



Original Research Paper

A Machine Learning-Integrated Electronic Nose Framework for Real-Time Seafood Freshness Evaluation and Spoilage Prediction

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Abstract— The freshness of seafood is crucial for food safety, quality assurance and consumer confidence. Spoilage causes ill health and financial losses. The work is a portable real-time e-nose system that using ML together with volatile chemical sensor information automatically assess the freshness of seafood. The analysis is conducted using Fish Freshness Evaluation data set from a Kaggle data sets. This data set encompasses five different kinds of seafood (Cod, Crab, Tuna, Salmon and Shrimp), and sensor data over a period of time for various levels of freshness. To select the features which considerably influence the categorisation of freshness and prediction of spoiling, PPS approach is used. Several ML techniques are implemented such as AdaBoost, RF, XGBoost, DT, NB, Gradient Boosting, and KNN for classification, and DT, XGBoost, AdaBoost, and KNN for regression. The model is assessed based on accuracy, precision, recall, F1-score, RMSE, R2 score and cross validation accuracy. The whole data is preprocessed using SMOTE, StandardScaler. Later, ensemble extensions are applied on RF, DT, NB, Voting Classifier (RF + DT soft voting), and Voting Regressor. XAI techniques such as LIME, SHAP are used to explain the model behaviour. The real-time prediction is done with Flask based interface along with SQLite. The CV Accuracy of 100% for the Voting Classifier and RF, and CV MSE of 0.0106 for the Voting Regressor, demonstrate excellent precision, resilience and generalisation in the prediction of seafood freshness.

Keywords— *Electronic nose, real-time, seafood freshness, sensor, detection, machine learning.*

I. INTRODUCTION

Seafood is an essential source of animal protein and has an important role in global nutrition, contributing significantly to the provision of animal protein in the world and addressing the growing global demand for nutritious food. According to FAO, seafood consumption per capita has increased from 9.9 kg in 1960 to 20.2 kg in 2020, highlighting the increasing dependence on seafood as a food source. This increase is fuelled by population expansion, increasing affluence and more understanding of the nutritional advantages of seafood [2]. Seafood is however highly perishable and maintaining its quality during harvest, processing, transport and retail is a challenge. Quality degradation leads to consumer hazard and generates huge economic losses due to spoilage and waste [3] [4].

Popular traditional methods of freshness assessment, such as chemical, microbiological and sensory analysis, have significant practical constraints. Such methods are often slow, labor intensive, expensive and typically require sophisticated laboratory facilities, thus limiting their feasibility for large-

scale and real-time applications [5]. About 35% of the total seafood production is lost or wasted globally, mainly because of detection delay of the rotting seafood during storage and transport [6]. The traditional methods are not efficient in capturing the dynamic biochemical process associated with seafood deterioration, including the release of VOCs including ammonia and hydrogen sulphide [7]. This limitation indicates the need for detecting the initial signs of spoilage and making timely decisions in the supply chain using rapid, non-invasive and inexpensive techniques.

To fill this shortage, this work proposes an intelligent aroma-sensing system for real-time freshness evaluation of seafood. The technology focuses on the VOC emission analysis of economically important and popular fish species like the tuna, salmon, prawns, cod and crab [8]. The approach leverages electronic olfaction along with data-driven analytical methods for accurate, scalable and adaptable freshness assessment of different species. An organized seafood dataset also provides good transparency, model re-constructability and model validation [9].

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Beyond quality control, such a technique affects the entire field of food safety and supply chain optimisation and sustainability. The freshness portable evaluation in real time can help to minimise post harvest losses, make consumers safer and give information for operation decisions of growers, distributors and retailers [10]. This breakthrough is a significant step towards modernizing seafood quality control using smart sensing technologies based on data.

II. RELATED WORK

In the last few years, due to the development of the food-quality sensing technology, smart systems based on aroma have been developed for seafood and meat freshness evaluation. The idea of freshness assurance is of high importance, as the GoI has emphasized the economic importance and export potential of crab commodities, necessitating freshness assurance to prevent post-harvest losses and to maintain the competitiveness of the commodities [11]. But traditional methods, like chemical assays and visual inspection, are not yet suitable for real time deployment. This has led to an increasing interest in the use of e-nose as an alternative, rapid and non-destructive method.

The portable e-nose system named Mastersense was developed by Grassi et al. [12] for detecting the freshness of meat and fish with high sensitivity to the VOCs and the ability to be used on site. However, sensor diversity was lacking and sensitivity to the environment was a problem. Jońca et al. [13] investigated application of e-nose in waste management and identified several issues for consistency of e-nose performance: calibration complexity, cross-sensitivity and signal drift. Research has shown there is a need for adaptive sensor arrays which can operate under varying environment and compositional conditions.

Wijaya et al. [14] presented an e-nose system with ML algorithms using RF and gradient boosting, which was tuned using a hyperparameter optimization algorithm and resulted in a significant improvement in accuracy. The data set however was species-specific and homogeneous, limiting the possibility for generalisation across species. Finally, Wijaya et al. [15] expressed the importance of structured data as they limited their application to the Beef domain with regards to consistency of the data for the beef categorisation and prediction of microbiology.

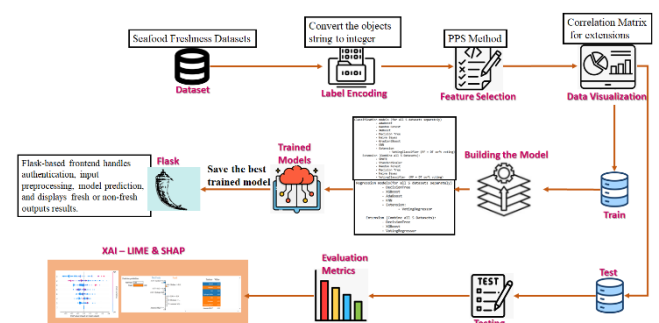
Subsequent research improved the ability to sniff out scents of various meal types. Feyzioglu and Taspinar [16] used dimensionality reduction techniques in the categorisation of beef and achieved a greater computational efficiency with no loss of accuracy. Oates et al. [17] confirmed the feasibility of using low-cost e-nose components to detect odours, but still the ability to distinguish small variations in freshness was not good. Lu et al. [18] have extended the use of e-nose to the classification of green tea quality, which could be used in other non-animal products, but at the same time has raised the concern on the scaling problem. Later, Wijaya et al. [19] suggested ensemble learning to enhance the resilience in signal processing and then aroma-based identification was optimised using ML to enhance reliability in feature extraction and classification [20].

Although there is much improvement, the systems in use today are frequently limited in datasets, are not adaptable to multiple species and have difficulties with the fluctuation of the environment altering gas sensor responses. Further, there

is a lack of frameworks that demonstrate in real time validated performance with complex mixtures of deteriorating gases. To overcome these drawbacks, the present study introduces an intelligent multi-species aroma-sensing system consisting of reconfigurable sensor arrays, powerful ensemble learning algorithms and an extensive database. This method can contribute in improving the generalisation, robustness and interpretability of the solutions developed for monitoring seafood freshness in a scalable and practical manner.

III. MATERIALS AND METHODS

A portable real-time electronic nose system is proposed with the advanced ML approaches for the seafood freshness assessment based on the volatile gas sensor outputs. The E-Nose-Based Fish Freshness Evaluation dataset from Kaggle is used for testing the system. It includes five types of seafoods (Cod, Crab, Tuna, Salmon and Shrimp) and multi-sensors signals of different freshness. The feature selection is done by the PPS technique to select the most influential features while the learning stability is increased and bias avoided by the StandardScaler normalisation and SMOTE-based class balancing. The classification module includes seven algorithms [21] such as AdaBoost, RF, XGBoost, DT, NB, Gradient Boosting, and KNN as well as a Voting Classifier (RF + DT, soft voting) ensemble to assure the reliable freshness classification. Regression [22] is done on the continuous progression of the spoiling using DT, XGBoost, AdaBoost, KNN and a Voting Regressor [23]. Furthermore, XAI, e.g., LIME and SHAP, can provide interpretability through visualisation of the sensor influence. The whole system is programmed through a web interface that is created using Flask and connected with SQLite and provides real time transparency and accuracy in determination of freshness of seafood [24].



“Fig. 1. System Architecture”

The overall scheme of the electronic nose (e-nose) for seafood freshness assessment is illustrated in Fig.1. This is based on three steps: Data collection and preprocessing from seafood data set, Feature selection using predictive metrics. Two modules, classification [25] and regression [26] are used to send the selected sensor features. The classification models, which are Gradient Boosting, AdaBoost, RF, KNN, DT, XGBoost and NB classify data in fresh or not fresh. The regression models (AdaBoost, KNN, DT and XGBoost) are used to predict the remaining freshness time. Outputs are shown thru the E-nose interface for real-time assessment.

A) Dataset Collection

This Seafood Freshness Dataset was obtained from an open access source which evaluated the freshness of five

different types of seafood (Cod, Crab, Tuna, Salmon and Shrimp) using E-nose sensor arrays. Data sets have a sample size range of 49,000 to 78,000. They are comprised of 11 features per dataset: 8 gas sensor responses, microbial load (TVC) and time based freshness indicators. The data set includes classification labels and continuous regression objectives, which makes it possible to perform dual-task learning of both freshness evaluation and spoiling prediction. The thorough coverage of real-world variability, with balanced representation of numerous types of seafood and high number of sensor inputs, makes it a perfect baseline for freshness analysis based on ML.

B) Label Encoding

Categorical class labels were coded using a Label encoding method to numerical values that could be used by ML techniques. This phase guarantees that freshness labels given as strings are transformed to integer values which makes calculation efficient and helps algorithms to deal with categorical data numerically. This method is used to create a numeric code for the target variables to minimize the ambiguity and to make it easier for the classification and regression models to learn the categorical differences for successful seafood freshness prediction.

C) Feature Selection

Feature selection was undertaken to find the most influential sensor variables to predict seafood freshness. PPS method was used. Using PPS, a quantitative estimation of the prediction capability of each feature with respect to the target is provided, which can be used to select the most informative values of gas sensors. It results in the use of only the most relevant of the features for classification and regression studies, which helps to minimise dimensionality, mitigate noise and hence improve interpretability and performance of the models.

D) Data Visualization

Correlation based approach was used to analyse interdependence between the sensor variables and interaction with the freshness indicators. Uses graphical analysis techniques, such as correlation matrices, to reduce multicollinearity and redundant sensor inputs and thus to optimize the system feature enhancing process in a more informed manner. This stage is beneficial for the validation results of feature selection, the explanation of dependency between sensors, and the selection of the best variables for improving the robustness, interpretability, and predictive reliability of the model in the context of a seafood freshness evaluation.

E) Data Balancing

We used the SMOTE to tackle the class imbalance of combined seafood datasets. It creates synthetic samples for the minority classes by leveraging interpolated similarities in the feature space to make the data distribution more uniform. The dataset balancing avoids the classification models from being biased towards the majority classes and enhances their generalisation abilities in the different freshness levels. Therefore, it can be concluded that the SMOTE can effectively improve the stability, accuracy, and fairness of the model in the seafood freshness classification.

F) Data Normalization

Data were normalised using a common scaling method as a way to scale feature distributions over multiple sensor ranges. This method transforms the input variables to a common scale, a mean of zero, and a unit standard deviation, avoiding the model being dominated by the most prominent features. Normalisation helps algorithms to converge better, notably distance based classifiers and regressors. It also allows for equal participation of each feature. Thus it increases the numerical stability, learning-efficiency and model performance for freshness prediction.

G) Train & Test

The preprocessed data was divided into 80% training and 20% testing data to fairly test the model. To check the generalisation capability of the model, the training subset was used to train the model and the testing subset was used for testing on unseen data. Stratified Split helps avoid overfitting and provides a steady level of performance as a baseline for both classification and regression problems. In this method, the representativeness of the data is preserved in both subsets, which also ensures valid assessment of the model and good prediction accuracy for various kinds of seafood.

H) Algorithms

AdaBoost is a classification and regression algorithm that combines many weak learners to create an ensemble model which is strong. For misclassified or high error cases it makes iterative adjustments to the weights, thus increasing accuracy and decreasing bias. The method is applied to the individual seafood freshness datasets and the combined dataset with the integration of the individual datasets, which increases the reliability of the forecast and decreases the overfitting. The adaptive weighting approach ensures a very good generalisation and stable performances on different feature distributions and freshness situations.

$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right) \quad (1)$$

RF, for classification and regression, constructs a multitude of trees of decisions from random samples of data and features and aggregates their results using majority voting or averaging. It is found to be performing on individual datasets and combined dataset and it is able to capture non-linear correlations between the sensory qualities [27]. This ensemble technique provides benefits in terms of robustness, scalability and accuracy, which also does not suffer from the overfitting problem and gives stable performance on the seafood freshness prediction tasks with high dimensional and diverse sensor data.

XGBoost is employed for classification and regression of individual and combined datasets to achieve maximum prediction accuracy and efficiency. Implementing gradient boosting optimisation with regularisation and pruning to minimise overfitting. To achieve high accuracy, robustness and adaptability of the model to different species of seafood and variable environmental conditions, XGB learns complicated patterns of freshness degradation in volatile sensor data by iterative reduction of residuals by gradient updates.

$$\hat{y}_i = \sigma \left(\sum_{k=1}^K f_k(x_i) \right), f_k \in F \quad (2)$$

DT for Classification and Regression on Single and Combined Data Sets. Constructs hierarchical sets of decisions which recursively divide the feature space. Each node is a feature based condition with which transparent decision making is possible. It has the advantages of interpretability and low computing complexity which is helpful to identify crucial freshness indices, to support precise categorisation and quantitative estimation of spoiling based on sensor data with well-defined decision surfaces [28].

NB is a probabilistic inference based on Bayes' theorem under conditional independence assumption, only used for the classification task on individual and combined datasets. It calculates posterior probabilities for each freshness class [29], and chooses the most probable conclusion. It is simple and efficient to compute, and can quickly be used to classify seafood quality and serve as a baseline performance model in high-dimensional and sensor-based freshness evaluation.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (3)$$

It is a ML algorithm called Gradient Boosting, and can be applied only on single item datasets for classification. It generates a set of weak DT models in an iterative manner that minimizes the prediction errors. It reduces some differentiable loss function using gradient descent, thus enhancing the accuracy of the model little by little. By learning non-linear relationships between the features sequentially, Gradient Boosting could have higher accuracy, sensitivity, and generalisation in the assessment of the freshness of seafood across different categories of sensors.

KNN, which is employed in classification and regression of individual data sets of seafood, is a prediction method that predicts values based on the closest like data points in the feature space. It is a non-parametric technique and can robustly characterise local relations of sensor features. However, its instance based method can still predict freshness levels [30] and spoiling developments in an adaptable way without having to make any assumptions about the data distribution based on distance.

Voting Classifier is designed to classify data from separate and combined datasets by making use of soft voting along with the predictions made by the RF and DT models. It merges the probability of models for better forecast stability, accuracy and robustness. The ensemble efficiently fills the gap of decision-making abilities of single models, and it helps to reduce biases in individual models and improve generalisation and consistency in the assessment of seafood freshness based on multi-sensor data.

$$\hat{y} = \operatorname{argmax}_c \left(\sum_{i=1}^n I(\hat{y}_i = c) \right) \quad (4)$$

The Voting Regressor is one regressor which is employed for the regression on single and combined datasets. It is an average of predictions of multiple base regressors (DT, XGB,

etc.). Reduces model variance and enhances stability by averaging of ensemble. This combination improves the freshness degradation prediction and makes the predicted trends smoother with consistent performance for quantitative assessment of seafood shelf-life and spoiling progression.

1) Integration of XAI & Flask Framework

It incorporates XAI frameworks to enhance transparency and interpretability of the predictions of seafood freshness. For visualisation and interpretation of the effect of individual sensor features on the model outputs we use LIME and SHAP. These explainers offer insights that are understandable to humans, revealing key gas sensor measurements that make the most impact on both classification and regression results, and thereby enhancing the confidence and correctness of model predictions.

The whole ML process is put into a web application that communicates with the user via the flask back-end. It has done so in a seamless fashion, adding the trained models, XAI visualisations and SQLite database to provide real-time seafood freshness rating. Using the interface, users can upload the sensor data, get freshness classification, view the prediction of the spoilage time and view dynamically feature-level explanations.

IV. EXPERIMENTAL RESULTS

Accuracy: The capacity of the test to discriminate between the patient and healthy patients is called accuracy. The proportion of true positive and true negative in all cases analysed is the measure of the accuracy of a test. This can be mathematically written as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

Precision: The number of correctly classified instances/samples divided by the number of classified positives. Hence, precision is calculated by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (6)$$

Recall: Recall is a measure of ML algorithms to retrieve all the relevant examples of a class. It is the ratio of correctly predicted positive observations to the all observations in actual class. It informs us that the model has learned all the examples of that class.

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

F1-Score: The F1 score is a ML metric which measures the accuracy of a ML model. Combination of precision and recall rating of a model. The accuracy measure is used to find out how many correct predictions are made by a model over the entire data set.

$$F1 \text{ Score} = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100 \quad (8)$$

Table.1 Performance Evaluation–Classification on Combined Data

ML Model	Accuracy	Precision	Recall	F1-Score	CV-Accuracy
RF	1.000	1.000	0.999	1.000	1.000
DT	0.999	0.999	0.999	0.999	0.999

NB	0.692	0.891	0.437	0.586	0.694
Voting	0.999	0.999	0.999	0.999	1.000

The results of classification are given in Table 1. Clearly the RF and Voting models performed well when compared to the other models, showing a remarkable accuracy and reliability.

Table.2 Performance Evaluation–Regression on Combined Data

ML Model	RMSE	R ² -Score	CV MSE
DT	0.0917	0.9997	0.0155
XGB	0.1211	0.9995	0.0148
Voting Regressor	0.0771	0.9998	0.0106

The results of the regression are summarised in Table 2. Voting Regressor has the top R2 score and the lowest RMSE value and is the best model of prediction accuracy.

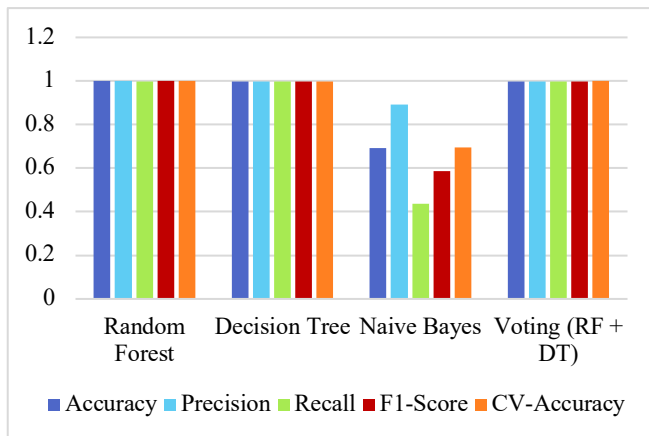


Fig.2 Comparison Graph for Classification on Combined Data

Comparative classification performance is shown as Fig. 2. RF and Voting classifiers consistently perform well and are stable with regard to accuracy for the combined seafood datasets.

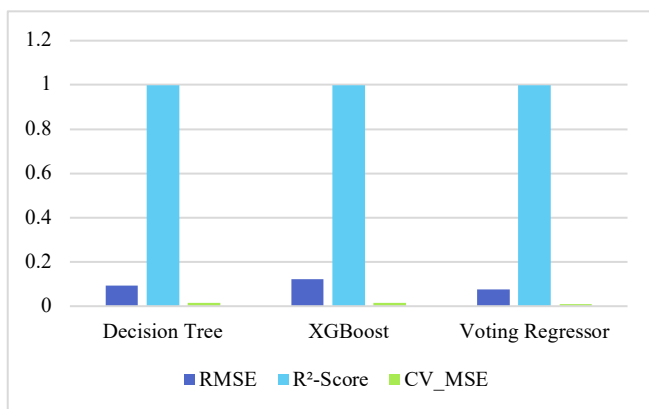


Fig.3 Comparison Graph for Regression on Combined Data

It illustrates the comparison of regression performance and shows that the Voting Regressor model is better than others regression algorithms in terms of prediction accuracy and error of predictions as shown in Fig.3.

Fig.4 Enter Sensor Data – 1

The user interface is shown in figure 4 in which user enters the sensor data for the prediction of the appropriate seafood freshness level.

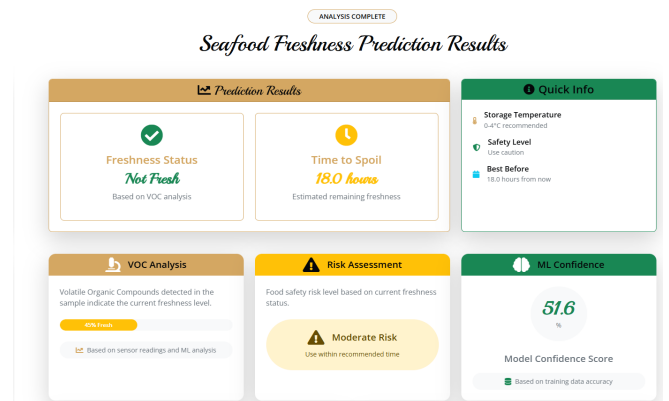


Fig.5 Prediction Results – 1

Figure Figure 5 shows the output interface with the anticipated freshness state of the seafood as "Not Fresh" and the predicted time for the deterioration is 18.0 hours.

Fig.6 Enter Sensor Data – 2

Fig.6 illustrates the user interface for the input values from the sensors to determine the exact condition and prediction of the seafood freshness.

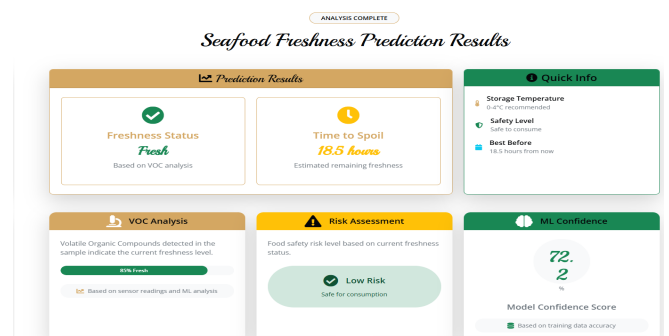


Fig.7 Prediction Results – 2

The output interface is depicted in Fig.7 where the model confidence is high and the seafood freshness is predicted as “Fresh” with an estimated TTS of 18.5 hours.

V. CONCLUSION

In summary, the integrated portable electronic nose, real-time analysis and ML system will prove to be an efficient and smart tool for seafood freshness assessment through the detection of volatile compounds in the sensors. By applying the E-Nose-Based Fish Freshness Evaluation dataset from Kaggle including Cod, Crab, Tuna, Salmon and Shrimp categories to the system, the amount of freshness can be successfully identified and predicted. By using the PPS technique in feature selection, it enables to increase the relevance of the input attributes, leading to better model understandability and performance. ML algorithms for classification and regression are: AdaBoost, RF, XGBoost, DT, NB, Gradient Boosting and KNN. Accuracies, Precision, Recall, F1-score, RMSE, R 2 score and cross validation accuracy were used for performance evaluation. To get the better generalisation and reliability all data sets were combined and SMOTE and StandardScaler approaches were applied and ensemble models like RF, DT, NB, Voting Classifier (RF + DT soft voting) and Voting Regressor (RF + DT soft voting + NB) were trained with this combined data sets. XAI methods, like LIME and SHAP, were used to interpret how much features contributed to the model decisions, and a Flask user interface with a SQLite database gave a real-time prediction and visualisation. The classification performance of Voting Classifier and RF was the best one (CV Accuracy = 100%) and the regression accuracy of the Voting Regressor was also extremely high (CV MSE = 0.0106), which showed the robustness, scalability and practicability of the system in the seafood quality monitoring.

Future Scope is to build better Seafood Freshness Rating framework with integration of advanced DL and fusion of various sensors such as Electronic nose, Electronic tongue and Electronic vision system for complete analysis. IoT enabled smart devices can be integrated to enable ongoing tracking of freshness across the supply chain. Cloud-based deployment and edge computing will enable the large scale seafood industry to grow in real-time and infer faster. Furthermore, blockchain can provide greater transparency in seafood supply chains, ensuring traceability and data integrity. Future works can explore adaptive learning models that continuously update themselves, incorporating additional sensor data for robust and intelligent freshness prediction.

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