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Seafood Quality Assessment with Explainable Artificial Intelligence

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***Abstract*—The Philippines' marine ecosystem supports a thriving fisheries industry, integral to national food security and economic growth. However, the perishable nature of seafood poses significant challenges in quality assurance, leading to food safety risks and economic losses. Traditional methods for assessing seafood quality, including sensory evaluation, chemical testing, and microbial analysis, are often destructive, labor-intensive, time-consuming, and dependent on specialized equipment and personnel and as such, impractical for large-scale applications. This study investigated the use of machine learning models as an electronic nose tool to classify seafood sample as either accept or reject. The study examined five machine learning models: Random Forest, k-Nearest Neighbors, Naïve Bayes, Linear Discriminant Analysis, and Quadratic Discriminant Analysis. Results showed that the random forest classifier outperformed the other models, generating a 100% accuracy, precision, recall, and F1-score. The study also incorporated Explainable Artificial Intelligence tools to enhance model interpretability. The excellent accuracy, recall and precision indicated the feasibility of using machine learning as a simplified tool to assess seafood quality reliably. Likewise, the study also indicated the effectiveness of harnessing machine learning as a supplementary tool in preventing foodborne illnesses addressing public apprehensions for health. Hence, electronic nose approach using machine learning techniques can pave the way for an expedient decision-making, reducing food wastage, protecting public health, and reinforce consumer trust in seafood products.**

Keywords—Seafood quality assessment, machine learning, electronic nose (e-nose), gas sensors

I. INTRODUCTION

The Philippine waters play a vital role in the nation's fisheries industry, which serves as a cornerstone for both economic growth and food security. Seafood, including fish, mollusks, and crustaceans, form a dietary staple for millions of Filipinos. In addition to its nutritional significance, the seafood industry supports livelihoods in coastal communities and contributes substantially to international trade [1]. The industry is also an indispensable source of foreign currency for many coastal countries where the trade activities of fisheries products account for a significant share of the Gross Domestic Product, emphasizing its critical role in national economic development [2].

Despite its importance, seafood is highly perishable due to its biochemical composition, which makes it susceptible to rapid spoilage. Factors such as microbial growth, enzymatic activity, and environmental exposure can compromise its quality, leading to food safety risks and economic losses [3]. In recent years, attention has been focused on seafood freshness to guarantee consumer safety. Traditional methods for assessing seafood quality, including sensory evaluation, chemical testing, and microbial analysis, are often destructive, labor-intensive, time-consuming, and dependent on specialized equipment and personnel, limiting their practicality for real-time or large-scale applications [4][5]. The growing global demand for fresh and safe seafood has intensified the need for improved quality monitoring systems. Technological advancements, particularly in machine learning (ML) and electronic sensors, offer promising solutions. To address these concerns, this study aims to explore the potential of ML models to classify seafood as either accept or reject based on quality. Leveraging data from an existing study on an electronic nose (e-nose), which uses gas sensors to detect spoilage-related compounds, this research study aims to develop a non-invasive model monitoring seafood quality assessment. This approach not only improves efficiency but also ensures food safety and reduces economic losses in the fisheries industry. Additionally, it proposes that the application of Explainable Artificial Intelligence (XAI) tools can enhance model interpretability and provide transparency in decision-making.

The significance of this research lies in its potential to bridge the gap between traditional seafood quality monitoring techniques and modern technological advancements. For consumers, the study ensures food safety and quality seafood. For food safety authorities, it offers streamlined quality control processes that can aid in regulatory compliance. Producers and distributors benefit from reduced spoilage and economic losses, while the transparency provided by XAI fosters trust in ML systems. For researchers, the study provides valuable insights into optimizing machine learning applications in food quality assessment and monitoring. Ultimately, this research seeks to revolutionize the seafood industry's approach to quality assessment, promoting food safety, economic sustainability, and technological innovation.

The outline of this study is depicted as follows: an introduction section is succeeded by a relevant literature review section emphasizing the current research studies regarding the use of ML algorithms on assessing seafood quality. The next section lays out the details of the methodology including the specification of the dataset, the preprocessing steps, and the ML algorithms harnessed in the study. The main findings of the study and its associated in-depth analysis are expounded in the Findings and Analysis section. Ultimately, the study concludes with a summary of the research and recommendations for future research work.

II. Relevant Literature

In a review by Rather et al., authors explored the utility of artificial intelligence (AI) procedures to advance the aquaculture industry and narrow the gap between food supply and demand [6]. AI boosts aquaculture efficiency, augments food industry while maximizing resource utilization. Rabehi et al., made a review of potential utility of an electronic nose (e-nose) in various applications including food analysis [7]. E-nose has been useful in assessing volatile organic compounds released by a variety of food products which can serve as a basis for the assessment of food freshness and safety. In [8], authors conducted a review of e-nose application in wine industry where olfactory sensory analysis demonstrated a significant role in assessing wine quality. Researchers firmly believe that this technique shall eventually replacing human panelists and thus transforming the entire quality control assessment in this industry. In the study by Makarichian et al., e-nose applied to garlic showed that the changes in the aroma can serve as a determining factor in the quality control of processed products together with the type of processing as well as the presence of fungal infection using a variety of ML algorithms [9].

In the assessment of seafood quality, e-nose has also played an important role. In [10], researchers employed various ML based models (Naïve Bayes, discriminant analysis, ensemble classifiers) to assess seafood quality after a 30-hour storage period under constant room temperature at 25°C and classify the samples as "accept" or "reject," conforming to rigorous quality measures. Authors concluded that these ML models can lead the way for expedient decision-making, lessening food wastage, and reinforce consumer confidence in seafood products. In a review made by Saeed et al., authors analyzed gas sensors in fish quality monitoring with the help of machine learning and concluded that ML can be a formidable supporting instrument for quality management [5]. In [11], researchers utilized machine learning (support vector machine, logistic regression, random forest, artificial neural networks) and deep learning via transfer learning (MobileNetV2, Xception, VGG16) to assess fish freshness. Their models generated a 100% success rate, emphasizing the utility of ML in averting contaminated food-related illnesses and maintaining the palatability and quality of fish products. Sanchez et al., evaluated fish freshness through e-nose by examining its odor using rapid and portable equipment as the olfactory pattern directly impacts with the growth of aerobic mesophilic microorganisms indicating its degradation in the samples [12]. Authors used Principal Component Analysis (PCA) and Partial Least Squares Discriminant Analysis (PLSDA) and were effective in distinguishing 95 % of the samples. Finally, Buratti et al., created an uncomplicated method using e-nose to examine five fish products freshness (cuttlefish, red mullet, Atlantic cod, Atlantic mackerel, and mantis shrimp [13]. Using principal component analysis, e-nose warning and control limits were generated based on odor strength.

In summary, while current research strategies have made noteworthy contributions to quality assessment using e-nose approach in various applications, very few research studies have been published on predicting seafood quality. Additionally, the utility of incorporating XAI tools to examine seafood quality remain largely unexplored. As such, this study addresses this research gap in this field.

III. Materials and Methods

The study follows a structured pipeline comprising several stages outlined in Figure 1. The dataset was extracted from the IEEE DataPort platform and composed of four sheets. It was then loaded into a unified data frame to combine those data. Pre-processing steps included checking missing values, data types, and negative values, and removal of duplicates. Exploratory Data Analysis (EDA) was used to understand and further prepare the dataset for analysis. The categorical features were converted into numeric ones and numerical features were standardized. Synthetic Minority Oversampling Technique (SMOTE) was applied to address the mild imbalance. XAI was incorporated to unveil the reasoning behind the classification results of the ML models.

A. *Dataset Specification*

The study utilized the Electronic Nose Dataset for Seafood Quality Assessment from the IEEE DataPort Repository [14]. The dataset included four seafood samples: nemipterus nematophorus, octopus, cuttlefish, and squid. There were

108,000 instances with 7 features and two labels, the Total Viable Count (TVC) and Label as shown in Table I. TVC represented the continuous label of microbial population which is determined using the Food Spoilage and Safety Predictor software and Label for seafood quality indicator, either accept or reject. The seafood was labeled "accept" if the TVC is less than 4.3 and "reject", otherwise. The dataset encompassed numerical variables such as Duration, MQ136, MQ137, MQ5, MQ8, Humidity, Temperature, TVC, and a categorical variable Label, which was used as the target variable. There is mild data imbalance with 69.46% for reject and 30.54% for accept.

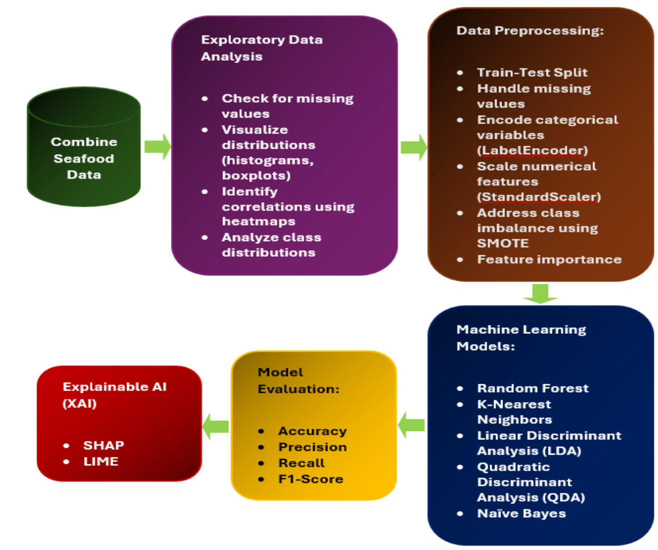

Fig. 1. Machine Learning Pipeline for Seafood Quality Assessment Study

TABLE I. SEAFOOD QUALITY DATASET

Attributes	Description
Duration	Sample Shelf Life (hour)
MQ136	Gas sensor with hydrogen sulfide selectivity
MQ137	Gas sensor with ammonia selectivity
MQ5	Gas sensor with selectivity for LPG, natural gas, and town gas
MQ8	Gas sensor with hydrogen selectivity
Humidity	Humidity level in the sensor box
Temperature	Temperature in the sensor box
TVC	Microbial population (log (cfu/g)) as continuous label
Label	Seafood class ("accept" or "reject") as discrete label

B. *Preprocessing Measures*

Data preparation for machine learning focused on data cleaning and pre-processing methods which included checking for missing values, data types, inconsistent values such as negative values and removal of duplicate records. The dataset was combined into a unified data frame. The Pipeline library was used to process the data in two main ways: the categorical encoding for the Label (accept: 0, reject: 1) variable using LabelEncoder to avoid misinterpretation, and the data was standardized using the StandardScaler library for uniformity across the dataset. The dataset was divided into training and testing sets, using the 75:25 ratio.

EDA was conducted using ProfileReport, which includes descriptive statistics, variable interactions, and a correlation matrix highlighting relationships between features and the target variable (Label). The heatmap as seen in Fig 2. revealed that duration, humidity, and MQ137 sensor readings were key predictors of the target variable. Duration measures time-related changes, with the time elapsed being critical for predicting the label. Longer durations are likely associated with greater changes in the target outcome. Humidity reflects environmental conditions that affect spoilage, as moisture levels significantly influence the outcome. Higher humidity can accelerate processes such as microbial growth or chemical degradation. MQ137 detects chemical byproducts of spoilage. For instance, during seafood spoilage, the breakdown of proteins releases volatile compounds, which MQ137 measures, making it a strong predictor for the label.

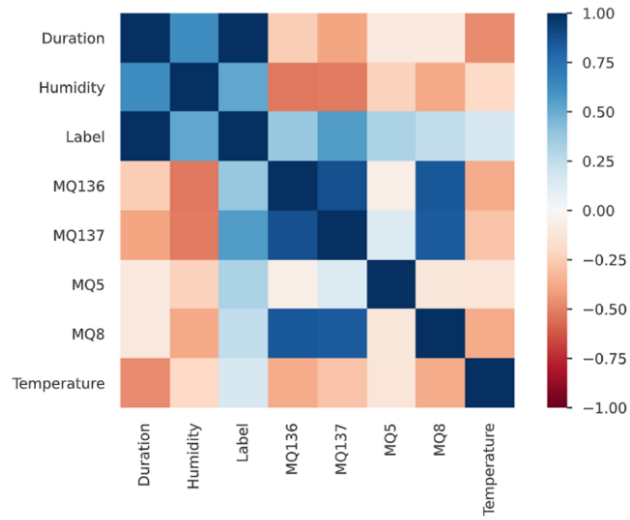

Fig. 2. Machine Learning Pipeline for Seafood Quality Assessment Study

C. *Addressing Class Imbalance*

The training dataset had a mild class imbalance with 70.49% for reject and 29.51% for accept. To handle the mild imbalance, the study used the SMOTE, which balances the dataset by creating synthetic examples that add more data points for the minority class by interpolating feature values between randomly selected minority class instances and one of their k-nearest neighbors [15]. This technique is used to enhance model learning and diminishing bias towards the majority class, ultimately upgrading the model's capability to recognize patterns between classes.

D. *Machine Learning Algorithms and XAI*

This study employed five machine learning models specifically k-Nearest Neighbors (kNN), Naïve Bayes (NB), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and random forest (RF), all with 5-fold cross-validation to classify the seafood quality as accepted or rejected. The study used Python and its libraries including pandas, numpy, seaborn, matplotlib, and scikit-learn for analysis. The performance indices computed included accuracy, precision, recall, and F1-score for classification tasks, with Accuracy as the main metric used in comparison of the models to determine the best model in the seafood quality dataset. XAI tools using SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) were integrated in the best model.

IV. Findings and Analysis

The performance indices for the various ML Models are shown in Table II. All models performed well in predicting reject samples with all indices ranging from 90.81 to 100.00. The best performing model was generated by RF obtaining 100.00 on all indices. Following very closely were kNN and QDA yielding excellent indices. These three models (RF, kNN and QDA) have yielded excellent accuracy, recall and precision indicating the feasibility of employing these tools in predicting seafood quality. The very high recall (98.90 to 100.00) suggests that these models reign supreme at recognizing all relevant "reject" seafood instances, minimizing false negatives (falsely accept a "reject" seafood sample). This is very important as missing a positive case (a reject seafood sample classified as accept seafood sample) has dire consequences ultimately leading to food-borne illnesses. Likewise, these three models have garnered very high precision (98.52 to 100.00) indicative of their accuracy when predicting a positive outcome, thus minimizing false positives (an "accepted" seafood sample classified as a "reject" seafood sample) leading to minimum food wastage.

TABLE II. Performance Indices for ML Models

ML Models	Accuracy	Precision	Recall	F1-Score
kNN	99.99	100.00	99.99	99.99
NB	95.35	100.00	93.40	96.59
LDA	93.56	100.00	90.81	95.18
RF	100.00	100.00	100.00	100.00
QDA	98.18	98.52	98.90	98.71

The best performing model, RF, was chosen to be utilized for SHAP and LIME. The SHAP explainer was used to determine the global importance of the features of the RF classifier. The global importance of each feature was represented by the mean absolute value for that attribute over all the given instances. As seen in Fig. 3, the topmost important feature in the RF classifier were duration and humidity. Fig. 4 illustrates the beeswarm plot for RF classifier. The lower duration values tend to negatively impact the output as shown with the negative SHAP values. This means pushing the model toward the negative ("accept seafood sample") class. On the other hand, the middle to high-duration values tend to positively impact the output with the positive SHAP values. This means pushing the model toward the positive ("reject seafood sample") class.

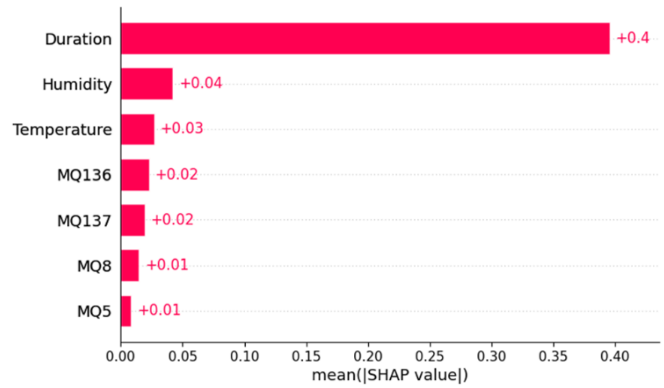

Fig. 3. SHAP global feature importance plot for RF classifier

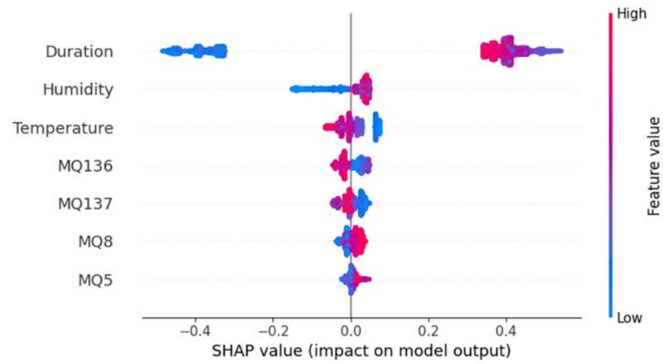

Fig. 4. Beeswarm plot for RF classifier

Fig. 5 shows an example LIME instance on a rejected seafood sample observation from the test set using the RF classifier. The selected instance was rejected by the classifier with 100% probability. As evidenced by the graph, duration had the highest importance in rejecting the seafood sample, since the shelf life of the selected sample was between -0.88 and 0.01. Likewise, humidity leans more on rejecting the instance since the seafood sample had a humidity between 0.02 and 0.80.

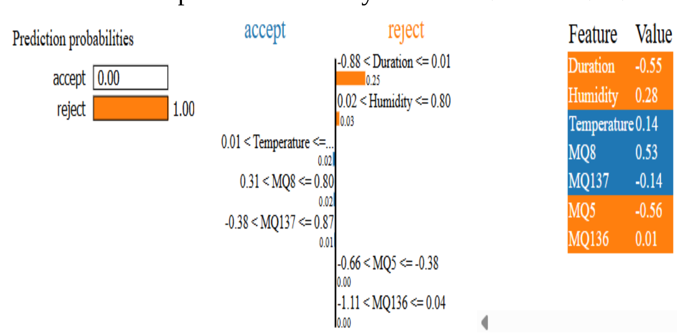

Fig. 5. A LIME output with RF classifier on a rejected seafood sample

On the other hand in Fig. 6, an example LIME output of an accepted seafood sample from the test set using the RF classifier is illustrated. The RF classifier accepted the seafood sample with a 100% probability. Likewise, it is evident that duration contributed the most to the prediction by a large margin since its duration is less than -0.88. Humidity also leans on accepting the instance because its value is less than -0.76.

Seafood Freshness is a crucial factor in evaluating the quality of seafood products. It is therefore imperative to employ a simplified and rapid analytical method tool such as an e-nose tool for appraising the acceptability of seafood products. In this study, RF model generated excellent performance indices with 100% accuracy, recall and precision which highlights the feasibility of a simplified tool to assess seafood quality. This also indicates the effectiveness of harnessing machine learning as a supplementary tool in preventing foodborne illnesses addressing public apprehensions for health. The added transparency and enhanced interpretability brought about by incorporating XAI in seafood quality assessment leads to development of trust in the use of machine learning as a predictive tool for seafood products safety indicators. The results derived from these machine learning techniques can pave the way for an expedient decision-making, reducing food wastage, protecting public health, and reinforce consumer trust in seafood products.

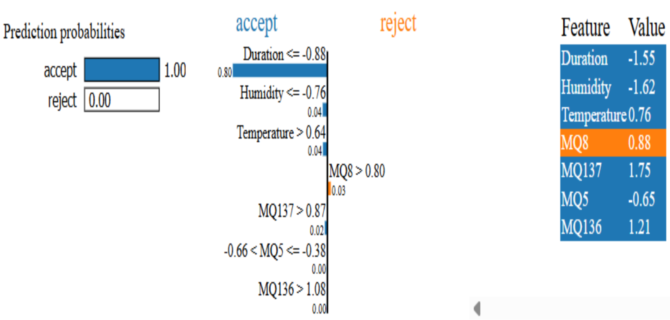

Fig. 6. A LIME output with RF classifier on accepted seafood sample

V. Summary and Recommendations

Assessing seafood quality is critical to ensure food safety, maintain consumer confidence, and reduce economic losses in the seafood industry. In this study, machine learning was utilized to develop a reliable and scalable alternative method for seafood quality assessment. Five machine learning classifiers were employed on a publicly available electronic nose dataset for seafood quality assessment. LIME and SHAP were implemented on the top-performing model configuration for explainability. Generally, all machine learning models performed well with more than 90% scores across performance indices. Random forest was the top-performing model with 100% accuracy, precision, recall, and F1-score illustrating its feasibility to assess seafood quality as well as indicating the effectiveness of harnessing machine learning as a supplementary tool in preventing foodborne illnesses addressing public apprehensions for health. In addition, SHAP results show that the most important features of the RF included duration or shelf life and humidity. Based on these findings, it supports the feasibility of harnessing machine learning in developing a highly reliable and interpretable tool for assessing seafood quality. The outcomes of this study derived from machine learning can pave the way for an expedient decision-making, reducing food wastage, protecting public health, and reinforce consumer trust in seafood products.

For future researchers, the use of different datasets that include a wider variety of seafood types and other environmental conditions should be considered. Furthermore, integrating the top-performing model with explainable AI into a live monitoring system could highlight its potential in large-scale applications.

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