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Temperature effect of electronic nose sampling for classifying mixture of beef and pork

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ABSTRACT

Strong demand and strong price of raw foodstuffs like beef was commonly used in conventional markets by beef dealers to commit fraud in order to gain larger income. The fraud has been in the form of combining beef and pork. In Indonesia, this has been a issue of food health in recent years. Via scent, some food safety concerns can be expected. By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef. According to its selectivity, the sensor can detect gas to make small icurrents that are the result of chemical sensor and gas interactions with oxygen. In this study, the classification method k-NN, SVM, Naïve Bayes, and Random Forest was used in 5 different meat variations with a ratio of 0%, 10%, 50%, 90% and 100% with temperatures of -22° C, Room Temp., And 55° C. The results showed the effect of temperature on increasing the accuracy, which is at a temperature of -22° C. The lower the temperature, the more stable the value obtained by electronic nose. At a temperature of -22° C, the method that produces the highest accuracy is the Random Forest method.

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1. INTRODUCTION

Strong demand and strong price of raw foodstuffs like beef was commonly used in conventional markets by beef dealers committing deception to gain more income. The fraud took the form of combining beef and pork [1]. In Indonesia, this has been a issue of food health in recent years. Via scent, some food safety concerns can be expected. By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef. Food protection and insurance cover a variety of things like nutrition, sanitation and legality [2]. The creation of blending beef and pork is often practiced in fresh state. It occurs because pork is an inexpensive animal protein source, and is readily available on the market, making it beef scam more lucrative for the rogue seller. The case of this mixed beef poses significant questions, given that Indonesia is the world's largest nation with a Muslim majority. However, certain classes of people are hypersensitive, too or aversion to pork [3]. Their scent can discern certain food safety issues.

By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef [4]. Depending on its selectivity, the sensor can detect gas by generating low currents which result from chemical sensor reations and gas between oxygen [5]. In this research, further analyzes using algorithms for machine learning algorithms with 3 temperature differences in each of the 5 variations of sample meat data was applied to determine optimum classification result. The temperature used were the temperature of -22° C, Room Temp And 55° C, while the variation of the meat mixture used were 0% Beef - 100% Pork; Beef 10% - Pork 90%; Beef 50% - Pork 50%;

Beef 90% - Pork 10%; and 100% Beef - 0% Pork. The algorithms used for machine learnig is k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Naïve Bayes, dan Random Forest.

2. RESEARCH METHOD

The research methodology was organized systematically as an analysis process. This is the phases used for the study as shown in Figure 1.

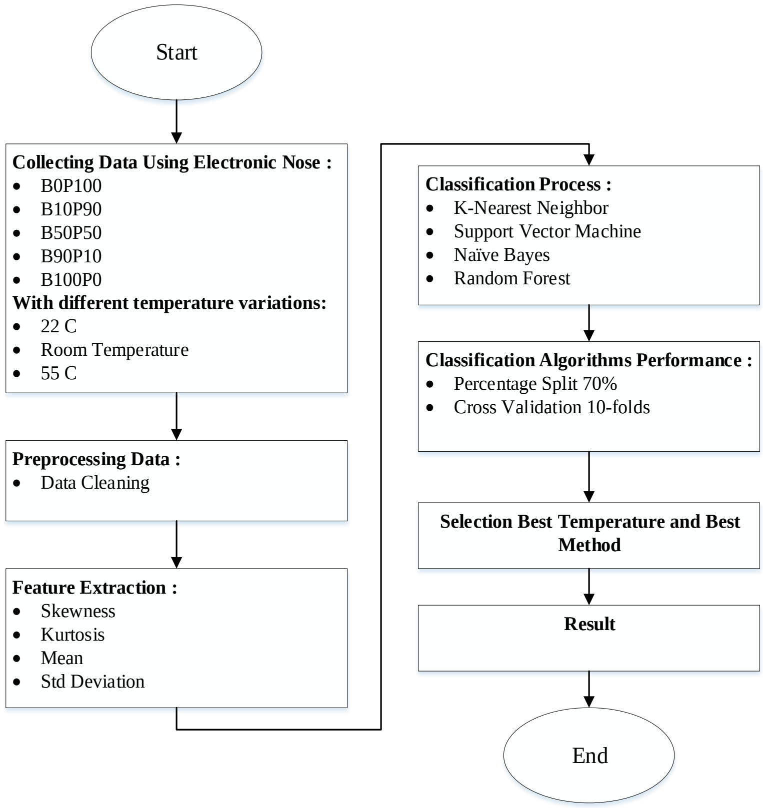


Figure 1. The proposed method

2.1. Collecting data using electronic nose

Data collection was done using electronic nose divided into 5 variations of meat and 3 temperature variations. Table 1 is a detailed composition of the data collection scenario.

Table 1. Scenario of data collection

Code	Beef	Pork	Temperature		
			-22° C	Room Temp.	55° C
B0P100	0%	100%	✓	✓	✓
B10P90	10%	90%	✓	✓	✓
B50P50	50%	50%	✓	✓	✓
B90P10	90%	10%	✓	✓	✓
B100P0	100%	90%	✓	✓	✓

2.2. Preprocessing data

Researchers apply data cleaning at the preprocessing level. Data cleaning is the method of eliminating redundant data, verifying incompatibility data and correcting data errors, such as write errors [6]. Information derived from all experimental tests usually has incomplete contents such as missing data, incorrect data or even a typo [7]. Additionally, there are data attributes which are not important to the theory of data mining. Cleaning up data would also impact the efficiency of data mining, as the data handled would reduce number and complexity [8].

2.3. Feature extraction

To determine whether or not the research is being performed properly, the first thing that must be ascertained is whether or not the data is usually transmitted. The sum of statistical metrics used in the features of the extraction phases is the sum of the kurtosis, skewedness, mean and stdev measured using the Microsoft Excel software.

2.3.1. Kurtosis

Kurtosis is a function of how smooth the upper section of the symmetric distribution compared with the same variant's normal distribution [9]. In fact, the score on the distribution tail is more affected by kurtosis than the fulfillment center score. In general, this is contrasted with regular distribution that has a kurtosis factor 3, named mesokurtic [10]. Symmetric distribution, with a coefficient of under 3 with a incisive peak, is named leptokurtic, whereas it is called platicurtic a distribution characterized by a flat apex, which has a kurtosis factor greater than 3 [11]. The following is the Kurtosiss equation:

$$Kurtosis\ (K) = \frac{1}{T\sigma^4}\sum_{t=1}^{T}(T_t - \mu)^4 \tag{1}$$

2.3.2. Skewness

Skewness is the pendulum of a data frequency curve for the distribution [12]. Below are two models of skewed positives and negatives. Positive slope, the slope of a data distribution frequency curve tends to be far to the left of the medium (value below the median) [13]. Therefore, the slope of the tail over the frequency curve is to the right. Likewise, the tail of frequency curve slopes in a negative slope is more to the left [14]. As shown in (2) is the formula of skewness, where the rt value for each data observed is, ÿ is the sample data standard deviation, μ is the sample data average and T is the number of observations.

$$Skewness\ (S) = \frac{1}{T\sigma^{34}}\sum_{t=1}^{T}(r_t - \mu)^3 \tag{2}$$

2.3.3. Mean

Mean is the mechanism on which the signal frequency will be centered, summarizing all sample data communities then divided by the sample number [15]. As shown in (3) is a skewness formula, where r2 is the value of any observed data, and T is the number of observed samples.

$$Mean\ (\mu) = \frac{1}{T}\sum_{t-1}^{T} r2 \tag{3}$$

2.3.4. Std. deviation

The strong value of σ implies that the data meaning is sprayed from its mid-range μ. If σ is small, the resulting value is grouped to the mean value [16]. As shown in (4) is a skewness formula, where r2 reflects the importance of every object observed, μ is the sample item average and T is the number of samples.

$$Variansi\ (\sigma^2) = \frac{1}{T}\sum_{t=1}^{T}(r2 - \mu)^2 \tag{4}$$

2.4. Classification

The classification process was divided into two phases: learning & test. In the learning phase, part of the data that was known for the data class was fed to form an approximate model [17]. Then in the test phase the model that had been formed was tested with some other data to determine the accuracy of the model. If the accuracy is sufficient this model can be used for predicting unknown classes of data. In this study there are 4 scenarios for data classification, namely:

– Scenario 1 (k-*Nearest Neighbor* method)
– Scenario 2 (*Support Vector Machine* method)
– Scenario 3 (Naïve Bayes method)
– Scenario 4 (*Random Forest* method)

2.5. Selection best temperature and best method

After getting the classification results from the 4 existing scenarios, the next step is to classify the ROC value of the area to the temperature and method [18]. The ROC curve is widely used to assess prediction results. The ROC curve is a two-dimensional tool used to assess classification performance using two decision classes, each object mapped to one element of a pair of pairs, positive or negative [19]. For data mining classification according to Gorunescu, the AUC value or Area under the curve that is often used as the sum of the ROC curves and as a measure of performance classifiers can be divided into several groups [20]:

- 0.90 – 1.00 = Excellent Classification
- 0.80 – 0.90 = Good Classification
- 0.70 – 0.80 = Fair Classification
- 0.60 – 0.70 = Poor Classification
- 0.50 – 0.60 = Failure

3. RESULTS AND ANALYSIS

In this sub-chapter, we discuss the classification testing on each data that has been obtained from electronic nose and evaluation of results

3.1. Scenario 1 testing (K-NN method)

In this testing scenario, a meat classification trial was conducted using the k-Nearest Neighbor method with 5 variations of meat with 3 different variations in temperature. In the testing of scenario 1, it was achieved by splitting data from the extraction function into training data and testing data with a ratio of 30%, and k = 3 as shown in Table 2. Detail accuration using K-NN method can be seen on Figure 2.

Table 2. Confussion matrix using K-NN method

	CODE	TEMPERATURE	PREDICTION -22°C	Room Temp.	55°C
ACTUAL	B0P100	-22°C	14	0	0
		Room Temp.	0	10	6
		55°C	1	7	7
	B10P90	-22°C	14	0	0
		Room Temp.	0	12	4
		55°C	2	2	11
	B50P50	-22°C	14	0	0
		Room Temp.	0	15	1
		55°C	0	1	14
	B90P10	-22°C	14	0	0
		Room Temp.	0	12	4
		55°C	3	1	11
	B100P0	-22°C	14	0	0
		Room Temp.	0	12	4
		55°C	2	3	10

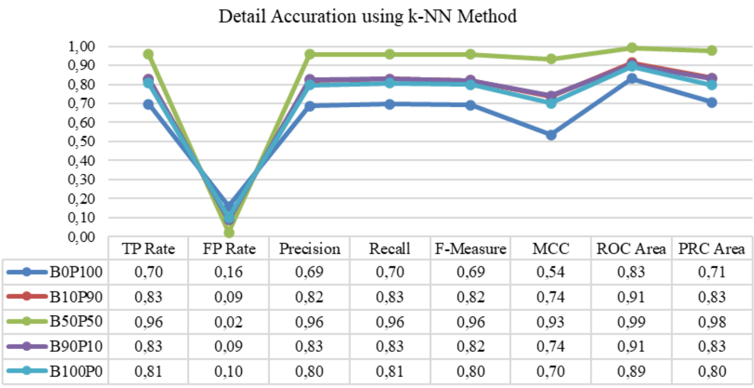


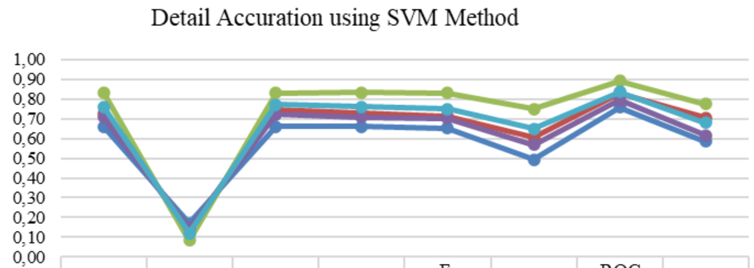
Figure 2. Detail accuration using K-NN method

3.2. Scenario 2 testing (SVM Method)

In this test scenario, a meat classification trial was conducted using the Support Vector Machine method with 5 variations of meat with 3 different variations in temperature as shown in Table 3. In the testing of scenario 2, this was performed using k-fold cross-validation, with k = 10 for the RBF kernel. The aim of testing using k-fold cross-validation is to pick the right temperature parameters according to the highest precision, so that the precision of SVM purity classification can be improved [21]. Detail Accuration using SVM Method as shown in Figure 3.

Table 3. Confussion matrix SVM method

	CODE	TEMPERATURE	PREDICTION -22°C	PREDICTION Room Temp.	PREDICTION 55°C
ACTUAL	B0P100	-22°C	43	2	5
		Room Temp.	8	32	10
		55°C	15	11	24
	B10P90	-22°C	47	1	2
		Room Temp.	6	39	5
		55°C	20	7	23
	B50P50	-22°C	50	0	0
		Room Temp.	2	39	9
		55°C	4	10	36
	B90P10	-22°C	40	8	2
		Room Temp.	6	39	5
		55°C	17	6	27
	B100P0	-22°C	48	2	0
		Room Temp.	5	39	6
		55°C	15	8	27



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0,66	0,17	0,66	0,66	0,65	0,49	0,76	0,59
B10P90	0,73	0,14	0,75	0,73	0,71	0,60	0,83	0,70
B50P50	0,83	0,08	0,83	0,83	0,83	0,75	0,89	0,77
B90P10	0,71	0,15	0,72	0,71	0,70	0,57	0,80	0,61
B100P0	0,76	0,12	0,77	0,76	0,75	0,65	0,84	0,68

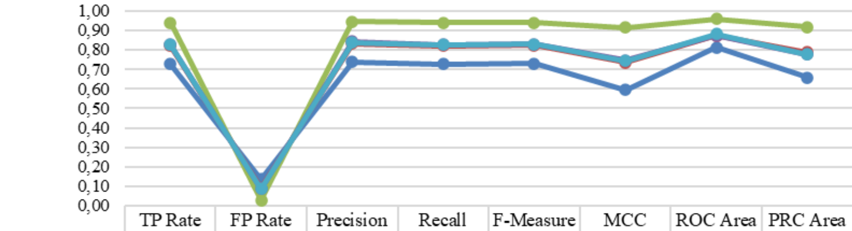
Figure 3. Detail Accuration using SVM Method

3.3. Scenario 3 testing (naïve bayes method)

In this testing scenario, a meat classification trial was conducted using the Naïve Bayes method with 5 variations of meat with 3 different temperature variations. Naive Bayes calculates destiny possibility predictions from facts or studies that had been given, based at the opportunity point ofview [22]. In the testing of scenario 3, k-fold cross-validation was used, with k = 10 as shown in Table 4. Detail accuration using naïve bayes method as shown in Figure 4.

Table 4. Confussion matrix naïve bayes method

	CODE	TEMPERATURE	PREDICTION -22°C	PREDICTION Room Temp.	PREDICTION 55°C
ACTUAL	B0P100	-22°C	46	2	2
		Room Temp.	0	29	21
		55°C	0	16	34
	B10P90	-22°C	43	3	4
		Room Temp.	0	38	12
		55°C	0	8	42
	B50P50	-22°C	48	1	1
		Room Temp.	0	43	7
		55°C	0	0	50
	B90P10	-22°C	42	4	4
		Room Temp.	0	38	12
		55°C	0	6	44
	B100P0	-22°C	44	3	3
		Room Temp.	0	38	12
		55°C	0	8	42



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0,73	0,14	0,74	0,73	0,73	0,60	0,81	0,66
B10P90	0,82	0,09	0,83	0,82	0,82	0,74	0,87	0,79
B50P50	0,94	0,03	0,95	0,94	0,94	0,91	0,96	0,92
B90P10	0,83	0,09	0,84	0,83	0,83	0,75	0,87	0,78
B100P0	0,83	0,09	0,84	0,83	0,83	0,74	0,88	0,78

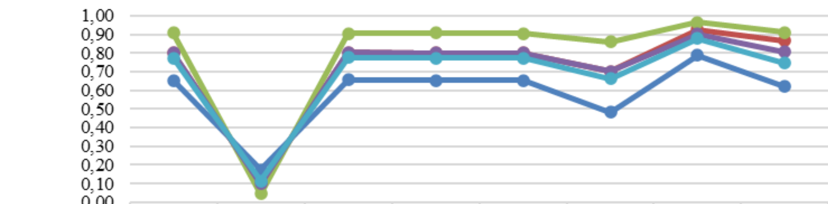
Figure 4. Detail accuration using naïve bayes method

3.4. Scenario 4 testing (random forest method)

In this test scenario, a meat classification trial was conducted using the random forest method with 5 variations of meat with 3 variations in temperature. Random forest have developed as genuine competitors to state-of-the-art strategies such as boosting [23] and back vector machines [24]. In the testing of this scenario, k-fold cross-validation was used, with k = 10 as shown in Table 5. Detail accuration using random forest method as shown in Figure 5.

Table 5. Confussion Matrix Random Forest Method

	CODE	TEMPERATURE	PREDICTION -22^{o}C	Room Temp.	55^{o}C
ACTUAL		-22^{o}C	49	1	0
	B0P100	Room Temp.	0	26	24
		55^{o}C	0	27	23
		-22^{o}C	49	0	1
	B10P90	Room Temp.	0	35	15
		55^{o}C	0	14	36
		-22^{o}C	50	0	0
	B50P50	Room Temp.	0	44	6
		55^{o}C	0	6	42
		-22^{o}C	49	1	0
	B90P10	Room Temp.	0	35	15
		55^{o}C	0	14	36
		-22^{o}C	49	1	0
	B100P0	Room Temp.	0	33	17
		55^{o}C	0	16	34



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0,65	0,17	0,66	0,65	0,65	0,48	0,79	0,62
B10P90	0,80	0,10	0,80	0,80	0,80	0,70	0,93	0,87
B50P50	0,91	0,05	0,91	0,91	0,91	0,86	0,96	0,91
B90P10	0,80	0,10	0,80	0,80	0,80	0,70	0,90	0,80
B100P0	0,77	0,11	0,78	0,77	0,77	0,66	0,88	0,75

Figure 5. Detail accuration using random forest method

3.5. ROC values based on temperature and method

A receiver operating characteristics (ROC) graph is atechnique for visualizing, organizing and selecting classifi-ers based on their execution [25]. To find the temperature and the best method in this experiment, the researcher grouped the ROC values against the method and temperature as in Table 6. At -22^{o}C, the method that has the highest accuracy is the random forest method with an average value of ROC 1.000. While the method that has the second highest accuracy is the k-Nearest Neighbor method with an average value of ROC 0.986. The naïve bayes method is ranked 3rd with an average value of ROC 0.971 and the SVM method is the method that has the lowest accuracy with an average ROC value of 0.872. At room temperature, the method that has the highest accuracy is the k-Nearest Neighbor method with an average value of ROC 0.886. While the method that has high accuracy to 2 is the Naïve Bayes method with an average ROC value of 0.856. The Random Forest method is ranked 3rd with an average value of ROC 0.839 and the SVM method is the method that has the lowest accuracy with an average ROC value of 0.820. At 55^{o}C, the method that has the highest accuracy is the Naïve Bayes method with an average ROC value of 0.864. While the method that has the second highest accuracy is the K-Nearest Neighbor method with an average value of ROC of 0.848. The Random Forest method is ranked 3rd with an average value of ROC 0.836 and the SVM method is the method that has the lowest accuracy with an average value of ROC 0.774

Table 6. ROC area value sort by methods and code

Temp	Method	Code	ROC Value
-22^{o}C	k-NN	S0B100	0.99
		S10B90	0.98
		S50B50	1
		S90B10	0.97
		S100B0	0.98
	Average of ROC Value		0.98
	SVM	S0B100	0.85
		S10B90	0.84
		S50B50	0.98
		S90B10	0.78
		S100B0	0.88
	Average of ROC Value		0.87
	Naïve bayes	S0B100	0.97
		S10B90	0.93
		S50B50	0.99
		S90B10	0.99
		S100B0	0.96
	Average of ROC Value		0.97
	Random Forest	S0B100	1
		S10B90	0.99
		S50B50	1
		S90B10	1
		S100B0	1
	Average of ROC Value		1

Temp	Method	Code	ROC Value
Room Temp	k-NN	S0B100	0.77
		S10B90	0.90
		S50B50	0.98
		S90B10	0.90
		S100B0	0.85
	Average of ROC Value		0.88
	SVM	S0B100	0.74
		S10B90	0.86
		S50B50	0.84
		S90B10	0.81
		S100B0	0.83
	Average of ROC Value		0.82
	Naïve bayes	S0B100	0.73
		S10B90	0.84
		S50B50	0.93
		S90B10	0.93
		S100B0	0.82
	Average of ROC Value		0.85
	Random Forest	S0B100	0.68
		S10B90	0.90
		S50B50	0.94
		S90B10	0.84
		S100B0	0.82
	Average of ROC Value		0.83

Temp	Method	Code	ROC Value
55^{o}C	k-NN	S0B100	0.73
		S10B90	0.85
		S50B50	0.98
		S90B10	0.83
		S100B0	0.83
	Average of ROC Value		0.84
	SVM	S0B100	0.66
		S10B90	0.78
		S50B50	0.84
		S90B10	0.78
		S100B0	0.79
	Average of ROC Value		0.77
	Naïve bayes	S0B100	0.73
		S10B90	0.83
		S50B50	0.94
		S90B10	0.94
		S100B0	0.85
	Average of ROC Value		0.86
	Random Forest	S0B100	0.67
		S10B90	0.88
		S50B50	0.94
		S90B10	0.86
		S100B0	0.81
	Average of ROC Value		0.83

3.6. Comparison of methods to temperature

After obtaining the average of each ROC value, the next step is to compare the 4 methods used with 3 temperature variations can be seen on Table 7 and Figure 6.

Table 7. Comparison of methods to temperature

	k-NN	SVM	Naïve Bayes	Random Forest
-22 C	0.986	0.872	0.971	1.000
Room Temp.	0.886	0.821	0.856	0.839
55 C	0.848	0.774	0.864	0.836

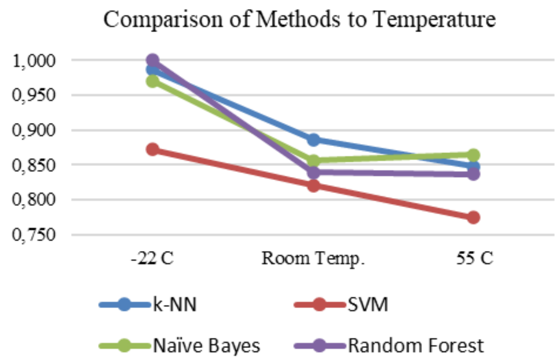


Figure 6. Comparison of methods to temperature

4. CONCLUSION

Based on the results of the research conducted by the author, the following conclusions are obtained: The researcher divided the experiment into 4 scenarios with each composition 5 variations of meat (Beef 0% - Pork 100%, Beef 10% - Pork 90%, Beef 50% - Pork 50%, Beef 90% - Pork 10% and Beef 100% - Pork 0%) with 3 temperature variations (-22^{o}C, Room Temperature, and 55^{o}C), namely: a. k-*Nearest Neighbor* Method, b. *Support Vector Machine* Method, c. Naïve Bayer Method, d. *Random Forest* Method. There is an effect of temperature on increasing accuracy, which is at -22^{o}C. Because the lower the temperature the more stable the value obtained by electronic nose is.

The following are methods that have high accuracy based on temperature: a) At -22^{o}C, the sequence of methods that has the highest to lowest accuracy is Random Forest with an average value of ROC 1.00; K-Nearest Neighbor with an average value of ROC 0.986; Naïve Bayes with an average value of ROC 0.971 and Support Vector Machine with an average ROC value of 0.872. b) At room temperature, the method sequence has the highest to lowest accuracy, namely K-Nearest Neighbor with an average value of ROC 0.886; Naïve Bayes with an average value of ROC 0.856; Random Forest with an average value of ROC 0.839 and Support Vector Machine with an average ROC value of 0.821. c) At 55^{o}C, the sequence of methods has the highest to lowest accuracy, namely Naïve Bayes with an average ROC value of 0.864; K-Nearest Neighbor with an average value of ROC 0.848; Random Forest with an average value of ROC 0.836 and Support Vector Machine with an average value of ROC 0.774.

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