AI-BASED CLASSIFICATION OF THE MEAT FRESHNESS USING CANTILEVER SENSOR DATA

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ABSTRACT

A novel approach for determining the freshness of fish and meat involves the use of cantilever sensors, which analyse the concentration of cadaverine on the surface. The cantilever sensor is excited with a voltage sweep around its resonance frequency and the frequency shift due to deposits on the sensor is measured. In this work, we present a draft of a distributed system and compare AI-based analysis of the stored cantilever sensor data with raw sweep data without preprocessing. We defined a meat quality index (mqi) range for the measurements, which depends on the frequency shift between a reference and cadaverine measurement. We investigated, that the best practice to predict the mqi value is to use classical machine learning models such as Random Forest, LightGBM, XGBoost where Random Forest performs best with an val. / test accuracy of up to 72.01 % / 71.67 %, precision of 72.37 % / 72.53 %, recall of 72.01 % / 71.67 % and F1-Score of 72.06 % / 71.72 %.

KEYWORDS

Cantilever, Machine Learning, Database, Distributed Systems, Sustainability

1. INTRODUCTION

Detecting the freshness of meat and subsequently estimating its shelf life is a complex issue, as the aging of meat during storage depends on intricate processes within the muscle tissue [1]. In traditional sensory tests, a panel of experts examines the odor of the meat, which is more sensitive compared to other chemical methods. The results are generated very fast but reflects the subjective actual perception of the human nose and remains expensive [2] [3]. Further more objective and reproduceable high-performance liquid chromatography (HLPC) and microbiological bacterial count can be applied for freshness detection [4] [5]. Using these methods is very time consuming and it can take several hours to complete the analysis [6] [7]. Another approach is the detection of meat freshness through advanced IoT sensors, such as environmental sensors, cameras, and electrochemical sensors [8]. The advantage of these sensors is that they are small, energy-efficient, and inexpensive compared with traditional analytical devices. One special sensor for this method is the use of cadaverine-selective cantilever sensors based on cyclam derivatives [9]. During the decomposition process, cadaverine (1,5-diaminopentane) is increasingly produced over time, which alters the resonance frequency of the sensor and thus provides information about the freshness of the meat. The key challenge is the inherent variability between sensor batches and measurement conditions, which affects the reliable identification of resonance frequencies, as well as the fact that the recorded sensor data do not directly measure cadaverine concentration but only correlate with its magnitude. In conjunction with intelligent algorithmic analysis, we aim to assess the shelf life of meat with greater precision. Our contribution is the AI based analysis and prediction

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of the meat quality by using the raw cantilever measurements from an existing database with cantilever measurements. By inferring over the entire measurement history, the aim is to determine food quality without the need for extensive feature engineering, thereby avoiding batch-related inconsistencies and invalid measurements. Therefore, we focus on the following research objectives:

- AI-classification of the meat quality index with cantilever sensor data.
- Comparison of AI-models for cantilever sensor data analysis.
- Database filtering of cantilever sensor data for analysis.
- Vector store for cantilever sensor data processing and analysis

2. Materials And Methods

The use of sensors and algorithms to detect the freshness of meat is an important research topic [4]. Zhang et.al. investigated a freshness detection via electrochromic film layers. In their study they recorded fresh meat on the first day of storage and spoiled meat at the seventh day of storage. In summary they stimulated the film layers with a DC voltage and were able to noticed a difference in the colorization of the film due to change of PH concentration between fresh and spoiled meat [10]. Liu et.al. developed a metal-oxide-semiconductor (MOX) sensor based electronic nose system with 7 sensors where they used hidden markov models (HMM) to evaluate the freshness of fish, beef and chicken. In their studies they were able to reach a sensitivity of up to $99.35\ \% \pm 0.27\ \%$ and specificity up to $99.82\ \% \pm 0.48\ \%$ for meet freshness level detection [11]. Grassi et al. investigated how a low-cost system based on MOX sensors can determine the spoilage of different types of meat. Using a Principal Components Analysis (PCA), four out of ten sensors were selected, which showed particular sensitivity to volatile organic compounds (VOCs), nitrogen dioxide (NO2), ozone (O3), carbon monoxide (CO), hydrogen (H2) and ethanol (C2H5OH). Subsequently, the freshness classes fresh, acceptable, and spoiled were classified using K-NN with a sensitivity of $\geq 83\ \%$ and specificity of $\geq 83\ \%$ [12].

In our classifications of meat freshness, we use former collected data of microcantilever sensors stored in an SQL Database from various samples such as beef, pork, chicken, fish and pure cadaverine. The microcantilever sensor has a thin, beam-like structure which is oscillating with its resonance frequency (f_0) when excited by a signal source. The mass (m) of the coating and cyclam-based binder, in addition to the spring constant (k), defines the resonance frequency (f_0) of the sensor. When the sensor is attached to the meat samples, the cadaverine molecules from the meat adhere onto the binder and the effective mass of the cantilever increases by Δm, resulting in a decrease in the resonance frequency ($f_0{}'$) of the cantilever [13]:

$$f_0 = \frac{1}{2\pi}\sqrt{\frac{k}{m}}$$

$$f_0' = \frac{1}{2\pi}\sqrt{\frac{k}{m + \Delta m}}$$

$$\Delta f = f_0 - f_0' = \frac{1}{2\pi}\left(\sqrt{\frac{k}{m}} - \sqrt{\frac{k}{m + \Delta m}}\right)$$

Lawrence et. al. used cantilever sensors to detect cadaverine in meat samples per long term measurements. They conducted tests on a functionalized piezoelectric microcantilever sensor by exposing it to cadaverine concentrations significantly above the nominal level found in meat and fish [14] [15] [16] [17]. The experiments revealed concentration dependent response mechanisms arising from the interaction of cadaverine with the binder, enabling identification of the upper analyte concentration limit for stable sensor performance. At the nominal concentration of $33\,\frac{mg}{kg}$, the sensor shows a linear response for up to $93.01\ minutes$ [15]. Further studies detect cadaverine in meat samples per long term cantilever measurements and reveal, that the variance of the sensor's frequency tolerance is around $80\ Hz$ by applying a controlled binder position [17].

For data processing we deployed a small local ai-pipeline using Docker, consisting of an SQL database and a Qdrant vector store. Interfaces and functions were executed on a notebook using Python scripts (Figure 1).

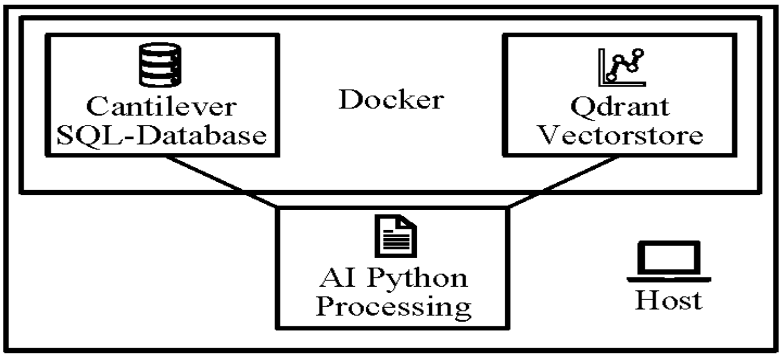

Figure 1: Block diagram of the ai-pipeline.

The measurements using the cantilever sensor were performed over a frequency range calibrated as a sweep around its resonance frequency. The recording procedure begins with a base sweep taken as a reference while the device is positioned away from the meat sample. The device is then placed on the sample and draws air from the sample into the system for a short period. After this exposure phase, the device is removed from the meat and a second sweep is recorded. The resulting data set contains the identification number of the measurement (id_measurement), the device (id_device), the frequency sweep recorded before the sensor was placed on the meat (sweep_base_id), and the frequency sweep recorded after exposure (sweep_after_exposure_id).

The start frequency (start_frequence) and its increment (frequence_increment) are included to determine the frequency properties. The datasets generated are described by the phase (phase_angle) (φ), impedance (impedance) (Z) and the meat quality index (mqi) as label (meat_quality_index). To prepare the model training process, we first extracted the existing meat quality index from the database and defined a range with seven classes from them:
$[1:\ \leq\ 0, 2: 1-5, 3: 6-10, 4: 11-15, 5: 16-20, 6: 21-30, 7:\ \geq\ 30]$.

The mqi ranges were estimated empirically regarding previous measurements and are simulating freshness of meat where the lowest values indicating the lowest spoilage. Regarding to the mqi values we exported the data from the existing SQL database. Each vector contains 110 complex impedance measurements from both a reference measurement ($Z_{reference}$, $\varphi_{reference}$) and a cadaverine measurement ($Z_{cadaverine}$, $\varphi_{cadaverine}$) resulting in an input shape of $110\ x\ 4$ (Figure 2).

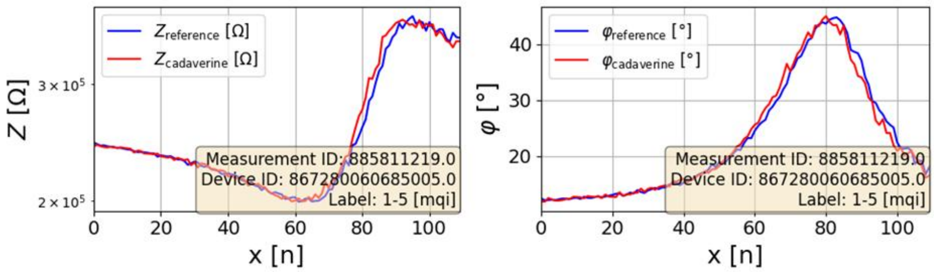

Figure 2: Exemplary cantilever measurements of ($Z_{reference}$, $Z_{cadaverine}$, $\varphi_{reference}$, $\varphi_{cadaverine}$) with [mqi] 1-5.

All vectors that do not match the data format and shape are filtered out. Furthermore, a vector with phase jumps in a sweep ϕ is added to the labels as [8: outlier], which is defined as two consecutive measurement values φ_x differ by more than ± 30 °, as such deviations would contradict the normal step response of the sensor. Valid vectors are defined by the following Formular:

$$\phi_{valid} = \{\varphi_x \| \varphi_x - \varphi_{x-1}| \leq \varphi_{threshold}\}\ where\ \varphi_{threshold} = 30\ °$$

In addition, the sweep ϕ is examined to determine whether a resonance frequency is present. To assess this, the vectors are checked for:

$$\Delta\varphi = \hat{\varphi} - \bar{\varphi} > 15\ ° \ \leftrightarrow \phi\ is\ valid$$

If this condition is not met the vector is added as label [9: no f_0]. The resulting training set consists of 1952 vectors and 9 labels with 4 input features [$Z_{reference}$, $Z_{cadaverine}$, $\varphi_{reference}$, $\varphi_{cadaverine}$]. Every feature representing a frequency sweep with 110 datapoints resulting in input size of 440 points. The number of vectors per label is shown in Table 1.

Label		Number of vectors per label [n]
1: ≤ 0	[mqi]	265
2: $1-5$	[mqi]	300
3: $6-10$	[mqi]	271
4: $11-15$	[mqi]	138
5: $16-20$	[mqi]	90
6: $21-30$	[mqi]	108
7: > 30	[mqi]	180
8: $outliers$	[mqi]	300
9: $no\ f_0$	[mqi]	300

Table 1: Number of vectors with features per label.

3. RESULTS

For clustering we use t-SNE with l2-norm metric, a perplexity of 50 and 1000 clustering iterations (Figure 3). The clustering shows a tendency of grouping nearby mqi values. The overlapping areas between the classes indicate that the sensor data has some similarities for adjacent mqi values, which is expected due to the gradual nature of meat spoilage. It also shows, that the classes can be discriminated well enough to train classification models on them. Outliers ([mqi] outliers) and measurements with a missing resonance frequency (no f_0) tend to form a well-separated cluster away from valid datasets in the feature space.

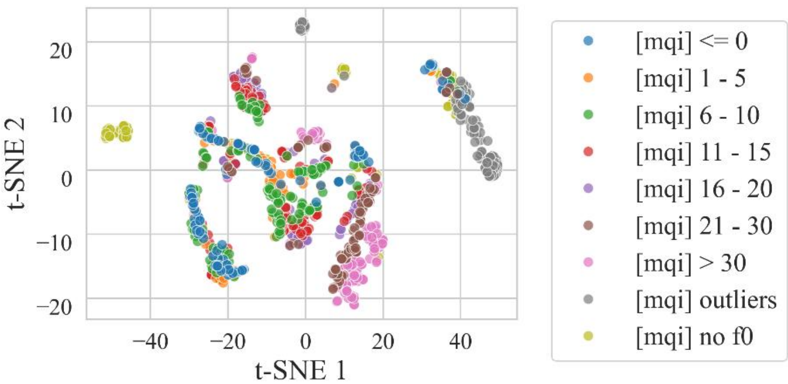

Figure 3: Results of the vector store clustering for cantilever sensor data.

Due to the characteristics of the signals, we focus on the use of gradients and regression models Decision Tree, Random Forest, LightGBM, XGBoost and Long Short-Term Memory (LSTM) to evaluate the cantilever measurements. We trained and evaluated the dataset using a stratified 70/15/15 train-validation-test-split. The performance of each model was assessed using accuracy, precision, recall, and F1-score metrics. The Random Forest model outperformed the others with an val. / test-accuracy of (72.01 % / 71.67 %), followed closely by LightGBM (72.01 % / 70.31 %) and XGBoost (71.67 % / 69.97 %). The Decision Tree and LSTM models achieved the lowest accuracies with (63.14 % / 61.09 %) and (49.83 % / 53.58 %), respectively (Table 2).

Model	Type	Accuracy [%] val. / test	Precision [%] val. / test	Recall [%] val. / test	F1-Score [%] val. / test
Random Forest	ML	72.01 / 71.67	72.37 / 72.53	72.01 / 71.67	72.06 / 71.72
LightGBM	ML	72.01 / 70.31	72.40 / 71.17	72.01 / 70.31	72.14 / 70.27
XGBoost	ML	71.67 / 69.97	72.02 / 70.96	71.67 / 69.97	71.64 / 70.34
Decision Tree	ML	63.14 / 61.09	65.03 / 63.12	63.14 / 61.09	63.37 / 61.93
LSTM	DL	49.83 / 53.58	58.14 / 64.61	49.83 / 53.58	45.96 / 48.62

Table 2: Vector classification model performance comparison using a stratified 70/15/15 train-validation-test-split.

The confusion matrix for the best-performing Random Forest model indicates that most misclassifications occur between adjacent mqi classes (Figure 4). Invalid datasets including phase jumps (outliers [mqi]) and measurements without a detectable resonance frequency (no f_0 [mqi]) can be identified with an accuracy of up to 93 %, indicating a robust capability for error detection.

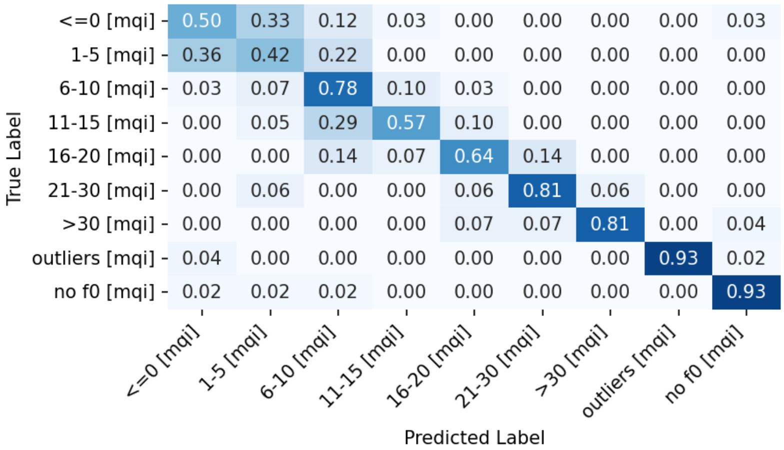

Figure 4: Best model confusion matrix (Random Forest) for test-accuracy while mqi prediction.

4. Conclusion And Outlook

In this paper we demonstrated a distributed pipeline with ai-based classification of mqi values regarding to complex cantilever sensor data. We showed that gradients and regression models such as XGBoost, LightGBM and Random Forest are suited for the classification of mqi values using raw cantilever sensor data stored in a qdrant vector database. The best val. / test-accuracy of (72.01 % / 71.67 %), was achieved with Random Forest, indicating that the approach is promising for practical applications in food quality monitoring. While some classification errors occurred, especially between adjacent mqi classes, the overall performance suggests that further refinement and tuning of the models hyperparameters could lead to even better results. Invalid datasets are classified with a best model accuracy of 93 % indicating a robust error detection. In further research a focus on expanding the cantilever sensor data with additional sensors could be investigated, to classify different types of meat.

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