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Detection of Beef Freshness using the E-nose Tool using the K-Nearest Neighbor (KNN) Method

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Abstract

Fast and accurate detection of meat freshness is very important in the food industry because it directly affects the quality and safety of consumption. Traditional sensory assessments are often inefficient and subjective, so more reliable technology is needed. This research develops a system to detect beef freshness using the E-Nose tool and the K-Nearest Neighbor (KNN) algorithm with accuracy, precision, and recall. E-Nose detects volatile compounds from beef, while KNN classifies sensor data. The research results show that this tool can identify the freshness level of beef with high accuracy so that it can be used to ensure meat quality in the food industry. The combination of E-Nose and KNN shows promising results in detecting beef freshness by identifying freshness biomarkers through aroma analysis. The KNN model trained with data from the E-Nose sensor can classify fresh, slightly fresh, and non-fresh meat with good precision, achieving an accuracy of 83%. Implementing this technology in the food industry can improve meat products' safety and quality standards, ensuring that consumers get safe products. Overall, E-Nose technology with the KNN method is an effective, efficient, and reliable tool for detecting the freshness of beef, providing significant benefits for the food industry in maintaining product quality and safety.

Keywords
Accuracy; E-Nose; Industry; K-Nearest Neighbor (KNN); Meat Freshness

1. Introduction
The quality of beef (Yuristiawan & Santoso 2015) is very important in the food industry because it affects consumers' taste, texture, and safety. Current meat freshness assessments (Lee & Shin 2019) often rely on less efficient subjective methods, such as human sensory assessments. Therefore, a more objective and reliable technological approach is needed to accurately assess the freshness level of meat E-Nose (Electronic Nose) (Ardelia Pratiwi et al. 2021) is one of the innovative technologies used in this research. E-Nose works by detecting volatile compounds produced by beef, identifying distinctive aromas that change along with the meat's freshness level. This technology is effective in various applications in the food industry, including in detecting the quality and freshness of food products quickly and accurately. The use of E-Nose (Esfahani et al., 2020) can also analyze the chemical changes in meat more deeply, which cannot be easily recognized through conventional methods such as visual observation.

K-Nearest Neighbor (KNN) (Kiwan; Hidayat 2019) is an algorithm in machine learning used to classify sensor data patterns from E-Nose. KNN (Purwanto et al. 2019) was chosen because of its ability to recognize complex and non-linear patterns from beef aroma data by testing accuracy, precision, and recall to provide a more objective and efficient freshness evaluation. Previous studies using similar methods have shown that KNN can produce accurate classification results regarding food quality evaluation, providing a solid basis for its use in the food industry.

The combination of E-Nose technology with the KNN method in this research can significantly contribute to the development of a more sophisticated and reliable beef freshness evaluation system. With a more detailed analysis of sensory data from E-Nose, results can reveal more specific and sensitive freshness biomarkers, which can be used to improve the quality control standards of beef products in the food industry.

2. Research Methods

Using the E-Nose tool with the K-Nearest Neighbor (KNN) method, this research method is designed to detect beef's freshness level. The research is carried out through several systematic stages, from planning to evaluating the final results. The following are the stages of this research.

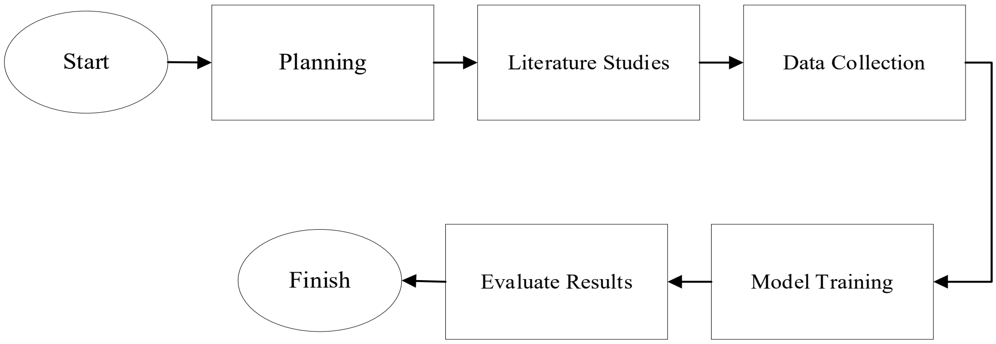

Figure 1. Research Flow Diagram

2.1 Planning

This initial stage involves designing the entire research, including determining the objectives, scope, and methods. At this stage, the researcher also identifies the underlying problems and needs of the research.

2.2 Literature Studies

Researchers conduct literature reviews to gather information and knowledge from relevant previous research. This includes the research of E-Nose technology, the KNN method, and their application in the food industry.

2.3 Data Collection

Data was collected using the E-Nose tool, which detects volatile compounds from beef samples at varying levels of freshness (Bhadury et al. 2021). Meat samples were taken from various supermarkets in Bogor City. The collected data is used as input for KNN model training. Information about the E-Nose device, including sensors that detect meat freshness, is also an important aspect of this research.

2.4 Model Training

Sensor data obtained from E-Nose was used to train the KNN model (Sheynin et al. 2022). At this stage, the KNN model is trained to recognize and classify different aroma patterns according to the beef's freshness level. The following are the stages in model training:

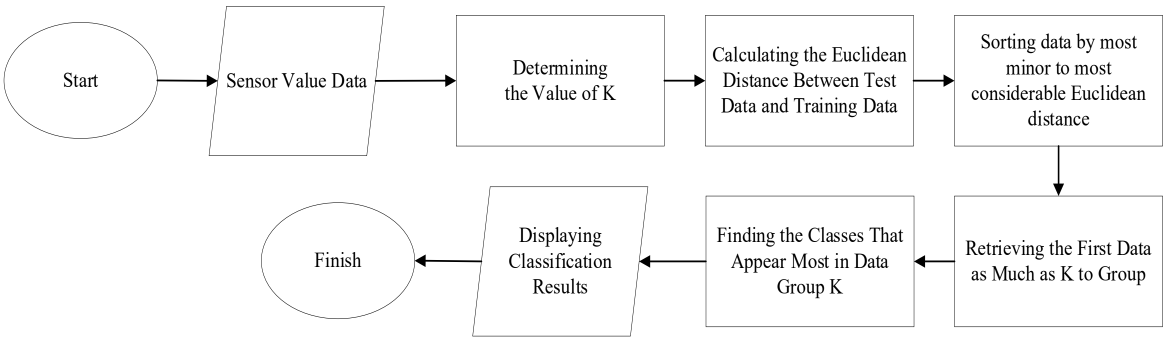

Figure 2. Model Training

2.5 Sensor Value Data

Training data was obtained from five sensors on the E-Nose device through the analysis of beef samples over a period of 30 days. This data comes from two different conditions: frozen beef and spoiled beef. Sensor values are recorded for both conditions on a daily basis, thus providing a comprehensive dataset for model training.

2.6 Determining the Value of K

The K value in the K-Nearest Neighbors (KNN) algorithm is the number of nearest neighbors (Gou et al.2019) considered in the classification process. The optimal K value is determined through a cross-validation process, which divides the training data into several subsets, trains the model on different subsets, and tests the model on the remaining subsets. The goal is to find the K value that provides the best classification accuracy.

1. Calculating the Euclidean Distance between Test Data and Training Data.
   This research used the KNN classification method, which required calculating the Euclidean distance between the test data and the training data (Beaver & Dean, 2019). The Euclidean Distance formula used is:

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (1)$$

   Information:
   $d = The\ Euclidean\ distance\ between\ two\ vectors\ or\ points\ in\ space\ with\ n\ dimensions.$
   $x_i = The\ i - element\ of\ the\ vector\ or\ the\ first\ point.$
   $y_i = The\ i - element\ of\ the\ vector\ or\ second\ point.$

2. Sorting Data Based on Smallest to Largest Euclidean Distance
   Once the Euclidean distance between the test data and all the training data has been calculated, the next step is to sort the training data based on the Euclidean distance from smallest to largest. This sequencing makes it easier to select the nearest neighbor K (Rico-Juan et al., 2019) with the test data, where the data with the smallest Euclidean distance shows the highest similarity or proximity to the test data.
3. Retrieving the First Data as Much as K to Group
   From the list of training data sorted by Euclidean distance, the top K data (with the smallest distance) is selected for further analysis. The selection of K of these nearby data is important because they are considered the most similar to the test data. These data are used to determine the class of the test data.
4. Finding the Most Appearing Classes in Data Group K
   Once the nearest data K is selected, the next step is determining the class that appears most frequently among the data K. This class is then used to predict the test data. This process involves calculating each class's occurrence frequency in the nearest data K, where the class with the highest frequency is chosen as the prediction class, as it is considered the most likely.
5. Displaying Classification Results
   The classification results are displayed based on the class that most frequently appears from K of the nearest data. This predicted class is then compared with the actual class to assess the model's accuracy. Thus, the classification results obtained can be used to determine beef's freshness level, whether it is fresh, less fresh, or rotten. These results can also be used to evaluate and refine the KNN model to be more accurate.

2.7 Evaluate Results

Once the KNN model is trained, the next step is to conduct tests using meat samples not included in the training set. This test data is used to evaluate the model's performance and the parameters generated by the E-Nose tool. The model evaluation was performed by measuring three key metrics: accuracy, precision, and recall, each of which was calculated using the following equation:

1. Accuracy
   Accuracy (*A*) (Ayudhitama et al., 2020) measures how often the model makes correct predictions and is calculated by the following equation:

$$A = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (2)$$

   Information:
   TP (True Positive): Number of correct predictions for positive classes.
   TN (True Negative): Number of correct predictions for negative classes.
   FP (False Positive): Number of false predictions for positive classes.
   FN (False Negative): Number of wrong predictions for negative classes.
2. Precision
   Precision (*P*) (Ayudhitama et al., 2020) measures the accuracy of the positive predictions made by the model and is calculated by the following equation:

$$P = \frac{TP}{TP + FP} \times 100\% \quad (3)$$

3. Recall
   Recall(R) (Ayudhitama et al., 2020) measures the model's ability to find all positive instances and is calculated by the following equation:

$$R = \frac{TP}{TP + FN} \times 100\% \quad (4)$$

The results of this evaluation provide an overview of the model's performance in real-world situations where new data is constantly emerging. Based on these results, it can be determined whether the model is good enough to be used in practical applications or needs further refinement.

Accuracy measurements provide an overview of the model's overall performance. Meanwhile, precision and recall provide deeper insight into the model's strengths and weaknesses in handling positive and negative predictions. For example, in meat freshness detection, a high recall is essential to ensure all non-fresh meat is correctly identified, while high precision is important to minimize the misidentification of fresh meat as unfresh.

By evaluating the model using these metrics, it can be ensured that the E-Nose tool combined with the KNN method provides reliable results for food industry applications, particularly in detecting beef freshness. The evaluation results can also be used to identify areas where the model needs to be improved, either through additional data collection, parameter adjustments, or algorithm improvements.

3. Results and Discussion

The results have been obtained from research on meat sensors with three different types of guarding: strict, simple, and no. Each data collected from various sensors on each type of guard was analyzed to measure the level of freshness of the meat during the observation period. The results of this analysis will provide insight into the effectiveness of each guarding method in maintaining meat quality and identify factors that affect changes in meat conditions. The data obtained were processed and presented in an easy-to-understand form to support further discussion of the findings of this research.

3.1 Data from Meat Censorship Closely Guarded

Strict guarding of the meat is carried out by using a cooling system equipped with automatic temperature controllers to ensure that the meat remains at the optimal temperature during storage.

Table 1. Data from Meat Censorship Closely Guarded

Strictly Guard Meat					
KET	S1	S2	S4	S8	S9
Day 1	1227.75	1012.375	1160.5	800.875	3168.25
Day 2	1281.25	1143.625	1226.5	827.75	3187
Day 3	1295	1139.625	1235.875	889.5	3191
Day 4	1375	945.625	1307.125	859.625	3216.5
Day 5	1452.375	1067.25	1378.375	955.25	3231.875
Day 6	1394.75	1095	1337.625	907.375	3225.5
Day 7	1480.125	990.5	1408	947.375	3241.625
Day 8	1361.75	1053.125	1298.375	962.375	3203.25
Day 9	1383.75	1032.25	1315.875	851.125	3218.125
Day 10	1432.375	1028.125	1357.5	877.5	3233.625
Day 11	1358.5	1020.75	1287.25	795.875	3208
Day 12	1384.375	1028.375	1312.375	825	3211.25
Day 13	1378.75	1055	1315.75	848.875	3216.875
Day 14	1347.625	1110.125	1286.125	880	3208.125
Day 15	1372.75	1110.75	1314.75	940.375	3225.75
Day 16	1369.75	1014.5	1294.25	890.875	3232.625
Day 17	1402	908.125	1319.875	857.5	3242.625

The above Table 1. Shows the observations and data from various sensors used to monitor the condition of the meat during the research period.mThe data showed the sensor results for meat that was strictly guarded for 17 days. There is a variation in sensor results on S1 to S9. On the first day, the S1 sensor result was 1227.75, which continued to increase until the 17th day when it reached 1402.

3.2 Medium-Care Meat Sensor Results Data

Simple care of meat is carried out without an automatic cooling system but only with more general storage conditions. The following are the observations and data from various sensors used to monitor the condition of the meat during the research period.

Table 2. Medium-Care Meat Sensor Results Data

	Medium Care Meat				
KET	S1	S2	S4	S8	S9
Day 1	1316.875	1145.875	1247	718.625	3201.5
Day 2	1413	1125.375	1337.75	695.625	3251.25
Day 3	1534.125	1279.125	1454.125	721.75	3285.75
Day 4	1434.625	1171.125	1358.875	713.875	3254.5
Day 5	1463.875	1233.25	1385.125	789.25	3260.375
Day 6	1467.75	1120.625	1389	784.125	3253.5
Day 7	1432.25	1155	1355.125	830.625	3240.75
Day 8	1472.125	1108.75	1402.875	831.5	3245
Day 9	1459.5	1217.25	1396.625	966.125	3239.375
Day 10	1480.625	1247.625	1420.625	1086	3270
Day 11	1405	1102.25	1335.75	962.125	3270
Day 12	1514	1210.375	1480.875	1045.625	3270
Day 13	1558.5	1233.25	1517.125	1156.75	3270
Day 14	1486.25	1239	1454.75	1083.5	3239.625
Day 15	1492.75	1249.625	1458.375	1092.625	3258.5
Day 16	1510.375	1211.25	1468	1046.625	3242.125
Day 17	1648.375	1297.125	1617	1184	3296
Day 18	1476.125	1244.125	1433.875	1051	3238.5
Day 19	1570.5	1364.125	1616.375	1237.25	3254.375
Day 20	1576.25	1378.625	1607.875	1228	3256.75
Day 21	1708.75	1589.875	1696.25	1269.625	3247.5
Day 22	1716.375	1600.25	1667.75	1207	3243.625
Day 23	1643.625	1616.375	1655.875	1438.75	3278.375
Day 24	1781.5	1734.625	1729.875	1342.625	3249
Day 25	1696.75	1788.5	1650.5	1323.25	3210.625
Day 26	1922.25	1855.25	1848.625	1633	3257.75
Day 27	1940	1780.125	1813.5	1333.25	3277.25
Day 28	1922.875	1882.5	1787.375	1537.125	3221.5
Day 29	1997.25	1816.375	1849	1360.375	3283
Day 30	2053.75	1750.375	1900.125	1421.5	3289.5

This data shows the sensor results for meat kept simply for 30 days. Sensor results on S1 to S9 showed a more significant improvement compared to tightly guarded meat. On the first day, the S1 sensor result was 1316.875, and on the 30th day, it was 2053.75.

3.3 Data on the Results of Unguarded Meat Censorship

In this condition, the data obtained reflects the natural conditions, thus providing an overview of the meat's basic characteristics or original conditions. Further explanation include analyzing the data generated, such as the level of cleanliness, health conditions, or general quality of the meat reflected in the sensor data.

Table 3. Data on the Results of Unguarded Meat Censorship

Unattended Meat					
KET	S1	S2	S4	S8	S9
Day 1	1490.75	1139	1410.875	734.5	3279
Day 2	2115	2111.5	2015.375	1220.375	3322.375
Day 3	2270.125	2247.125	2093.25	1717.625	3302.25
Day 4	2332.125	2354.75	2133.125	1669.5	3312.125
Day 5	2361.875	2479.125	2149.875	2027.5	3278.125
Day 6	2392.375	2316.5	2197.75	1992.5	3320

Sensor results for unguarded meat showed a very significant improvement over six days. Sensor results in Q1 increased from 1490.75 on the first day to 2392.375 on day 6.

3.4 Categorization Stage

The categorization process involves normalizing all data and determining each sensor's value limits to categorize the meat's freshness level.

1. Data Normalization

Data normalization transforms raw data into a standard form so that data is more accessible to interpret and compare. The primary goal of normalization is to eliminate anomalies or biases that may appear in the data, such as different scales or uneven distributions. With normalization, data is treated at a uniform scale.

(Table 4. is given in Appendix -A)

2. Determination of Value Limit

Based on the average value (M) and standard deviation (SD), the freshness level of meat is divided into three categories: Low ($X < M - 1SD$), Medium ($M - 1SD \leq X < M + 1SD$), and High ($M + 1SD \leq X$).

Table 5. Determination of Value Limit

Value Constraints	
Rendah	$X < M - 1SD$
Sedang	$M - 1SD \leq X < M + 1SD$
Tinggi	$M + 1SD \leq X$

3. Sensor Categorization

The sensor result data is grouped based on a predetermined freshness category. The table shows the categorization of sensors for different meat care conditions. On the first day, meat with strict care is categorized as "Segar," while meat without strict care is quickly categorized as "Agak Segar".

(Table 6. is shown in Appendix -B)

3.5 KNN Classification Test

Data analysis classifies objects based on existing training datasets. This algorithm works by looking for the most common category or class among the closest neighbors of the object under test.

1. Determining the K Parameter

$$k = \sqrt{53} = 7.28 = 7$$

2. Data Normalization

Table **7.** Meat Data by Supermarket

Supermarket	S1	S2	S4	S8	S9
GS the Fresh	0.16	0.022358	0.161003	0.166495	0.477697
Lotte Mart	0.15	0.023154	0.149916	0.158142	0.430657
Hypermart ekalokasari	0.15	0.026814	0.150157	0.15542	0.423358
Superindo Pajajaran	0.15	0.027769	0.157628	0.148475	0.432279
Superindo Bondongan	0.15	0.019971	0.159074	0.144345	0.429035
Superindo Tajur	0.64	0.532384	0.590383	0.284655	0.818329

Euclidean Distance Calculation
The formula for the Euclidean distance between two points (x1,x2,x3,x4,x5 and (y1,y2,y3,y4,y5):
Distance = $\sqrt{(x1-y1)^2+(x2-y2)^2+(x3-y3)^2+(x4-y4)^2+(x5-y5)^2}$

a) Test Data: Supermarket GS The Fresh////
Test Data: [0.16, 0.022358, 0.161003, 0.166495, 0.477697]

b) Train Dataset (which is close)
Test Data 4: [0.13, 0.02387, 0.1413, 0.123, 0.313]
Test Data 5: [0.19, 0.1, 0.21, 0.19, 0.41]
Test Data 6: [0.14, 0.118, 0.17, 0.1589, 0.37]
Test Data 7: [0.22, 0.0524, 0.238, 0.189, 0.476]
Test Data 10: [0.18, 0.076, 0.1899, 0.1365, 0.424]
Test Data 16: [0.12, 0.0677, 0.129, 0.1465, 0.417]
Test Data 17: [0.15, 0, 0.153, 0.121, 0.48]

c) Distance Calculation
Distance to training data 4

$$\sqrt{(0.16-0.13)^2+(0.022358-0.02387)^2+(0.161003-0.141359)^2+(0.166495-0.123135)^2+(0.477697-0.313058)^2}$$

= 0.174

Distance to training data 5

$$\sqrt{(0.16-0.19+(0.022358-0.101289)^2+(0.161003-0.210051)^2+(0.166495-0.194932)^2+(0.477697-0.412814)^2}$$

= 0.12

Distance to training data 6

$$\sqrt{(0.16-0.14)+(0.022358-0.118953)^2+(0.161003-0.170764)^2+(0.166495-0.158986)^2+(0.477697-0.371452)^2}$$

= 0.1455

Distance to training data 7

$$\sqrt{(0.16-0.22)+(0.022358-0.052435)^2+(0.161003-0.238612)^2+(0.166495-0.189019)^2+(0.477697-0.476075)^2}$$

= 0.1

Distance to training data 10

$$\sqrt{\begin{array}{c}(0.16-0.18)+(0.022358-0.076384)^2+(0.161003-0.189925)^2+\ (0.166495-\ 0.136556)^2\\ +(0.477697-0.424169)^2\end{array}}$$

= 0.089

Distance to training data 16

$$\sqrt{\begin{array}{c}(0.16-0.12)+(0.022358-0.067712)^2+(0.161003-0.128947)^2+\ (0.166495-\ 0.146598)^2\\ +(0.477697-0.41768)^2\end{array}}$$

= 0.093

Distance to training data 17

$$\sqrt{\begin{array}{c}(0.16-0.15)+(0.022358-0)^2+(0.161003-0.153651)^2+\ (0.166495-\ 0.121539)^2\\ +(0.477697-0.482563)^2\end{array}}$$

= 0.052

Nearest Neighbors to Supermarket "GS the Fresh"

1. Training Data 4: Distance 0.174→ Kategori: AGAK SEGAR
2. Training Data 5: Distance 0.12 → Kategori: AGAK SEGAR
3. Training Data 6: Distance 0.1455 → Kategori: AGAK SEGAR
4. Training Data 7: Distance 0.1 → Kategori: AGAK SEGAR
5. Training Data 10: Distance 0.089 → Kategori: AGAK SEGAR
6. Training Data 16: Distance 0.093 → Kategori: AGAK SEGAR
7. Training Data 17: Distance 0.052 → Kategori: AGAK SEGAR

Category: AGAK SEGAR

Table 8. KNN Method Test Results

Supermarket	S1	S2	S4	S8	S9	K = 7	Kategori	Hasil
GS the Fresh	0.16	0.022358	0.161003	0.166495	0.477697	0.174	Agak Segar	Agak Segar
						0.12	Agak Segar	
						0.145	Agak Segar	
						0.1	Agak Segar	
						0.089	Agak Segar	
						0.093	Agak Segar	
						0.052	Agak Segar	
Lotte Mart	0.15	0.023154	0.149916	0.158142	0.430657	0.125	Agak Segar	Agak Segar
						0.113	Agak Segar	
						0.115	Agak Segar	
						0.129	Agak Segar	
						0.076	Agak Segar	
						0.1267	Agak Segar	
						0.06	Agak Segar	
Hypermart ekalokasari	0.15	0.026814	0.150157	0.15542	0.423358	0.117	Agak Segar	Agak Segar
						0.1	Agak Segar	
						0.108	Agak Segar	
						0.12	Agak Segar	
						0.07	Agak Segar	
						0.121	Agak Segar	
						0.056	Agak Segar	
Superindo Pajajaran	0.15	0.027769	0.157628	0.148475	0.432279	0.125	Agak Segar	Agak Segar
						0.11	Agak Segar	
						0.1113	Agak Segar	
						0.1261	Agak Segar	
						0.067	Agak Segar	
						0.059	Agak Segar	
						0.1263	Agak Segar	
Superindo Bondongan	0.15	0.019971	0.159074	0.144345	0.429035	0.12	Agak Segar	Agak Segar
						0.1167	Agak Segar	
						0.1164	Agak Segar	
						0.128	Agak Segar	
						0.125	Agak Segar	
						0.07	Agak Segar	
						0.0649	Agak Segar	
Superindo Tajur	0.64	0.532384	0.590383	0.284655	0.818329	0.4265	Agak Segar	Agak Segar
						0.43	Agak Segar	
						0.428	Agak Segar	
						0.393	Agak Segar	
						0.23	Agak Segar	
						0.243	Agak Segar	
						0.2979	Agak Segar	

3.6 Validation Trial

The validation trial was carried out to evaluate the performance of the beef freshness level detection system using an e-nose device using the K-Nearest Neighbor (KNN) method. Table 9 shows the results of this trial, where sensor data from various supermarkets such as GS the Fresh, Lotte Mart, Hypermart Ekalokasari, Superindo Pajajaran, Superindo Bondongan, and Superindo Tajur have been collected and analyzed. Each supermarket has several sensor variables (S1, S2, S4, S8, S9) that are measured to determine the level of freshness of the meat. The results of statistical classification, classification using software, and classification based on real evaluation show that most samples are classified as "Agak Segar", except for Superindo Tajur, which is labeled "Tidak Segar". This experiment shows that the KNN model can provide predictions consistent with manual classification based on sensory assessment and statistical evaluation.

Table 9. Validation Trial

No	Supermarket	S1	S2	S4	S8	S9	Statistical Classification	Software Classification	Real Classification
1	GS the Fresh	1410	943.25	1327.5	917.375	3241.875	Agak Segar	Agak Segar	Agak Segar
2	Lotte Mart	1397.5	944.5	1316	906.25	3234.625	Agak Segar	Agak Segar	Agak Segar
3	Hypermart ekalokasari	1397.625	950.25	1316.25	902.625	3233.5	Agak Segar	Agak Segar	Agak Segar
4	Superindo Pajajaran	1407.625	951.75	1324	893.375	3234.875	Agak Segar	Agak Segar	Agak Segar
5	Superindo Bondongan	1408.125	939.5	1325.5	887.875	3234.375	Agak Segar	Agak Segar	Agak Segar
6	Superindo Tajur	1970.25	1744.5	1772.875	1074.75	3294.375	Agak Segar	Agak Segar	Tidak Segar

The next step in determining the model's performance is to create a confusion matrix table, which will also be used to find the accuracy, precision, recall, and F1-Score values. The following is a table of confusion matrix:

Table 10. Confusion Matrix

	Predicted: Agak Segar (P)	Predicted: Tidak Segar (N)
Actual: Agak Segar (P)	5	0
Actual: Tidak Segar (N)	1	0

1) Accuracy

$$A = \frac{5+0}{5+0+1+0} = \frac{5}{6} = 0.8333$$

2) Precision

$$P = \frac{5}{5+1} = \frac{5}{6} = 0.8333$$

3) Recall

$$R = \frac{5}{5} = 1$$

4) F1-Score

$$F1 - Score = 2 \times \frac{P \times R}{P + R} = 2 \times \frac{0.8333 \times 1}{0.8333 + 1} = 2 \times 0.45454 = 0.9091$$

Table 11. Accuracy

	Precision	Recall	F1-Score	Support
Agak Segar	0.8333	1	0.9091	5
Tidak Segar	0	0	0	1
Akurasi			0.8333	6

From the table above, it can be seen that the accuracy value obtained is 0.8333 or in percent 83%. The accuracy value shows that the model's performance is quite good.

4. Conclusion

Using the E-nose tool combined with the K-Nearest Neighbor (KNN) method shows promising results in detecting the level of freshness of beef, with the ability to identify biomarkers of freshness through the analysis of the resulting aroma. The KNN model trained using data from the E-nose sensor has high accuracy in classifying the freshness level of beef, distinguishing fresh, slightly fresh, and non-fresh meat with good precision. The table above shows that the accuracy value obtained is 0.8333, or within 83% percent, which shows the model's performance is quite good. The application of this technology in the food industry has the potential to improve the safety and quality standards of meat products, ensuring that consumers get safe products for consumption. In conclusion, E-nose technology with the KNN method is an effective, efficient, and reliable tool for detecting the freshness of beef, providing significant benefits for the food industry in maintaining product quality and safety.

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APPENDIX -A

Table 4. Whole Meat Data

S1	S2	S4	S8	S9
1227.75	1012.375	1160.5	800.875	3168.25
1281.25	1143.625	1226.5	827.75	3187
1375	945.625	1307.125	859.625	3216.5
1452.375	1067.25	1378.375	955.25	3231.875
1394.75	1095	1337.625	907.375	3225.5
1480.125	990.5	1408	947.375	3241.625
1361.75	1053.125	1298.375	962.375	3203.25
1383.75	1032.25	1315.875	851.125	3218.125
1432.375	1028.125	1357.5	877.5	3233.625
1358.5	1020.75	1287.25	795.875	3208
1384.375	1028.375	1312.375	825	3211.25
1378.75	1055	1315.75	848.875	3216.875
1347.625	1110.125	1286.125	880	3208.125
1295	1139.625	1235.875	889.5	3191
1372.75	1110.75	1314.75	940.375	3225.75
1369.75	1014.5	1294.25	890.875	3232.625
1316.875	1145.875	1247	718.625	3201.5
1413	1125.375	1337.75	695.625	3251.25
1534.125	1279.125	1454.125	721.75	3285.75
1434.625	1171.125	1358.875	713.875	3254.5
1463.875	1233.25	1385.125	789.25	3260.375
1467.75	1120.625	1389	784.125	3253.5
1432.25	1155	1355.125	830.625	3240.75
1472.125	1108.75	1402.875	831.5	3245
1459.5	1217.25	1396.625	966.125	3239.375
1480.625	1247.625	1420.625	1086	3270
1405	1102.25	1335.75	962.125	3270
1514	1210.375	1480.875	1045.625	3270
1558.5	1233.25	1517.125	1156.75	3270
1486.25	1239	1454.75	1083.5	3239.625
1492.75	1249.625	1458.375	1092.625	3258.5
1510.375	1211.25	1468	1046.625	3242.125
1648.375	1297.125	1617	1184	3296
1476.125	1244.125	1433.875	1051	3238.5
1570.5	1364.125	1616.375	1237.25	3254.375
1576.25	1378.625	1607.875	1228	3256.75
1708.75	1589.875	1696.25	1269.625	3247.5
1716.375	1600.25	1667.75	1207	3243.625
1643.625	1616.375	1655.875	1438.75	3278.375
1781.5	1734.625	1729.875	1342.625	3249
1696.75	1788.5	1650.5	1323.25	3210.625
1922.25	1855.25	1848.625	1633	3257.75

1940	1780.125	1813.5	1333.25	3277.25
1922.875	1882.5	1787.375	1537.125	3221.5
1997.25	1816.375	1849	1360.375	3283
1490.75	1139	1410.875	734.5	3279

APPENDIX-B-

Table 6. Sensor Categorization

No	S1	S2	S4	S8	S9	Category	Result
1	1227.75	1012.375	1160.5	800.875	3168.25	R, S, R, S, R	Segar
2	1281.25	1143.625	1226.5	827.75	3187	R, S, R, S, R	Segar
3	1295	1139.625	1235.875	889.5	3191	R, S, R, S, R	Segar
4	1375	945.625	1307.125	859.625	3216.5	S, R, S, S, S	Agak Segar
5	1452.375	1067.25	1378.375	955.25	3231.875	S, S, S, S, S	Agak Segar
6	1394.75	1095	1337.625	907.375	3225.5	S, S, S, S, S	Agak Segar
…	…	…	…	…	…	…	…
8	1361.75	1053.125	1298.375	962.375	3203.25	S, R, S, S, S	Agak Segar
9	1383.75	1032.25	1315.875	851.125	3218.125	S, S, S, S, S	Agak Segar
10	1432.375	1028.125	1357.5	877.5	3233.625	S, S, S, S, S	Agak Segar
11	1358.5	1020.75	1287.25	795.875	3208	S, S, S, S, R	Agak Segar
12	1384.375	1028.375	1312.375	825	3211.25	S, S, S, S, R	Agak Segar
13	1378.75	1055	1315.75	848.875	3216.875	S, S, S, S, S	Agak Segar
14	1347.625	1110.125	1286.125	880	3208.125	S, S, S, S, R	Agak Segar
15	1372.75	1110.75	1314.75	940.375	3225.75	S, S, S, S, S	Agak Segar
16	1369.75	1014.5	1294.25	890.875	3232.625	S, S, S, S, S	Agak Segar
17	1402	908.125	1319.875	857.5	3242.625	S, R, S, S, S	Agak Segar
18	1316.875	1145.875	1247	718.625	3201.5	S, S, R, R, R	Segar
19	1413	1125.375	1337.75	695.625	3251.25	S, S, S, R, S	Agak Segar
20	1534.125	1279.125	1454.125	721.75	3285.75	S, S, S, R, T	Agak Segar
21	1434.625	1171.125	1358.875	713.875	3254.5	S, S, S, R, S	Agak Segar
22	1463.875	1233.25	1385.125	789.25	3260.375	S, S, S, S, S	Agak Segar
23	1467.75	1120.625	1389	784.125	3253.5	S, S, S, S, S	Agak Segar
24	1432.25	1155	1355.125	830.625	3240.75	S, S, S, S, S	Agak Segar
25	1472.125	1108.75	1402.875	831.5	3245	S, S, S, S, S	Agak Segar
26	1459.5	1217.25	1396.625	966.125	3239.375	S, S, S, S, S	Agak

							Segar
27	1480.625	1247.625	1420.625	1086	3270	S, S, S, S, S	Agak Segar
28	1405	1102.25	1335.75	962.125	3270	S, S, S, S, S	Agak Segar
29	1514	1210.375	1480.875	1045.625	3270	S, S, S, S, S	Agak Segar
30	1558.5	1233.25	1517.125	1156.75	3270	S, S, S, S, S	Agak Segar
31	1486.25	1239	1454.75	1083.5	3239.625	S, S, S, S, S	Agak Segar
32	1492.75	1249.625	1458.375	1092.625	3258.5	S, S, S, S, S	Agak Segar
33	1510.375	1211.25	1468	1046.625	3242.125	S, S, S, S, S	Agak Segar
34	1648.375	1297.125	1617	1184	3296	S, S, S, S, T	Agak Segar
35	1476.125	1244.125	1433.875	1051	3238.5	S, S, S, S, S	Agak Segar
36	1570.5	1364.125	1616.375	1237.25	3254.375	S, S, S, S, S	Agak Segar
37	1576.25	1378.625	1607.875	1228	3256.75	S, S, S, S, S	Agak Segar
38	1708.75	1589.875	1696.25	1269.625	3247.5	S, S, S, S, S	Agak Segar
39	1716.375	1600.25	1667.75	1207	3243.625	S, S, S, S, S	Agak Segar
40	1643.625	1616.375	1655.875	1438.75	3278.375	S, S, S, T, S	Agak Segar
41	1781.5	1734.625	1729.875	1342.625	3249	S, S, S, S, S	Agak Segar
42	1696.75	1788.5	1650.5	1323.25	3210.625	S, T, S, S, R	Agak Segar
43	1922.25	1855.25	1848.625	1633	3257.75	T, T, T, T, S	Tidak Segar
44	1940	1780.125	1813.5	1333.25	3277.25	T, T, T, S, S	Tidak Segar
45	1922.875	1882.5	1787.375	1537.125	3221.5	T, T, T, T, S	Tidak Segar
46	1997.25	1816.375	1849	1360.375	3283	T, T, T, S, T	Tidak Segar
47	2053.75	1750.375	1900.125	1421.5	3289.5	T, S, T, T, T	Tidak Segar
48	1490.75	1139	1410.875	734.5	3279	S, S, S, R, S	Agak Segar
49	2115	2111.5	2015.375	1220.375	3322.375	T, T, T, S, T	Tidak Segar
50	2270.125	2247.125	2093.25	1717.625	3302.25	T, T, T, T, T	Tidak Segar
51	2332.125	2354.75	2133.125	1669.5	3312.125	T, T, T, T, T	Tidak Segar
52	2361.875	2479.125	2149.875	2027.5	3278.125	T, T, T, T, S	Tidak Segar
53	2392.375	2316.5	2197.75	1992.5	3320	T, T, T, T, T	Tidak Segar

Information:
R = Rendah
S = Sedang
T = Tinggi