Evaluation of the Internal Quality for Pineapple Based on the Spectroscopy Approach and Neural Network

Nonlapun Meenil, Pisitpong Intarapong, Thitima Wongsheree, Pranchalee Samanpiboon

***Abstract*—**In Thailand, once pineapples are harvested, they must be classified into two classes based on their sweetness: sweet and unsweet. This paper has studied and developed the assessment of internal quality of pineapples using a low-cost compact spectroscopy sensor according to the spectroscopy approach and Neural Network (NN). During the experiments, Batavia pineapples were utilized, generating 100 samples. The extracted pineapple juice of each sample was used to determine the Soluble Solid Content (SSC) labeling into sweet and unsweet classes. In terms of experimental equipment, the sensor cover was specifically designed to install the sensor and light source to read the reflectance at a five mm depth from pineapple flesh. By using a spectroscopy sensor, data on visible and near-infrared reflectance (Vis-NIR) were collected. The NN was used to classify the pineapple classes. Before the classification step, the preprocessing methods, which are class balancing, data shuffling, and standardization, were applied. The 510 nm and 900 nm reflectance values of the middle parts of pineapples were used as features of the NN. With the sequential model and ReLU activation function, 100% accuracy of the training set and 76.67% accuracy of the test set were achieved. According to the abovementioned information, using a low-cost compact spectroscopy sensor has achieved favorable results in classifying the sweetness of the two classes of pineapples.

***Keywords*—**Spectroscopy, soluble solid content, pineapple, neural network.

I. Introduction

In the process of pineapple cultivation, a significant amount of effort and patience from the farmer is necessary. The plants take considerable time to grow and produce fruit, and the frequency of harvests is relatively low compared to other crops. Additionally, prevailing market prices often result in meager prices for pineapples. The large batch of pineapple would be randomly investigated for internal quality using a chemical method. The pineapples that did not satisfy the requirements would be discarded and became a bio-waste that is only partially utilized.

Numerous methods of evaluating the internal quality of fruits have been developed during the past 20 years [1]-[9], [11]-[13]. The high accuracy method called the Dielectric Constant was developed to assess the acidic level of apple flesh [1]. Near Infrared (NIR) and Mid Infrared (MIR) wavelengths were used to perform a freshness assessment of cut pineapple flesh stored in different temperatures based on an optical technique known as the spectroscopy method [2]. Durian maturity was determined using Microwave Moisture Sensing [3]. The assessment of translucency in pineapple using an X-ray was presented [4]. In addition, spectroscopy was used to automatically classify peach maturity into different levels [5]. Consequently, these methods were used to measure the internal quality of fruits.

According to researches, the nondestructive measurement method called the Acoustic Impulse Response was used to separate the maturity levels of pineapples which are significantly related to SSC and Fresh Firmness (FF) of pineapple [6]. A meter to evaluate total SSC and the acidity in pineapple pulp using an optical technique was developed in [7]. SSC prediction of pineapples using non-invasive, low-cost visible and shortwave NIR in the range of 650-1000 nm, including with Artificial Neural Networks (ANN) was performed in [8]. Furthermore, the analysis of SSC in pineapples using NIR spectroscopy to predict the SSC in pineapples with different harvest dates in the wavelength of 662-1005 nm was performed in [9].

Consequently, the spectroscopy is an exciting method for the internal quality assessment of pineapples. It uses light's reflection, transmission, absorption, and scattering properties. Light is a type of electromagnetic wave that can be classified by frequency or wavelength: radio, microwave, infrared, visible, ultraviolet, x-ray, and gamma-ray. Since incident light strikes an object such as a fruit, the chemical composition of the fruit absorbs the light energy, which is different in each wavelength, the reflected light is measured using a spectrometer for further analysis [10]. In the past, the spectroscopy has been applied for several purposes. Accordingly, a predictive study of nitrate content in Batavia pineapples was conducted using the Vis-NIR wavelengths [11]. The feasibility of using a portable NIR spectrometer to detect and predict SSC in pineapples was studied and achieved 85% of prediction accuracy [12]. In addition, the portable NIR sensor from Light Emitting Diode and photodiode with the use of ANN was investigated. The wavelengths from 700-1100 nm were used to classify the

Nonlapun Meenil is with the Department of Electrical Engineering, King Mongkut's University of Technology Thonburi, Bangkok, 10140 Thailand (e-mail: nonlapun.m@mail.kmutt.ac.th).

Pisitpong Intarapong is with King Mongkut's University of Technology Thonburi, Ratchaburi Campus, Ratchaburi, 70150 Thailand (e-mail: pisitpong.int@kmutt.ac.th).

Thitima Wongsheree is with the Institute of Technology Services and Research Center, King Mongkut's University of Technology Thonburi, Bangkok, 10140 Thailand (e-mail: thitima.won@kmutt.ac.th).

Pranchalee Samanpiboon is with Department of Control System and Instrumentation Engineering, King Mongkut's University of Technology Thonburi, Bangkok, 10140 Thailand (e-mail: pranchalee.rat@kmutt.ac.th).

internal quality of pineapple. By utilizing the scaled conjugate gradient algorithm, the proper number of hidden neurons is seven with 70% accuracy [13].

Consistent with the information, the relation between the chemical substance of pineapple and electromagnetic radiation in the Vis-NIR wavelength ranges was studied in this research. A spectroscopy-based apparatus was conceived and built to evaluate the quality of Batavia pineapples. NN was used to classify pineapple classes. The research purpose is to assist farmers and purchasing industries in precisely assessing the internal quality of each pineapple prior to trade in order to reduce the number of pineapples discarded due to unqualified traditional random sampling findings.

II. Materials and Methods

A. Measurement of the Vis-NIR Reflectance Spectra

According to the purpose of this research, SparkFun Triad Spectroscopy Sensor AS7265x was used as a sensor detector which detects 18 different channels of light wavelength from 410 nm (UV) to 940 nm (IR). The sensor would be operated via the Arduino mega 2560.

OSL2-High-Intensity Light Source (OSL2) was used as the light source. The operational wavelength range of 400-1600 nm was utilized under condition of a 150 W, 3400 L, EKE/10H lamp at 25% light intensity. The light was transmitted to the object using the 8 mm diameter fiber probe.

The major function of the black cover is to install the fiber tip of OSL2 light source and the body of AS7265x sensor, and to protect the sensor from being interfered with external light due to the black ABS material and its specified form. The complete design of the cover is shown in Fig. 1, in which area (a) is used to install the fiber tip of OSL2, and area (b) is used to install the sensor.

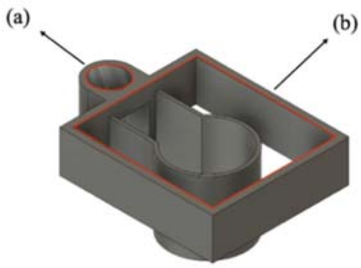

Fig. 1 The designed sensor cover: (a) OSL2 fiber tip installation's hole; (b) Sensor installation's area

The (a) area of Fig. 1 is intended for the installation of the OSL2 fiber tip, which forms a 25° angle with the cover's perpendicular line, as shown in Fig. 2. According to the designed angle, the sensor is able to read the reflectance at a five mm depth from outer surface to ensure that the reflectance point is the flesh of pineapple.

According to the experimental apparatus used in the measurement of the Vis-NIR reflectance spectra, the measurement setup is shown in Fig. 3.

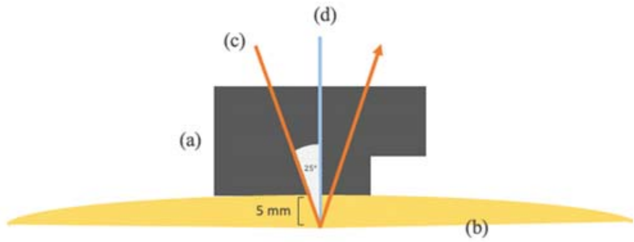

Fig. 2 The cover angle design (a) The cover, (b) Pineapple, (c) Light direction, (d) Perpendicular line of the cover

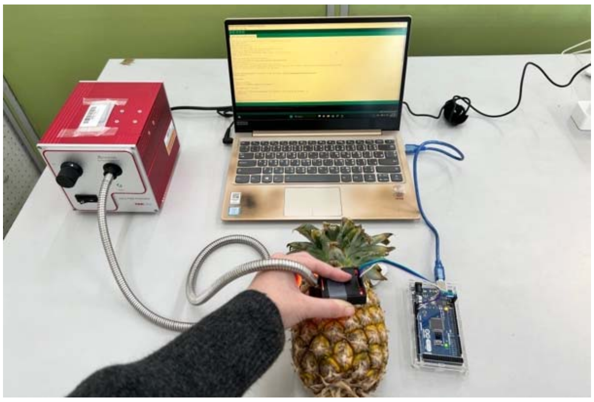

Fig. 3 The measurement setup

The reflectance spectra were obtained by the measurement at the specific positions on a pineapple shown in Fig. 4. The reflectance of three points (middle, upper-middle, and lower-middle point) was measured as a sample of the NN input. In the experiment, the reflectance spectra of middle point were measured initially, then we turned the pineapple to the right for 45° angle and the reflectance spectra of upper-middle and lower-middle point were measured. The processes were repeated to the next 45° angle for the second sample until the reflectance spectra of four samples of a pineapple were wholly obtained and stored. According to the experiment, 100 samples were recorded and used for the training set and test set of the NN.

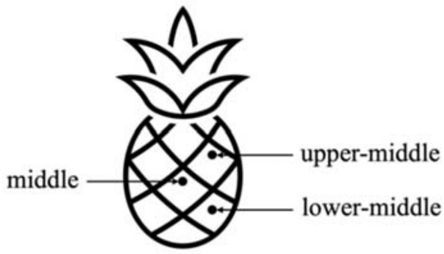

Fig. 4 The specific position of the measurement

B. Measurement of the Reference SSC

In the process of SSC acquisition, the peel of the pineapple at the specific position shown in Fig. 4 was peeled off for about 2-3 mm depth and then we used a fruit picker to scoop out small pieces of flesh. After that, we squeezed the pineapple juice and dropped it onto the digital refractometer (PAL-1 Pocket Refractometer, ATAGO). The SSC of each point was recorded and matched with the reflectance value at the same point.

C. Classification of Pineapple Class

To classify the sweetness of pineapples, the NN was utilized. The NN consists of an input layer, hidden layers, and an output layer that are connected by nodes. Its purpose is to train the data and enhance the precision of the model through learning. Before training, class identification and class balancing were performed as shown in Table I. At the class identification, the sample with an average SSC value of middle, upper-middle, and lower middle point less than 8.99 °Brix was identified as "unsweet" class, whereas greater than 8.99 °Brix was identified as "sweet" class.

TABLE I
CLASS IDENTIFICATION AND CLASS BALANCING

°Brix	Number of samples	Number of samples per class	Class
< 5.99	1		
6.00-6.99	7	49	unsweet
7.00-7.99	16		
8.00-8.99	25		
9.00-9.99	20		
10.00-10.99	6		
11.00-11.99	4		
12.00-12.99	6	51	sweet
13.00-13.99	9		
14.00-14.99	5		
15.00-15.99	1		
Total	100	100	

To perform NN, the Google Colaboratory was utilized, which enables users to write and execute Python code directly in a web browser. Two reflectance of 510 nm and 900 nm wavelengths were used as the features of the sample. After class identification and class balancing were performed, the data were shuffled and separated into training and test set. The data frames of the training and test set are shown in Figs. 5 and 6, respectively.

Before training, all features were standardized to ensure that the data's mean set to zero and the standard deviation set to one. During the training process of the NN, by utilizing the deep learning library called TensorFlow, the sequential model was utilized to group a stack of layers and deliver the data in sequential order through the model. A ReLU activation function was employed for all seven hidden layers with the Adam optimizer. The total number of NN parameters is 103,577 which all are trainable parameters. This information shown in Table II.

TABLE II
METHODS AND PARAMETERS USED IN NN

	Description
Pre-processing methods	Class identification Class balancing Data shuffling Standardization‡
Model	Sequential
Activation function	ReLU
Optimizer	Adam
Number of parameters	103,577

III. RESULT AND DISCUSSION

After the SSC of each position was obtained, the data were recorded and analyzed. Table III shows the statistical analysis record of the SSC. The maximum and minimum values of the SSC between the two classes were significantly different. The average value of the class sweet is 11.2 °Brix whereas the class unsweet is 7.7 °Brix. The sweet class has a greater standard deviation of 2.1, indicating a broader range of data than the unsweetened class. On the other hand, the standard deviation for the unsweet class was only 0.8, revealing a narrower distribution of data. This revealed the difference between the two classes of independent variable.#

	mid_900	upper_mid_900	lower_mid_900	mid_510	upper_mid_510	lower_mid_510	class
0	770	740	790	481.489	478.554000	572.236	unsweet
1	970	780	890	684.455	523.301111	660.609	sweet
2	860	980	990	415.435	517.272000	483.766	unsweet
3	760	680	790	446.959	312.054000	362.017	sweet
4	910	700	960	531.234	489.426000	506.546	unsweet
...	...	...	...	...	...	...	...

Fig. 5 The data frame of training set

	mid_900	upper_mid_900	lower_mid_900	mid_510	upper_mid_510	lower_mid_510	class
0	740	780	840	482.886	615.144	669.809	unsweet
1	800	990	830	646.836	761.771	677.760	sweet
2	850	860	810	615.065	736.230	639.685	sweet
3	750	770	810	687.455	718.304	685.147	sweet
4	650	620	650	309.558	308.675	300.739	sweet
5	1010	720	830	689.533	636.374	677.760	sweet

Fig. 6 The data frame of test set

TABLE III
STATISTICAL RECORD OF THE SSC

Class	Minimum	Maximum	Average	Standard Deviation
sweet	9.0	15.3	11.2	2.1
unsweet	5.7	8.7	7.7	0.8

The accuracy of NN classification in the training set and the test set was determined. Table IV shows the accuracy of the training and the test set classification, which achieves 100% accuracy in the training set and 76.67% accuracy in the test set. In the training set, 70 samples were correctly classified, whereas 23 samples out of 30 samples were correctly classified in the test set. This result clearly indicates the consistency between the SSC and the reflectance. Besides, the reflectance shows its substantial property as the dependent variable of the experiment.

TABLE IV
THE ACCURACY OF CLASSIFICATION IN THE TRAINING SET AND THE TEST SET

	Number of Samples	Correct Classification	Wrong Classification	Accuracy
Training set	70	70	0	100%
Test set	30	23	7	76.67%

According to the result in the test set, the confusion matrix showing the efficiency of the model was obtained as shown in Fig. 7. Nine true positives, four false positives, three false negatives, and 14 true negatives were obtained. In this case, positive refers to the class unsweet whereas negative refers to the class sweet.

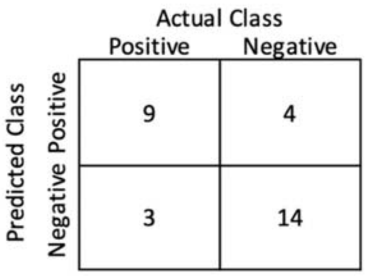

Fig. 7 Confusion Matrix

TABLE V
PRECISION RECALL AND ACCURACY

	Precision	Recall	Accuracy
Positive	0.69	0.75	0.7667
Negative	0.82	0.78	

Based on the confusion matrix, precision, recall, and accuracy can be calculated as shown in Table V. The precision is 0.69 and 0.82 in the classes positive and negative, respectively. It indicates the precision of the model to predict each class. The value 0.82 suggests that the model has a better accuracy in the negative class. Since, in negative class, it prominently shows higher consistency between the SSC and the reflectance. The recall is 0.75 and 0.78 in the classes positive and negative, respectively. It indicates the number of correctly determines true positive or true negative from all actual positive or all actual negative of the model. The total accuracy was calculated to be 0.7667.

IV. CONCLUSION

According to the precise design of the sensor cover, the selection of the sensor, and the light source, the property of the chemical substance which is pineapple flesh at five mm depth was obtained as the reflectance. The 500 nm and 900 nm reflectance at the upper middle, middle, and lower middle points were used as the features of the NN, whereas the SSC was used to identify the class of each sample. Eventually, the NN gave 76.67% accuracy in test set classification. Consequently, this study shows strong consistency between the reflectance and SSC. The use of a low-cost compact spectroscopy sensor and the NN to classify the sweetness of pineapple could be accomplished with high accuracy.

ACKNOWLEDGMENT

Nonlapun Meenil thanks University for Community and Society and the Department of Control System and Instrumentation Engineering, King Mongkut's University and Technology Thonburi for financial support of experimental equipment, conference registration, and publication.

REFERENCES

[1] V. Semenov, Y. Mitelman, 2020, "Non-destructive Fruit Quality Control Using Radioelectronics: A Review", *Ural Symposium on Biomedical Engineering, Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT*), pp. 0281–0284, May. 2020.

[2] V. D. Egidio, N. Sinelli, S. Limbo, L. Torri, L. Franzetti, E. Casiraghi, "Evaluation of shelf-life of fresh-cut pineapple using FT-NIRand FT-IR spectroscopy," *Postharvest Biol. Technol.*, vol. 54, Nov. 2009, pp. 87–92.

[3] T. Rutpralom, P. Kumhom, K. Chamnongthai, "Nondestructive Maturity Determination of Durian by Using Microwave Moisture Sensing," *IEEE ICIT,* vol. 1, pp. 155–158, Dec. 2002.

[4] R. P. Haff, D. C. Slaugther, Y. Sarig, A. Kader, "X-ray assessment of translucency in pineapple," *J. Food Process. Preserv.*, vol. 30, Oct. 2006, pp. 527–533.

[5] S. Matteoli, M. Diani, R. Massai, G. Corsini, D. Remorini, "A Spectroscopy-Based Approach for Automated Nondestructive Maturity Grading of Peach Fruits," *IEE Sens. J.,* vol. 15, Oct. 2015, pp. 5455–5464.

[6] S. Pathaveerat, A. Terdwongworakul, A. Phaungsombut, "Multivariate data analysis for classification of pineapple maturity," *J. Food Eng.*, vol. 89, Nov. 2008, pp. 112–118.

[7] R. Lapcharoensuk, N. Jirakannukul, T. Pheinvirattanachai, P. Rungvithu, "Development of a Meter for Evaluation of Total Soluble Solid Content and Acidity in Pineapple Pulp using Optical Technique," *The* 18^{th} *TSAE National Conference and the* 10^{th}*TSAE International Conference*, Sep. 2017.

[8] K. S. Chia, H. A. Rahim, R. A. Rahim, "Prediction of soluble solids content of pineapple via non-invasive low cost visible and shortwave near infrared," *Biosyst. Eng.*, vol. 113, Oct. 2012, pp. 158–165.

[9] K. S. Chia, H. A. Rahim, R. A. Rahim, "Analysis for soluble solid contents in pineapples using NIR spectroscopy," *Jurnal Teknologi.*, vol. 69, July 2014.

[10] H. S. El-Mesery, H. Mao, A. E. Abomohra, "Applications of Non-destructive Technologies for Agricultural and Food Products Quality Inspection," *Sensors (Basel),* vol. 19, Feb. 2019.

[11] S. Srivichien, A. Terdwongworakul, S. Teerachaichayut, "Quantitative prediction of nitrate level in intact pineapple using Vis–NIRS," *J. Food Eng.*, vol. 150, April 2015, pp. 29–34.

[12] C. L. Y. Amuah, E. Teye, F. P. Lamptey, K. Nyandey, J. Opoku-Ansah, P. O. Adueming, "Feasibility Study of the Use of Handheld NIR Spectrometer for Simultaneous Authentication and Quantification of Quality Parameters in Intact Pineapple Fruits," *J Spectrosc (Hindawi)*, vol. 2019, Aug. 2019, pp. 1-9.

[13] M. N. H. Jam, K. S. Chia, "A Five Band Near-Infrared Portable Sensor in

Nondestructively Predicting the Internal Quality of Pineapples," *IEEE 13th International Colloquium on Signal Processing & its Applications (CSPA),* pp. 135-138, March 2017.

Nonlapun Meenil (born at Nonthaburi, Thailand, July 1st, 1996) is a master's degree student of the Department of Electrical Engineering at King Mongkut's University of Technology Thonburi. Her research major field is about the postharvest technology and artificial neural network. She earned the bachelor's degree of Automation Engineering in 2018 from King Mongkut's University of Technology Thonburi, Bangkok, Thailand.

Pisitpong Intarapong, Ph.D. (born at Bangkok, Thailand, January 4th, 1984) received his doctoral degree from Petroleum and Petrochemical College, Chulalongkorn University, Bangkok, Thailand in 2015, coupled with relevant experience from Wayne State University.

He has worked as a lecturer for King Mongkut's University of Technology Thonburi, Residential college, Thailand. He has collaborated work with outside organizations such chemical, and coconut food industry. He recently published his research on the topic of "Effect of Human Massage and Machine Stirring Processes on Dehydration Correlating Physical Texture of White Radish" as well as three Thai petty patents that involved with radish process for local entrepreneur, and equipment for climbing coconut trees for Chiwadi company, Thailand in 2022. His research interests include carbon dioxide utilization (CO2RR), life cycle assessment (LCA), and chemical and food technology.

Thitima Wongsheree (Ph.D. in Postharvest Technology) graduated from Kasetsart University, Kamphaeng Sean Campus, Nakhon Pathom, Thailand in 2007. She has worked as a researcher for King Mongkut's University of Technology Thonburi since 1993. She has been focusing on multidisciplinary in postharvest technology which involves with food and commodities for small farmers and the social lab of King Mongkut's University of Technology Thonburi.

Her workplace was received under well-known publisher as recorded on ResearchGate website on the topic of "Vanilla cultivation and curing in Thailand" and " Vanilla content evaluation in cured bean by near infrared technique". Recently, she is working on technology for increasing efficiency and well-being group of small farmers and visually impaired people.

Asst. Prof. Pranchalee Samanpiboon, D.Eng., received her doctoral degree from the Department of Systems Engineering at the Nippon Institute of Technology, Saitama, Japan, in 2005. Her research interests lie in the areas of image processing, artificial intelligence, assistive device, and sensing.

Since 2005, she has worked for the Department of Control Systems and Instrumentation Engineering, King Mongkut's University of Technology Thonburi, Thailand. Her recent publication is on the topic of "Chest Expansion Measurement in 3-Dimension by Using Accelerometers" in Engineering Journal.