30	99.43	99.16	99.29
GBC	99.02	99.05	98.87	98.96
RF	99.07	99.29	98.83	99.05
HGBC	99.12	99.28	98.92	99.09
DT	98.70	98.71	98.60	98.65

To evaluate the obtained results by KNN model, a confusion matrix was employed to assess the classification performance and analyze the distribution of correct and incorrect prediction. Upon examining it in the Figure 2. It was found that the class with the fewest errors was the "acceptable" class with 0 errors, in contrast, the "excellent" class exhibited the highest number of errors, with 12 false predictions.

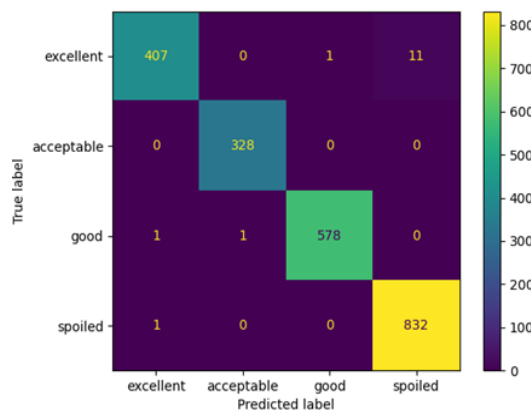


Figure 2. Confusion matrix for KNN model

After applying SMOTE, the training set increased from 8,424 to 13,120 samples. the accuracies achieved by the KNN, ET, GBC, RF, HGBC, and DT models were 99.83%, 99.78%, 99.36%, 99.78%, 99.57%, and 99.53%, respectively. The KNN model outperformed all other classifiers, with an accuracy of 99.83%, a precision of 99.86%, a recall of 99.80%, and an F1-score of 99.83%, followed by the ET and RF models, each achieving an accuracy of 99.78%. all resulted are summarized in Table 6.

Table 6. Performances of different machine learning algorithm with SMOTE

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
KNN	99.83	99.86	99.80	99.83
ET	99.78	99.78	99.75	99.77
GBC	99.36	99.36	99.39	99.46
RF	99.78	99.78	99.76	99.75
HGBC	99.57	99.63	99.49	99.56
DT	99.53	99.52	99.50	99.51

Figure 3 presents confusion matrix for extra trees model; it is evident that the errors have been significantly reduced. The class with the most errors is “good”, with 3 errors, while the class with the fewest errors is “spoiled”, with just 1 error.

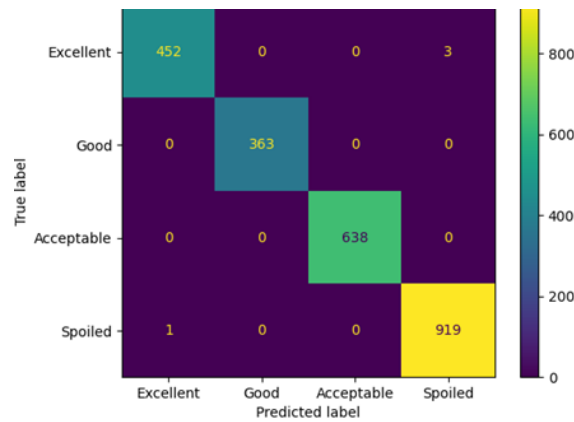


Figure 3. Confusion matrix for extra trees model

4. DISCUSSION

This study aims to recognize the state of beef meat across four classes: excellent, good, acceptable, and spoiled; through an open dataset which is extremely unbalanced. After preprocessing done, 6 machine learning algorithms were used for classification, for this purpose KNN, ET, GBC, RF, HGBC, and DT models were built, the evaluation of these models was performed using performance metrics such as accuracy, precision, recall and F1-score. To minimize errors in prediction, the hyperparameters were optimized and the training is made on the train-set of the dataset, after that these models are evaluated using cross validation. In the first scenario, the original samples of the dataset were used, 99.3% of accuracy, 99.43% of precision, 99.16 % of recall, and 99.29% of F1-score made by ET model, the evaluation score was 99.65 % which is a good performance but the model didn't generalize equally on all over the dataset, that why in the second scenario, SMOTE was applied, which increases the size of train set from 8,424 to 13,120 samples, with 3,280 samples in each class, we notice that all models performance, We observed that the performance of all models improved, especially the KNN model, which increased from 98.98% to 99.83%, with an evaluation score of 99,83%. For confusion matrix, the number of errors in the class "excellent" went from 12 to 3 errors, in overall of the dataset the number of errors went from 15 to 4 errors. This improvement can be attributed to data balancing achieved through SMOTE, which reduced the bias toward majority classes. By generating synthetic samples for minority classes, SMOTE enabled the model to better learn class boundaries. Furthermore, future scalability may benefit from machine learning-driven data preparation (MLDP) pipelines, which can improve data preprocessing efficiency when handling larger datasets [25].

5. CONCLUSION

In the study, an open imbalanced dataset was utilized to detect the freshness of beef meat using 10 sensors and 6 machine learning algorithms. Using the original dataset containing 10,800 samples, the extra trees Classifier achieved an accuracy of 99.3%, due to the dataset imbalance, this performance does not reflect the performance across all classes, Because the machine learning model is biased toward the majority class compared to the other classes, to deal with this problem, the train set of the dataset is balanced using the SMOTE method, to ensure equal representation across all classes resulting of 15,446 samples. Following this, the performance of all classifiers improved, with the extra trees classifier reaching an accuracy, precision, recall, F1-score of 99.82%, using the test-set these results are confirmed with confusion matrix and cross-validation with 99.80%, while these results demonstrate the effectiveness of traditional classifiers on balanced datasets, the growing volume of sensory data necessitates a shift toward more scalable architectures.

Future research will focus on applying machine learning algorithms to larger datasets, as the rapid growth of the machine learning field requires processing significantly larger amounts of data, On the other hand, deep learning is becoming an important tool in many fields especially in healthcare and food safety, it consists to learn complex patterns from large and high-dimensional data, which makes it particularly suitable for food quality assessment applications.

FUNDING INFORMATION

The authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Noredidine Kazitani	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Miloud Chikr-El-Mezouar	✓	✓		✓		✓		✓	✓	✓	✓	✓	✓	✓
Elhocine Boutellaa	✓		✓	✓	✓		✓	✓		✓	✓		✓	✓

- | | | |
|-------------------------------|---------------------------------------|------------------------------------|
| C : C onceptualization | I : I nterpretation | Vi : V isualization |
| M : M ethodology | R : R esources | Su : S upervision |
| So : S oftware | D : D ata Curation | P : P roject administration |
| Va : V alidation | O : Writing - O riginal Draft | Fu : F unding acquisition |
| Fo : F ormal analysis | E : Writing - Review & E ditng | |

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study is openly available in Mendeley Data at <https://data.mendeley.com/datasets/mwmhh766fc/3>.




REFERENCES

- [1] C. Whitton, D. Bogueva, D. Marinova, and C. J. C. Phillips, “Are we approaching peak meat consumption? Analysis of meat consumption from 2000 to 2019 in 35 countries and its relationship to gross domestic product,” *Animals*, vol. 11, no. 12, p. 3466, Dec. 2021, doi: 10.3390/ani11123466.
- [2] D. R. Wijaya, R. Sarno, E. Zulaika, and S. I. Sabila, “Development of mobile electronic nose for beef quality monitoring,” *Procedia Computer Science*, vol. 124, pp. 728–735, 2017, doi: 10.1016/j.procs.2017.12.211.
- [3] W. Wojnowski, T. Majchrzak, T. Dymerski, J. Gębicki, and J. Namieśnik, “Electronic noses: powerful tools in meat quality assessment,” *Meat Science*, vol. 131, pp. 119–131, Sep. 2017, doi: 10.1016/j.meatsci.2017.04.240.
- [4] J. Tan and J. Xu, “Applications of electronic nose (e-nose) and electronic tongue (e-tongue) in food quality-related properties determination: a review,” *Artificial Intelligence in Agriculture*, vol. 4, pp. 104–115, 2020, doi: 10.1016/j.aiaa.2020.06.003.
- [5] M. A. Craven, J. W. Gardner, and P. N. Bartlett, “Electronic noses — development and future prospects,” *TrAC Trends in Analytical Chemistry*, vol. 15, no. 9, pp. 486–493, Oct. 1996, doi: 10.1016/S0165-9936(96)00061-1.
- [6] D. R. Wijaya, R. Sarno, and E. Zulaika, “Noise filtering framework for electronic nose signals: an application for beef quality monitoring,” *Computers and Electronics in Agriculture*, vol. 157, pp. 305–321, Feb. 2019, doi: 10.1016/j.compag.2019.01.001.
- [7] L. M. Abouelmagd, “E-nose-based optimized ensemble learning for meat quality classification,” *Journal of System and Management Sciences*, vol. 12, no. 1, pp. 308–322, Feb. 2022, doi: 10.33168/JSMS.2022.0122.
- [8] X. Hong, J. Wang, and Z. Hai, “Discrimination and prediction of multiple beef freshness indexes based on electronic nose,” *Sensors and Actuators B: Chemical*, vol. 161, no. 1, pp. 381–389, Jan. 2012, doi: 10.1016/j.snb.2011.10.048.
- [9] D. R. Wijaya, R. Sarno, and E. Zulaika, “Electronic nose dataset for beef quality monitoring under an uncontrolled environment,” *Mendeley Data*, vol. V3, 2018, doi: 10.17632/mwmhh766fc.3.
- [10] F. Tian, S. X. Yang, and K. Dong, “Circuit and noise analysis of odorant gas sensors in an E-nose,” *Sensors*, vol. 5, no. 1, pp. 85–96, Feb. 2005, doi: 10.3390/s5010085.
- [11] A. Demircioğlu, “The effect of feature normalization methods in radiomics,” *Insights into Imaging*, vol. 15, no. 1, p. 2, Jan. 2024, doi: 10.1186/s13244-023-01575-7.
- [12] K. Mahmud Sujon, R. Binti Hassan, Z. Tusnia Towshi, M. A. Othman, M. Abdus Samad, and K. Choi, “When to use standardization and normalization: empirical evidence from machine learning models and XAI,” *IEEE Access*, vol. 12, pp. 135300–135314, 2024, doi: 10.1109/ACCESS.2024.3462434.
- [13] N. Pudjihartono, T. Fadason, A. W. Kempa-Liehr, and J. M. O’Sullivan, “A review of feature selection methods for machine learning-based disease risk prediction,” *Frontiers in Bioinformatics*, vol. 2, p. 927312, Jun. 2022, doi: 10.3389/fbinf.2022.927312.
- [14] W. Fan, K. Liu, H. Liu, P. Wang, Y. Ge, and Y. Fu, “AutoFS: automated feature selection via diversity-aware interactive reinforcement learning,” in *2020 IEEE International Conference on Data Mining (ICDM)*, IEEE, Nov. 2020, pp. 1008–1013, doi: 10.1109/ICDM50108.2020.00117.
- [15] E. Ileberi, Y. Sun, and Z. Wang, “Performance evaluation of machine learning methods for credit card fraud detection using SMOTE and AdaBoost,” *IEEE Access*, vol. 9, pp. 165286–165294, 2021, doi: 10.1109/ACCESS.2021.3134330.
- [16] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “SMOTE: synthetic minority over-sampling technique,” *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, Jun. 2002, doi: 10.1613/jair.953.




- [17] K. M. M. Uddin, A. Al Mamun, A. Chakrabarti, R. Mostafiz, and S. K. Dey, "An ensemble machine learning-based approach to predict cervical cancer using hybrid feature selection," *Neuroscience Informatics*, vol. 4, no. 3, p. 100169, Sep. 2024, doi: 10.1016/j.neuri.2024.100169.
- [18] G. M. Toche Tchio, J. Kenfack, J. Voufo, Y. Abessolo Mindzie, B. Fouedjou Njoya, and S. S. Ouro-Djobo, "Diagnosing faults in a photovoltaic system using the Extra Trees ensemble algorithm," *AIMS Energy*, vol. 12, no. 4, pp. 727-750, 2024, doi: 10.3934/energy.2024034.
- [19] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Machine Learning*, vol. 63, no. 1, pp. 3-42, Apr. 2006, doi: 10.1007/s10994-006-6226-1.
- [20] M. Zareapoor and P. Shamsolmoali, "Application of credit card fraud detection: based on bagging ensemble classifier," *Procedia Computer Science*, vol. 48, pp. 679-685, 2015, doi: 10.1016/j.procs.2015.04.201.
- [21] A. Natekin and A. Knoll, "Gradient boosting machines, a tutorial," *Frontiers in Neuroinformatics*, vol. 7, p. 00021, 2013, doi: 10.3389/fnbot.2013.00021.
- [22] M. Pal, "Random forest classifier for remote sensing classification," *International Journal of Remote Sensing*, vol. 26, no. 1, pp. 217-222, Jan. 2005, doi: 10.1080/01431160412331269698.
- [23] R. Liu and Y. Dong, "Fault diagnosis of jointless track circuit based on ReliefF-C4.5 decision tree," *Journal of Physics: Conference Series*, vol. 2383, no. 1, p. 012047, Dec. 2022, doi: 10.1088/1742-6596/2383/1/012047.
- [24] S. Bates, T. Hastie, and R. Tibshirani, "Cross-validation: what does it estimate and how well does it do it?," *Journal of the American Statistical Association*, vol. 119, no. 546, pp. 1434-1445, Apr. 2024, doi: 10.1080/01621459.2023.2197686.
- [25] D. Krajnc *et al.*, "Automated data preparation for in vivo tumor characterization with machine learning," *Frontiers in Oncology*, vol. 12, Oct. 2022, doi: 10.3389/fonc.2022.1017911.

BIOGRAPHIES OF AUTHORS






Noredine Kazitani    received the Engineering degree in Electronics from the University of Abdel Hamid Ibn Badis, Mostaganem, Algeria, in 2020. He is currently pursuing a Ph.D. degree in Electrical Engineering at Djillali Liabès University, Sidi-Belabès, Algeria. His research interests include artificial intelligence, signal processing, and embedded systems, with a particular focus on the development of intelligent electronic devices and real-time data analysis. He can be contacted at email: noredine.kazitani@univ-sba.dz.



Miloud Chikr-El-Mezouar    is currently professor in the Department of Electronic, Electrical Engineering Faculty, at the University of Djillali Liabès, Sidi Bel Abbes, in Algeria, where he has been teaching since 2003. He received the Dipl.Ing. and Magister degrees in electrical engineering from the University of Djillali Liabès, in 1996 and 1999, respectively. Then he obtained the Ph.D. degree in signal and image processing, under joint supervision, from the Djillali Liabès University and from the Institut National des Sciences Appliquées (INSA), Rennes, France in 2012. In December 2014, Miloud Chikr-El-Mezouar has gotten the university habilitation to direct research in signal and image processing domain, from Djillali Liabès University, as a part of the "Communication Networks, Architecture, and Multimedia" Laboratory. His principal research interests are in the fields of digital signal and image processing, image analysis, medical and satellite image applications, pattern recognition, electrical and computer engineering and artificial olfaction systems, he participates in the national project (2016-2019) on the implementation of electronic nose for medical diagnosis. He can be contacted at email: miloud.chikrelmezouar@univ-sba.dz.



Elhocine Boutellaa    received Ph.D. degree in Computer Science from Ecole Nationale Supérieure d'informatique in Algiers, Algeria. He has been working as a research associate with Centre de Développement des Technologies Avancées since 2010. Currently he holds the position of postdoctoral researcher at Centre de Développement des Technologies Avancées in Algiers, Algeria. His research interests include face analysis, biometrics and computer vision. He can be contacted at email: e.boutellaa@univ-boumerdes.dz.