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PeCAR: Integrating Penalized Conditional Absolute Regularization Loss Function in ANN for Enhanced Food Spoilage Prediction Accuracy

Pandey Shourya Prasad*, Barath S Narayan* and Madhav Rao

Abstract— **In the context of food spoilage prediction, the accuracy of predictive models is critical for ensuring food safety and minimizing waste. Traditional loss functions often fail to adequately prioritize errors based on the varying significance of prediction intervals. This research introduces a customized loss function - PeCAR (Penalized Conditional Absolute Regularization) loss, tailored to enhance the predictive performance of ANNs for food spoilage time estimation. The proposed loss function incorporates the actual spoilage time of food items, thereby penalizing errors in short-term predictions more heavily than the same amount of error in long-term predictions. The proposed approach ensures that an absolute prediction error is weighted according to the relative importance of the time frame, reflecting the need for precise short-term predictions in items with shorter spoilage times. The result indicates a substantial improvement of 35.78% in Mean Absolute Error (MAE) and 25.32% in Mean Squared Error (MSE), enhancing the reliability of the model's predictions for food spoilage. A unique chamber setup is designed for acquiring the dataset for different sets of food items. The 4-layer ANN model with the dataset of all the food items is made publicly available for easy adoption and further usage by the researchers and developers community.**

I. Introduction

Food waste management is one of the significant steps recommended by the United Nations in the Sustainable Development Goals (SDGs) for all countries [1], owing to the emerging realization of limited natural resources worldwide. Across developing nations, spoiled food consumption has led to irreparable food-borne diseases, causing long-term health problems along human digestive systems [2]. Besides, the food once spoiled, requires more carbon footprint to dispose safely [3]. Hence if the spoilage of the food is predicted early, preemptive action in the form of not only saving the effort for disposing of spoiled food but also utilizing them more appropriately for the needy ones is possible. Along this thought-process, food freshness index is a vital metric that aids in serving and distributing quality and safe food to larger community [4], [5]. Existing predictive methods typically are human biased and hence are ineffective in modern day fast serving and mass scale distribution of food [6], [7]. Currently, the estimation of food spoilage and its prediction depends on experts' examination of multi-modal aspects, including the texture, odour, turbidity, any bacterial growth, and other parameters [4]–[7], and thus are likely to be biased and inconsistent. Hence technological intervention is imperative to make a consistent and robust decision for determining the expiry of the food item.

Classical Machine learning (ML) and newer Artificial Intelligent (AI) algorithms has the capability to extract relevant discriminative features from the multi-modal dimensions and is successfully applied to food products [8], [9]. Vision-based methods [9]–[11], microbial colony counting method [12], [13], electronic nose [14], [15] are some of the profound approaches that have shown successful outcomes for recognizing the food intake, and nutrients intake. However, the vision-based method lacks sufficient critical information to predict the spoilage, while microbial activity is cost ineffective for mass-scale adoption. The gas sensing module has shown superior performances across wide applications ranging from environmental monitoring to medical diagnostics [16]–[18]. The cost-effective electronic nose design, modelled from the array of gas sensor, succeeds over the other two by constantly measuring the concentrations of Methane, Propane, and other Volatile Organic Compounds (VOCs) released from the food items [19]–[28].

Typically, the module comprising of array of gas sensors detects and quantifies the concentrations of Methane, Propane, and other Volatile organic compounds (VOCs) from continuous vapours released from the food item under investigation. Besides, temperature and humidity of the surroundings are also recorded to further aid in detecting the condition of the food item. The electronic nose module with similar gas sensors are employed successfully in diverse segments including industrial sectors, healthcare, environmental monitoring, and food industry [8], [29]–[32]. Wide coverage of applications has also evoked different styles of signal processing. The earlier methods of applying classical signal processing techniques on the gas sensor data had limitations in extracting the adequate information due to the sensor drifting issues, cross-sensitivity among the sensors, and complexity of gases involved [33]. In the past, the response of multiple digital filters applied with their coefficients does not necessarily generate the desired outcome consistently, and hence it requires design-space effort to identify the optimal set of filters with the possibility of some being higher order of degree. Artificial Neural Networks (ANNs) adopts the supervised dataset to formulate sequence of coefficients and evolve higher-order filters that works for diverse set of data. ANNs have shown to extract discriminative spatio-temporal features, which is beneficial to model the predictive odor patterns at high precision. This work delves deep into the customized loss function for ANNs, for extracting predictive features of multi-modal gas sensors more appropriately, thereby introducing a new loss function in the field of ANNs. The new custom loss function was modelled to penalize the error more for short-term predictions over long term. The detection of food spoilage for fruits, vegetables, and meat items is reported in the literature [5], [15], but

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spoilage prediction over time is not explored, which is a better characteristic parameter in the scheme of food waste management. Accurate prediction of food spoilage time for edible items helps to characterize the shelf life which not only aids in pushing for food distribution strategies, but also encourages us to prepare for disposing of the waste in advance. In this work, the proposed predictive 4-layer ANN model was evaluated for milk, banana, bread, and curd with the new loss function and compared with conventional loss function. A novel chamber setup is designed to acquire the dataset for different food items. The dataset compiled for food items and ANN model with customized loss function was made publicly available for easy adoption and further usage by the researchers and designers community [34].

II. Related Works

In the past, many works have employed gas sensor arrays for various applications, but E-Nose for food spoilage detection is limited. There are a few review works that analyze the uses of each gas sensor and the actual gases that are detected. The work [35] discusses the gas sensors used to identify various gases released from the rotting food items and the bacteria and fungi present in rotten food items. This also talks about some inherent limitations and problems of using gas sensors. Few works in the past also used these sensors to analyze food spoilage but concentrated primarily on the gas concentrations released during the lifetime of the food item. The work stated in [15] discusses on the design of gas sensor arrays to identify and the approximate concentration using the Fourier transform to classify the freshness of fruits. CNNs are used for this purpose to determine the concentration of gases. The proposed research builds upon the success of the previous research works and tries to improve the robustness of the sensory system and improve the accuracy of the predictions made by the ML models by introducing a more suitable loss function for the task at hand.

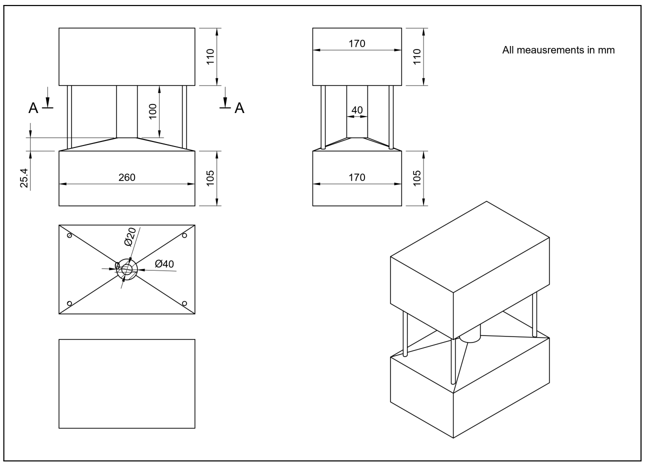

Fig. 1. Measurements and Design of the Acrylic Chamber of the E-Nose system.

III. Proposed Setup

A. Gas Sensor Chamber

Figure 1 shows the measurement of the setup, while Figure 2 presents a complete view of the entire setup which is made up of two cuboidal acrylic boxes, one at the bottom and other at the top, connected by a steel pipe at the centre. Four columns of acrylic, at the four corners, are designed to provide stability to the structure for holding the upper box. The cuboidal box at the bottom has a sloping roof to concentrate all the gas vapours at the centre and flow freely through the steel pipe. Since gases are not dense, they rise naturally to the top cuboidal box, which contains 9 gas sensors to measure the concentrations released.

Table II lists the gas sensors placed next to the opening of the steel pipe to ensure that the sensors take accurate measurements of the concentrated vapours available. The gas sensors are chosen in such a way that a variety of gases are detected. Food items tend to release a variety of hydrocarbons and other compounds when they ripe and rot. A set of sensors is employed to detect the release of typical gases including ammonia, methane, and butane from the food items. For example, bananas release ethylene gas, while milk releases gases like acetic and propionic acid. The release of specific gases is attributed to food items' composition and longevity. The outlet at the top box of the chamber ensures that the vapours escape post measurements are taken. The chamber has an Arduino Mega controller which collects readings from sensors and a Raspberry Pi 3B which captures images through the camera attached to it. The collected images serves as ground truth for the complete experiment.

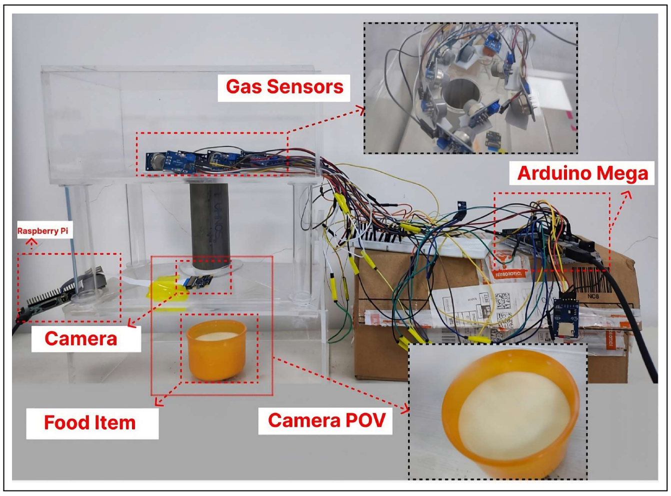

Fig. 2. Snapshot of the gas sensor chamber setup. The chamber contains multiple gas sensors (highlighted) for detecting various gases. A camera monitors the food item placed inside the chamber, providing visual feedback (ground truth) for labelling the dataset.

B. Dataset

The data from all the sensors were collected at a rate of 2 Hz for varying time duration since the expiry of food items vary over time. The approximate expiry time for the food items investigated is listed in Table I. This parameter presents a relative measure of spoilage time between different food items, which is adopted to define the custom loss function. The dataset is exhaustive, containing data points from the food item's initial fresh state to subsequent hours after its spoilage. The dataset with comprehensive sensory readings makes it suitable for developing ML models to predict the spoilage of the food item under investigation.

TABLE I

TYPICAL SPOILAGE TIME OF FOOD ITEMS.

Food item	Actual Spoilage Time(in hrs)
Milk	5
Curd	6
Banana	43
Bread	48

IV. METHODOLOGY

Data is continuously collected for individual food items by placing them in the gas sensor chamber for longer than their freshness span to acquire spoilage data as well. The overall gas sensor data collection through the chamber setup and its supply to the ANN model is illustrated in the Figure 4. Once the sensory data is collected for sufficient duration, it is fed to the trained neural network model to detect the food item under investigation, given the set of sensory measurements. This is achieved by training the model on the data, and then predicting for the sensory readings to characterize the model accuracy. The training is performed on the *PeCAR* loss function to attain better accuracy, which is further elaborated in the upcoming section.

TABLE II

SUMMARY OF SENSORS AND THEIR RESPECTIVE VOC GAS DETECTION ATTRIBUTES IN THE PROPOSED EXPERIMENTAL SETUP.

Sensor	Gas Detected
MQ2	Methane, Butane, Carbon monoxide
MQ3	Ethanol
MQ5	Liquefied Petroleum Gas(LPG)
MQ6	Liquefied Petroleum Gas(LPG), Alcohols
MQ8	Hydrogen gas
MQ9	Carbon Monoxide and Methane
MQ135	Ammonia, Benzene, Smoke, Carbon dioxide
Temperature (DS18B20)	Temperature
Humidity (DHT22)	Relative humidity

V. NEURAL NETWORK BASED PREDICTION

A. Data Preprocessing & Model

The range of collected sensory data varied, hence standard scaling was performed to normalize the data with a mean of 0 and standard deviation of 1 for better training of the Neural Network model. The model is an Artificial Neural Network (ANN) with four hidden-layers. The hidden layers have 128, 64, 32, and 16 neurons, respectively. The first hidden layer has an activation function as ReLU (Rectified Linear Unit) and then SELU (Scaled Exponential Linear Units) is used in subsequent layers. SELU was employed due to its self-normalizing properties. It helps stabilize the activations during training by maintaining a mean of 0 and standard deviation of 1. This removes the vanishing or exploding gradients problem, leading to faster and more stable convergence. The weights of the architecture were initialized using *He initialization* [36], considering it applies non-linear characteristics of activation functions in the hidden layer, thus helping in optimizing the performance of neural network. The model was further trained on the *PeCAR* loss function, which is specific to the time-series characteristic of the food experiment.

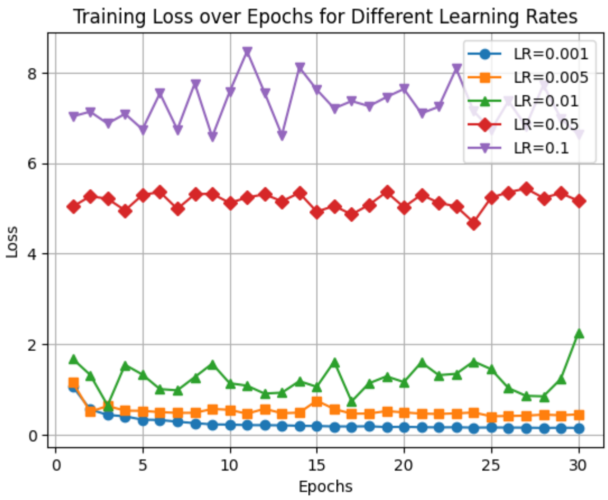

Fig. 3. Training loss over 30 epochs for different learning rates of ANN architecture with our proposed *PeCAR* loss function.

$$\frac{\sum_{i=0}^{N} \frac{|\hat{y}_i - y_i|}{\alpha + \frac{y_i}{T}}}{N} \tag{1}$$

$\hat{y}_i$: Predicted value for Observation i

y_i : Actual Observed value for Observation i

α : Regularization Parameter

T : Actual Spoilage Time of Food Item

N : Total No. of Data-points

B. PeCAR Loss Function

The PeCAR loss function expressed in Equation 1, was used to train the model since it was more appropriate to include the actual spoilage time of the food item in the loss function, which helped to penalize the error in short-term predictions more than the same amount of error in long term prediction. For instance, an absolute prediction error of 30 minutes in a food item with an actual spoilage time of 6 hours should be considered more significant than the same absolute error occurring in another food item with an actual spoilage time of 48 hours. The loss is divided by the ratio of true value of the label (y_i) to the actual spoilage time (**T**) of the item plus a small correction term ($\alpha = 0.001$) to achieve the necessary penalty for prediction error. Note that the true value is a relative term which is effectively applied to different term predictions.

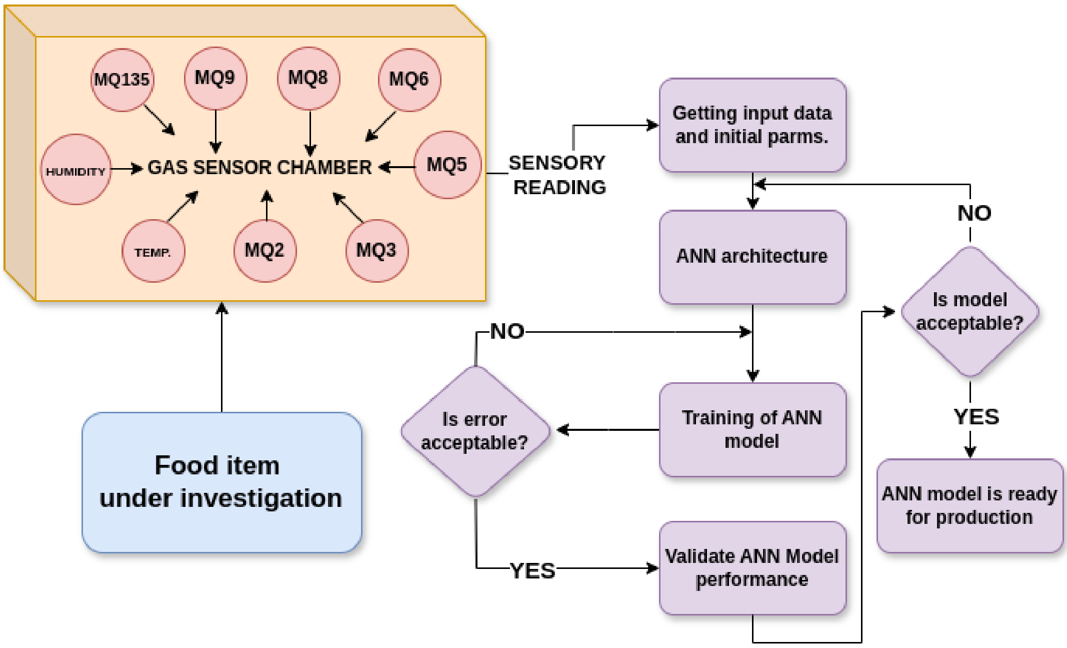

Fig. 4. Food spoilage prediction process flow with a novel Gas sensor chamber setup which is supplied to the Artificial Neural Network (ANN) model. The chamber houses various sensors (MQ135, MQ9 and others) to monitor the quantity of gases. The right side illustrates the steps in developing and validating the ANN model, including input data, ANN architecture design, model training, and performance validation.

TABLE III
COMPARISON OF LOSS ERROR FOR DIFFERENT FOOD ITEMS.

Food Item	PeCAR Loss Function		MSE Loss Function		Reduction	
	MAE (mins)	**MSE (mins^2)**	**MAE (mins)**	**MSE (mins^2)**	**MAE**	**MSE**
Milk	4.48	0.63	4.60	0.67	2.61%	5.97%
Bread	3.81	0.47	11.27	0.51	66.19%	7.84%
Banana	5.75	1.24	8.85	2.48	35.02%	50.00%
Curd	2.02	0.20	3.33	0.32	39.33%	37.5%
Average Reduction Using PeCAR Loss Function					**35.78%**	**25.32%**

VI. RESULT AND DISCUSSIONS

The architecture was trained on the proposed *PeCAR* loss function and traditional Mean-Squared-Error (MSE) loss function. The Table III presents the Mean Absolute Error (MAE) and Mean Squared Error (MSE) of the model's predictions, comparing results with and without the use of *PeCAR* loss function. The ANN model accurately predicted the spoilage time in both cases, having a mean absolute error of 11.27 minutes in the worst case when trained without the *PeCAR* loss function due to the large shelf life of the food item. When trained with the *PeCAR* loss function, the predictions are more accurate. The MAE error for this case is 3.81 minutes, which is far superior, reporting a reduction in error by 66.19%. On average, 35.78% improvement is observed in MAE and 25.32% in MSE, using *PeCAR* compared to traditional loss functions like MSE loss function in training the model. Figure 3 shows different learning rates for the *PeCAR* loss function. It is observed that the training loss is improved with the number of epochs but ceases to improve towards the end due to the over-fitting of the model. A low learning rate offers a consistent decrease in loss values over the number of epochs. Considering minimal training time and the speed of inference is fast, the model is ideal for real-time industry implementation.

VII. FUTURE RESEARCH WORK

Gas sensor arrays have immense potential in applications in Food and Health. The cost-effectiveness of E-Nose systems paired with the usefulness of Machine Learning Algorithms make them the perfect candidate for use in the above-mentioned industries. The next steps in this research work should be to build a fully integrated system that can store food items, such as refrigerators, and monitor the freshness of sections of food items to indicate any food spoilage. This integration of the storage and spoilage identification systems and analysis of the freshness period of food items can provide critical insights into the management of food wastes and effective utilization of resources.

VIII. CONCLUSION

Food wastage regulation is paramount in this era when a large population has limited food production. Hence optimal usage of food resources is essential, and the proposed system allows the food industry to gauge its supply based on the prediction of its spoilage. The proposed gas sensor chamber is a simple yet effective setup to collect gases released from the food items under investigation. The setup, along with the usage of Artificial Neural Networks, trained with a tailored loss function, is adequately equipped to predict the spoilage time of food item accurately. The proposed system serves as a decision-making tool for food usage at the industry and domestic levels. The dataset and the model are made freely available at [34] for easy adoption and further analysis by the community.

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