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Deep Learning Model Based on E-Noses Sensors in Food Production Controlling System

Mohammad A. Al Sharaiah [1], Ahmad Adel Abu-Shareha [2], Laith H.Baniata [3], Ahmad Sami Al-Shamayleh [4], Hussam N. Fakhouri [5], Adeeb Al-saaidah [6]

[1, 2, 3, 4] Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan

[5] Department of Data Science and Artificial Intelligence, Faculty of Information Technology, University of Petra. Amman, Jordan

[6] Department of Networks and Information Security, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan

Abstract:- In the agricultural food manufacture region, ensuring and evaluating food quality is vital because it directly affects human health and the profitable price of the invention. The aroma of the product is a crucial characteristic that reflects its quality. A prominent trend in this area is the utilization of electronic noses (e-noses) for automated replication of smells. This involves deploying multiple sensors to detect specific compounds that contribute to the product's odor and overall quality. The reliable assessment of food quality depends on the proper functioning of these sensors, which provide digital data used for classifying food quality. However, addressing this issue has led to the implementation of various strategies, often focusing on correcting data from digital sensors. In our research, we propose an innovative approach using a Deep Learning model to leverage digital time series data from sensors for classification tasks. To maintain overall prediction accuracy, we employ a Multiple Layer Perceptron (MLP) neural network for classification prediction tasks. This method trains the proposed MLP classifier on a dataset from food production that includes 11 digital sensors (such as hydrogen sulfide, ammonia, and hydrogen sensors) across various types of beef cuts, including brisket. As a result, unlike traditional machine learning models, our approach can effectively handle data generated from sensors and address the different classes –categories-(excellent(1),good(2),acceptable(3),spoiled(4))thereby enhancing food quality assessment. Consequently, this study demonstrates the effectiveness of our proposed model through a case study focused on predicting the quality of beef cuts, yielding promising results that can be applied to general food quality assessment.

***Keywords**:* Control system, food quality, machine learning, deep learning, classifier, multiple layer perceptron, beef cut quality prediction.

1. Introduction

In the realm of agricultural food manufacture, managing and evaluating food quality stands out as a pivotal concern that directly influences both human well-being and the profitable worth of the item. Food quality encompasses the vital and distinctive features that render food suitable for consumption by individuals. [1] These attributes encompass external aspects like appearance, texture, and taste, as well as internal elements such as chemical, physical, or microbial properties. Among these critical attributes, the smell of the product plays a significant role in determining its quality, contributing substantially to its overall taste and scent. The term olfaction, which refers to the sense of smell, is defined as the ability to perceive odors and is typically assessed by skilled human assessors [2].

However, a notable development in this scope is the concept of machine olfaction [1], which entails the automated replication of the sense of smell through devices like electronic noses or e-noses. Machine olfaction finds applications across various domains, including but not limited to food quality assurance [2], assessment of meat freshness [3], determination of freezing times for fresh vegetables [4], detection of illicit substances [5], identification of infections [6], and identification of diseases [7]. This technology employs electronic nose systems, commonly referred to as e-noses, to analyze airborne chemical compounds [8]. Diverse types of e-noses [9] are under development, utilizing gas identification mechanisms [10]based on gas sensors. These gas sensors, tailored to specific applications, are designed to detect and identify various gases Examples encompass MOSFET, optical, piezoelectric sensors like Surface Acoustic Wave and Quartz Crystal Monitor, along with conductivity sensors such as polymer composites, intrinsically conducting polymers, and metal oxides [11]. These various sensors collectively enhance the capabilities of e-nose systems. Despite the effectiveness of these advanced gas sensors and gas recognition systems, numerous challenges remain unresolved [12] .

One of the key defies pertains to the intricacy of gas sensing principles and jobs. Certain gas sensors may be adversely influenced through another gases that have similar chemical characteristics. Additionally, environmental features like wetness and temperature can affect sensor correctness [12]. This issue, known as sensor drift, is multifaceted and compromises sensor constancy [13] , consequently impacting the performance of e-noses and gas identification systems. Various factors including humidity, pressure, and external pollutants can contribute to such instability problems, leading to a decline in data quality over time [13]. Researchers have identified two primary causes of sensor drift [14] : first-order drift is linked to chemical interactions between the sensor and its environment, while second order drift stems from sensor noise. One potential solution to address this challenge is the adoption of robust sensors designed to mitigate drift-related issues [15].

In reward research and sensor drift, the latest advancements involve the integration of machine learning methods, a widely utilized approach in various fields [13] . These techniques offer a significant advantage as they eliminate the need for sensor recalibration. Numerous machine learning based strategies have been introduced and tested to address sensor drift issues across several implementations, as detailed in the Related Work section. Numerous of these investigations focus on calibrating or rectifying drift-induced sensor data discrepancies. In this particular investigation, we propose and validate a machine learning and deep learning technique based on the multiple layer perceptron neural network (MLP) [16]. This method employs MLP rule to integrate outputs from individual hidden neural layers, enhancing the controlling system to sense and classify the data from sensors.

While this methodology can be broadly applicable, our focus in this research is on evaluating the quality of perishable foods like chicken, fish and beef. Specifically, we present a case consideration on beef cut quality. Over the p [17] last five decades, per capita consumption of animal-based proteins has risen to 42.20 kg annually, with beef projected to remain a popular choice through 2050. However, beef quality may suffer from potential pathogenic microorganisms, leading to meat degradation. Numerous factors for example the transportation, temperature fluctuations, and the meat chill chain can contribute to this degradation. The microbiological techniques (like gas chromatography and sensory panels) are considered as time overwhelming and demand specialized expertise, e-noses and Fourier Transform Infrared spectroscopy (FTIR) [18] have emerged as alternatives for meat fineness assessment. Considering that e-nose hardware offer cost-effectiveness, rapidity, and comparable performance to FTIR methods, they are well-suited for monitoring beef quality. Nonetheless, the weakness of e-noses lies in sensor instability caused by diverse environmental circumstances.

In this research, we conducted our investigations utilizing a publicly available dataset accessible via the link [19]. While this dataset has been utilized by prior researchers on multiple occasions such as [20], the potential of employing a customized MLP classification method for this specific problem remains unexplored. Our objective in this study is to assess the suitability of MLP classification techniques in predicting beef cut quality. To estimate the efficiency of our proposed methodology, we have done numerous experiments utilizing 11 sensors data (e.g., ammonia, hydrogen sulfide, hydrogen sensors) across a type of beef cuts such as brisket.

Mainly, the classification labels were denoted by four distinct categories (excellent, good, acceptable, spoiled). An integrated MLP classifier was constructed by integrate outputs from individual hidden layers with specific customization and employing multi class technique. The other of this research is structured as follows: Section 2 outlines the relevant literature. Section 3 details the methodology utilized. Section 4 demonstrations our findings. Section 5 offers a discussion, while Section 6 presents our conclusions

2. Related Work

Numerous methodologies have been established and validated to address the issue of classifying the sensors data in food production quality systems. Given that our model hinges on a classification method tolerant to data loss, this section primarily focuses on techniques developed using machine learning methodologies [21].

De Vito and colleagues [22] utilized semi supervised learning methodologies to enhance the effectiveness of regression and classification methods. Their investigation illustrated the efficacy of SSL techniques in mitigating sensor drift's impact and reducing performance degeneration. Liu et al. [23]implemented a domain adaptation strategy to address sensor drift, demonstrating its superiority over conventional methods. Yan and co-authors [24] introduced a novel technique named maximum independence domain adaptation (MIDA) to extract domain-invariant variables and employed on semi-supervised variant, SMIDA, to tackle the sensor drift issue. Xue et al. [25] recommend a Boolean version of Particle Swarm Optimization specifically designed for this challenge, noting its robustness without the need for recalibration. Moreover, strategies based on Component Correction [26] and methodologies relying on Sequential Minimal Optimization [27] have also exhibited effectiveness in adjusting models to counter sensor drift.

Zhang and colleagues [28] presented a concept named domain adaptation extreme learning machine, showcasing its effectiveness compared to other methods for compensating drift. Zhao et al. [29] Merged Support Vector Machines (SVM) with an enhanced Long Short-Term Memory (LSTM) algorithm. Concurrently, Vergara et al. [30] Elaborated an ensemble approach using (SVM) that combines weighted classifications from methods trained at diverse time intervals. Their prime aim was to differentiate and distinguish six gases/analytes such as ammonia, and toluene.

Apart from the previously mentioned approaches to combat sensor drift, numerous investigations have focused on predicting the quality of beef cuts. [20] Explored the robustness of feature selection algorithms in optimizing sensor arrays, analyzing 12 datasets concerning to various beef cuts. Their results revealed that no individual feature selection algorithm can consistently provide accurate sensor recommendations. In contrast, our study concentrated solely on one dataset. Sarno and Wijaya [20] addressed the difficulties in using e-nose software's to evaluate beef fineness. Wijaya et al. [24] presented a noise filtering model for monitoring beef quality, demonstrating its effectiveness in improving the effectiveness of multi-class classification and regression algorithms. In another study, Wijaya et al. [31] Proceed various experiments and gathered time series data concerning beef quality monitoring. Additionally, Wijaya et al. [32] classify beef into 2/3/4 categories through K-Nearest Neighbor algorithm to and exhibited its ability to differentiate between fresh and spoiled beef.

Based on the literature reviewed in this section the MLP classifiers with selected parameters can be utilized for the prediction problem that related to meat quality. Therefore, our proposed model presents unique portion and attributes tailored for this specific challenge. Furthermore, we noted that existing machine learning models proposed and assessed the classification task with complex model with high processing time with low accuracy.

In pursuit of constructing a highly accurate prediction model, our goal was to create a novel prediction model for the beef cut quality issue using the MLP method. Our aim was not solely focused on attaining the utmost performance; rather, we sought to devise a prediction model that remains effective even in instances of sensor loss since the deep learning model can support the decision making for classify the products.

3. Methodology

The diagram illustrating the abstract model for monitoring food quality controlling system using machine olfaction is depicted in Fig.1 In this type of system, the data gathered from the array that contains sensor is transmitted to the server through an access point. These raw signals are then transformed to numerical values and utilized as input for classification by Machine learning and Deep learning algorithms. The automated assessment of food newest and quality assists professionals in determining appropriate values strategies.

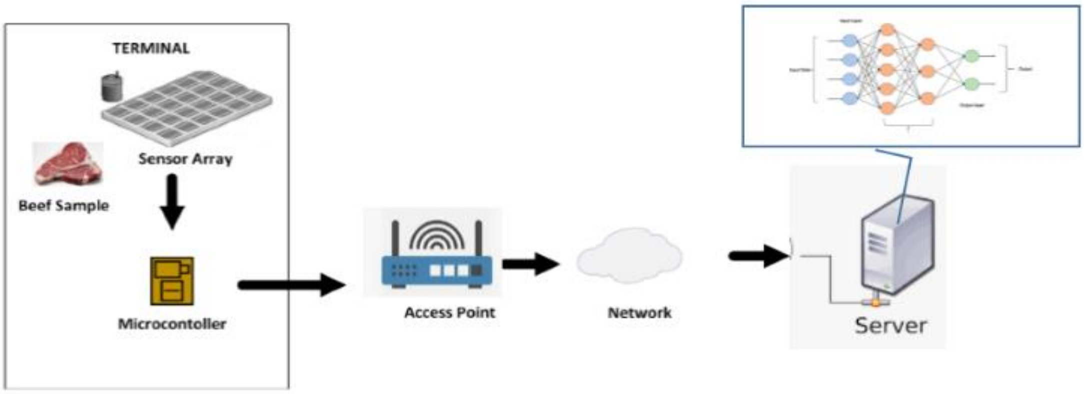

Fig. 1 Conceptual food quality controlling system

However, external factors such as fluctuations in intensity of heat can compromise the accuracy of sensors. This situation, referred to as sensor drift, poses a significant challenge in chemical sensing, resulting in potential inaccuracies in measurements and subsequently impacting the reliability of prediction models. Sensor challenges can be divided into two categories. First-order sensor drift involves chemical interactions through the sensor and its environment, while second-order drift is associated with sensor noise. Herein, we address the issue of sensor drift and introduce an innovative model designed to mitigate sensor losses. The primary advantage of our proposed model lies in its ability to withstand the absence of sensor-derived features. In ideal scenarios where all sensors are functioning optimally, individual classifiers demonstrate higher accuracy.

The suggested approach is engineered to withstand sensor malfunctions. In the event of a failure scenario some sensors are disregarded, the system can seamlessly stay its automated quality assessment process. An outline of the suggested prediction methodology is delineated in Fig.2. The gathered data from sensors is divided into training and testing sets, after which models are trained using every sensor's individual data. For experimentation, a 10-fold cross-validation technique [33] is employed for generalization. The dataset comprises 2200 samples, with each step utilizing one fold as the test set and the rest folds as the training set. The training set exclusively comprises data without sensor failures. The proposed MLP model during the prediction phase, the outputs from this base model considered as the final prediction output. The subsequent subsections elaborate on the proposed MLP classifiers and the dataset that employed.

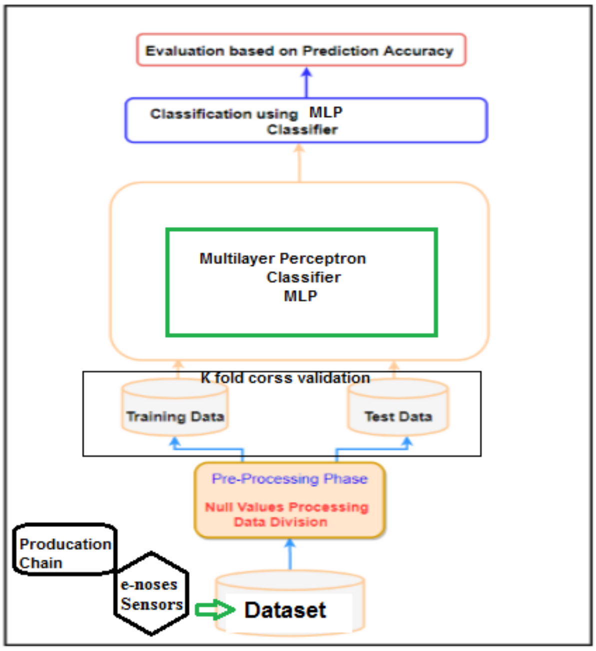

Fig.2 The proposed prediction methodology

The MLP classifer

The experimental setup utilized the MLP as classifier. Our initial classifier, MLP, stands out as a widely employed both classification tasks [34] .It is often regarded as one of the most standard machine learning algorithms due to its straightforward nature. Unlike more intricate machine learning algorithms such as kNN does not involve function optimization or parameter regulation throughout training. However, this characteristic makes kNN less suited for machine learning challenges involving extensive datasets.

The Multi-layer Perceptron (MLP) represents a supervised learning technique that acquires knowledge about a function f(.): Rm->Ro through training on a dataset, where m signifies the input's dimensionality, and o denotes the output's dimensionality. When presented with a group of features X=x1,x2,…,xm and a target Y, the MLP can develop a non-linear function approximate suitable for classification or regression tasks. Unlike logistic regression, MLP includes one or multiple non-linear layers known as hidden layers situated between the input and output layers. Fig.3 illustrates a general MLP with an input layer, set of hidden layers and output layer [11].

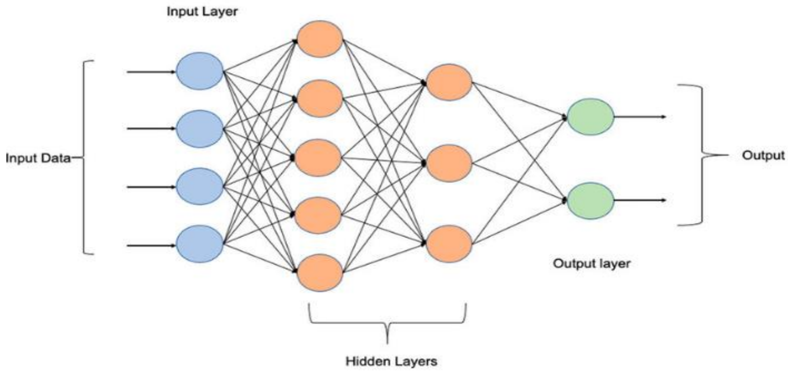

Fig.3 Multi-layer perceptron (MLP)

The MLP Classifier utilizes a multi-layer perceptron (MLP) algorithm [35], which undergoes training via Backpropagation. MLP training involves Stochastic Gradient Descent, Adam, or L-BFGS methods. Stochastic Gradient Descent (SGD) changes parameters by calculating the gradient of the loss function concerning the parameters requiring adaptation. Adam functions akin to SGD as a stochastic optimizer but can autonomously regulate parameter updates based on adaptive estimations of lower-order moments [35].

If the number of classes exceeds two, Instead of being processed by the logistic function, it undergoes the softmax function, denoted as, Softmax (1) .

$$\text{Softmax}(z)\text{i} = \frac{\exp\text{(zi)}}{\sum_{\text{i}=1}^{\text{k}} \exp\text{(zi)}} \qquad (1)$$

Where zi denotes the i th element of the input to softmax, representing class i, and k indicates the overall number of classes. This yields a vector that includes the probabilities of sample x pertinence to each class. The class with the highest probability in the output is then identified.

Dataset

Our investigates were conducted using an open popular available time series dataset collected with an e-nose specifically designed for beef quality monitoring studies [36]. It encompasses readings from 11 distinct metal oxide semiconductor gas sensors. For instance, Gas sensors are crafted to identify a range of gases such as Methane, Iso-butane, propane, LPG, LNG, hydrogen, carbon monoxide, among others. Their importance lies in monitoring gas concentrations across diverse settings to uphold safety standards.

Moreover, gas sensors are capable of identifying substances like carbon dioxide, alcohol, ammonia, smoke, benzene, hydrogen sulfide, toluene, acetone, and similar compounds. Their pivotal function involves the detection of potentially hazardous gases and pollutants present in the atmosphere.

Data collected from these sensors is recorded continuously over a span of 2220 minutes. Each minute, a single data point is collected from every sensor. The dataset encompasses samples obtained from diverse distinct beef cuts such as namely such as brisket [37]. Herein, the brisket data set was utilized in the development process for MLP proposed model.

Furthermore, this research applied a correlation study between the data sets variables. For instance, the correlation coefficient serves as the metric utilized for quantifying the strength of the linear association among variables within a correlation analysis. This metric, denoted by the symbol 'r,' is readily recognizable and typically ranges between 1 and -1, representing a dimensionless value. Fig.4 presents the correlation heat map between the Briskets data set features.

Fig. 4 the correlation heat map between the Briskets data set features.

Performance Metrics

The effectiveness of the suggested framework is assessed through the accuracy and confusion matrix metrics [38] .Additionally, recall, precision, and F-score metrics are employed for the assessment [38]. The confusion matrix, also known as the error matrix, is a statistical tool that provides a visual representation of the model's performance, as delineate in Fig. 6.

		Predicted	
		Negative	Positive
Actual	Negative	True Negative Prediction	False Positive Prediction
	Positive	False Negative Prediction	True Positive Prediction

Fig. 6 Confusion matrix

The confusion matrix reveals various metrics. True Positive (TP) signifies the correct prediction count of positive data points, where the predicted value matches the actual positive value. False Positive (FP) denotes the count of negative values mistakenly classified as positive. True Negative (TN) represents the number of correctly predicted negative data points, where both predicted and actual values are negative. Conversely, False Negative (FN) indicates the count of positive values wrongly labeled as negative. The accuracy metric calculates the proportion of correctly classified instances using TN and TP metrics, as depicted in Equation (3) [38].

The accuracy is determined by dividing TP by the overall number of samples labeled positive by the classifier, as shown in (2). The evaluation of recall is based on TP divided by the total number of positive samples within the dataset, as shown in (3). Also the Precision presented in (4), The F-score, calculated according to (5), combines precision and recall measures.. These metrics produce results ranging from 0 to 1 or can be expressed as a percentage up to 100% [38].

$$Accuracy=TP+TN / (TP+TN+FP+FN) \quad (2)$$

$$Recall=TP/(TP+FN) \quad (3)$$

$$Precision=TP / (TP+FP) \quad (4)$$

$$F\text{-}Measure=2 * precision*Recall / (precision+Recall) \quad (5)$$

During the experiments, a 10-fold cross-validation technique is employed to reduce estimation variability. This involves dividing the dataset into 10 folds or subsets. Each fold serves as a testing subset, while the remaining folds are utilized for model building during the training phase. Initially, parameter adjustments are made as part of the experimental execution. Subsequently, experiments are carried out to evaluate and report the classification process's performance.

4. Experimental Results

Throughout our experiments, we utilized the MLP classifier for implementing the classification approach. The MLP method is selected due to their efficiency in training and testing processes. Moreover, it directly applied to the datasets and the Classifier method are denoted as “MLP”. The MLP model with specific architecture, compiles it with suitable optimizer and loss function, and trains it for a specified number of epochs and batch size to perform a multi-class classification task. The setup of a Multi-Layer Perceptron (MLP) model entails configuring several layers. Initially, the model comprises a primary hidden layer within the neural network architecture, housing 128 neurons. Here, the utilization of the 'relu' activation function serves to imbue the model with non-linear characteristics, enhancing its representational capacity. Subsequently, a secondary hidden layer, also equipped with 64 neurons, is incorporated into the architecture, applying the 'relu' activation function anew to foster non-linear transformations. Additionally, the output layer of the neural network, referred to as the Dense layer, accommodates 'n' neurons, aligning with the classification task's class count. To facilitate the conversion of raw outputs into class probabilities, the 'softmax' activation function is employed. In terms of training parameters, the model is trained over a defined number of epochs, signified by the parameter 'epochs=20', dictating the frequency with which the entire dataset undergoes forward and backward propagation through the neural network during training. Furthermore, the experiment stipulates a batch size of 32, denoted by 'batch_size=32', indicating the quantity of samples per gradient update. This parameter delineates the number of training instances utilized within a single iteration. Notably, the optimizer 'adam' is selected for its efficacy as a gradient-based optimization algorithm. Meanwhile, the loss function 'sparse_categorical_crossentropy' is adopted, deemed suitable for multi-class classification scenarios wherein target labels are integer-based.

Proposed model outcomes based on Brisket Dataset.

The dataset encompasses a variety of beef cuts, encompassing 2200 distinct samples. The results pertaining to this category are delineated herein. Subsequently, the efficacy of the Multilayer Perceptron (MLP) model is expounded upon in a tabular format. This table serves to encapsulate the classification report, which offers a inclusive assessment of the model's ability to categorize instances across various classes.

Table.1 The classification report

Class	Precision	Recall	f1-score
1-Excellent	98%	99%	99%
2-Good	99%	98%	98%
3-Acceptable	95%	94%	94%
4-Spoiled	99%	99%	99%

Furthermore, Fig.7 explains how the Accuracy values is decreased over the training process.

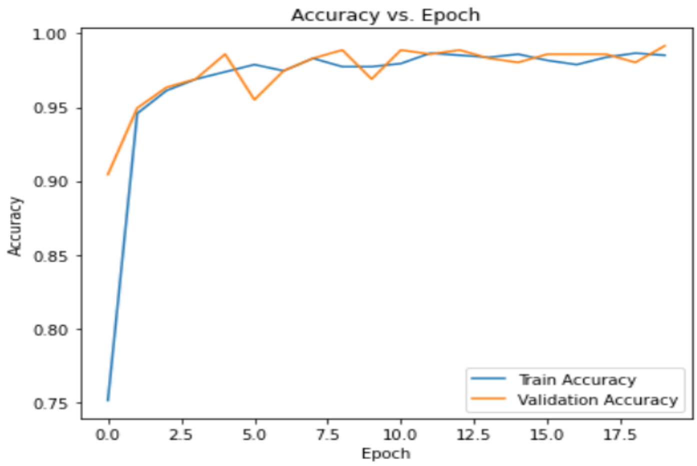

Fig. 7. Accuracy and epoch's analysis.

In addition, Fig. 8 explains how the loss values is decreased over the training process.

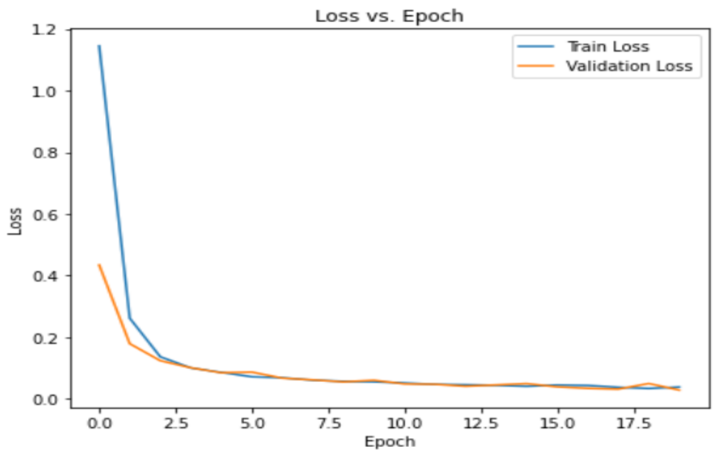

Fig. 8. Loss value over the epoch number.

Moreover, the prediction summary is clarified in the confusion matrix as shown in Fig. 9.

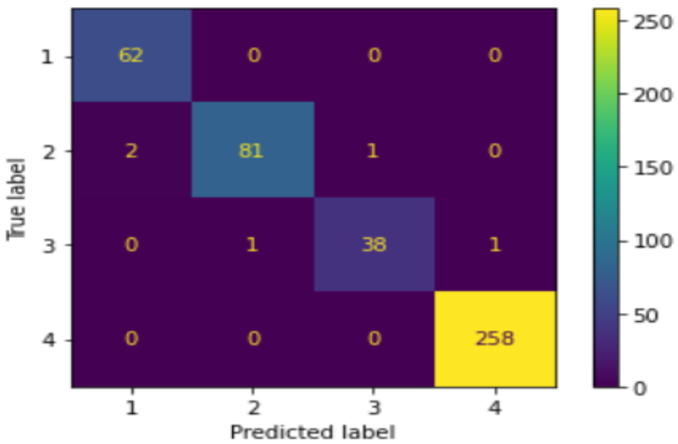

Fig. 9. Confusion matric for the brisket prediction

The outcomes of the classification with the Brisket dataset are showcased in Fig.10. The proposed classifier demonstrated superior Classification Accuracy 99%, On the other hand, the Ensemble model such as [39] method achieved the highest classification accuracy at 93.73%. [40] Developed a composite model with an Accuracy level 98%, the KNN, Linear Discriminant, Decision Tree are integrated by [41]. The Artificial neural network with on FPGA proposed as a model, this model achieved an accuracy level with 93.73%. Furthermore, Extreme Learning Machine (ELM), SVM employed to developed classification mode by [42] the Accuracy was 98% for classification task. [43] Utilized a Support Vector Regression as classifier and the accuracy level was 97.7 %

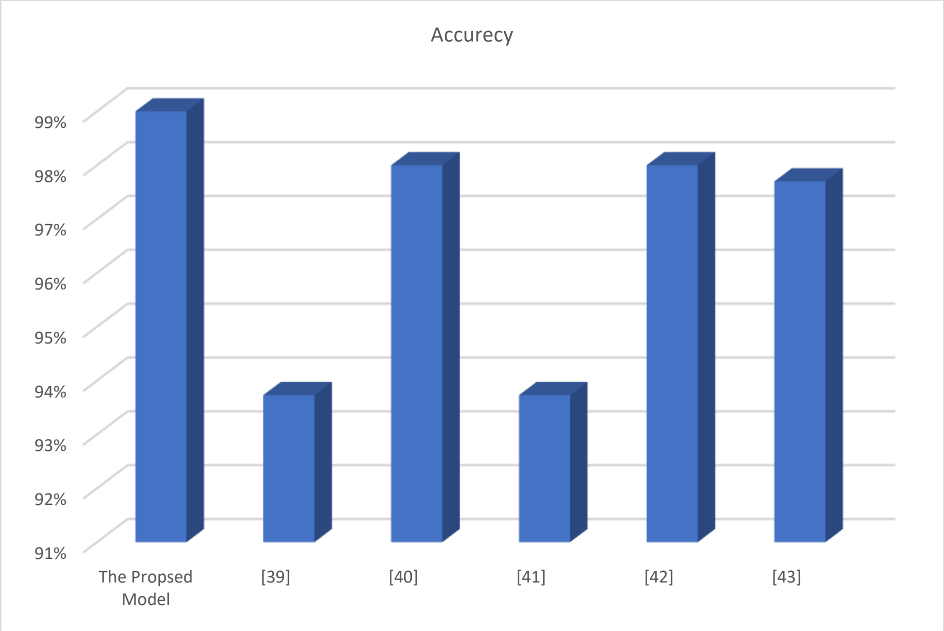

Fig.10. Comparison analysis between the proposed models and other literature models.

For instance, the ensemble classifier exhibited the highest Classification Accuracy (CA) at 98.3 % [44] with KNN 98.9 and LR model provide Accuracy with 98.6%, the Tree-based SPVS technique attained the highest accuracy for classification task 82.8%. Particularly, the MLP method exhibited superior performance on datasets compared to all classification methods. While other methods such as the Linear Discriminant and kNN classifiers showed poorer performance in such scenarios.

5. Discussion

Our findings shows that the MLP classifier exhibits greater tolerance compared to other traditional machine learning classifiers. While some base classifiers may achieve higher classification accuracy when all features are utilized during training, this ideal scenario isn't always feasible, especially in rapidly changing IoT environments. Factors like external effects or sensor malfunctions can lead to feature loss or incorrect data, presenting challenges for accurate predictions. Our proposed method addresses this challenge effectively, demonstrating efficiency and effectiveness in handling such scenarios. The key contributions of our study are outlined as follows: We present a mechanized approach for forecasting beef cut quality, employing an MLP classifier which is a promise approach in the context of food quality prediction. We present a MLP classifier for food quality prediction. Various base classifiers, including KNN, DT, and LDA, are engaged and valuated the prediction in food quality. While our study focuses on beef cut quality, the proposed model can be broadly applied to food quality estimation. However, like all experimental investigation, there are potential threats to the quality of being logically or factually sound. Our results are specific to the dataset used, and outcomes may vary with different data sources, highlighting the need for diverse datasets in future research.

6. Conclusions and Future Work

Automated sensing of food smell, known as machine olfaction, is essential for food quality assessment using electronic noses (e-nose). The reliability of this assessment heavily relies on the proper functioning of various sensors employed to detect specific compounds. However, sensor failures can compromise the accuracy of the assessment, making it less reliable. To figure out and cross over this issue, this research propose a deep learning method that influences classifier mechanism to tolerate sensor failures. Our study focuses on predicting beef cut quality using a publicly available dataset. We conducted experiments using eleven sensors across beef cuts. Accurate prediction of food quality is crucial for pricing decisions as the freshness of food directly influences market prices. During our experiments, we simulated sensor problems to evaluate the performance of our proposed technique under such conditions. Our results demonstrate that our approach is highly effective in dealing quality degradation caused by sensor drift or other failures. MLP technique, as showcased, exhibit significant potential and accurately predicting food quality. For future research, we aim to explore various deep learning approaches with different configurations to further enhance performance and validate our findings across additional datasets.

References

[1] Guthrie, B. , "Machine Olfaction," In Springer Handbook of Odor; Springer: Cham, Switzerland, p. pp. 55–56., 2017.

[2] Gardner, J.W.; Persaud, K.C.; Gouma, P.; Gutierrez-Osuna, R., " Special issue on machineolfaction," IEEE Sens. J. , p. 3105–3107, 2012, 12,.

[3] Chen, J.; Gu, J.; Zhang, R.; Mao, Y.; Tian, S., "Freshness evaluation of three kinds of meats based on the meats based on the on the electronic nose," Sensors, pp. 19, 605, 2019.

[4] Liu, L.; Li, X.; Li, Z.; Shi, Y, "Application of Electronic Nose in Detection of Fresh Vegetables Freezing Time," Considering Odor Identification Technology.Chem. Eng. Tran, pp. 68, 265-270., 2018.

[5] Stassen, I.; Bueken, B.; Reinsch, H.; Oudenhoven, J.; Wouters, D.; Hajek, J.; Van Speybroeck,, "Towards metal–organic framework based field effect chemical sensors:," Chem. Sci., pp. 7, 5827–5832., 2016.

[6] van Geffen, W.H.; Bruins, M.; Kerstjens, H.A, "Diagnosing viral and bacterial respiratory infections in acute COPD exacerbations by an electronic nose: a pilot study," J. Breath Res, 2016.

[7] Eamsa-Ard, T.; Seesaard, T.; Kitiyakara, T.; Kerdcharoen, T, "Screening and discrimination of Hepatocellular polymer/carbon nanotube," In Proceedings of the 2016 9th Biomedical Engineering International Conference, pp. Laung Prabang, Laos, 7–9 December 2016; pp. 1–5., 2016.

[8] Alphus D. Wilson, Manuela Baietto, "Applications and Advances in Electronic-Nose Technologies," sensors, pp. 5099-5148, 2009.

[9] Alphus D. Wilson , M Baietto, "Advances in Electronic-Nose Technologies Developed for Biomedical Applications," Sensors, vol. 11, no. 1, 2011.

[10] Bang, Y.K.; Lee, C.H., "Design of a Hierarchically Structured Gas Identification System Using Fuzzy Sets and Rough Set," Trans. Korean Inst. Electr. En, pp. 67, 419–426, 2018.

[11] Arshak, K.; Moore, E.; Lyons, G.M.; Harris, J.; Cliffor, "A review of gas sensors employed in electronic nose application," sensors, pp. 24, 181–19, 2004.

[12] Shiv Nath Chaudhri, "Automatic Selection and Adaption in Sensor Array for Intelligent Artificial Olfaction Systems," EEE Sensors Letters, vol. 7, no. 9, pp. 1-4, 2023.

[13] Oroos Arshi ; Surajit Mondal, "Advancements in sensors and actuators technologies for smart cities: a comprehensive review," SpringerLink, vol. 18, no. 1, 2023.

[14] Ma, Z.; Luo, G.; Qin, K.; Wang, N.; Niu, W., "Online sensor drift compensation for E-nose systems using domain adaptation and extreme learning machine," sensors, Vols. 18, 742, 2018.

[15] Xia Zhao;Pengfei Li , "Sensor Drift Compensation Based on the Improved LSTM and SVM Multi-Class Ensemble Learning Models," sensors, vol. 19, no. 8, 2019.

[16] "Neural Networks: A Comprehensive Foundation," Prentice Hall., no. ISBN 0-13-273350-1, 1998.

[17] Sans, P.; Combris, P., "World meat consumption patterns: An overview of the last fifty years (1961–2011)," PubMed, Vols. 109, 106–111, 2015.

[18] Maria Govari ;Paschalitsa ; Efstathios Z. Panagou *, "Application of Fourier Transform Infrared (FT-IR) Spectroscopy, Multispectral Imaging (MSI) and Electronic Nose (E-Nose) for the Rapid Evaluation of the Microbiological Quality of Gilthead Sea Bream Fillets," foods, Vols. 11(15), 2356, 2022.

[19] "https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/XNFVTS," [Online]. Available: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/XNFVTS.

[20] Wijaya, D.R.; Afianti,, "Stability Assessment of Feature Selection Algorithms on Homogeneous Datasets," IEEE Access, Vols. 8, 33944–33953, 2020.

[21] Indrajeet Kumar; Jyoti Rawat, "Opportunities of Artificial Intelligence and Machine Learning in the Food Industry," Journal of Food Quality, vol. 2021, 2021.

[22] De Vito, S.; Fattoruso, G.; Pardo, M.; Tortorella, "Semi-supervised learning techniques in artificial olfaction: A novel approach to classification problems and drift counteraction," IEEE, Vols. 12, 3215–3224, 2012.

[23] Huichao Zhu; Yu Wu,Ge Yang, "Electronic Nose Drift Suppression Based on Smooth Conditional Domain Adversarial Networks," sensors, no. 24(4), 1319, 2024.

[24] Yan, K.; Kou, L.; Zhang, D., "Learning domain-invariant subspace using domain features and independence maximization," IEEE, Vols. 48, 288–29, 2017.

[25] Ur Rehman, A.; Bermak, A, "Heuristic random forests (HRF) for drift compensation in electronic nose applications," IEEE sens, Vols. 19, 1443–1453, 2018.

[26] Ziyatdinov, A.; Chaudry, A., "Common principal component analysis for drift compensation of gas sensor array data," AIP Con, Vols. 1137, 566–569., 2009.

[27] Rebholz, J.; Weimar, U, "Influence of conduction mechanism changes on the sensor performance of SMOX based gas sensors," Procedia En, Vols. 87, 20–23, 2014.

[28] D. Zhang, "Domain adaptation extreme learning machines for drift compensation in E-nose systems," IEEE Trans., pp. 64, 1790–180, 2014.

[29] Zhao, X.; Li, P.; Xiao, K.; Meng, X.; Han, L.; Yu, C, "Sensor Drift Compensation Based on the Improved LSTM and SVM Multi-Class Ensemble Learning Models," sensors, Vols. 19, 3844, 2019.

[30] Vergara, A.; Vembu, S.; Ayhan, "Chemical gas sensor drift compensation using classifier ensembles," Sens, Vols. 166, 320–329., 2012.

[31] Wijaya, D.R.; Sarno, R.; Zulaika, E, "Electronic nose dataset for beef quality monitoring in uncontrolled ambient conditions," Data Brief, Vols. 21, 2414–2420, 2018.

[32] Wijaya, D.R.; Sarno, R.; Zulaika, E.; Sabila, "Development of mobile electronic nose for beef quality monitoring," Procedia Compu, Vols. 124, 728–735, 2017.

[33] Sanjay Yadav; Sanyam Shukla, "Analysis of k-Fold Cross-Validation over Hold-Out Validation on Colossal Datasets for Quality Classification," IEEE, 2016.

[34] A. Iversen ; Nick Taylor, "Classification and verification through the combination of the multi-layer perceptron and auto-association neural networks," IEEE International Joint Conference, vol. 2, 2005.

[35] Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams, "“Learning representations by back-propagating errors.”," vol. 223, 1986.

[36] Wijaya, D.R., "Dataset for Electronic Nose from Various Beef Cuts," ieeedataport, 2020.

[37] Prescott, L.M.; Harley, J.P.; Klein, D.A, "Microbiology," McGraw Hill, no. 6, 2005.

[38] A. Tharwat, "Classification assessment methods," Applied Computing and Informatics, vol. 17, pp. 168-192, 2021.

[39] "E-nose-based Optimized Ensemble Learning for Meat Quality Classification," Journal of System and Management Sciences, vol. 12, pp. 308-322, 2022.

[40] Kaya, A.; Keçeli, A.S.; Catal, C.; Tekinerdogan, "Sensor failure tolerable machine learning-based food quality prediction mode," sensors, no. 20, 3173, 2020.

[41] Enériz, D.; Medrano, N.; Calvo, B, "An FPGA-based machine learning tool for in-situ food quality tracking using sensor fusio," Biosensors, pp. 11, 366, 2021.

[42] Pulluri, K.K.; Kumar, V.N, " Development of an Integrated Soft E-nose for Food Quality Assessmen," IEEE Sens, Vols. 22, 15111–15122, 2022.

[43] Hibatulah, R.P.; Wijaya, D.R.; Wikusna, W, "Prediction of Microbial Population in Meat Using Electronic Nose and Support Vector Regression Algorithm," In Proceedings of the 2022 1st International Conference on Information System & Information , 2020.

[44] Aydin Kaya;Ali Seydi Keçeli, "Sensor Failure Tolerable Machine Learning-Based," sensors, Vols. 20, 3173;, 2020.

[45] Feng, S.; Farha, F.; Li, Q., "Review on Smart Gas Sensing Technology.," sensors, pp. 19, 3760, 2019.

[46] Enériz, D.; Medrano, N.; Calvo, B, "An FPGA-based machine learning tool for in-situ food quality tracking using sensor fusio," sensors, pp. 11, 366, 2021.