2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE) | 979-8-3503-9961-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICITISEE57756.2022.10057787

IMPROVEMENT OF E-NOSE SENSOR SIGNAL USING MVA, FFT, DWT METHODS ON PINEAPPLE FRUIT MATURITY

[a,b]Mhd Arief Hasan, [a*]Riyanarto Sarno, [a]M. Syauqi Hanif Ardani
[a]Informatics Department, Intitut Teknologi Sepuluh Nopember, Surabaya, Indonesia
[b]Informatic Engineering Study Program,Universitas Lancang Kuning, Pekanbaru, Indonesia
[*]Corresponding author's Email: riyanarto@if.its.ac.id

***Abstract*— In this study, we built an Electronic Nose to detect pineapple ripeness. We designed a prototype E-Nose using a wooden crate. Inside the box, we built the E-Nose using 9 MQ sensor circuits connected to the Arduino Microcontroller. In the crate, we put an object, namely a pineapple with three levels of ripeness (ripe, half ripe, and unripe), each weighing 1kg placed in three different positions (5cm, 20cm, and 35cm) from the position of the sensor array (E-nose). We converted the signal output results into ppm units. We compared the value of each fruit signal based on the level of ripeness and distance using E-Nose. We used several signal processing methods (wavelets) for signal processing. Then, we improved the signal generated using wavelet. The wavelet methods used are Moving Average, Fast Fourier Transform (FFT), and Discrete Wavelet Transform (DWT). The contribution of this research is to see the influence of the signal valuegenerated from the sensor (MQ Sensor) to the position (distance) of the object (fruit) and its influence on the level of maturity (fruit). Then signalgenerated from the sensor we make improvements with the mva, fft, and dwt methods.**

Keywords— E-Nose, FFT, DWT, MVA, Pineapple

I. BACKGROUND

Pineapple is a fruit plant in the form of a shrub of which scientific name is Ananas comosus. Pineapple comes from Brazil, South America, which was domesticated there before the time of Columbus. In the 16th century, the Spaniards brought pineapple to the Philippines and Peninsular Malaysia, entered Indonesia in the 15th century (1599). In Indonesia, pineapple was only used as a garden plant, and it was widely planted on dry land (moor) throughout the archipelago. This plant is now maintained in the tropics and sub-tropics. Pineapple is suitable for planting at an altitude of 1 – 1300 m above sea level. The optimum growth of pineapple plants is between 100-700 m asl.

There are several techniques for detecting the ripeness of pineapples, including by looking at the differences between unripe pineapples and ripe pineapples, the skin of an unripe pineapple is green, the flesh is white, and has a hard texture. Meanwhile, the skin of a ripe pineapple started to look yellowish. The color of the flesh is more yellow, the texture is softer, and the scent can be smelled from the outside. For the pineapple processing industry, indeed, detecting the ripeness of pineapple is still done manually by sorting the fruit one by one, so this will certainly take a long time.

Electronic nose, abbreviated as e-nose, is an artificial olfactory system to analyze, recognize, and detect simple or complex odors and volatile compounds. E-nose is a device that mimics the way the human smell works. E-nose has been widely applied in various fields, such as the food, beverage, chemical, defense, health, and other industries. The output of the E-nose is in the form of a signal wave value generated from each sensor array used. In signal processing, we can use the Wavelet Signal Processing approach.

Wavelet-based Transformation Method is one of the tools that can be used to analyze non-stationary signals. In recent years, this method has proven its usefulness and is popular in various fields of science. Wavelet analysis can be used to indicate the temporary behavior of a signal, for example in the fields of geophysics (seismic signals), fluids, and medical. The Wavelet Transform method can be used to filter data or improve data quality; can also be used to detect certain events and for data compression.

In this study, we built an Electronic Nose to detect pineapple ripeness. We designed a prototype E-Nose in a crate. We built the E-Nose using 9 series of MQ sensors connected to an Arduino Microcontroller. We put the sensor array in a crate. In the crate (wooden box), we put an object, namely a pineapple with three levels of ripeness (ripe, half ripe, and unripe), placed in three different positions (5 cm, 20 cm, and 35 cm) from the sensor array position (E-Nose). We compared the value of each fruit signal based on the level of maturity and distance using E-nose. We used a number of signal processing (wavelet) methods, which involve changing or transforming data in a way that allows for analyzing, optimizing and correcting signals [1], [2]. This study aims to determine the effect of comparing the position of the E-nose distance with fruit objects that have different levels of maturity on the gas concentration detected by the E-Nose. The contribution of this research is to see the influence of the signal value generated from the sensor (MQ Sensor) to the position (distance) of the object (fruit) and its influence on the level of maturity (fruit). Then signal generated from the sensor we make improvements with the mva, fft, and dwt methods.

II. E-NOSE LITERATURE REVIEW

A. E-Nose

Electronic nose, abbreviated as e-nose, is an artificial olfactory system to analyze, recognize, and detect simple or complex odors and volatile compounds. It has been utilized in various industrial, agricultural, medical, and smart home functions. Compared to its human counterpart, it has an epithelium consisting of sensory neurons that transduce and transmit chemicals in their immediate environment into signal patterns so that they are capable of pattern recognition [3][4].

In the food industry, genose can be used for aroma identification which is useful in monitoring production processes, such as research on the detection of mold appearance in food [5], various processed meats, such as fish freshness [6], mixed meat [7], fresh quality of meat [8]. E-Nose is also used in the fruit processing industry, such as predicting the quality of olives [9], predicting microorganisms that can make fruit rot [10], detect fruit ripeness level [11]–[13]. In previous studies, we have classified pineapple ripeness using pineapple fruit samples in three categories, namely ripe, half-ripe and uripe [14].

B. Signal Processing

Wavelet theory is a relatively recently developed concept. The word "wavelet" itself was coined by Jean Morlet and Alex Grossmann in the early 1980s, and comes from the French, "ondelette" which means small wave. Signal processing has long been dominated by Fourier transforms. However, there is an alternative transformation that has gained popularity recently and that is the wavelet transform[15]. The wavelet techniques used here are Moving Average (MVA), Fast Fourier Transform (FFT), and Discrete Wavelet Transform (DWT)..

- Moving Average (MVA)

Moving Average is an indicator that calculates the average of a signal wave over a certain period of time, then connects it in the form of a line. The average value can come from the beginning of the signal (open), close (close), the highest signal (high), the lowest signal (low), or the middle (median). Moving Average is part of the lagging indicator. The simple moving average (SMA) is an arithmetic moving average that is calculated by adding up the most recent signals and then dividing that number by the number of time periods in the calculated average [16]. The Simple Moving Average can be calculated by the following equation:

$$SMA = \frac{S1 + S2 + \cdots + Sn}{n} \tag{1}$$

Where :

Sn = Signal value in period n
n = Total number of periods

- Fast Fourier Transform (FFT)

FFT (Fast Fourier Transform) is an algorithm to speed up calculations on DFT (Discrete Fourier Transform) to obtain the magnitude of many frequencies in a signal so that it is faster and more efficient. This algorithm is more likely to be used on microcontroller devices with a small memory. Before reading or studying FFT, it would be better to comprehend DFT first because the basis of FFT is DFT. FFT is the same as DFT meaning that it can determine how many frequencies in a signal in the time domain are converted into the frequency domain; the only difference is that FFT can perform calculations faster [17].

DFT performs full computation on a signal of n. If the number of N is large enough, the calculation takes longer because DFT multiplies N^2 times, so the more the number of n, the longer the calculation.

$$Multiplication\ of\ DFT\ N\ samples = N^2 \tag{2}$$

From the DFT formula,

$$X_{(k)} = \frac{1}{N}\sum_{n=0}^{N-1} \chi_n e^{-j2\pi\frac{k}{N}n} \tag{3}$$

It can be seen that each value of the frequency index k has a total of 8 sample multiplications because the number of samples N is 8, then the total k is equal to the number of N, i.e. k is equal to 8 so the total multiplication is $N\ x\ k$ equals N^2 equals 8 x 8 equals with 64 multiplication. If the number of samples increases, the number of multiplications in the DFT increases, as well. As much as the square of the number of samples (N^2), so it takes a longer calculation time depending on the number of samples, where the more samples the longer the DFT calculation. The multiplication referred is the multiplication between n th or χ_n sample values in discrete values with exponential numbers or better known as multiplication of complex numbers.

To simplify the writing of the FFT formula above, it can be done by assuming an exponential number with W where the exponential number with a sample of $N/2$ can be written as follows:

$$\cos\frac{2\pi R}{N} - j\sin\frac{2\pi R}{N} = e^{-j\frac{2\pi R}{N}} = W\frac{R}{N} \tag{4}$$

So FFT can be simplified as follows:

$$X[k] = \underbrace{\sum_{r=0}^{\frac{N}{2}-1} \chi(2r)W_{\frac{N}{2}}^{rk}}_{\text{DFT N/2 Even Sample}} + W\frac{k}{N}\underbrace{\sum_{r=0}^{\frac{N}{2}-1} \chi(2r+1)W_{\frac{N}{2}}^{rk}}_{\text{DFT N/2 Odd Sample}} \tag{5}$$

- Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform) is one of the digital signal processing techniques. This technique is developed in the community because it is easier to apply and the results are better, namely the Fourier transform. DWT divides a signal dimension into two parts, namely high frequency (High Pass Filter) and low frequency (Low Pass Filter)[18].

The implementation of discrete wavelet transformation can be done by passing the signal into two DWT filters, namely High Pass Filter (HPF) and Low Pass Filter (LPF) so that the frequency of the signal can be analyzed and then down sampling on the output of each filter. Signal analysis is carried out on the results of the High Pass Filter (HPF) and Low Pass Filter (LPF) where HPF is used to analyze high frequencies and LPF is used to analyze low frequencies. Analysis of the frequency is carried out by using the resolution generated after the signal passes through filtering.

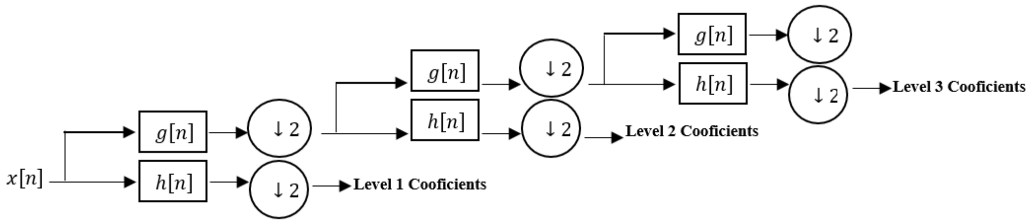

Fig. 1. Discrete Wavelet Decomposition

This decomposition process can go through one or more levels. One-level decomposition is written with the following mathematical expression:

$$\gamma_{high}[K] = \sum_n x[n]h[2k-n] \quad (6)$$

$$\gamma_{low}[K] = \sum_n x[n]g[2k-n] \quad (7)$$

$\gamma_{high}[K]$ and $\gamma_{low}[K]$ is the result of High Pass Filter and Low Pass Filter, $x[n]$ is the original signal, $h[n]$ is High Pass Filter, and $g[n]$ is Low Pass Filter. For decomposition of more than one level, the procedures in equation (1) and (2) can be used at each level.

C. Part Per Million (PPM)

When measuring gases such as carbon dioxide, oxygen, or methane, the term concentration is used to describe the amount of gas by volume in the air. The two most common units of measurement are parts per million, and percent concentration. Parts-per-million (abbreviated as ppm) is the ratio of one gas to another. For example, 1,000 ppm CO means that if you could count one million molecules of a gas, 1,000 of which would be carbon monoxide and 999,000 of which would be other gases.

In the air pollution literature, ppm is applied to gases, always means parts per million volume or mol. These are identical for ideal gases, and practically identical for most gases of air pollution importance at 1 atm. Another method of expressing this value is ppmv. One part per million (by volume) is equal to a certain volume of gas mixed in one million volumes of air. The formula for calculating the PPM on gas can be formulated as follows:

$$1ppm = \frac{1\ Gas\ Volume}{10^6\ Air\ Volumes} \quad (8)$$

D. RS/RO

Data were collected by characterizing the sensor in a closed room using a sensor, where the gas produced is analyze by the value of the voltage it produces. After that, the result can be processed as voltage data into the sensor resistance value ($RS/R0$) using equation 9. We can derive the formula to determine RS using Ohm's Law.Which in the E-Nose series we built is the same as:

$$I = \frac{VC}{(RS + RL)} \quad (9)$$

III. Research Method

In this study, we built a box made of wood. The box is 60 cm long, 26 cm wide and 22 cm high which can be seen in Figure 2. Inside the container, we install a sensor array that is connected to a PC computer. One sensor array consists of 9 MQ-Series sensors. This sensor array circuit functions as an E-nose which will detect the smell of the object, namely the pineapple in the container. The process was followed by putting a sample of pineapple that we have peeled off. There are 3 types of pineapple that we put in the box (ripe, half ripe, and unripe). We placed the sample in 3 different positions (5 cm, 20 cm, and 35 cm) from the sensor distance. Each pineapple object (ripe, half ripe, and unripe) weighs 1 kg. We will detect the effect of object position (pineapple) with signal capture power generated from each sensor array based on a predetermined position distance and ripeness level. The details of this E-nose design will be described in the following explanation.

Fig. 2. Wooden crates used

In Figure 2, it is explained that the box used in this study was made of wood with a length of 60 cm, a width of 26 cm, and a height of 22 cm. This wooden box has a lid that is easy to open in order to move one object to another or from one position to another. At the left end of this box, there is a hole for the exit of the cable that connects the E-nose to the computer.

A. Tools and Materials

The E-nose that was designed in this study consisted of one sensor array which had 9 MQ sensors. We cover this sensor array with a box so that it can be close to each other. This MQ sensor is connected to Arduino as a microprocessor, so we can analyze the data values generated by each sensor. The E-nose designed was put at the base of the wooden box. The MQ sensors used can be seen in Figure 3 and Table 1.

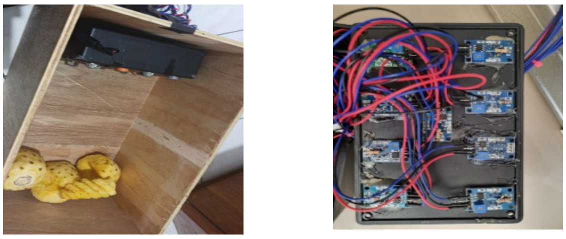

Fig. 3. The Mq sensor used

In Figure 3 and Table 1, it is explained that there are 9 MQ sensors used in the E-nose system. The position of the sensor can be seen in Figure 2 and the explanation of the sensor used can be seen in Table 1.

TABLE I. TYPES OF MQ SENSORS USED

No	MQ Sensor Type	Detected gas
1	MQ 2	LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide
2	MQ 3	Alcohol Gas.
3	MQ 4	Natural Gas/Methane.
4	MQ 5	LPG, natural gas, coal gas detection and monitoring
5	MQ 6	LPG, iso-butane, propane, alcohol, smoke.
6	MQ 7	carbon monoxide
7	MQ 8	Hydrogen, H2 sensor
8	MQ 9	LPG, CO, CH4
9	MQ 135	NH3, NOx, alcohol, benzene, smoke and CO2

B. System Requirements

In order for the designed E-nose to work as expected, we connected the sensor Array with Arduino Uno as a microcontroller to analyze the signal generated from the sensor array (E-nose). We used the Python programming language to compile the E-nose coding and the Wavelet Process on the sensor signal filtering that had been generated.

C. Sample Data

In this study, the sample used is pineapple with three levels of ripeness (ripe, half ripe, and unripe). The pineapple we used is a pineapple that was planted in Blitar. Blitar is the capital of one of the districts in the East Java Province, Indonesia. Blitar is a center for producing pineapples in this province. The pineapple we took consisted of 3 types of pineapple (ripe, half ripe, and unripe). We picked directly from the garden on the same day with the aim of maintaining the same quality of pineapples and the purity of the data. Each type of pineapple was respectively peeled and measured to one kilogram.

D. Proposed method

This section briefly explains the principle of the E-nose work system used in this study, as well as the signal repair process carried out using the MVA, FFT and DWT methods. The proposed methodology in this study can be seen in Figure 4.

Figure 4 explains how this study was conducted. The main objective of this study is to correct the E-nose signal resulting from detecting pineapple signal. This E-nose signal was obtained by conducting an experiment on a pineapple sample put into a wooden box with the E-nose installed in it (as shown in Figure 3). The E-nose system was tested to compare the results of the signals obtained from the experiment based on the level of ripeness (ripe, half ripe, and unripe) and to the distance position of the E-nose. As for the process in collecting the signals using E-Nose, it can be seen in Figure 3. We collected large amounts of data with the aim that we can conduct a classification process based on the distance and degree of ripeness of the pineapple in the future. Fig. 4. Proposed method

However, in this initial study, we first corrected the signal aiming that the accuracy can be improved.

After doing an experiment to obtain the E-Nose signal on pineapple based on the level of ripeness and distance, we grouped the data obtained according to its category. The file was collected in the form of csv (comma separated values). We proceed to make the graph from the original csv file that we received directly from the E-nose.

After obtaining the csv data from the E-nose, we started to compile a program for signal filtering. We compiled the program using the Python programming language with several libraries including matplotlib and pandas. We, then, created a function for filtering using three methods (MVA, FFT and DWT). The results of this filtering processing output produced a csv file that has been filtered using these 3 methods. At the end of this study, we can compare the original signal by the E-Nose and the signal that has undergone a filtering process using these 3 methods. Therefore, it can be concluded whether the filtering process using the MVA, FFT and DWT methods can improve signal results and which method is better in terms of performance.

IV. RESULT AND DISCUSSION

The result of this study is the concentration of gas produced by E-nose in detecting the level of ripeness of pineapples and the effect of distance from the sensor. The signal value becomes the reference data in this study. The reference data is improved with the wavelet process in signal processing using three methods, namely MVA, DWT, and FFT; so that, it can be observed the effect of the comparison of reference data before and after the signal repair process. The results we obtained are as follows.

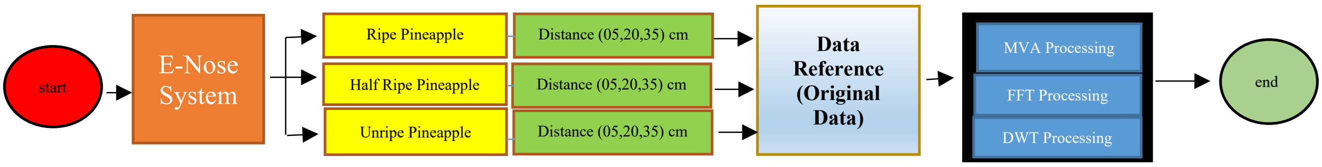

Fig. 4. Proposed Method

A. Original Reference Data

We obtained the original signal data directly from E-nose. We measured it based on the distance and maturity level of the pineapple. We measure 1 kg of pineapple (ripe, half ripe, and unripe) with E-nose in different positions (5 cm, 20 cm, and 35 cm). Each data consists of 163 rows of data. There are 9 files generated which were compared for processing data in signal processing. The signal results obtained can be seen in the following figure.

Original Reference Data

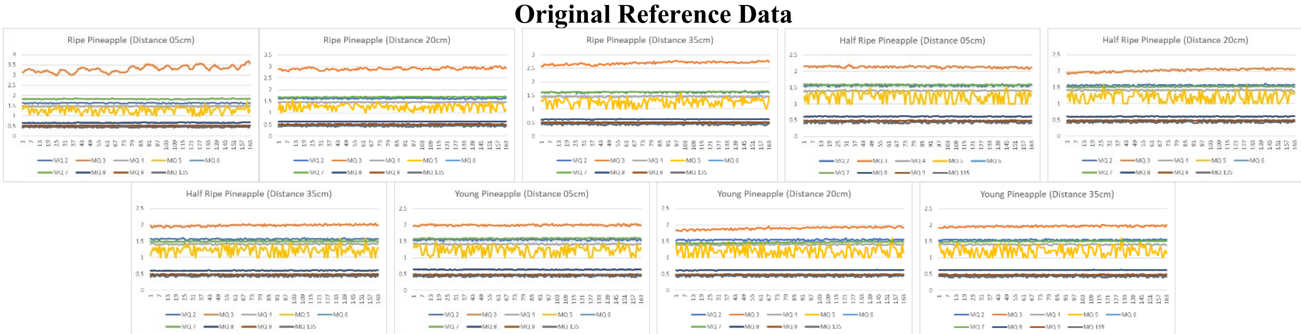

Fig. 5. Original Data

Figure 5 explain the original data directly obtained from E-nose, with 3 ripeness levels and distance positions. The signal that produces the highest value is ripe pineapple with a distance of 5 cm on the MQ3 sensor. The resulting signal value range is 3 - 3.5 ppm, while the range of the lowest signal value is the signal value produced by unripe pineapple with a distance of 35 cm with the resulting signal value range below 2 ppm. The resulting reference data still has a lot of noise. It can be seen that several types of sensors have not produced regular values; therefore, we process them using several MVA, FFT and DWT methods.

B. Original Reference Data processed by Moving Average (MVA) Method

After we obtain the original data, we attempted to experiment using one of the signal processing methods, namely the Moving Average. Moving Average is the simplest and easiest signal processing method. The results of signal improvement using a moving average can be seen in the following Figure.

Original Reference Data – MVA Signal Processing

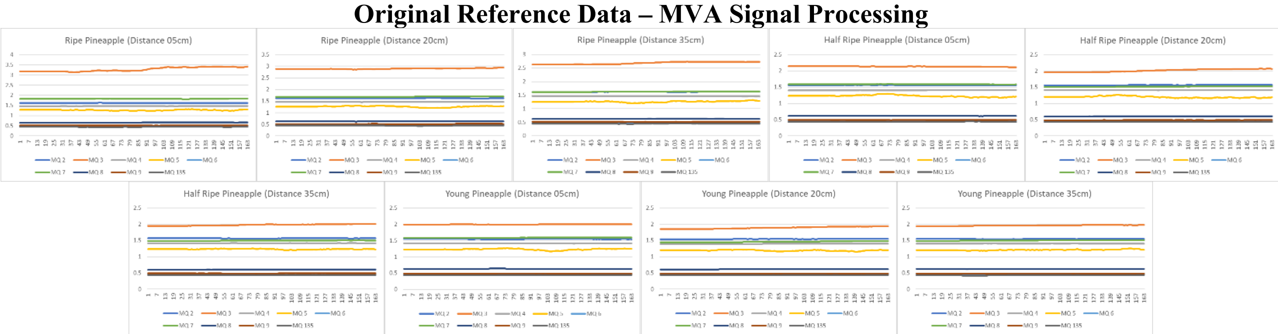

Fig. 6. MVA Signal Processing

It can be seen in Figure 6 that the Moving Average can reduce the noise in the signal as well as maintaining the signal waveform generated. However, the moving average, in this case, indicates it still has a slight weakness in separating one frequency band from another. It can be seen in Figure 6 that there are several intermittent signal wave frequencies that do not connect with the next frequency; therefore, we proceeded to the next technique, namely the Fast Fourier Transform (FFT).

C. Original Reference Data processed by Fast Fourier Transform (FFT) Method

After trying the signal processing technique with the MVA technique, we did a follow-up by comparing it to the FFT method in signal processing, where the results obtained by FFT are better than the previous method (MVA). The FFT method is able to generate the frequency content contained in the signal. The results of signal repair using the FFT method can be seen in the following Figure 7.

Original Data – FFT Signal Processing

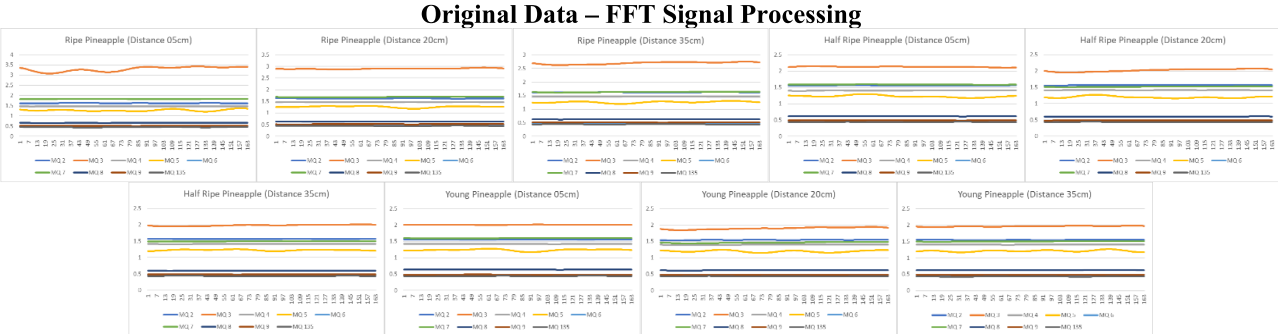

Fig. 7. FFT Signal Processing

D. Original Reference Data processed by Discrete Wavelet Transform (DWT) Method

After we compared the signals from MVA and FFT, we re-compared them with the Discrete Wavelet Transform (DWT) method. DWT is able to divide a signal dimension into two parts, namely high frequency and low frequency, which is called decomposition. The output of the High Pass Filter and Low Pass Filter produced the DWT coefficient. Through this coefficient, the original signal value can be reconstructed. Signal analysis is carried out on the results of the High Pass Filter and Low Pass Filter, where the High Pass Filter is used to analyze high frequencies and the Low Pass Filter is used to analyze low frequencies. The results of signal processing using the DWT method can be seen in the following Figure 8.

Original Data – DWT Signal Processing

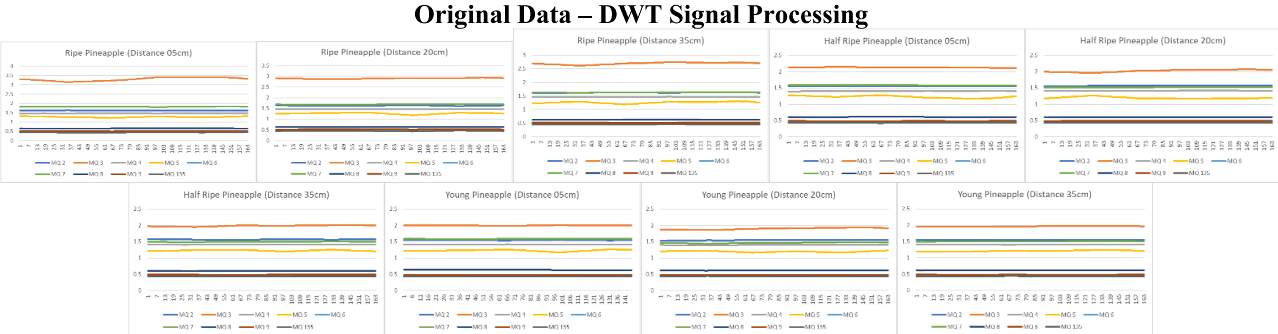

Fig. 8 : DWT Signal Processing

V. CONCLUSIONS AND SUGGESTIONS

The result of the signal obtained is the one that produces the highest value, that is ripe pineapple with a distance of 5 cm. The resulting signal value range is 3-3.5 ppm. Meanwhile, the range of the lowest signal value is the signal value generated by unripe pineapple with a distance of 35 cm with the resulting range of signal values below 2 ppm. The result was obtained after the signal comparison using the MVA, FFT and DWT methods. The results of signal improvement using the Discrete Wavelet Transform (DWT) method are better because DWT is able to divide a signal dimension into two parts, namely high frequency and low frequency, which is called decomposition. The output of the High Pass Filter and Low Pass Filter produced a DWT coefficient, from which the original signal value can be reconstructed. Signal analysis is carried out on the results of the High Pass Filter and Low Pass Filter where the High Pass Filter is used to analyze high frequencies and the Low Pass Filter is used to analyze low frequencies.

ACKNOWLEDGMENT

This study is an integral part of the research of the Doctor of Computer Science program at Institut Teknologi Sepuluh Nopember, under the guidance and direction of Information Intelligence Management Laboratory, Department of Informatics, Institut Teknologi Sepuluh Nopember.

REFERENCES

[1] M. S. H. Ardani, R. Sarno, Malikhah, D. P. Purbawa, S. I. Sabilla, K. R. Sungkono, C. Fatichah, D. Sunaryono, R. Susilo. "A new approach to signal filtering method using K-means clustering and distance-based Kalman filtering," *Sens Biosensing Res*, vol. 38, p. 100539, Dec. 2022, doi: 10.1016/j.sbsr.2022.100539.

[2] M. S. H. Ardani, R. Sarno, M. M. Khosasih,M. Malikhah2,D. P. Purbawa1,C Fatichah1, D Sunaryono1., "Electronic Nose Signals for Analysing Similarity of Male and Female Axillary Odour to Food Material Aroma"." *International Journal of Intelligent Engineering and Systems"*, vol. 15, no. 5, p. 601, 2020, doi: 10.22266/ijies2022.1031.52

[3] M. Mirshahi, V. Partovi Nia, and L. Adjengue, "Automatic odor prediction for electronic nose," *J Appl Stat*, vol. 45, no. 15, pp. 2788–2799, 2018, doi: 10.1080/02664763.2018.1441382.

[4] J. Trihaas, "Electronic nose : Smelling the microbiological quality of cheese," *Culture*, pp. 1–5.

[5] V. Sberveglieri, E. Comini, D. Zappa, A. Pulvirenti, and E. N. Carmona, "Electronic nose for the early detection of different types of indigenous mold contamination in green coffee," *Proceedings of the International Conference on Sensing Technology, ICST*, pp. 461–465, 2013, doi: 10.1109/ICSensT.2013.6727696.

[6] S. Guney and A. Atasoy, "Fish freshness assessment by using electronic nose," *2013 36th International Conference on Telecommunications and Signal Processing, TSP 2013*, pp. 742–746, 2013, doi: 10.1109/TSP.2013.6614036.

[7] D. Wang, X. Wang, T. Liu, and Y. Liu, "Prediction of total viable counts on chilled pork using an electronic nose combined with support vector machine," *Meat Sci*, vol. 90, no. 2, pp. 373–377, 2012, doi: 10.1016/j.meatsci.2011.07.025.

[8] E. Górska-Horczyczak, D. Guzek, Z. Molęda, I. Wojtasik-Kalinowska, M. Brodowska, and A. Wierzbicka, "Applications of electronic noses in meat analysis," *Food Science and Technology (Brazil)*, vol. 36, no. 3, pp. 389–395, 2016, doi: 10.1590/1678-457X.03615.

[9] D. M. Martínez Gila, J. Gámez García, A. Bellincontro, F. Mencarelli, and J. Gómez Ortega, "Fast tool based on electronic nose to predict olive fruit quality after harvest," *Postharvest Biol Technol*, vol. 160, no. November 2019, p. 111058, 2020, doi: 10.1016/j.postharvbio.2019.111058.

[10] A. A. AlieroA, A.D. Ibrahim, A. Sani, "Microorganisms Associated with Volatile Metabolites Production in Soft Rot Disease of Sweet Pepper Fruits (Tattase)," *International Journal of Biotechnology and Biochemistry*, vol. 7, no. 6, pp. 25–35, 2011.

[11] Q. Grading, *Electronic-Nose Applications for Fruit Identification, Ripeness and Quality Grading*. 2015. doi: 10.3390/s150100899.

[12] J. Brezmes, Ma.L.L. Fructuoso, E. Llobet, X. Vilanova, I. Recasens, J. Orts, G. Saiz, X. Correig, "Evaluation of an Electronic Nose to Assess Fruit Ripeness," vol. 5, no. 1, pp. 97–108, 2005.

[13] M. Mallick, S. Minhaz Hossain, and J. Das, "Graphene Oxide Based Fruit Ripeness Sensing e-Nose," *Mater Today Proc*, vol. 5, no. 3, pp. 9866–9870, 2018, doi: 10.1016/j.matpr.2017.10.179.

[14] M. A. Hasan, R. Sarno, and S. I. Sabilla, "Optimizing Machine Learning Parameters for Classifying the Sweetness of Pineapple Aroma Using Electronic Nose," *International Journal of Intelligent Engineering and Systems*, vol. 13, no. 5, p. 122, 2020, doi: 10.22266/ijies2020.1031.12.

[15] R. Patil, "Noise Reduction using Wavelet Transform and Singular Vector Decomposition," *Procedia Comput Sci*, vol. 54, pp. 849–853, 2015, doi: 10.1016/j.procs.2015.06.099.

[16] R. Samad and H. Sawada, "Edge-Based Facial Feature Extraction Using Gabor Wavelet and Convolution Filters," 2011.

[17] A. A. Girgis and F. M. Ham, "A Quantitative Study of Pitfalls in the FFT."

[18] D. Zhang, "Wavelet Transform," 2019, pp. 35–44. doi: 10.1007/978-3-030-17989-2_3.