International Journal of Computer Applications (0975 - 8887)
Volume 57 - No. 16, November 2012

Mango Fruit Quality Prediction using Associative Classification Rules

Rattapol Pornprasit
Postharvest Technology Research Institute
Chiang Mai University, Chiang Mai, Thailand.
Postharvest Technology Innovation Center
Commission on Higher education, Bangkok, Thailand

Juggapong Natwichai
Department of Computer Engineering
Faculty of Engineering, Chiang Mai University
Chiang Mai, Thailand

Bowonsak Srisungsittisunti
Department of Computer Engineering
Faculty of Engineering, Chiang Mai University
Chiang Mai, Thailand

ABSTRACT

Near-infrared (NIR) spectroscopy is a non-destructive technique which can provide the quality measurement for agriculture products. In this paper, we propose an approach to utilize the NIR spectrum for mango fruits quality prediction. The prediction model is based on one of the most prominent machine learning approaches, associative classification. The associative classifiers are trained from the spectrum data of each mango fruit, and the chemical property represented fruit quality as the class label. When a classifier is to be applied to predict the quality, the spectrum of the mango fruits is measured, and the class label is determined by the classification rules subsequently. Series of experiments were conducted under various parameter settings to evaluate the accuracy of the prediction. The results showed that the highest accuracy, the optimal performance, can be obtained when the number of boxes, the number of partitions of each spectrum for rule generation, was set at 10, and the minimum support threshold and the minimum confidence threshold were set at 1% and 50%, respectively. Based on the thorough experiments, a guideline for optimal parameter determination is also proposed for the practitioners.

General Terms:

Classification, Prediction, Machine learning

Keywords:

Associative classification rules, Mango fruits, Near-infrared spectroscopyifx

1. INTRODUCTION

The mango (*Mangifera indica* L.) is a tropical fruit, which there is a high demand in the world market. In 2010, Office of Agricultural Economics (OAE) of Thailand reported that, Thailand had exported 22 million tons of mangoes creating 505 million Thai Baht revenue. Furthermore, the number was increased to 703 million Thai Baht by 37.5 million tons of mangoes in 2011. Although, the mango fruits are highly demanded but the quality classification is still an important issue since the customers cannot taste the ripeness fruit. Furthermore, the precise quality-classification will need the mango fruits to be destroyed by the chemical testing [7, 17].

Near-infrared (NIR) spectroscopy is a non-destructive technique which can provide the quality measurement for agricultural products. NIR spectroscopy was first used in agricultural applications by Norris to measure moisture in grains [13]. Since then it has been used for rapid analysis of mainly moisture, protein and fat content of a wide variety of agricultural and food products [4, 6]. For mango fruits, it was first reported that NIR was used by Guthrie and Walse to assess dry matter (DM) [7]. Subsequently, the NIR had been applied for mango fruits in various ways.

Typically, the NIR reflectance information in the spectra from a sample fruit is used to predict the chemical composition of such sample by extracting the relevant information from many overlapping peaks. Then, the predicted chemical composition is interpreted as the quality. Before the quality measurement by the NIR can be applied, the system has to be calibrated for the accuracy result. In general, the calibration can have the difficulties which are caused by the complex nature of the NIR reflectance spectra. In which each of the interesting spectrum is almost completely overlapping by the others. The calibrated models require routine checking for improving the accuracy and reducing the estimation errors [14].

Generally, statistical analysis is used to analyze the spectrum data for discovering relationship between the spectrum and the chemical properties. After the particular spectrum is identified, the analysis is preceded. Multiple linear regressions (MLR), principle component regression (PCA), and partial least squares (PLS) are often applied for the calibration [11]. However, it might not be appropriated in practices, since the sample data can be updated. Or, the calibrated prediction model can be affected by the changing environments, and it can cause the error in the analysis.

An approach to build the prediction model, which can avoid the mentioned problems, is the machine learning. The prediction model update caused by the additional samples can be done without re-learn the whole samples. Additionally, more samples can help the prediction models more robust subjected to the change of the environment.

In this paper, we propose to an approach to apply one of the most prominent machine learning approaches, associative classifiers [10] for the mango fruit quality prediction using NIR. Such approach is based on Apriori algorithm [2]. The associative classifiers are rule-based classification derived from the training dataset. Each rule in the prediction model has to satisfy the predefined minimum support and minimum confidence constraints. In this work, the prediction models, or the classifiers, are built by firstly determining the frequent items found in the NIR spectra. In which an item in the context of the NIR quality measurement is the reflectance of each spectrum. In order to use the reflectance in the prediction models,the range of it is partitioned into the ranges, so called "box". A box number together with its spectrum number represents a part of the left-hand side (LHS) of the rules, while the chemical property represents the right-hand side (RHS) of the rules. After the set of rules are derived, the model will be used to predict the class of quality of the testing mango fruits, and the accuracy is calculated by comparing the predicted class and the actual class from the chemical property. Additionally, the performance of the proposed prediction method are evaluated by the experiments. The minimum support threshold, the minimum confidence threshold and number of boxes will be investigated in the experiments, since they are the main factors for the accuracy.

2. RELATED WORK

Kawano *et al.* were the first group of researchers who proposed to apply NIR spectroscopy for sugar content determination in intact peaches and mandarins. Since then, NIRs have been widely applied in fruit and vegetable processing [8, 9]. Choi *et al.* developed a sorting-line based on NIR reflectance spectroscopy for real-time determination of sugar content [3]. In this work, a good result with a low root mean square error of prediction (SEP) of 0.78 $^\circ$Brix was obtained in Fuji apples. Greensil and Newman reported the performance of three simple wavelength dispersion elements (single equilateral prism, two equilateral prisms in series, and ruled diffraction grating) for the design of a simple, low-cost, and robust NIR spectrometer for application in automated fruit grading systems [5]. They also proposed an effective the duel-prism NIR instrument and demonstrated a highly-reliable, rapid fruit sorting-line.

For mango fruits, Mizrach *et al.* shown that using a non-destructive ultrasonic measurement system in the appropriate frequency domain can assess the components of mango fruit maturity as well as estimate the shelf life [12]. Saranwong *et al.* have shown that NIR has the capability to evaluate soluble solid content (SSC) and DM in ripe mango fruits [15, 16]. And, Subedi *et al.* used the short wave NIR spectroscopy to predict the total soluble solids of green mango fruits after ripening which leads to the eating quality prediction [18].

Although, NIR spectroscopy technique has the capability to predict the quality of the mango fruits, the calibration can be difficult as mentioned in the introduction section. The calibration models obtained with derivative spectra are sometimes not robust to the environment changes. Thus, much experience, or expertise to preprocess NIR data are highly desired for the calibration model building. However, optimal preprocessing method selection is often trial and error process, and it depends largely on the nature of the data and the practitioner's experience or expertise.

For the associative classification [10, 19], it is based on the association rule mining [1, 2] which is to find all rules satisfying a minimum support threshold and a minimum confidence threshold.It was initially proposed to solve the co-relation analysis for market basket problem in transaction databases. Subsequently, it has been extended to solve many other types of problems such as classification problem. In which, the right-hand-side (RHS) of the rules is the pre-defined class label for the classification purpose. Typically, association rules are considered interesting if they satisfy both a minimum support threshold and a minimum confidence threshold. Such thresholds can be set by user or domain experts.

3. MATERIALS AND METHODS

Our work aims at applying the associative classification to predict the Brix values which is measured from total soluble solid (TSS) of the inside of the mature mango fruits at the harvesting period without destruction by NIR spectroscopy measurement. Such values affect the eating quality of the fruits after ripening [16, 18].

The mango fruits cv. Nam Dok Mai Si Thong used in the evaluation were harvested form a farmer orchard in Phrao, Chiang Mai province. 300 mango fruits were harvested in 100, 110 and 120 days after the fruit set (100 fruits per each period). All of the fruits were transported to the evaluation site by a controlled temperature truck at 25 degree Celsius.

3.1 Spectroscopy acquisition

A commercially available NIR spectrophotometer, 'HAMAMATSU Mini-Spectrometers model C10083CAH (TM-VIS/NIR-CCD)' in the interactance mode was used to measure the NIR spectra. The NIR measurements were obtained in the long wavelength region from 300 nm to 1000 nm. All of the spectra for the prediction model generation and prediction were the average value from 50 scans. A ceramic disc was used as the reference. During the NIR measurement, the temperature of the sample of mango fruits was controlled at 25 degree Celsius.

3.2 Chemical analysis

After the spectra acquisition, a portion of flesh of each fruit, which was illuminated by NIR radiation, was taken and analyzed for determination of the TSS (Brix). For the Brix value, the ripe mango portion was squeezed in fingers and then the juice was analyzed using a digital refractrometer model PAL-1 (ATAGO, Tokyo, Japan).

For eating quality, it was decided by the Brix values, i.e. the fruits were classified into (1) excellent and (2) acceptable groups. If the Brix value of a fruit was at least 17, it was classified as the excellent group. The rest were classified as the acceptable group.

3.3 Data processing

First, we describe the approach used for creating the training dataset. In order to obtain each data record, the spectra of each mango fruit formed the features of the training data record, its Brix value was used as the class label. In each spectrum, the difference between the minimum value and the maximum value of the spectra was calculated to form the range of each feature.

These different values of each spectrum were partitioned into equal parts, so called "box". For example, suppose that the minimum absorbance and maximum of absorbance of a spectrum are 0.5 and 1.0 respectively. When the number of boxes is set at 5, the gap of the range is 0.1. So, the box number 1, 2, 3, 4, and 5 of this spectrum will have the range of 0.50-0.60, 0.61-0.70, 0.71- 0.80, 0.81-0.90 and 0.91- 1.00, respectively. If a fruit has its absorbance of the spectrum at 0.74, the box number of this sample is 3. The number of the boxes is pre-specified in a training process.

Subsequently, the dataset is to be used in the training process for generating a prediction model based on the associative classification rules. In which, the rules are discovered by exploring all of the frequent items, subjected by the minimum support and minimum confidence thresholds. The rules will be discovered when it has the number of items more or equal the minimum support thresholds. And, the discovered rules will be filtered out by the confidence value. The confidence value of each rule is ratio between number of item with actual class and number of item with all class. So, the discovered rules have the confidence value more or equal the minimum confidence thresholds become the performance rules. The form of the rules is $\mathrm{b}_i\wedge$ $\mathrm{b}_j\wedge$ ...$\wedge$ b_n class, where any b_i is the box number of the i-spectrum, and the class can be (1) excellent and (2) acceptable groups as mentioned before. So, the performance rule discovery will find all rules that satisfy the user-specified minimum support and minimum confidence thresholds. If the minimum support threshold and the minimum confidence threshold are not set on suitable values, the number of performance rules may be too small which poor performance prediction. On other side, if the number of rules may be too large because there are many noise rules. The noise rules may disturb the prediction and reduce the accuracy. So, the performance rules will filter out by the suitable minimum support and minimum confidence threshold.

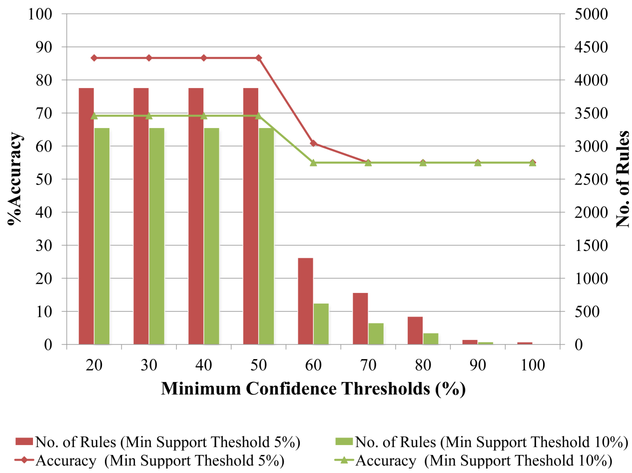
3.4 Prediction class for testing dataset

For the quality prediction, the mango fruits will be measured their reflectance spectra by the NIR measurement. Each spectrum of a fruit was converted to the box number designated from the training phase. The classifier contained the classification rules from training dataset. Each fruit will be predicted its class of Brix or the class label. After the spectrum measurement and the class prediction are carried on, the Brix values are determined as the actual class. The accuracy of prediction will be computed by comparing the actual class with the predicted class.

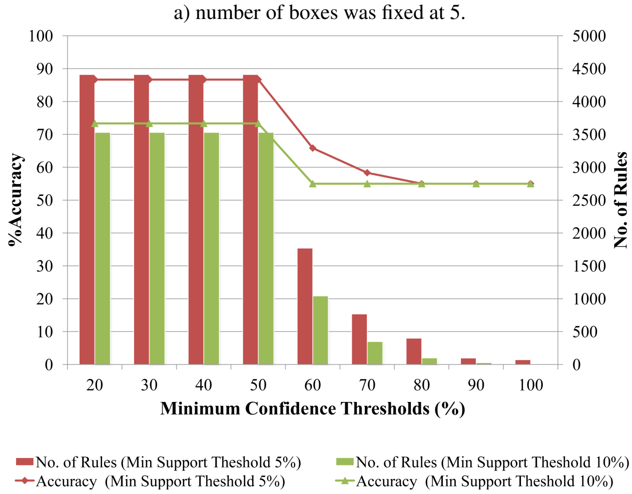
4. RESULTS AND DISCUSSIONS

After the spectrum data and the TSS of the mango fruits are measured for using as the training dataset. Such data records were classified into two classes, i.e. (1) excellent and (2) acceptable groups. The excellent group condition is that its Brix value is at least 17. Meanwhile the rest is to be classified as the acceptable group. For the spectrum data, 2048 spectrum in the NIR wavelength are measured for each mango fruit. And, the range of the TSS values of the mango fruits in the dataset were at 11-22 °Brix approximately. The ratio between the number of class (1) and class (2) was approximately 1:1. The minimum confidence threshold, minimum support threshold, and the number of boxes were investigated to evaluate the accuracy of the classification. Note here that the number of rules is also reported to further discuss the accuracy in details, since such number affects the performance of the rule-based classification which the associative classification is one among them.

For the first experiment results, the effects of the minimum confidence threshold to the accuracy are reported. The minimum confidence thresholds are the criteria for filtering out the low confident associative classification rules. The minimum confidence threshold is varied from 20% to 100% to evaluate their effects. In this experiment, the minimum support threshold was fixed at 5% and 10%, meanwhile the number of boxes was fixed at 5 and 6. From Fig1, the results showed that the prediction accuracy and number of rules increased when the minimum confidence thresholds were reduced. Particularly, both values rapidly increased after the threshold value was changed from 60% to 50%. The highest accuracy was 86.67% at 50% minimum confidence threshold and all the number of boxes. Although the accuracy were remained intact, when the minimum confidence threshold was decreased less than 50%. In addition, from the results, it can be seen that the numbers of rules is correlated to the predicting accuracy, i.e. the larger number of rules results in the higher accuracy. This is because the increased number of rules in a rule-based classification can directly help increasing the performance of the classification. Also, the results showed that the accuracy of the classifier using 5% minimum support threshold was higher than the accuracy of the classifier using 10% minimum support threshold, in which the effect of such thresholds will be showed in next experiment. From the experiment, to find the optimal confidence threshold, it should begin with the highest minimum confidence threshold (100%). Subsequently, the threshold was reduced. This is an efficient approach to determine the optimal



a) number of boxes was fixed at 5.



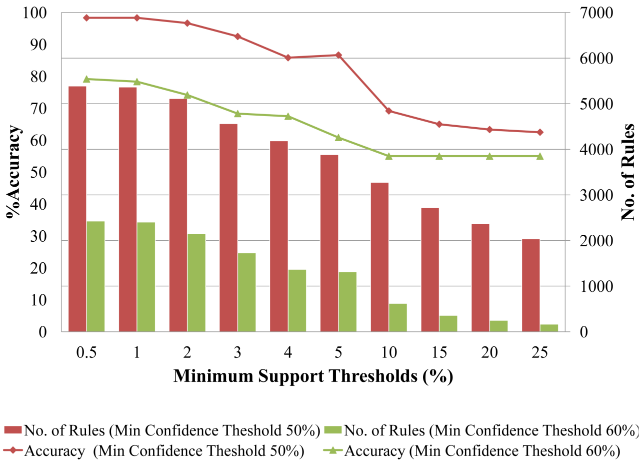
b) number of boxes was fixed at 6.

Fig. 1. Effects of the minimum confidence threshold to the accuracy.

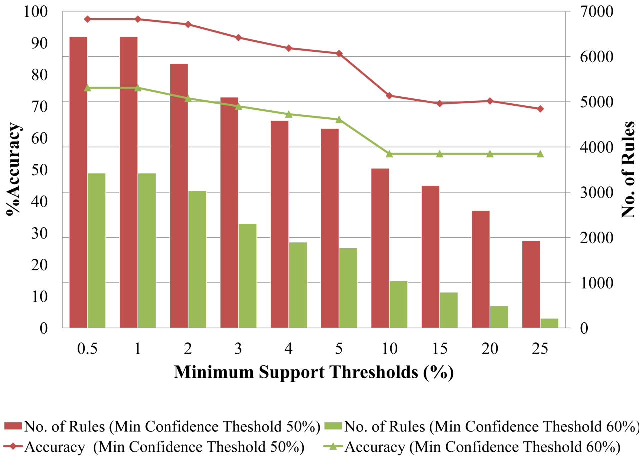
threshold in practice, since the higher threshold experiments can be conducted faster.

In this experiment, the effects of the minimum support threshold to the prediction accuracy were evaluated. The number of boxes was fixed at 5 and 6, and the minimum confidence threshold was fixed at 50% and 60%. The minimum support threshold was varied from 0.5% to 25% for the evaluation. From Fig 2, the highest prediction accuracy was at 98.33% at 50% minimum confidence threshold and the number of boxes was set at 5, when the minimum support threshold was set at 0.5 - 1%. Subsequently, the prediction accuracy decreased when the minimum support threshold increased. The reason behind this is that the minimum support threshold was used as a criterion for filtering out the less interested rules. Typically, the number of rules is reduced when the minimum support threshold is increased. But, lacking of rules can degrade the performance of the prediction.

The result of the last experiment is shown in Fig 3. The prediction accuracy subjected to the number of boxes was evaluated. In this experiment, the minimum support threshold was set at 5% and 10%, the minimum confidence threshold was set at 50% and 60%, and the number of boxes was varied from 2 to 20. From Figure 3, the highest accuracy was 97.5% when the minimum support threshold, the minimum confidence threshold and the number of boxes were set at 5%, 50% and 10, respectively. Moreover, it can be seen that the number of rules increased when the number of boxes was increased until 10-15 boxes. Such in-

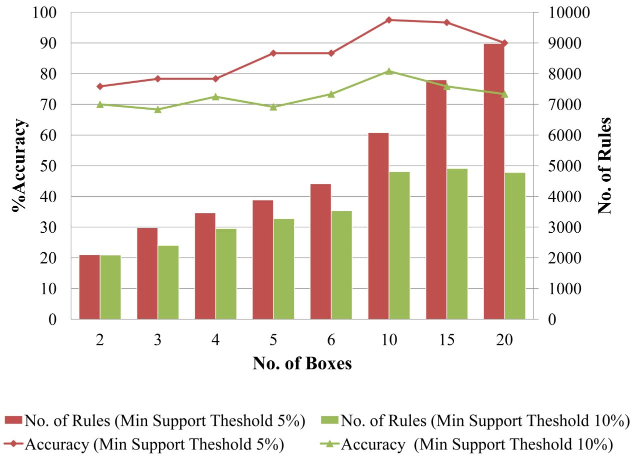


a) number of boxes was fixed at 5.

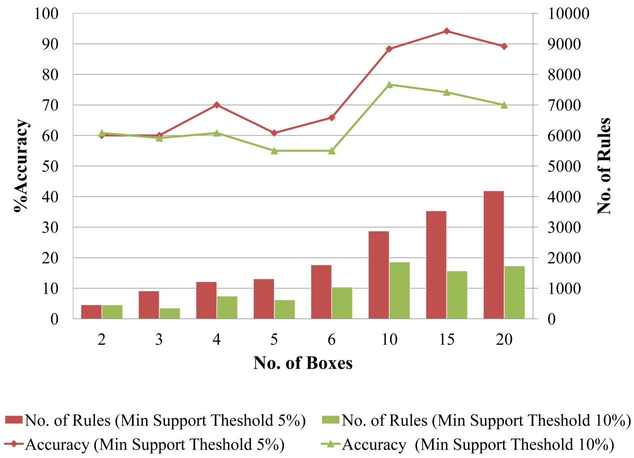


b) number of boxes was fixed at 6.

Fig. 2. Effects of the minimum support threshold to the accuracy.



a) minimum confidence threshold was fix at 50%.



b) minimum confidence threshold was fix at 60%.

Fig. 3. Effects of the number of boxes threshold to the accuracy.

creasing number of rules resulted in the higher prediction accuracy as well. When the number of boxes was increased up to 10-15, the accuracy started to drop. The reason is that the number of boxes affects the gap size between the boxes. Recalled here that a gap size is derived from the range of the maximum and minimum of the absorbance in a spectrum, in which such range is subsequently divided equally by the number of boxes. So, if the number of boxes is smaller, the gap size becomes wider. In the experiment, when the number of boxes was increased, the number of rules was higher because such smaller gap size can increase the number of literals for the derived rules. Such higher number of rules can then increase the prediction accuracy. However, when the number of boxes was increased higher than 10-15, the gap size becomes too small. This is because of the minimum support threshold which can lessen the number of discovered rules. In addition, it can be seen that the prediction accuracy was decreased when the number of boxes reached 20. Although the number of rules was still high, in the case where the minimum support threshold was set at 5%. At such environment, the prediction accuracy was decreased due to the fact that the classification model considered the noise data as the knowledge, and thus it contained a lot of low-performance rules.

It can be seen that the quality of mango fruit quality can predict by NIRs technique, i.e. high accuracy can be achieved. In this research, the prediction model was developed by the classification association rules. The minimum confidence, the minimum support and the number of box were used as the criteria for developing the optimal performance prediction model. From the experiments, the optimal performance was obtained when, the minimum confidence threshold was set at 50%, the minimum support threshold was set at 1%, and the number of boxes was set at 10. These parameters not only brought in the highest performance in terms of the prediction accuracy, but also the number of rules which affects the performance directly.

From our thorough experiments, we propose that the optimal parameters can be set as follows. First, the minimum confidence threshold should be set as the highest firstly. Then it should be decreased to determine the optimal point. The reason behind this approach is that a too-high minimum confidence threshold will cause less number of generated rules. So, decreasing the threshold will increase the number of rules. Once the number of rules is stable, the optimal minimum support threshold is determined. In addition, this approach can help reducing the classification training, since such process with a high minimum support threshold can be executed in less time. Subsequently, the optimal minimum support threshold is to be determined in the same approach as the minimum confidence threshold, i.e. beginning with the highest values to the point which the number of rules is stable. Last, the number of boxes is to be determined. It can be done by varying the parameter from a low number to a high number. This approach can increase the number of rules for the prediction model, and thus it can increase the prediction accuracy. Once the accuracy starts to drop, the optimal number of boxes is discovered. This is because of the low-performance rules have been generated by noise data. In addition, with the NIR spectrum properties, we suggest that the setting should begin with five boxes since it is not too low to capture the details of the spectrum.

5. CONCLUSION

In this paper, a quality prediction approach of mango fruit based on the NIR measurement was proposed. Such prediction model was based on the associative classification. Each model in the experiments was generated under different parameters by varying the minimum support threshold, minimum confidence threshold, and the number of boxes. All parameters were discovered the suitable values for generating the performance model. In the experiments, the quality prediction processes began with measuring the NIR spectrum of the fruit samples. The fruit samples were evaluated their chemical component, the Brix values. By such values were used as the actual class label. The spectrum data and the actual class label were combined to a training dataset. Then, the prediction models were generated from the training. Subsequently, the spectrum data of the sample were measured and the class label of such sample was predicted by the prediction model.

For accuracy evaluation, the actual class label and the predicted class label are compared. Such parameters can generate proper number of rules, as well as capture the details of the spectra. From this experiment, the suitable threshold for training the dataset was 50% of the minimum confidence threshold, the minimum support threshold was 1% and the number of boxes was 10. The suitable thresholds can give the performance rules.

From the experiments, we can derive a guideline for the practitioners as follows. First, the minimum support threshold should be fixed at a less number for using to less time in training. Then, the minimum confidence threshold should be found from backward number by varied from 100% until the number of rules is stable. Finally, the dataset have to be trained for finding the number of boxes. The number of boxes will begin from the low number to high number. Increasing the number of boxes will increase the number of rules when the number of rules stabled or decreased, this number can perform the rules.

In our future work, we will further investigate an approach to eliminate the irrelevant spectrum. Furthermore, ensemble-based classification models will be studies, since the model robustness issue is to be addressed in the real-world environment.

6. REFERENCES

[1] R. Agrawal, T. Imieliski, and A. Swami. Mining association rules between sets of items in large databases. *SIGMOD Rec.*, 22(2):207–216, June 1993.

[2] R. Agrawal and R. Srikant. Fast algorithms for mining association rules. pages 487–499, 1994.

[3] C.H. Choi. Development of apple sorter by soluble solid content using photodiodes. In *Proceeding of Winter Conference of KSAM*, 1, pages 362–367, 1998.

[4] A. M. C. Davies and A. Grant. Review: Near infra-red analysis of food. *International Journal of Food Science and Technology*, 22(3):191–207, 1987.

[5] C.V. Greensil and D.S. Newman. An experimental comparison of simple nir spectrometers for fruit grading applications. 17:63–76, 2001.

[6] S. Gunasekaran and J. Irudayaraj. *Nondestructive food evaluation: techniques to analyze properties and quality*, chapter Optical methods: visible NIR and FTIR spectroscopy. Marcel Dekker Inc., New York, USA, 2001.

[7] J. Guthrie and K.B. Walsh. Non-invasive assessment of pineapple and mango fruit quality using near infrared spectroscopy. 37:253–263, 1997.

[8] S. Kawano, T. Fujiwara, and M. Iwamoto. Nondestructive determination of sugar content in satsuma mandarin using near infrared (nir) transmittance. *Journal of the Japanese Society for Horticultural Science*, 62(2):465–470, 1993.

[9] S. Kawano, H. Watanabe, and M. Iwamoto. Determination of sugar content in intact peaches by near infrared spectroscopy with fiber optics in interactance mode. *Journal of the Japanese Society for Horticultural Science*, 61(2):445–451, 1992.

[10] J. Li, H. Shen, and R. Topor. Mining optimal class association rule set. In David Cheung, Graham Williams, and Qing Li, editors, *Advances in Knowledge Discovery and Data Mining*, volume 2035 of *Lecture Notes in Computer Science*, pages 364–375. Springer Berlin / Heidelberg, 2001.

[11] H. Martens, K. H. T. Naes, Norris, and P. C. Williams. *Near-Infrared Technology in the Agricultural and Food Industries (second edition)*, chapter Multivariate Calibration by Data Compression. American Association of Cereal Chemists, Inc., St. Pual, Minnesota, USA, 2001.

[12] A. Mizrach and U. Flitsanov. Nondestructive ultrasonic determination of avocado softening process. *Journal of Food Engineering*, 40(3):139 – 144, 1999.

[13] K. H. Norris. Design and development of a new moisture meter. *Agricultural Engineering*, 45(7):370–372, 1964.

[14] B. G. Osborne, T. Fearn, and P. H. Hindle. *Practical NIR Spectroscopy with Applications in Food and Beverage Analysis*. Longman Scientific and Technical ; Wiley, Harlow, Essex, England; New York, 2nd edition, 1993.

[15] S. Saranwong, J. Sornsrivichai, and S. Kawano. Improvement of pls calibration for bixavalue and dry matter of mango using information from mlr calibration. *Journal of Near Infrared Spectroscopy*, 9:287–265, 2001.

[16] S. Saranwong, J. Sornsrivichai, and S. Kawano. Performance of a portable near infrared instrument for brix value determination of intact mango fruit. *Journal of Near Infrared Spectroscopy*, 11:175–181, 2003.

[17] S. Saranwong, J. Sornsrivichai, and S. Kawano. Prediction of ripe-stage eating quality of mango fruit from its harvest quality measured nondestructively by near infrared spectroscopy. *Postharvest Biology and Technology*, 31(2):137 – 145, 2004.

[18] P.P. Subedi, K.B. Walsh, and G. Owens. Prediction of mango eating quality at harvest using short-wave near infrared spectrometry. *Postharvest Biology and Technology*, 43(3):326 – 334, 2007.

[19] Z. Tang and Q. Liao. A new class based associative classification algorithm. In *IMECS'07*.