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MICROCONTROLLER-BASED SOUND ACQUISITION AND CONVERSION FEATURE WITH MACHINE LEARNING ALGORITHMS TO DETERMINE LEVEL OF COCONUT MATURITY

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ABSTRACT: This paper is about developing a microcontroller-based system that will extract the sound features of post harvested coconuts (cocosnucifera) and with machine learning to determine the level of maturity. The microcontroller-based system is used as the data gathering feature with sound acquisition application, conversion, and digital signal processing for machine learning operation. The sampling rate used is 44.1 kHz. The three maturity stages for the coconut maturity considered are the immature, mature, and over-mature. The machine learning algorithm considered are Artificial Neural Network, Support Vector Machine, and Random Forest Classifier to perform classification and prediction of the coconut samples according to its maturity level.The data partition of 70%, and 30%of the whole samples are used, as the training dataset and the testing dataset, respectively.The data feature in time-domain and frequency-domain shows that the time-domain shows better results than the frequency-domain. The data partition 70-30 percentage performed well, where the three machine learning algorithms have an above 80% accuracy. The ANN accuracy for training and testing was 82.3% and 85.21 %, the SVM accuracy was 92.1% and 80.86%, and the RF Classifier was 92.48% and 84.34% with the data used in time-domain.

KEYWORDS:*microcontroller, sound processing, machine learning, coconut, maturity*

1.0 INTRODUCTION

The Philippines is one of the largest producers and importer of coconuts in Asia.

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Coconut production was estimated at 3.31 million metric tons this April-June,2019, slightly lower by 0.8 percent than the 2018 same quarter level of 3.34 million metric tons, according to the Philippines Statistics Authority. According to the Philippine Coconut Authority (PCA), there are all over 3.5 million coconut farmers in the Philippines, and 26% of these farmers devote themselves to coconut farming. There is an annual average of 5.97% to the country's gross value added (GVA) and 1.14% to gross domestic product (GDP) of the country's contributions based on the statistics shown on PCA[2]. The Philippine Statistical office identified the Coconut, which scientifically known as Cocos Nucifera, as the leading agricultural export commodity. According to the Department of Trade and Industries (DTI), the Philippines is one of the biggest exporting countries of coconut; hence, accuracy in measuring fruit maturity is an excellent need before exporting. With the increase in the demand for coconut in the food processing industries, classifying their correct age is urgent. Committing errors in the selection for fruit maturity would yield losses due to the quality of raw material and would incur a vast amount of cost for large operations[1]. The most important entity for commercial products is the selection of the correct level of maturity[2].

There are three maturity levels identified; (1) immature, (2) mature, (3) over-maturedefine by the Philippine National Standard (PNS). The identification of maturity usesthe calendar method or the scientific method. However, most coconut farmers in the Philippines use sound to test the coconut's maturity by tapping the coconut during harvest. Studying sound should begin with understanding the properties of thesound[6]. The basic properties of sound are frequency, amplitude, spectrum, and duration[7].To establish numerical data for classifying coconut maturity through the use of tapping sound, there is a need to convert the generated sound into useful information. Merely using the raw audio stream as input in machine learning is not practical; thus,there is a need for feature extraction[8]to identify coconut maturity. This process is commonly known as Digital Signal Processing (DSP). The signal may transform for a particular purpose, such as amplifying or filtering out embedded information, pattern detection, and finding information encoded in a different domain.

An automated method for coconut grading based on audioception[9]used in India;wherein, audioception refers to the ability to perceive or hear a sound. A sound was produced from the impact made with the contact of coconut with the granite slab and is recorded using a mono microphone at 16,000 Hz, placed in a constant distance, under a controlled environment. For sound extraction, the Fast Fourier transform was applied.The study concluded that the concept of audioception could be used to segregate coconuts into good or bad.

A total of 300 new intact, uniformly sized young coconuts at three stages of maturity used in determining the physical, mechanical, acoustic, and physiological properties using an acoustic method through an acoustic property tester machine. The young Thai coconutplaced on a support at the center of the tester and impact force to

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the equator of the coconut sample in six positionswas applied.The sound signal captured by a microphone mounted in a few millimeters above the sample surface opposite the strike point. Fast Fourier transformation of the sound signal gave the frequency spectrum of the young coconut[10].It relates to young coconuts and uses an existing acoustic property machine.

Japan successfully identified watermelon maturity by applying the use of sound wherein, such principle was also employed by the University of Philippines-Diliman in 1994[1]. It concluded a scientific base in the sound waves produced in tapping coconut fruits.Advancement of technology, such as the embedded systems, and machine learning are used toimprove further the efficiency and accuracy of determining the maturity level of coconut. With the use of machine learning, it avoids biases in the classification compared to human judgments. Three machine learning algorithms classification considered for prediction are Artificial Neural Network(ANN), Support Vector Machine(SVM), and Random Forest Classification(RF).

2.0 METHODOLOGY

2.1 System Design

First, a microcontroller-based machine is developedto automate the knocking of the coconut and recording of the sound impact.It is divided into two sections: the recording area and the control area, as shown in figure 1. The control area on the right side of the recording box shows the placement of the laptop computer with the desktop software application, microcontroller, and the motor connected to the knocking mechanism in the recording area.

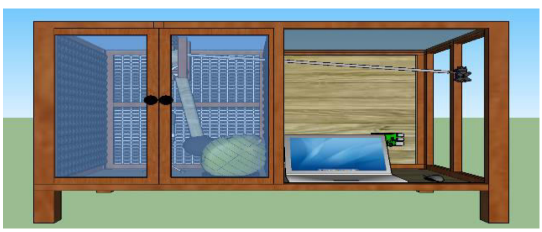
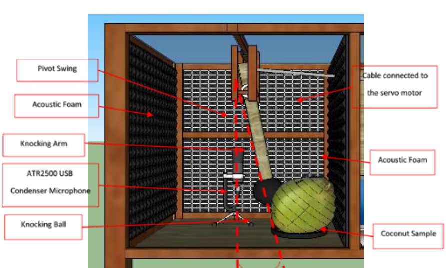
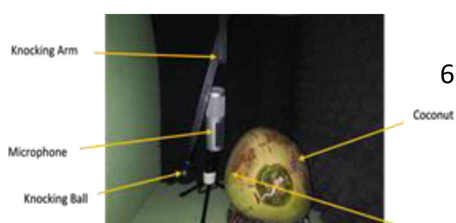


Figure 1: Front View of the Microcontroller-based Recording Box

The recording area shows the set-up of the tapping, the microphone,and the placement of the coconut.It is covered with acoustic foam to lessen the noise and to contain the sound. The microcontroller controls the servo motor and is interface with a desktop application. The system starts tapping the coconut when the button in the application was clicked and followed the rotation of the motor connected to the knocking mechanismin 360 degrees for three times.





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(a) (b)

Figure 2:Recording Area Set-up (a)prototype (b)actual

2.2 System Flow

Inside the microcontroller-system design follows the processes shown in figure 2. The system flow shown in figure involves automated sound

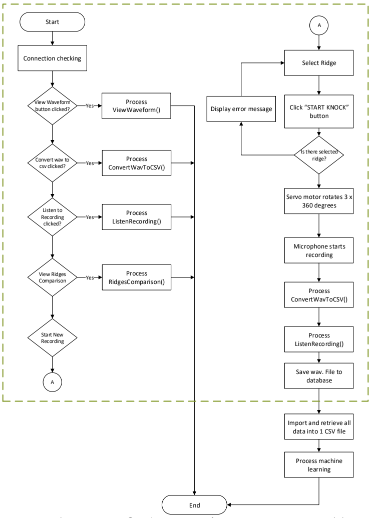

Figure 3: System Flow of the Microcontroller-based System

acquisition of coconut, digital processing of sound, and development of an intelligent classification of coconut's maturity level. The flow of the system starts with the checking of all connections. An error message displays in cases of disconnection. The sound acquisition is the recording of audio data of each coconut.The coconut knockedfor three times by the knocking arm connected to amicrocontroller-controlled servo motor, and the sound produced will be then recorded using the microphone. The audio data is save into the database. In the noise reduction, it retrieves the audio files from the database and removes the internaland audio noise of audio with the use of Fast Fourier Transform. Analog-to-Digital values conversion transform the audio signal into a number value equivalent. The audio data undergo three processes: Sampling, Quantization, and Coding. The data values save into the database and retrieve into a spreadsheet format. The datasets areimported as training and testing datasets for machine learning operation.

2.3 Sound Acquisition

A total of 134 coconut fruit samples, from a tall and dwarf coconut bearing fruits, areharvested in Llorando's hacienda in Argao, Cebu, Philippines, last January 12, 2019. These coconutsare pre-classified by a coconut farmer and coconut tree climbernamed Mr. Randolph Geneva resident ofArgao, Cebu, Philippines, according

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to three levels of coconut maturity. Each coconut is tapped using the developed microcontroller-based system for sound data collection. The coconut sample is post-classified by further verifying and validating it through opening the coconut fruit sample.

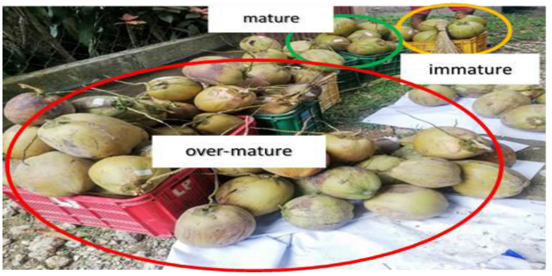

Figure 4: Pre-classification of Coconut According to Maturity

For each coconut sample, there are three audio data, as it has three ridges, and each ridge is knocked three times. Thus, collating a total of 381 audio data samples. Each ridge recording is considered one sample for its respective maturity level. The number of coconut audio data samples per maturity level are present in Table1.

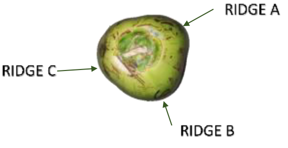

Figure 5: Ridges of a Coconut

Table1: Number of Samples

Maturity Level	No. of Coconuts	No. of Recordings per coconut	Total Number of Recordings per maturity
Immature	8	3	24
Mature	36	3	108
Over-mature	83	3	249
Total	**127**	**9**	**381**

Each recording for a ridge has a period of 3 seconds, and that has recorded the three knocks, as shown in Figure 6. All audio data of each ridge have the same recording period throughout the data gathering process. As to see the comparison between the recordings per ridge is shown in Figure 6. It has been observed to have a slight difference in the starting point of impact due to the distinct size and formation of the coconut sample.

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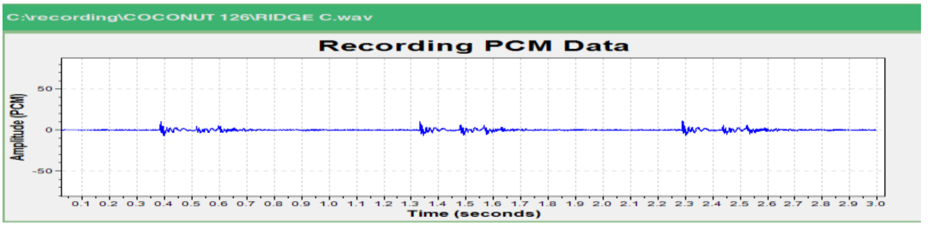

Figure 6: Recording Data Graph

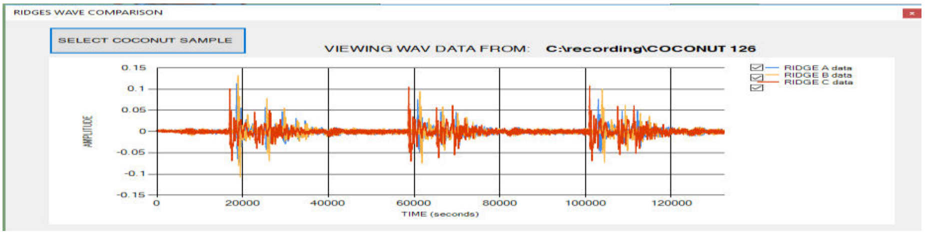

Figure 7: Comparison Graph of 3 Ridges of a Coconut

2.4 Feature Extraction

For the sound feature extraction, it considers the Time-domain and Frequency-domain. Between the two data feature to perform good accuracy results, the two data features are compared.

(1) Time-domain

The CSV file is used to collate the converted PCM graph or time-domain waveform signals to numeric values. A 44,100 Hz sampling rate was taken for each audio data sample. Thus, making 132,300 data points.

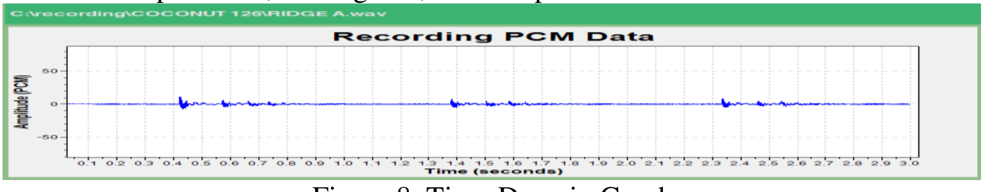

Figure 8: Time-Domain Graph

(2) Frequency-domain

The FFT (Fast Fourier Transform) graph presents the frequency of the sound. The Fast Fourier Transform (FFT) is an efficient algorithm for calculating the Discrete Fourier Transform (DFT) and is the de facto standard to calculate a Fourier Transform. Figure 9 is the transformed time-domain to FFT from one of the coconut sample recordings. The graph's y-axis is the amplitude in power based on the frequency range of the x-axis of the sound recorded. For the FFT transformation having the parameters of the converted data values in the CSV file of each recording with the number of data points was coded in python.

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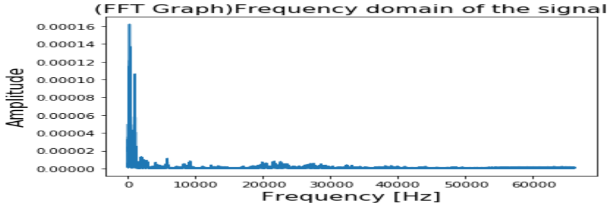

Figure 9: Frequency Domain Graph

3.0 RESULTS ANDDISCUSSION

3.1 Time-Domain Analysis

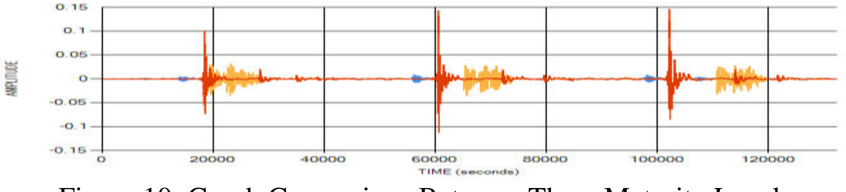

Figure 10: Graph Comparison Between Three Maturity Level

Based on Figure 10, it shows the over-mature(red-orange) has the highest amplitude among the three classifications followed by the mature graph(yellow-orange), and the immature(blue). Figure 11 shows the chart comparison of immature and mature to view a significant difference between the two. The graph in yellow-orange is the mature classification, and behind it, the graph in blue is the immature classification. The amplitude of the sound of the mature level is higher than of the immature level.

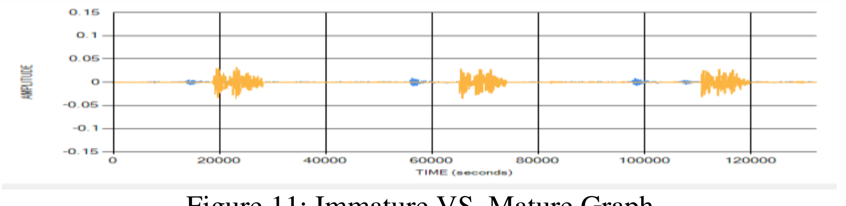

Figure 11: Immature VS. Mature Graph

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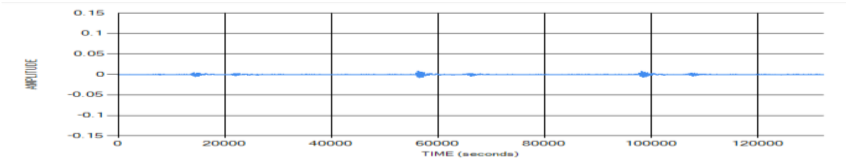

Figure 12: Mature Graph

Figure 12 shows the graph of an immature taking out the other two classifications. The amplitude value of the chart ranges near the 0 value. Figure 13 shows the comparison of the mature(yellow-orange) vs. over-mature(red-orange). In figure 13, tells the height of the amplitude of an over-mature is higher compared to the mature.

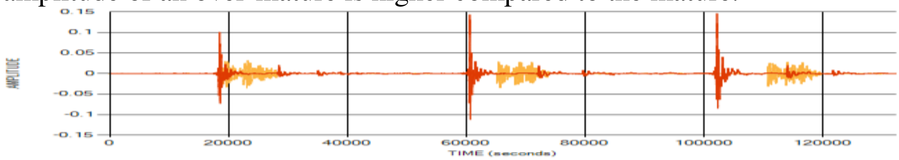

Figure 13: Mature VS. Over-mature

3.2 Frequency-Domain Analysis

The second finding is on the recording presented in Frequency-Domain.

(1) Immature

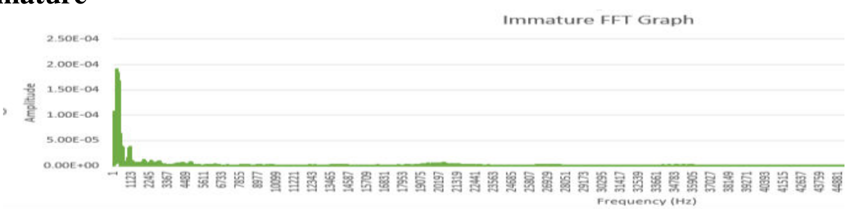

Figure 14: Immature Sample

(2) Mature

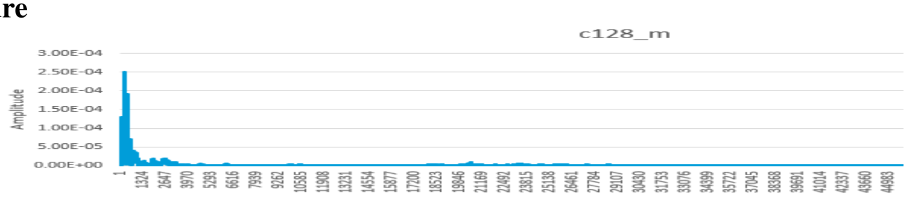

Figure 15: Mature Sample

(3) over-mature

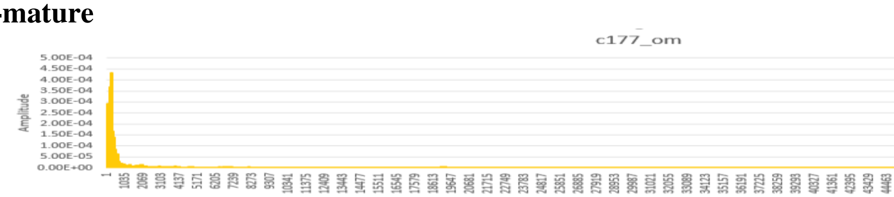

Figure 16: Over-mature Sample

Therein with the data presented in time-domain and frequency-domain. In time-

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domain, with the above graph representations show that as maturity level increases, the amplitude of the sound also increases. On the other hand, in frequency-domain, it is observed that as the level of maturity increases, the power amplitude on a frequency range also increases.
In regards to the validation of these findings, the Philippine Coconut Authority and National Coconut Research Center – Visayas are consulted to validate.However,the departments do not have the data of qualifying coconut maturity level using its sound property thus, interviews are conducted with the coconut farmers, coconut vendors, and coconut tree climber. As stated on one of the interviews: an immature coconut is describe to have a firm in structure, full of water and has less coconut meat thus, creating the least sound vibration when tapped; a mature coconut is also firm in structure however, it has a more and tender coconut meat and is also full of water, and there is a distinct sound comparing with the immature; an over-mature coconut is less firm in structure, has the most and hard coconut meat and contains less water wherein the presence of water inside is very obvious when shaking it thus, creating a distinctive sound from the other two when tapped.

3.3 Machine Learning Parameters

Shown in Table 2 is the exact data samples per partition, and per level of maturity of the total data samples, use as testing and training datasets for the machine learning operations.

Table 2: Dataset Partition

	Level of Coconut Maturity/ Coconut Classification			
Partition	**Immature**	**Mature**	**Over-mature**	**Total**
(70%) No. of Training Data Samples	16	75	174	265
(30%) No. of Testing Data Samples	8	33	75	116
Total Samples	**24**	**108**	**249**	**381**

Table 3: Machine Learning Algorithms Parameters

Machine Learning Algorithm	**meters**
Artificial Neural Network	hidden_layer_sizes[32,16,8], maximum iteration=200
Support Vector Machine	kernel='rbf', C = 1, gamma = 0.5
Random Forest Classifier	n_estimators = 100, maximum depth=3

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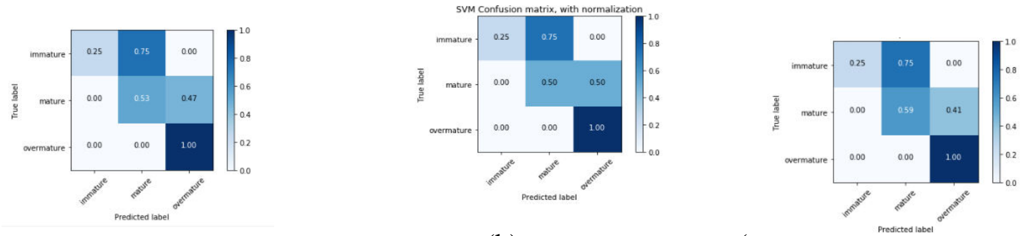
3.4 Machine Learning Algorithms Result

The following shown below are the results in the confusion matrix of the three machine learning algorithms. The common result between the three machine learning algorithms is a consistency of 100% prediction for over-mature level and a 25% correct prediction for immature.

(1) Using Time-Domain Data Feature Results



(a) (b) (c)

Figure 17: Confusion Matrix Results (a)ANN, (b)SVM, (c) RF

COMPARISON

Figure 18 shows the comparative training and testing accuracy result of the three machine learning algorithms using the time-domain data feature. It indicates that Random Forest Classifier(RF) is the highest training accuracy, while the highest testing accuracy is ANN. Based on the criteria, that accuracy for both training and testing should be at least 80% and above. Over-all, RF shows the best results among the three.

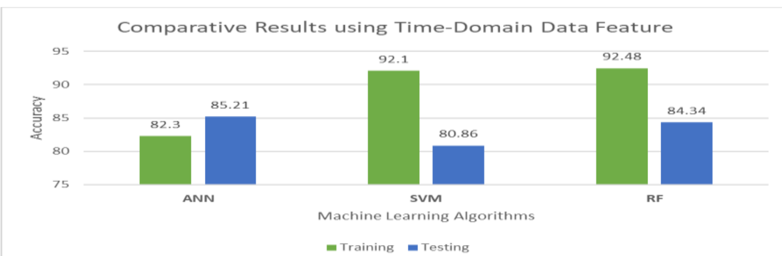


Figure 18: Comparative Results of the 3 Machine Learning Algorithms

(2) Using Frequency-Domain Data Feature Results

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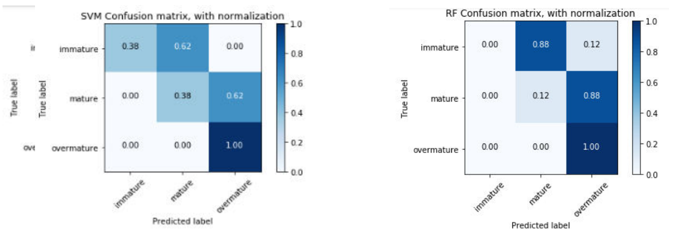
The frequency-domain data feature uses the FFT wherein we cut until 22,050 data points, and it yielded the following confusion matrix result for the three machine learning algorithms, as shown in Figure 19. A consistency of 100% correct prediction for the over-mature level for the three algorithms and varying prediction for the immature and mature level.



(a) (b) (c)

Figure 19: ANN Confusion Matrix Result using FFT: (a)ANN, (b)SVM, (c) RF

COMPARISON

Figure 20 shows the comparative training and testing accuracy results of the three machine learning algorithms using the FFT dataset. It shows that SVM gained the highest training accuracy while ANN gained the highest testing accuracy of results, 78%and 80%, respectively. The ANN results recorded an accuracy of 71% for training accuracy that is below target. The RF results were the lowest of accuracy, 64% and 70%, respectively. In this case, SVM shows the highest performing algorithm, followed by ANN then the RF model.

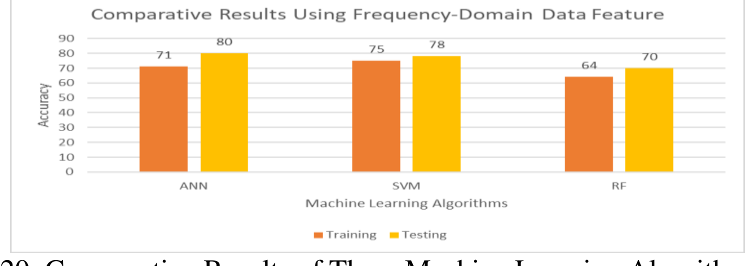


Figure20: Comparative Results of Three Machine Learning Algorithms using Frequency-Domain

4.0 CONCLUSION

A microcontroller-based knocking and recording system with a machine learning algorithm to gather and to determine the level of coconut maturity is successfully develop as an innovation for the agriculture sector. The manual tapping and classification of the coconut are usually done by a person who is replaced by mechanical knocking arm controlled by a microcontroller serially communicated by a desktop application that controls the servo motor that rotates three times to produce a sound and sound recorded by a condenser microphone stored in a database.With this, the force and the frequency of knocking are more consistent and uniform throughout

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the gathering of data. Through digital signal processing, the recorded sound goes processing. Furthermore, the duration of time to tap the coconut would take 3 seconds for one recording. The focus is not just on one variant of coconut maturity but the three levels namely, immature, mature, and over-mature. The usage of the Time-Domain data feature performs well compared to the Frequency-Domain. The three machine learning algorithms, namely Artificial Neural Network, Support Vector Machine, and Random Forest,can generate good classification results using 70% of the dataset for training and 30% of the dataset for the testing and yielded an above 80% accuracy percentage of predicting maturity level of coconut.

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REFERENCES

[1] M.M.Gatchalin, S.Y.De Leon, & T. Yano, "Measurement of Young Coconut (Cocos nucifera, L.) Maturity by Sound Waves. Journal of Food Engineering." 23(3). 253-276. DOI: 10.1016/0260-8774(94)90053-1, 1994

[2] Britannica, The Editors of Encyclopaedia. (2019). *Fruit.* Encyclopædia Britannica, Encyclopædia Britannica, Inc.[Online] Available: https://www.britannica.com/science/fruit-plant-reproductive-body.

[3] S. Chen,et. al. "Discrete Signal Processing on Graphs: Sampling Theory." *IEEE Transactions on Signal Processing*, vol. 63, no. 24, 2015, pp. 6510–6523., doi:10.1109/tsp.2015.2469645.

[4] R.J. Urbanowicz, and J.H. Moore. "Learning Classifier Systems: A Complete Introduction, Review, and Roadmap." *Journal of Artificial Evolution and Applications*, vol. 2009, 2009, pp. 1–25., doi:10.1155/2009/736398.

[5] O. Mitalo.(2015).*Fruit Maturity and Maturity Indices*. Fruits and Vegetables[Online].Available: https://omitalowitere.wordpress.com/2015/02/11/fruit-maturity-and-maturity-indices/.

[6] R.E. Berg.(2019).*Sound. Encyclopædia Britannica*, Encyclopædia Britannica, Inc.[Online]. Available at https://www.britannica.com/science/sound-physics.

[7] J.Ellinger,J.Trevino.(2014).*Unit 1 Reading - Six Properties of Sound*, [Online]. Available: https://acad.carleton.edu/courses/musc108-00-f14/pages/01/01SixBasicPropertiesofSound.html.

[8] R.Muller-Cajar. *Detecting Advertising in Radio Using Machine Learning.* University of Canterbury, Christchurch, New Zealand, 3, 2007

[9] P.Thomas, & H B, A., Dr. (2017, May 31). *A Novel Automated Method for Coconut Grading Based On Audioception*.[Online]Available:

ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

http://www.jatit.org/volumes/Vol95No10/18Vol95No10.pdf
[10] A.Terdwongworakul, et al. "Physical Properties of Fresh Young Thai Coconut for Maturity Sorting." *Biosystems Engineering*, vol. 103, no. 2, 2009, pp. 208–216., doi:10.1016/j.biosystemseng.2009.03.006.