ILKOM Jurnal Ilmiah Vol. 13, No. 3, December 2021, pp. 206-215
Accredited 2nd by RISTEKBRIN No. 200/M/KPT/2020; E-ISSN 2548-7779 | P-ISSN 2087-1716

**Research Article** 

# Effects of spectral transformations on support vector machine in predicting ‘arumanis’ mango ripeness using near-infrared spectroscopy

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**Article history:** Received May 07, 2021; Revised July 04, 2021; Accepted July 04, 2021; Available online August 08, 2021

**Abstract**

One of the challenges of Arumanis mangoes export is the ability of accurate grading, because Mango does not experience color change during ripening. Near Infrared (NIR) spectroscopy is a non-destructive method that is quite reliable for detecting the internal ripeness of fruit. However, NIR absorbance bands are often non-specific, broad, and overlapping. Although the SVM modeling is considerably good in its performance, it can still be improved by spectral transformation. This study compares 11 spectral transformation operations with their combinations to find the best input model. Spectral transformation operations include SAVGOL, RNV, BASELINE, MSC, EMSC, NORML, CLIP, RESAMPLE, DETREND, SNV and LSNV. In the 2 classes classification model, the highest accuracy was obtained using RNV and SAVGOL. The TPT content prediction model producing the best MSE value uses 3 combinations of spectral transformation operations, namely DETREND, LSNV, and SAVGOL with parameter values: 'deriv_order': 0, 'filter_win': 31, 'poly_order': 6. The best MSE value uses 2 combinations of spectral transformation operations, namely LSNV and SAVGOL with parameter values: deriv_order': 0, 'filter_win': 15, 'poly_order': 6.

**Keywords:** Ripeness Prediction; Arumanis Mango; Near Infrared; Support Vector Machine; Spectral Transformation

## Introduction

Mango has a fresh and delicious taste with a distinctive aroma and contains vitamins and antioxidants. Mango only grows in tropical countries. Therefore, mango is a large export potential. However, mangoes are easily damaged and have a relatively short shelf life, so that quality degradation and even damage can occur in the distribution process before reaching the customer [1]. Along with the growing level of awareness of the internal quality of fruit [2], consumers are more concerned with internal attributes such as taste, aroma and texture of fruit flesh [3]. Mango ripeness is a determining factor for consumer acceptance because underripe fruit at the time of harvest has a low total soluble solids (TSS) content which affects fruit quality, especially taste [4].

The sorting and grading stages are the initial stages that classify mangoes based on their ripeness level. These stages determine the success of the next stage in the mango fruit trade. Mango is a climacteric fruit and is usually harvested when it is still hard with green color. Mango produces ethylene which can trigger the ripening process. This can cause the quality of ripeness that does not match the predictions when it reaches consumers, could cause losses due to rotten mangoes. The challenge of the fruit industry in the Arumanis mango trade is the ability to detect the level of ripeness. Paull and Duarte 2011 stated that mango ripeness was determined using criteria such as color change, endocarp hardening and the presence of yellowing flesh [5]. Other physical parameters are shape, size, lenticels, and specific gravity. Chemical parameters including total soluble solids (TSS), acidity, and carbohydrate content have also been used [6], [7]. However, determining the ripeness of Arumanis mango is quite difficult by using physical parameters because the mango does not experience physical or skin color changes during ripening.

In determining the ripeness of Arumanis mangoes, the fruit industry uses a method based on the number of days after blooming (HSBM) and observations of flesh hardness, skin hardness, and fruit shape. In some plantations the HSBM method is widely used but becomes less accurate due to the difficulty in practices and the influence of the external environment [8]. Due to the subjective aspect in determining the ripeness index based on physical

http://dx.doi.org/10.33096/ilkom.v13i3.856.206-215

characteristics as well as the inconsistency of assessment and the use of destructive chemical parameters [9], non-destructive methods have been proposed as a tool to determine mango ripeness and Near Infrared (NIR) spectroscopy is one of them. NIR spectroscopy has been used to determine TSS, titratable acidity (TA), hardness, dry matter content, starch content in mangoes [10–12].

NIR spectroscopy is a non-destructive analytical technique which is able to provide chemical and structural information on a particular sample very fast (usually less than 1 minute). NIR has a wavelength of 750-2500 nm. The target sample is illuminated with light and the reflected light or backscatter is measured by a spectrometer. NIR active molecular bonds in the sample absorb incoming light in different spectral bands and spectral combinations, resulting in NIR absorbance spectral [13]. Compared to other infrared spectroscopy methods, NIR is able to increase the depth of penetration. In addition, the requirements for sample preparation are less stringent [14]. However, the absorbance bands in the near infrared region of the spectrum are often non-specific, broad, and overlapping. NIR spectrum analysis requires a multivariate method which is highly subjective to noise arising from instrumentation, scattering effects, and measurement settings.

NIR calibration models for prediction have been developed in several studies. Support Vector Machine (SVM) is the most widely used algorithm in prediction models both classification and regression for fruit quality detection. This technique has a fairly good accuracy. Bruise detection in blueberries [15], TSS detection in melons [16], hardness detection in pears [17], TSS detection in oranges [18] and other studies yielded an accuracy of more than 90%. Until now, there is no standard protocol for modeling mango ripeness determination using NIR spectrum. Several models have been developed with and without spectral transformation techniques. The selection of the best spectral transformation technique requires trial and error.

Spectral transformation or preprocessing techniques can improve model performance and interpretability [19]. This technique comprises of 6 categories namely Clipping, Scatter Correction, Smoothing, Derivatives, Trimming and Resampling. The order of preprocessing operations applied can affect the performance of the model [20]. Clipping aims to remove or replace data points with values that exceed a user-defined threshold. Scatter correction aims to counteract the effects of particle size. Smoothing is to smooth the NIR spectral which can help eliminate environmental or instrumentation-related noise. Trimming allows the extraction of continuous and non-continuous wavelength regions from full spectral data. Finally, resampling processes a new spectral resolution using the Fourier method which can combine the obtained spectral with several devices having different spectrum resolutions.

Researches on mango prediction models development using NIR to improve accuracy have included spectral transformations. Prediction of TSS content in Indramayu mango using second derivative produces better model accuracy compared to smoothing and original [21]. Prediction of Arumanis mango content for the best spectral transformation starch content uses first derivative, TSS content uses first derivative and 3 point smoothing and water content use 3 point smoothing [10]. Prediction of dry material of mango from Pekalongan and East Lampung with the best input model uses the second derivative [22]. Prediction of Gedong Gincu mango content with input model for TSS uses 3 point smoothing, acid content uses first derivative, insoluble solids and sugar acid ratio use Multiplicative Scatter Correction (MSC) [23]. Prediction of Arumanis mango content resulted in the best input model for TSS using baseline correction and for vitamin C using MSC. Prediction of sugar content in Gadung mango with baseline correction resulted in an error value of 0.782 [24]. Prediction of dry material in mango using first derivative and combination of SNV and second derivative provides efficiency [25]. Prediction of vitamin C and acid levels provides a good input model using MSC and baseline [26]. Prediction of Kent mango using MSC [27]. This study will explore the best spectral transformation as the input of the SVM model with the highest accuracy to predict the maturity level of Arumanis mangoes.

## Method

The stages and methods in this study include sample preparation, data acquisition, data processing, modeling and model evaluation which can be seen in **Figure 1**.

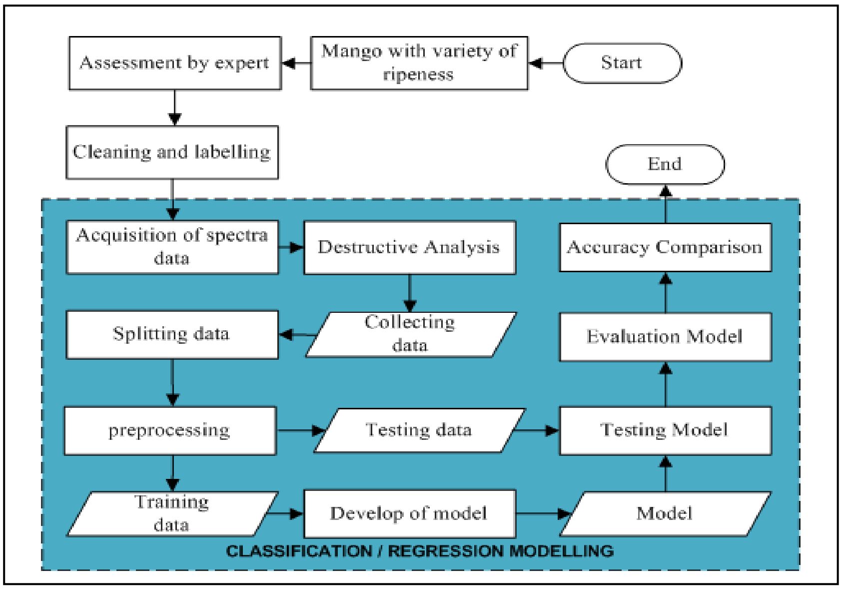



**Figure 1.** Research Method

### *A. Sample preparation*

A total of 100 Arumanis mangoes were purchased from the Majalengka plantation, West Java, Indonesia in December 2020 with a composition of 50 fruits with a maturity level of 80 and 50 fruits with a maturity level of 90 based on subjective assessments from experts. The mangoes were picked starting at 09.00 and then taken to the laboratory of the Faculty of Agricultural Technology, Bogor Agricultural University. At 15.00 the samples were labeled and then carried out a non-destructive test with NIR spectroscopy. Furthermore, mangoes were stored at a room with temperature between 21 and 24 °C to maintain the effect of temperature on the predicted results [28] and a destructive test was carried out on the next day for hardness and TSS values.

### *B. Data Acquisition*

The spectrals of Arumanis mango were collected using Bucchi's NIRFlex N-500 device with a wavelength of 1000-2500 nm. Spectra were taken 3 times for each sample. The NIR dataset retrieval process can be seen in Figure 2a. Destructive data retrieval for TSS measurements uses Atago Pocket Refractometer while hardness measurements uses Penetrometer GY-4. The data collection process can be seen in **Figures 2b and 2c**.

a. Data of NIR b. Data of TSS c. Data of

**Figure 2**. Non-destructive and destructive data collection

### *C. Initial spectral data processing and modelling development*

The calibration model is built with SVM. This is based on the results of previous studies that SVM is considerably reliable in both classification accuracy and regression on NIR data for fruit. SVM will classify mangoes into 2 classes, namely ripeness 80 and 90 using Support Vector Classification (SVC) and regress TSS values and hardness using Support Vector Regression (SVR). This study uses a linear kernel. Data sharing and spectral transformation were carried out before developing the model. Data sharing is the result of slicing X and Y using the ***train_test_split()*** function from the scikit learn module with a composition of training data of 80%, testing data of 20% and random states of 22. The spectral transformations used are scatter correction, smoothing and derivatives. Scatter correction consists of several methods, namely standard normal variate (SNV), multiplicative scatter correction (MSC), robust normal variate (RNV), localized version of SNV (LSNV), the extended version of MSC (EMSC), normalization and baseline. Application of savitzky golay filtering with parameters: filter windows

(7, 11, 15, 21, 31, 51), order of the polynomial = 3, and order of the derivative (0, 1, 2). The details can be seen in **Table 1**.

SNV can make corrections based on the mean and spectral standard deviation. RNV is more suitable for data with more noise. The concept of correction is based on the median value and the interval between quartiles. LSNV is conceptually similar to SNV with partial operations in the spectral window. MSC's correction principle is only for the spectral mean whereas EMSC takes into account both linear and quadratic in the correction. Spectral normalization is carried out in a certain range of values or alternatively with Euclidean. The baseline only centers the spectral mean.

**Table 1.** Operation, Parameter, and Value of Transfom Spectra Method

| Transform Spectra Method | Transform Spectra Operation | Parameter | Value |
|---|---|---|---|
| Clipping | CLIP | threshold<br>substitute | 1e4<br>None |
| Scatter Correction | SNV | | |
| | RNV | iqr | 75-25, 90-10 |
| | LSNV | | |
| | MSC | | |
| | EMSC | | |
| | NORML | | |
| | DETREND | | |
| | BASELINE | | |
| Smoothing | SAVGOL | filter_win<br>poly_order<br>deriv_order | 7, 11, 15, 21, 31, 51<br>3, 6<br>0, 1, 2 |
| Trimming | TRIM | bins | |
| Resampling | RESAMPLE | rasio | |

## D. Accuracy comparison

This study builds a model with the highest accuracy by identifying the most optimal spectral transformation. The input model resulting from the spectral transformation or its combination from the spectral data of the Arumanis mango will improve the performance of the model. The calculation of accuracy in the classification uses the accuracy_score and mean_squared_error functions to determine the error rate in the regression model. Both functions use the scikit learn module.

# Results and Discussion

## *A. Sample Data*

**Table 2** shows the TSS and hardness values of 100 samples. It can be seen that the TSS ranges from 3.9 to 11 with a standard deviation (SD) of 1.196 while the hardness value ranges from 47.8 to 76.29 with an SD of 5.321

**Table 2**. Statistical data of TSS dan harness value of samples

| Data set | No. of Samples | Min | Max | Mean | SD |
|---|---|---|---|---|---|
| TSS | 100 | 3,9 | 11 | 6,492 | 1,195926 |
| Hardness | 100 | 48 | 76 | 62,2774 | 5,320723 |

## *B. Features and Spectral Transformations in Classification*

The spectral range used in the modeling is 1000 - 2500 nm. Three spectrals measured from the same fruit are used as the transmission spectrum of each fruit. The transmittance spectrum of 100 pieces is shown in **Figure 5a**. Three significant absorption peaks were at around 1150, 1450, and 1900 nm respectively found from the original transmittance spectrum.

To find the best input classification model, 13 spectral transformation operations were tested, namely SNV, RNV, LSNV, MSC, EMSC, SAVGOL, BASELINE, NORML, TRIM, CLIP, RESAMPLE, DERIVATIVE and DETREND. The first test was to measure the accuracy of the SVM model for each spectral transformation compared to the condition without spectral transformation (RAW). The accuracy value without spectral transformation is 0.8667, while by using spectral transformation there was an increase in accuracy RNV and MSC of 0.900 and 0.833 respectively. There was no increase in accuracy for other spectral transformation operations. The overall accuracy value can be seen in **Figure 4**.

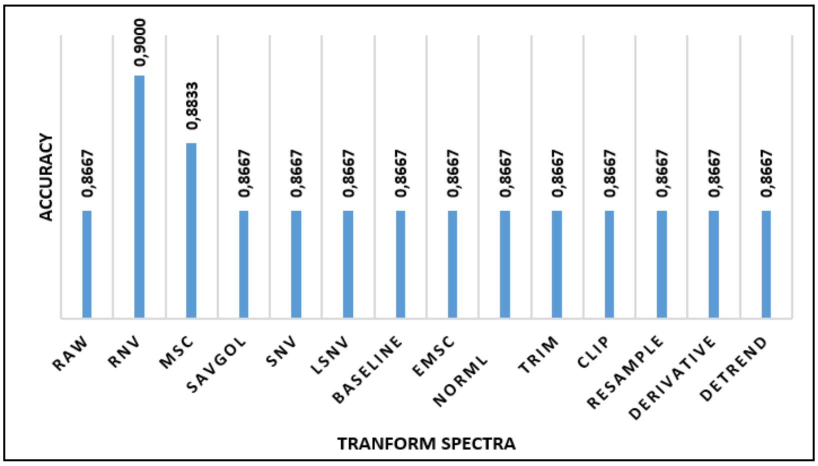
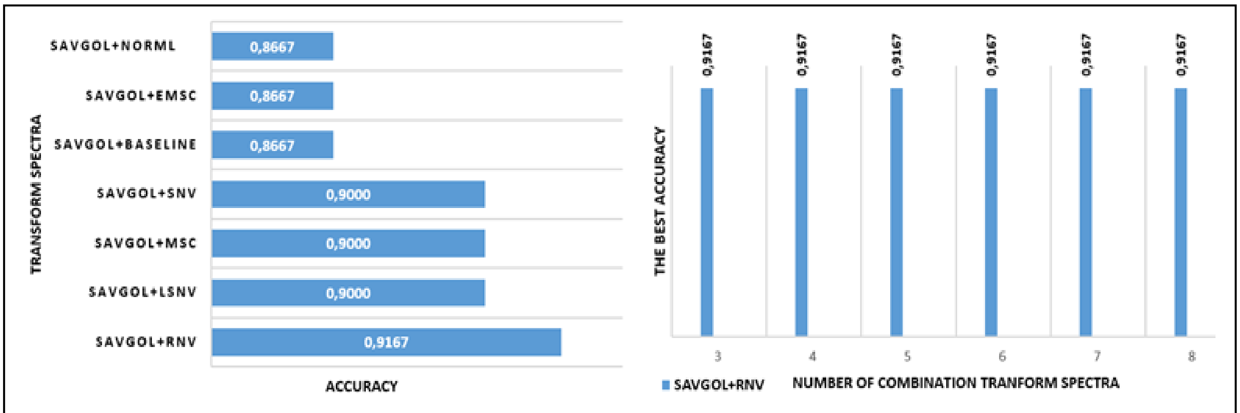



**Figure 4**. Comparison of the Use of Spectral Transformation without Combination on the Accuracy of the Classification Model.

The next test is a combination of 2 spectral transformation operations, namely comparing SAVGOL with other spectral transformations. This combination is able to increase the accuracy of the model. SAVGOL and RNV increased accuracy to 0.9167, while SAVGOL with LSNV, SNV and MSC increased accuracy to 0.9000. The others did not increase the accuracy of the model. Furthermore, the combination of 3 to 8 spectral transformations has an accuracy of 0.9167. The comparison value of the combination of spectral transformations on accuracy can be seen in **Figures 5a and 5b**. **Figure 6** shows the spectrum curve of the results from the use of the spectral transformation operation.




a. 2 Combination of Transform Spectra b. 3 - 8 Combination of Transform Spectra

Figure 5. Comparison of the Combination of Spectra Transformation on the Accuracy of the Classification Model

The highest value of 0.9167 resulted from the iteration of the comparison of the accuracy of the model with the spectral transformation operation. The highest accuracy is obtained in the combination of spectral transformation operations shown in **Table 3**.

**Table 3**. Parameters and Values of Spectra Transformation Operation with Highest Accuracy

| Tranform Spectra Operation | Parameter and value |
|---|---|
| RNV<br>SAVGOL | {'iqr': [75.0, 25.0]}<br>{'deriv_order': 0, 'filter_win': 51, 'poly_order': 3} |
| RNV<br>SAVGOL | {'iqr': [75.0, 25.0]}<br>{'deriv_order': 0, 'filter_win': 21, 'poly_order': 3} |
| RNV<br>SAVGOL | {'iqr': [75.0, 25.0]}<br>{'deriv_order': 0, 'filter_win': 31, 'poly_order': 3} |
| RNV<br>SAVGOL | {'iqr': [75.0, 25.0]}<br>{'deriv_order': 0, 'filter_win': 51, 'poly_order': 6} |

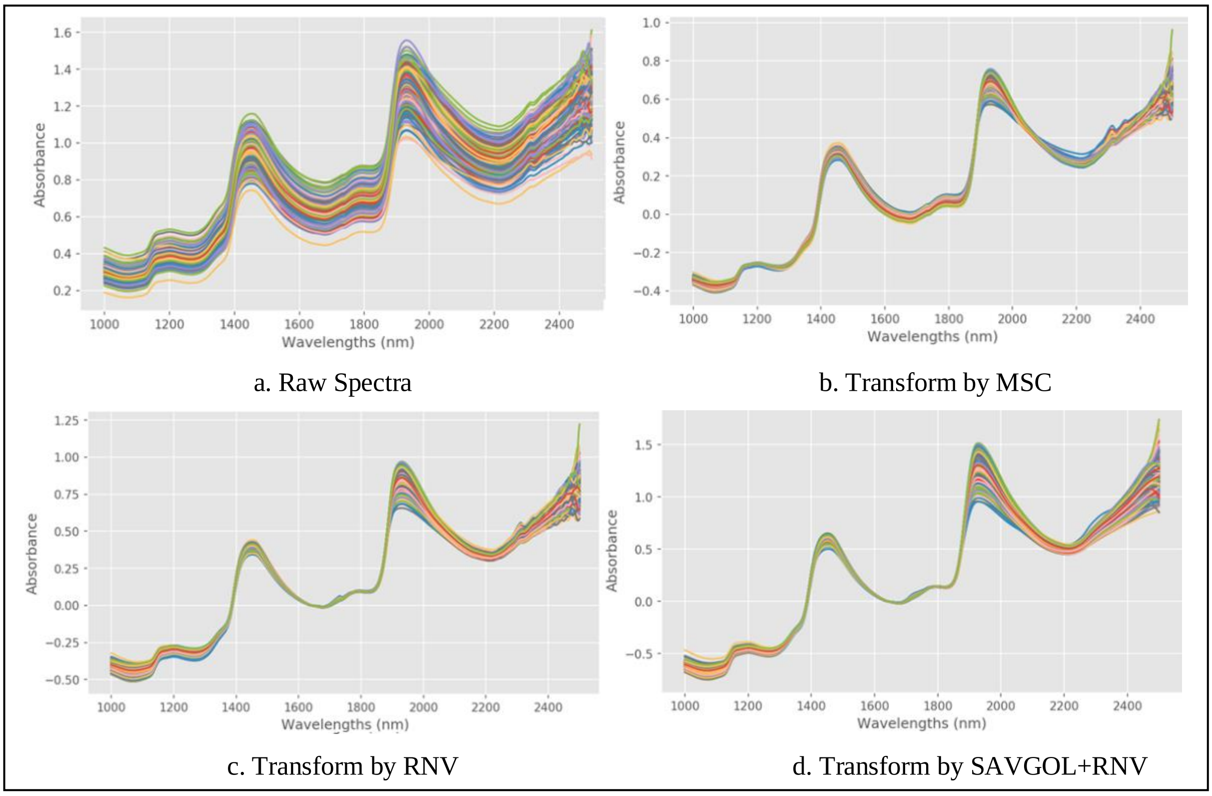



**Figure 6**. Spectra Curve after using Spectra Transform

### *C. Features and Spectral Transformation of Regression*

Regression modeling was used to predict TSS content and Hardness in Arumanis mangoes. Spectral transformation is performed to obtain a model with the smallest error . The following are the results of the spectral transformation test results for the prediction of TSS and Hardness of the mangos.

1) Hardness prediction of Arumanis mango

Prediction model development uses Support Vector Regression which can measure the smallest error value. This model uses Mean Square Error (MSE). Spectral data processing without spectral transformation resulted in an MSE of 0.02892. Furthermore, the tests were carried out with 11 spectral transformation operations separately, namely SAVGOL, RNV, BASELINE, MSC, EMSC, NORML, CLIP, RESAMPLE, DETREND, SNV and LSNV. The test results in Figure 6 show that 2 spectral transformation operations reduced the error better, namely LSNV with an MSE of 0.02595 and SNV with an MSE of 0.02861. The testing of the combination of LSNV with SAVGOL gives a better error value with MSE of 0.02557 while the combination of LSNV with other spectral transformation operations resulted in MSE of 0.02595. The testing of the combination of 3 to 11 spectral transformation operations still produces an MSE of 0.02557 as the value of the previous 2 combinations of spectral transformation operations. Comparison of MSE values from the combination of spectral transformation operations can be seen in **Figures 7a and 7b**.

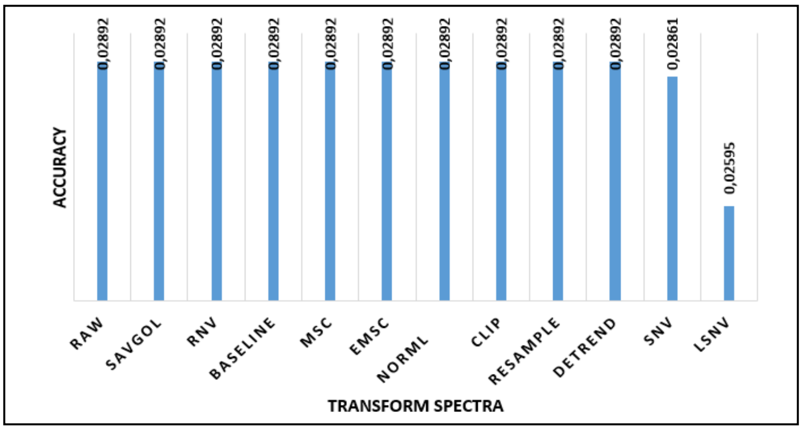
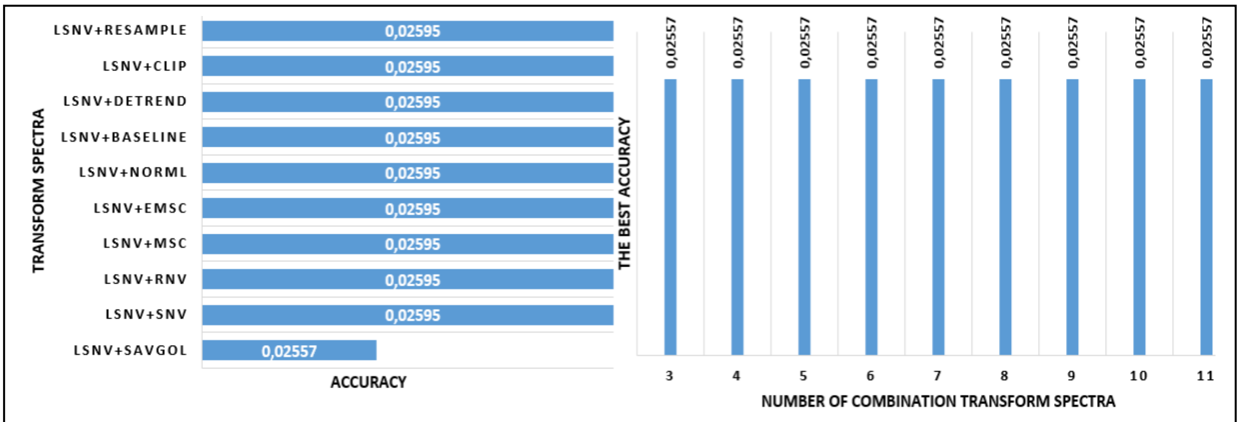



**Figure 7**. Comparison of the Use of Spectral Transformation without Combination on the MSE value of the Regression Model




a. 2 Combination of Transform Spectra b. 3 - 8 Combination of Transform Spectra

**Figure 8**. Combination of Spectral Transformation on the MSE value of the Regression Model

**Table 4** shows the combination of spectral transformation operations with parameter values that produce the best MSE values in the developed model after an experiment of up to 2368 iterations.

**Table 4**. Parameters and Values of Spectra Transformation Operation with Smallest MSE

| Transform Spectra Operation | Parameter and value |
|---|---|
| LSNV<br>SAVGOL | {}<br>{'deriv_order': 0, 'filter_win': 15, 'poly_order': 6} |

2) Prediction of TSS content of Arumanis Mango

The development of the TSS content prediction model using SVR and without performing spectral transformation operations resulted in an MSE value of 0.02882. Spectral transformation operations were performed to improve the model. Tests were carried out on each spectral transformation operation and combination to find the best MSE value. The first test that calculates the MSE value in each spectral transformation operation which results in 8 spectral transformation operations has improved the MSE value. The best MSE was obtained using SAVGOL with an MSE of 0.02741. NORML, CLIP and RESAMPLE with the same MSE without spectral transformation. The MSE value of the spectral transformation operation test can be seen in **Figure 8**. The next test is to combine the spectral transformation operations starting from 2 to 11 combinations.

**Figure 9a** shows the MSE value of the model with a combination of 2 spectral transformation operations. The combination of SAVGOL and LSNV fixes the error with an MSE value of 0.02608. The combination of 3 spectral transformation operations produces a better error value with an MSE of 0.02504. Testing of 4 to 11 combinations of spectral transformation operations still produce the same MSE value as previous. The comparison of the test results of the combination of spectral transformation operations on the MSE value can be seen in **Figure 9b**.

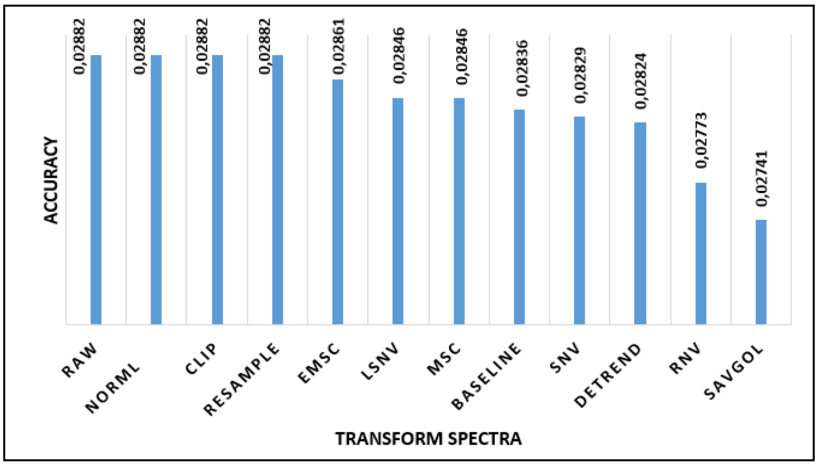
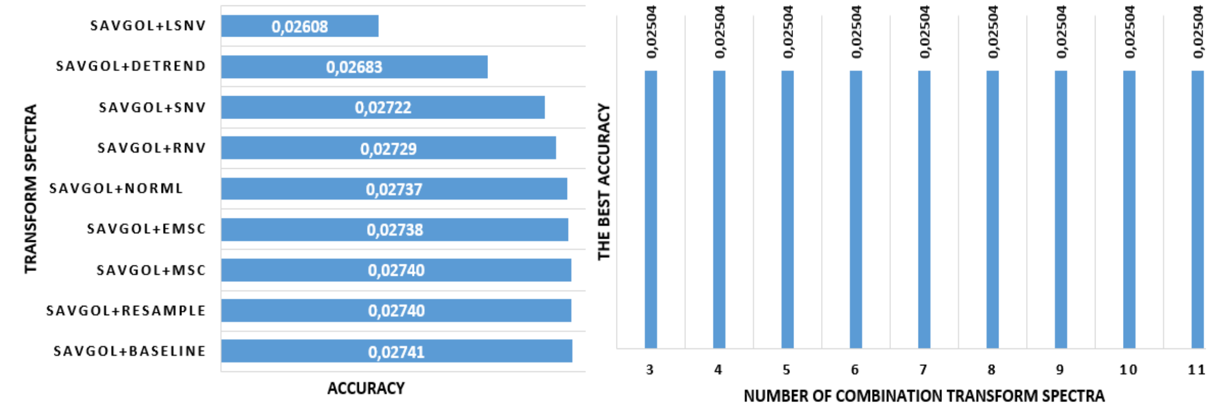



**Figure 9**. Comparison of the Use of Spectral Transformation without Combination on the MSE value of the Regression Model




a. 2 Combination of Transform Spectra b. 3 - 8 Combination of Transform Spectra

**Figure 10**. Comparison of the Combination of Spectral Transformation on the MSE value of the Regression Model

**Fig. 10** shows the results of iteration comparisons of model accuracy with spectral transformation operations, the smallest MSE value starts at a combination of 3 spectral transformation operations and does not change up to 11 combinations. Spectral transformation operations that produce model inputs for prediction of TPT content are DETREND, LSNV and SAVGOL. for more details can be seen in **Table 5**.

Table 1. Parameters and Values of Spectra Transformation Operation with the smallest MSE

| **Transform Spectra Operation** | **Parameter and value** |
|---|---|
| DETREND | {'bp': [0]} |
| LSNV | {} |
| SAVGOL | {'deriv_order': 0, 'filter_win': 31, 'poly_order': 6} |

## Conclusion

The TPT content prediction model with SVR employs three combinations of spectral transformation operations, namely DETREND, LSNV, and SAVGOL, with parameter values of "deriv order," "filter win," and "poly order," respectively, to achieve the best MSE value. With regard to the hardness prediction model, mango, the best MSE value was achieved by combining LSNV and SAVGOL, with the following parameter values: deriv order': 0, 'filter win': 15, 'poly order': 6. For better model performance, spectral transformation can be used as an input to increase model accuracy. It is preferable to have models for efficient wave selection and other computational techniques.. Spectrals with a wavelength of 1000-2500 nm from Arumanis mangoes were collected using the NIRFlex N-500 device to predict ripeness, TPT content and mango hardness. spectral transformation operations are performed to improve the performance of the model. In the classification model of 2 mango ripeness classes with a combination of 8 spectral transformation operations, the highest accuracy was obtained using RNV and SAVGOL. The TSS content prediction model used SVR with the best MSE value using 3 combinations of spectral transformation operations, namely DETREND, LSNV, and SAVGOL with parameter values: 'deriv_order': 0, 'filter_win': 31, 'poly_order': 6. As for the hardness prediction model of mango with the best MSE value using 2 combinations of spectral transformation operations, namely LSNV and SAVGOL with parameter values: deriv_order': 0, 'filter_win': 15, 'poly_order': 6. Spectral transformation as input can improve model accuracy. To obtain better model performance, selection of effective wave and other algorithmic approaches as models can be performed.

## Acknowledgement

We would like to thank LPDP for funding through the RISPRO Invitation 2020 and all the teams who have assisted in the research.

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