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# Non-destructive measurement of internal browning in mangoes using visible and near-infrared spectroscopy supported by artificial neural network analysis

Suzan H.E.J. Gabriëls*, Puneet Mishra*, Manon G.J. Mensink, Patrick Spoelstra, Ernst J. Woltering

*Wageningen Food & Biobased Research, Building 118, Wageningen University and Research, P.O. Box 17, 6700 AA Wageningen, the Netherlands*

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ABSTRACT

Visible and near infrared spectroscopy (VNIRS) (400 – 1000 nm) is a key emerging non-destructive technique for fruit quality assessment. This, because it is a unique method which allows rapid access to fruit pigments and chemical properties linked to fruit quality. In the present work, VNIRS has been used to predict the internal browning in 'Keitt' mangoes halves. The reference analysis was performed by cutting individual mango into halves and quantifying the extent of internal browning with a standardized color imaging (CI) cabinet as a browning index (BI). The CI provided a value for the "browning index" for each mango reflecting the presence and severity of internal browning. The data modelling involved both regression and classification analysis. The regression was performed to link the VNIR spectra with the BI values obtained from the internal color analysis. The classification analysis was performed for binary classification of mango into healthy or brown. Two different analysis techniques i.e. artificial neural network (ANN) and partial least square (PLS) were utilized. The study shows that VNIRS combined with ANN can classify mangoes as healthy or having internal brown with an accuracy of over 80 %. A robust and reliable classification system can potentially improve quality decisions through the mango supply chain, thereby reducing post-harvest losses.

## 1. Introduction

Mangoes (*Mangifera indica* L.) are tropical fruits, originally grown in India, where they have been cultivated for over the past 4000 years (Tharanathan et al., 2006). Over centuries, mango production gradually moved to other countries. Initially to Asia and later to other tropical countries in America (Mitra, 2016). In tropical countries, mango belongs to one of the most economically important fruit, with 1.3 million tons of mangoes exported from countries like Brazil, Mexico, India, Peru and Thailand (Faostat, 2016).

The increase in commercial production areas and improved transport conditions allowed the introduction of mangoes to Europe (Morton, 2003). In Europe, mangoes first arrive at the wholesalers, where they may be sorted based on their ripening stages. Ripe mangoes are sold to nearby supermarkets, while unripe mangoes are either stored under ripening conditions or can be transported to locations at greater distances. Apart from ripeness, a major quality indicator for mangoes is the presence of internal browning. Mangoes with internal browning are considered as low-quality and should be identified as early as possible in the supply chain to avoid any disappointments at the consumer, as well as mango processing industry level. So far, detection of internal browning requires destructive measurements, and is, therefore, detected either by the processing industry (upon cutting mangoes for the fresh-cut product) or by the consumer during consumption.

The background causes of internal browning in fruits are not clearly understood in the scientific domain. In general, internal browning disorders in fruits are often associated with extreme storage conditions comprising of low temperatures, low oxygen ($O_2$) and high carbon dioxide ($CO_2$) concentrations (Mellidou et al., 2014). The observed browning is associated with increased oxidative stress and a loss of cell membrane integrity. The loss of membrane integrity can lead to the disruption of cellular compartmentalisation. Phenolic compounds may be released from the vacuole and be oxidized by polyphenol oxidase to form o-quinones and eventually brown-coloured compounds (Tomás-Barberán and Espín, 2001). In mangos, a clear understanding of internal browning process is still lacking. A hypothesis is that mangoes with internal browning might be at a stage of over-ripeness. Mango is a

* Corresponding authors.
*E-mail addresses:* suzan.gabriels@wur.nl (S.H.E.J. Gabriëls), puneet.mishra@wur.nl (P. Mishra).

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climacteric fruit (White, 2002), which ripen further after harvest. In general, ripening changes the composition and structure of the primary cell wall. Components like pectin and hemicellulose are enzymatically altered after harvest and during ripening. Also, the changes in bonding and rigidity cause texture changes and softening. These changes lead to a soft and tasty mango (Posé et al., 2018). Besides structural changes, ripening causes color changes by the conversion from chloroplasts to chromoplasts and the accumulation of carotenoids (Klee and Giovannoni, 2011). Mango has a high content of carotenoids in the mesocarp tissue, causing the intense yellow color (Singh and Dwivedi, 2008). However, over-ripening might lead to loss of cell membrane integrity (cell death) and accompanying tissue browning.

Non-destructive sensing techniques such as visible and near-infrared spectroscopy (VNIRS) are gaining human interest for rapid quality prediction of fresh fruits. Various applications of VNIRS related to mango quality analysis have been described. Some applications include the prediction of soluble solid content (SSC), firmness, dry matter (DM), maturity and flesh color (Saranwong et al., 2004; Subedi et al., 2007; Valente et al., 2009; Rungpichayapichet et al., 2016; Marques et al., 2016; dos Santos Neto et al., 2017; Nordey et al., 2017; Santos Neto et al., 2018). VNIRS prediction models (linear models) generally allow proper prediction of one specific quality trait, in one specific cultivar produced at one specific orchard and stored under standardized conditions. However, the models often fail when they are used for practical application in the mango supply chain dealing with different mango cultivars and variability due to production and storage circumstances. Therefore, robust VNIRS models, defined as models with accurate prediction accuracy regardless of these external factors are crucial for the application of VNIRS models in the mango chain (Nicolaï et al., 2007). There are two approaches to obtain a robust model. In a first case, a large sample set covering different chemical and physical variations is required to provide a generalized model (Nordey et al., 2017). However, obtaining such a wide sample set for fruits can be tedious and sometimes not feasible. When only a limited number of samples is available, moving to advance non-linear pattern recognition methods which can model the complex biological, environmental and instrument variation can be considered as a second approach to develop robust models (Kuang et al., 2015).

VNIRS has been widely used for predicting the quality traits of mango such as SSC, DM, flesh color and acidity (Nordey et al., 2017). However, its potential to predict possible internal defects such as internal browning in mangoes is unexplored. VNIRS is an interesting technique for internal defects as the spectral range of 700 − 1000 nm explains the physicochemical information about the materials (Mishra, Asaari et al. 2017). A work related to the detection of Brownheart in the 'Braeburn' apple showed that the NIR in range of 700 − 900 nm was able to successfully predict defect with a $R_p^2$ of 0.91 (Clark, McGlone et al. 2003). Further, a complete on-line system operating in the range of 650 − 950 nm was developed and used for detecting internal browning in 'Braeburn' apples (McGlone, Martinsen et al. 2005). Another recent study showed that the spectral range of 600 − 830 nm was the most weighted information for detection internal browning in the 'Cripps Pink' apples during cold storage (Mogollon, Jara et al. 2020). A study involving a spectral range of 550 − 1650 nm for detecting the internal defect in apples found out that apart from the change in color the major differences were located in the spectral range of 700 − 1000 nm (Huang et al., 2020). All these studies support us to use the VNIRS (400 − 1000 nm) for the detection of internal browning in mangoes.

Internal browning in mangoes is a major quality trait which requires rapid non-destructive testing techniques to reduces the losses in the supply chain. The present study utilizes the VNIRS for non-destructive classification of mango with internal browning. To cover a range of variability in mango, the study involved a broad sample set covering 576 'Keitt' mangoes. harvested from different orchards at different periods during the season, with varying levels of browning. The reference analysis for the level of internal browning was performed by cutting mangoes into halves and utilizing color imaging (CI). Data modelling was performed using both linear and non-linear data modelling with partial-least square (PLS) and artificial neural network (ANN) respectively.

## 2. Materials and method

### 2.1. Mango samples

576 'Keitt' mangoes were used in the experiments. Mangoes were sourced from commercial orchards in the Petrolina area in Brazil. Mangoes were transported to the Netherlands in reefer containers overseas, for approximately 3 weeks at a controlled temperature of approximately 10 °C. At arrival in The Netherlands, mangoes were delivered to a fresh-cut processing company where they were subject to a primary quality check by an in-house quality expert. The checks involved selecting a random subset of twenty mangoes per batch (pallet) and cutting them in halves to visually judge internal quality. Batches containing over 5% of mangoes with unacceptable internal browning were rejected and either destroyed or sold at local markets (personal communication with processing company). Batches that were considered unsuitable for processing in the period between September and December 2017 were transported to Wageningen Food and Bio based Research (WFBR), Wageningen for further research. Transport to Wageningen took approximately 3 h and done under ambient conditions (15 − 20 °C). Three different rejected batches, containing 206, 108 and 262 mangoes, respectively were used in the investigations. On each mango halves, VNIR spectral measurement and color imaging after cutting individual mango in halves was performed. All measurements were done at 20 °C on mangoes that were held for at least 3 h. at 20 °C.

### 2.2. Spectral measurements

VNIR reflectance spectra in the range of 300–1100 nm were collected on the outer peel of the intact mango at a position near the equatorial region. The equatorial region was defined being at equal distance from proximal and distal ends (dos Santos Neto et al., 2017). A portable FELIX 750 handheld device was used to collect the spectra according to the methodology described by (Subedi et al., 2007). The FELIX 750 device utilizes a Carl Zeiss MMS-1 spectrometer with a spectral resolution of 8 − 13 nm and a spectral sample size of 3 nm. This device utilizes a xenon tungsten lamp for illumination and a white reference standard. All the data were recorded with the FELIX 750 and temporarily stored in the memory card. The data stored in the memory card were extracted to. csv files utilizing the F750 data viewer software. The data were automatically calibrated in the FELIX 750 and pre-processed by estimating the absorbance and later the second derivative. For the first rejected batch of 206 mangoes, VNIR spectra were collected from one side of the mango. For the second and third batch of 108 and 206 mangoes respectively, it was decided to collect more data by measuring VNIR at the two opposite sides of each mango. In total, 946 spectra ($1 \times 206 + 2 \times 108 + 2 \times 262$) were collected, all at a similar position on the equatorial region of mango.

### 2.3. Measurement of internal browning

The internal browning in the mango pulp was visually judged (expert panel) by estimating the surface area showing browning as a percentage of the total surface of mango halves. In addition, objective measurements of internal browning were performed in a light and color standardized cabinet (Weblink: Color Cabinet, 2020). The color measurements were done on mango halves; the mango was cut alongside the pit. In total, color measurements were done on: 206 mango halves from the first rejected batch from which only a half per mango was measured, plus 216 mango halves from the second rejected batch

consisting of 108 mangoes measured on both halves, and 524 mango halves from both halves of the 262 mangoes from the third rejected batch.

Each mango half was photographed using a digital camera mounted inside the cabinet. The color standardized pictures were analyzed to quantify the color information in a two-step approach. Firstly, using color-learning software, colors of the mango pulp were determined as either healthy mango tissue, or tissue with internal browning. Green color was associated with the peel and was excluded from further analysis. Secondly, using the color analysis software the ratios of the color pixels related to healthy tissue to that of brown tissue were determined. Finally, the natural logarithm (ln) of this ratio was calculated as explained in Eq. 1.

$$Internal\ browning = LnHB = ln\left(\frac{Healthy\ pixels}{Brown\ pixels}\right) \quad (1)$$

The level of internal browning was defined as the LnHB ratio, with healthy being the amount of color pixels with a hue value associated to healthy mango pulp, and brown being the amount of color pixels with a hue value associated to brown mango pulp.

### 2.4. Data analysis

The VNIR spectra and the color measurement data (LnHB ratios) were analyzed with two different modelling approaches i.e. regression and classification. The regression modelling was performed to link the spectra with the LnHB ratios obtained from the destructive color analysis. The classification modelling was performed to classify mangoes into healthy or brown classes. To perform classification modelling, a LnHB ratio below 2.5 was assigned as class 0, defined as mango with internal browning, while a LnHB ratio of 2.5 or higher was assigned as class 1 and defined as a healthy mango. The use of 2.5 as threshold to distinguish mangoes with internal browning from the healthy mangoes was based on the visual observation of the mangoes by expert panel and by wholesalers. Applying this threshold identified 648 mango halves with internal browning and 298 mango halves without internal browning. PLS and ANN based modelling were performed for regression and classification analysis. The dataset was randomly divided into calibration (70 %), validation (15 %) and test set (15 %) for data analysis. The validation set was used for optimizing and fine-tuning the calibration model. The model was first tested on the 15 % test data which were not used for training or validation. Later, the model was also tested on an extra test set consisting of 350 mango halves. These extra test data allowed us to have an extra test of the model performance to check whether a mango which was predicted to have internal browning based on the model, proved to be “truly” brown after cutting the mango in halves. In the present work, both PLS and ANN were implemented in MATLAB 2017b (Mathworks, Natwick, MA, USA).

#### 2.4.1. Partial least square analysis

PLS regression (PLSR) is a popular chemometric method used to deal with the multicollinearity in the multivariate signal (Nordey et al., 2017). PLSR operates by identifying the latent variables (LVs) before performing a typical multi-linear regression modelling. The LVs are high dimensional vectors which explain the most useful variation in the data. The PLSR identifies the LVs by exploring the subspaces which maximizes the co-variance between the predictor and the response variables. In the present work, the PLSR was used to link the VNIRS and the LnHB ratios. Before feeding to PLSR, the data were mean centered. The LVs were selected by utilizing venetian blind cross-validation (10 random splits) and the output of the regression is presented as correlation coefficient's and standard errors.

#### 2.4.2. Artificial neural networks

ANN are advanced non-linear pattern recognition methods which can model the complex biological, environmental and instrument variation (Allouche et al., 2015; Martelo-Vidal and Vázquez, 2015; Silalahi et al., 2016). ANN’s are the mathematical simplification of the complex biological nervous systems and consist of a net of small processing units (neurons) that are interconnected with weighted connections. The neuron takes the weighted sum of the inputs and passes it through a non-linear transfer function to provide an output signal (Dębska and Guzowska-Świder, 2011). In the present work, MATLAB’s ‘neural fitting’ tool was used for performing the regression and ‘neural net pattern recognition’ tool was used for the classification. A default ten hidden neurons model was chosen for the task. The optimization of the regression model was performed with Levenberg-Marquardt approach, and the classification model was performed utilizing conjugate gradient backpropagation. These approaches train the models automatically until the generalization stops improving. The generalization performance is judged based on the mean square error and stops when the error starts increasing on the validation samples. There was a total of 946 samples (mango halves) of which 648 classified as brown and 298 as healthy. Prior to classification analysis a balanced dataset was prepared consisting of an equal amount of brown and healthy mangoes. The balanced dataset is needed in the classification modelling to avoid overfitting of the model for the class having large number of samples. Our balanced data set consists of all 298 healthy mango halves plus an equal amount of 298 randomly chosen brown mango halves. The remaining 350 brown mangoes were used to test (extra testing) the model by checking whether the model indeed predicts that these mango halves are brown (extra testing).

## 3. Results

### 3.1. Internal quality of samples

Visual appearance of selected mango halves with different LnHB ratios are shown in Fig. 1. Fig. 1A presents the mango halves with LnHB ratio less than 2.5 (designated brown), Fig. 1B presents samples with LnHB ratio of more than 2.5 (designated healthy). It can be visually observed that with decreasing LnHB ratios the severity of internal browning increases. The mangoes which have the most internal browning even have a negative LnHB ratio (Fig. 1 A). The higher the LnHB ratios, the less browning is visible. For mangoes with a LnHB ratio of more than 2.5 the internal browning is almost negligible and these can be defined as healthy (Fig. 1B). The decision to classify mango halves as either brown (unacceptable) or healthy (acceptable) was made based on visual judgements by experts from research and industry. Therefore, 2.5 was defined as the threshold to assign binary class labels to the dataset, to enable classification of mangoes into either “brown” or “healthy”.

In this study, 3 different rejected batches were used. To have an understanding regarding the level of internal browning in the different batches, the LnHB ratios are presented as frequency distributions in Fig. 2. In Fig. 2A, the frequency distribution of the LnHB ratio of mango halves from the first batch shows relatively more mango halves with a LnHB ratio higher than 2.5 compared to less than 2.5. The frequency distribution of the LnHB ratio of mango halves of the second batch shows a relatively larger portion of mangoes having a LnHB ratio lower than 2.5. (Fig. 2B). Most mango halves of the third batch have LnHB ratios higher than 2.5, while mangoes with LnHB ratios lower than 2.5 are still frequently represented in this batch (Fig. 2C). Taking all three rejected batches together the frequency of the LnHB ratios showed a wide range of LnHB ratios (Fig. 2D) indicating that this complete dataset is valuable to build a classification and regression model based on the LnHB ratios of mango halves.

### 3.2. Spectral profiles

The spectral profiles of the mango halves with maximum (6.53) and

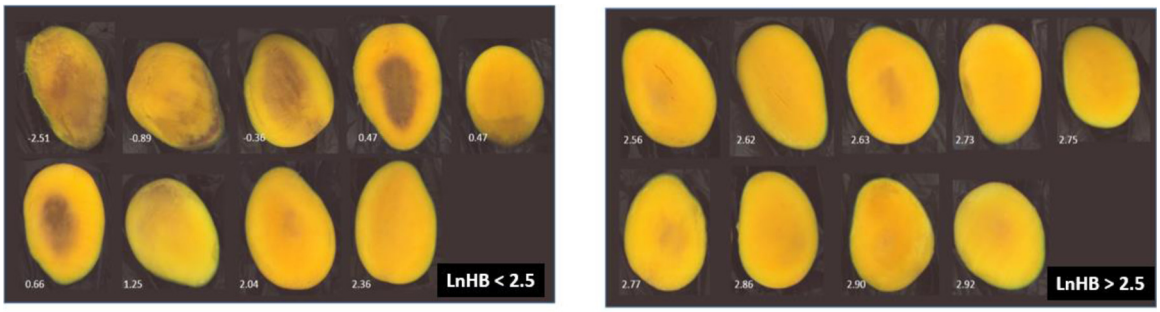


**Fig. 1.** Mango halves with different severity of internal browning. The numbers at the bottom of the mango halves are the LnHB values (A) Samples with LnHB ratios less than 2.5 designated "brown", and (B) samples with LnHB ratios greater than 2.5, designated "healthy.

minimum (-5.31) LnHB ratios are shown in Fig. 3. This shows that the major differences in the spectral intensities of mangoes with high versus low LnHB ratios are in the spectral range of 700 − 900 nm. The region is dominant for the 3rd stretching overtones of the O—H, C–H and N—H bonds corresponding to a complex mix of signals emerging from the moisture, fatty acids and amino acids respectively.

### 3.3. Regression modelling

The results of the PLSR analysis are presented in Fig. 4 and 5. The evolution of root mean squared error of calibration (RMSEC in red) and root mean squared error of cross-validation (RMSECV in blue) along with the increasing number of LVs extracted is shown in Fig. 4. The green line shows the number of LVs extracted. There was no clear stable shoulder point to automatically select the number of LVs, therefore, 14 LVs were manually selected as the error showed a slight increase after that. However, errors keep on decreasing even after 14 LVs, making it difficult to choose between an under and an over fitted model. Finally, the model based on 14 LVs was calibrated and tested and the corresponding plots are presented in Fig. 5A and 5B, respectively.

In Fig. 5(A) the measured versus predicted values with the PLSR model in the calibration data are presented. Analysis of the calibration

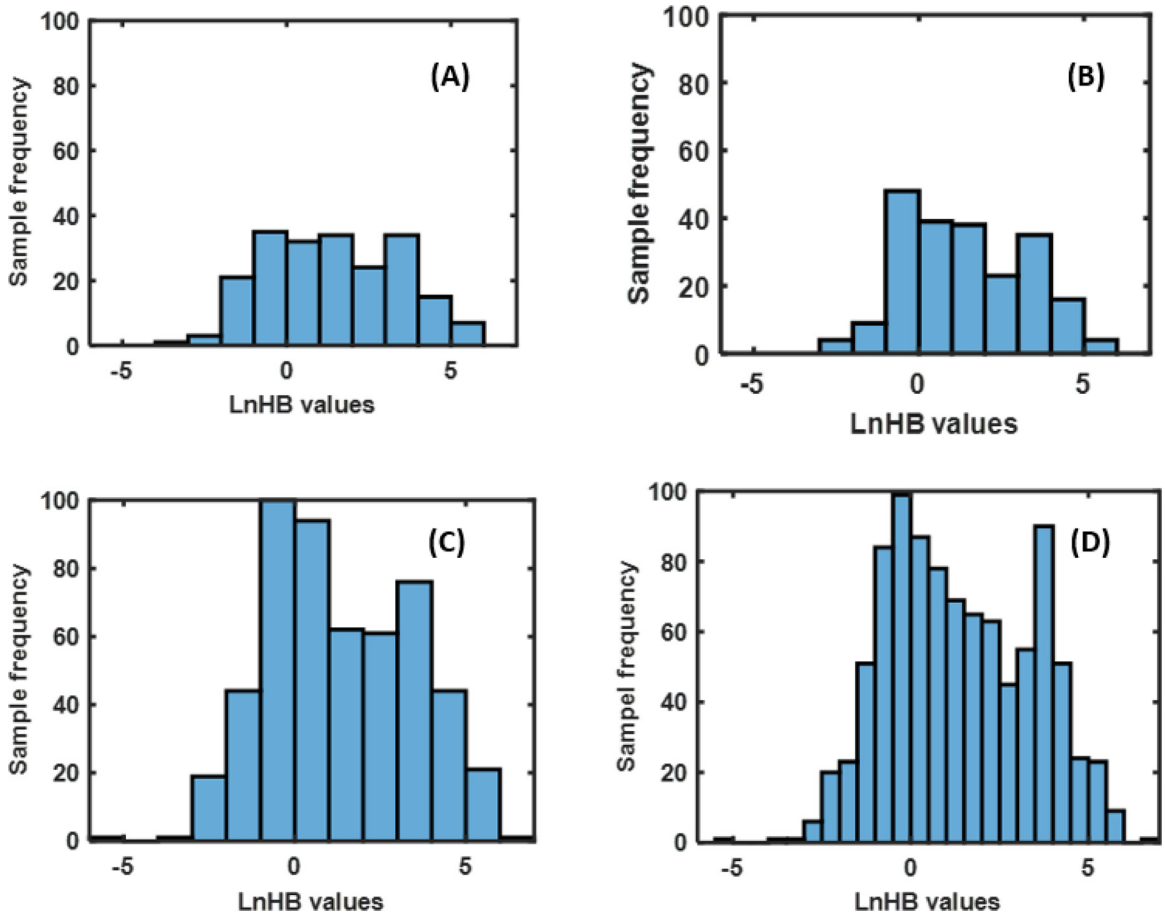


**Fig. 2.** Frequency distribution of the LnHB ratios of mango halves in the three rejected pallets. (A) The LnHB ratios of most mangoes in batches 1 is higher than 2.5, (B) the LnHB ratios of second batches is lower than 2.5 (C) the LnHB ratios of most mangoes in batches 3 is below 2.5. (D) Frequency distribution of the LnHB ratios for all three batches represent a normal distribution.

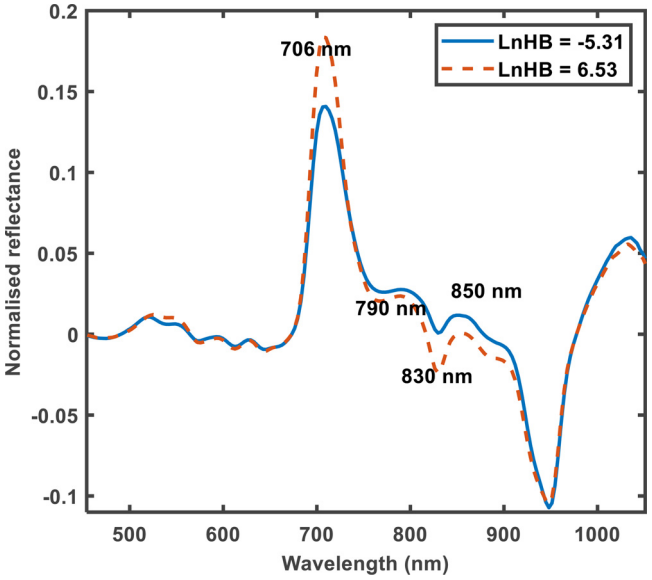


**Fig. 3.** Spectral profile of mango halves with high (in red dashed line) and low (in blue solid line) LnHB ratios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

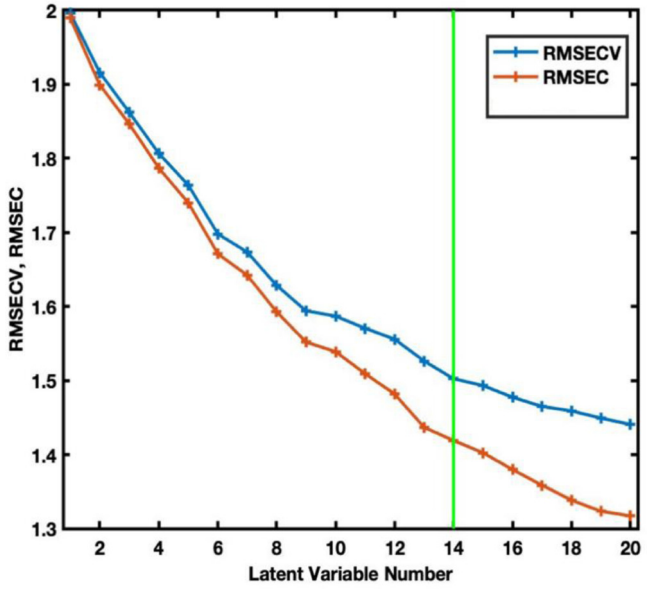


**Fig. 4.** Evolution of root mean squared error of calibration (RMSEC in red) and root mean squared error of cross-validation (RMSECV in blue) with increasing number of latent variables. 14 LVs were selected and highlighted by a vertical green line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

set shows that a $R^2$ of 0.515 was obtained with a RMSEC of 1.41 and RMSECV of 1.50. In Fig. 5(B) the measured versus predicted LnHB ratios for the test samples is presented. A $R^2$ of 0.53 was obtained for the test set (composed of 15 % of the data) with root mean square error of prediction (RMSEP) of 1.39. The correlation obtained with PLSR was too low to conclude anything on the potential of VNIRS to predict the severance of internal browning (Fig. 5). A reason for the poor performance of PLSR can be due to the linear modelling performed by the PLSR. It is likely that the VNIRS data maps the LnHB ratios better in the non-linear space. To understand it, the same data was processed with ANN regression.

The results of the ANN regression are presented in Fig. 6, where Fig. 6A presents calibration, and Fig. 6B presents the test set. It can be seen in Fig. 6 that the calibration $R^2$ increased to 0.72 compared to an PLSR $R^2$ of 0.51 obtained with the PLSR model. The test $R^2$ increased from 0.53 with the PLSR model to 0.57 with ANN regression. This shows that the relation between LnHB and the VNIR was not simply linear as explained by a PLSR model, rather could be a non-linear one explained by a ANN based model.

### 3.4. Classification modelling with ANN

The classification results from ANN classification are presented in Table 1. The results presented are based on the calibration (Table 1-part A) and testing (Table 1-part B) performed on the balanced dataset consisting of 298 healthy and 298 mango halves with internal browning. In addition, the results obtained utilizing the remaining 350 brown mango halves as an extra test set, are depicted in Table 1-part C. An overall calibration classification accuracy of 87.1 % was obtained with a sensitivity and specificity of 85.4 % and 88.7 % respectively (Table 1). The sensitivity in this experiment explains the probability of mango halves which were having internal browning and classified correctly with the classification model. The specificity explains the probability of mango halves which have no internal browning and predicted having no-internal browning with the classification model. The accuracy with the test set consisting of 15 % of the balanced data set was 83.1 % with a sensitivity and specificity of 86.3 % and 80.0 % respectively (Table 1). The test results showed that overall, the model performed better in identifying mango halves with internal brown (86 % sensitivity) compared to identifying healthy mango halves (80 % specificity).

The classification accuracy obtained on the extra test set consisting of 350 internally brown mango halves is presented Table 1 row C. The 350 mango halves were the remaining samples which were not part of the balanced dataset used for validating and testing the model. An accuracy of 82.3 % was obtained for this extra test set. The high accuracy levels, especially for the extra test set consisting of mango halves which were not used to build the model, shows the potential of VNIRS to predict internal brown in mangoes.

## 4. Discussion

Internal browning in mangoes is a major quality issue causing substantial post-harvest losses, especially during inter-continent export. There are no clear symptoms of the internal browning visible from the outside of the mango. Further, there is a lack of scientific understanding regarding the physiological process of internal browning in mangoes. One hypothesis is that the internal browning could be due to the over-ripening of the mangoes. The normal ripening process brings changes in the physicochemical properties of the cell walls leading to composition and structural changes in the cell wall (Posé et al., 2018). However, the over-ripening could lead to cell death and associated tissue browning. A link between ripeness and internal browning can be explored. However, accurate ripeness prediction in mangoes is a challenging task as it is a combined effect of physical and chemical changes occurring during the ripening process. There is a large variation in quality and maturity of mangoes depending on the time of harvest, the variety, the storage condition and various environmental factors. In the case of inter-continental export (e.g. from South America to Europe), the time of harvest is crucial as the growers need to account for the 2–3 weeks of overseas transport during which the physiological stage of the mango tissue changes (Mohammed and Brecht, 2002; Gill et al., 2017). This harvest time in the case of inter-continental export can hugely affect the post-harvest quality including the internal browning (Lechaudel et al., 2010).

Currently, to judge on the quality of incoming mangoes, the European wholesalers utilize a pre-calibrated VNIRS based model and impact acoustics measurements to predict the firmness levels of incoming mangoes. The firmness values obtained from the measurements

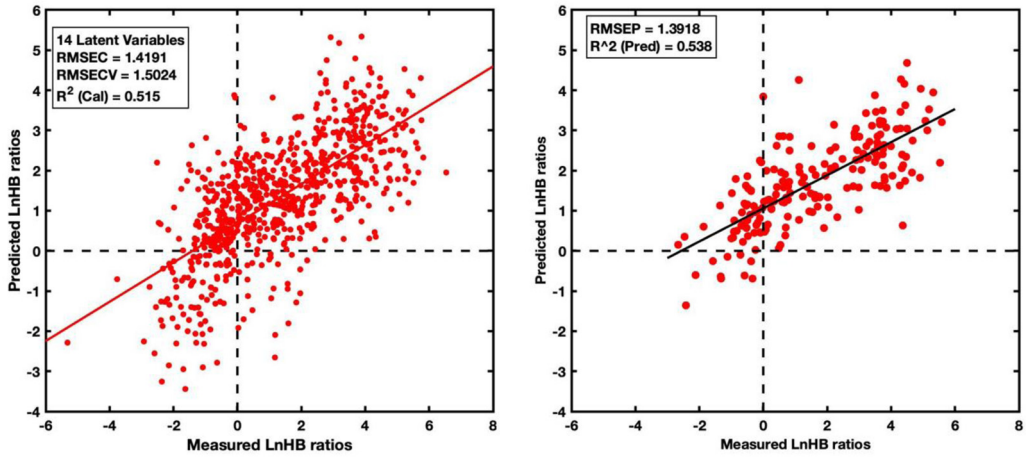


**Fig. 5.** PLSR modelling performed with 14 latent variables. The measured and predicted LnHB ratios are presented as x and y-axis respectively. (A) Calibration set and (B) test set.

are used as input to a standard linear classifier model to classify the imported mangoes into different ripening stages. However, in around 50 % of the cases mangoes are misclassified (personal communication with industrial partners). Poor performance of VNIRS model can be understood as the lack of robustness in dealing with the samples with a wide diversity such as different origin, grade, variety, among others. An improved VNIRS based non-destructive approach, is demonstrated in present work to predict intern browning in mango halves with accuracy > 82 %, could directly benefit the wholesalers to judge on the quality of incoming mangoes.

The VNIRS models lack robustness in case the models are developed on a specific cultivar while tested on another cultivar. A reason for this could be the differences in the absorption and scattering characteristics due to compositional and physical structure of different cultivars (Renfu et al., 2020). Such absorption and scattering characteristics bring slight shifts in the spectral profile of the samples of different cultivars, and thus, the model developed on one cultivar might underestimate- or overestimate- the responses. In recent work, global PLSR-VNIRS models were used for robust prediction of mangoes quality based

**Table 1**
Classification accuracies (mango halves) obtained from ANN based classification. Classification was performed into two classes with LnHB ratio < 2.5 (brown)) or LnHB ratio ≥ 2.5 (Healthy).

| (a). Calibration | | | |
|---|---|---|---|
| *Sample type* | *Number* | *Correctly predicted* | *% Accuracy* |
| *Brown* | 206 | 176 | 85.4 |
| *Healthy* | 212 | 188 | 88.7 |
| ***Overall accuracy*** | | | 87.1 |
| **(b). Test** | | | |
| *Brown* | 44 | 38 | 86.4 |
| *Healthy* | 45 | 36 | 80.0 |
| ***Overall accuracy*** | | | 83.1 |
| **(c). Extra test** | | | |
| Brown | 350 | 288 | 82.3 |

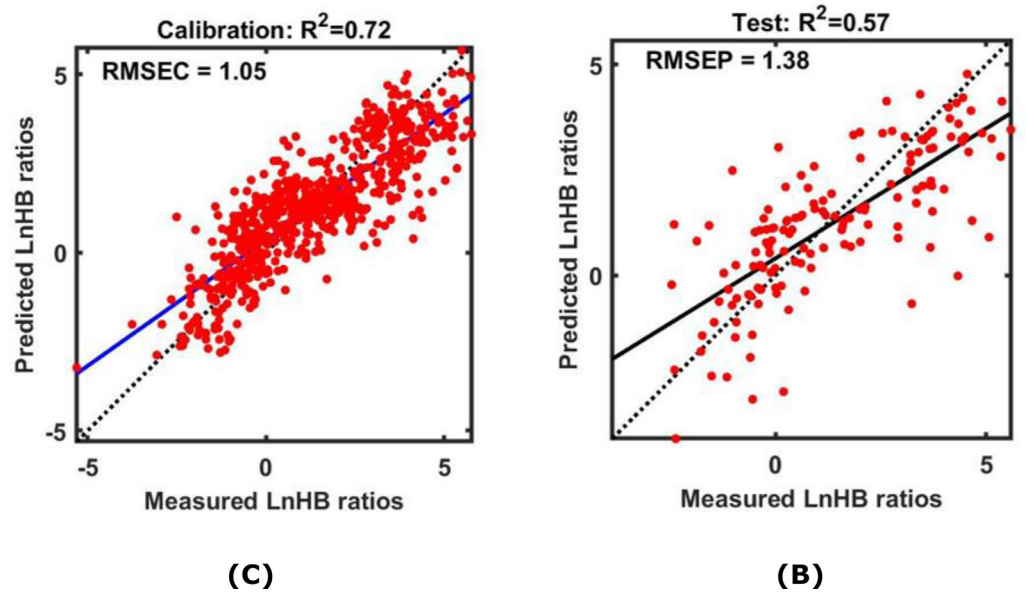


**Fig. 6.** Results of ANN regression performed using VNIR spectra and LnHB ratios. (A) calibration set, and (B) test set.

on total soluble solids, dry matter, titratable acidity and flesh color independent of the pre- or post-harvest circumstances (Nordey et al., 2017). However, such a global model requires huge experiments covering samples from all possible cultivars and pre- and post-harvest conditions which can be difficult, time-consuming and costly. When only a limited number of samples is available, moving to advance non-linear pattern recognition methods (such as ANN's) which can model the complex biological, environmental and instrument variation can be considered as a better solution to develop robust models. ANN's have been widely used in the VNIRS data modelling for qualitative as well as quantitative assessment of food products (Allouche et al., 2015; Martelo-Vidal and Vázquez, 2015; Silalahi et al., 2016). In some comparable work, the ANN has already outperformed the traditional PLSR in terms of higher prediction accuracy (Benoudjit et al., 2004; Singh et al., 2009; Bampi et al., 2013; Kuang et al., 2015).

In the present work, the ANN model ($R_P^2$ of 0.57) outperformed the PLS based linear regression model ($R_P^2$ of 0.53) in predicting the level of internal browning. A reason for this could be the inability of linear regression to deal with non-linearity in the data set. Non-linearity in the VNIRS data could arouse from multiple sources such as sample surface inhomogeneity, noise in the detector, illumination inhomogeneity and even due to ambient factors such as temperature and relative humidity. Some of these factors can be directly observed in the acquired data as additive and multiplicative effects. In a model like PLSR, it is highly recommended to perform pre-processing such as normalization to remove these effects and make the relation between spectral data and the response of interest as linear as possible. However, pre-processing to remove these effects can also remove useful information such as the scattering characteristics of the samples which often can be noticed as additive or multiplicative effects in the raw spectral data. Unlike linear PLSR method, the ANN does not require the data to be pre-processed as it already assumes a non-linear relation between the predictor and the response variable. It is highly likely that the modelling performed by the ANN also covered the scattering characteristics of different samples and not just the absorbance/reflectance responses of the samples.

In the present study, the VNIRS signatures showed distinct intensity differences between the healthy and internal brown mangoes. The major differences were dominantly in the range of $700-900$ nm. In previous research, the similar regions and nearby bands i.e. 720 nm, 750 nm, 760 nm, 780 nm and 810 nm were also identified to represent internal defects in apple fruits (Upchurch et al., 1997; Vanoli et al., 2010, 2014). The spectral differences showed that the internal browning does not have much effect on the outer color of the mango, as all the spectral bands showing major differences are in the NIR range ($>700$ nm). The spectral differences in the NIR highlight that the mangoes with internal browning have different physicochemical properties compared to healthy mangoes. However, it is not clear what exactly are the changes in the composition of mangoes, as NIR captures a mixture of effects resulting from absorption by multiple chemical components (moisture, protein, fats) and scattering from the texture. These differences in the spectral signature of mangoes were utilized in the data modelling to develop regression and classification models. It should also be noted that the internal browning is an internal defect in mangoes and NIR light cannot penetrate deep inside food products to directly capture the chemical and physical changes due to internal browning. However, it is most likely that NIRS is capturing some secondary effects causing changes in the mangoes outer layers which might reflect the internal browning. This experiment lacks reference chemical analysis of outer layers of mangoes which limits the explanation of the real dynamics captured by NIRS related to internal browning, as, this was not the primary aim of the present experiment.

The result showed that the ANN modelling increased $R_P^2$, however, the VNIRS was still only able to explain 57 % of the variation in the LnHB ratios, which is not enough to be implemented in industrial mango sorting. However, the main aim was to be able to utilize the VNIR for non-destructive prediction in mangoes into either mango with internal browning or healthy mangoes, thus defining a binary classification. The reference measurement and the consultation with the project partners resulted in the identification of the critical threshold LnHB ratio of 2.5 in the primary experiment. Therefore, transforming the regression case to a binary classification was possible by setting a threshold of 2.5 on the LnHB ratios and assigning samples with LnHB ratios $< 2.5$ as brown and the samples with LnHB ratios $> 2.5$ as healthy. The non-linear classification based on ANN resulted in a prediction accuracy of 83.1 % for the test set with a sensitivity and specificity of 86.3 % and 80.0 %. This higher sensitivity and lower specificity values indicates that the model is slightly better in predicting whether a mango half has internal browning rather than predicting whether a mango half is healthy. The accuracy to detect internal browning on the extra test set of 350 mangoes was 82.3 %, almost like the test accuracy of the modelling set (83.1 %), These comparable results present the stability of the classification model and the potential of the VNIRS.

The results obtained from the research cannot be directly translated to high throughput sorting at wholesalers as the experiments were performed with a portable VNIRS spectrometer. However, portable VNIRS spectrometers could be sufficient for growers to estimate the optimum harvest date. For high-throughput sorting of mangoes at wholesalers and processing industry sites, automated VNIRS measurements platforms are recommended. For further application, the boundary of LnHB ratio could be adjusted depending on the demands from the industry. Increasing the LnHB ratio boundary would lead to a stricter sorting in which hardly any level of internal browning is allowed during mango sorting. This would be an advantage for the processing industry, since there is a high probability that mangoes classified as healthy will be truly healthy. However, the percentage mangoes classified as brown while they are in fact healthy will increase and will lead to the discarding of good quality mangoes and thus more waste and less profit for the wholesaler. Setting the boundary to classify mangoes depends on the desires of all players in the mango chain, including the production and logistics. For example, if mangoes come from orchards with adverse pre-harvest conditions due to heavy rainfall or high humidity, or if they are transported under less optimal conditions due to technical failure or delays, those mangoes are expected to have internal defects. In that situation, a certain percentage of misclassification might still be economically worthwhile. Therefore, the boundary of the LnHB ratio could be decreased allowing to have more healthy mangoes while realizing that among those healthy mangoes there could be a certain percentage of mangoes with internal browning due to the setting of LnHB boundary. A robust and reliable classification system using non-destructive methods could improve quality decisions throughout the mango supply chain, thereby reducing post-harvest losses. Further research using automated VNIRS measurements such as hyperspectral camera, instead of hand-held devices, is required before implementing high throughput classification of mangoes in industry level, throughout the supply chain.

## 5. Conclusions

So far, mango quality predicted by VNIRS models were described for traits such as dry matter, SSC-content and firmness. For the first time, we assessedinternal browning in mangoes, and investigated prediction of the internal browning based on VNIRS spectra. The results showed that utilizing non-linear regression modelling such as ANN, a prediction correlation $R_P^2$ of 0.57 can be attained. This while PLSR based linear modelling provided a lower prediction correlation $R_P^2$ of 0.53. However, the non-linear classification to classify mango halves into "brown" or "healthy" based on ANN resulted in a prediction accuracy of $> 80$ % The results indicate that a portable VNIRS spectrometer in combination with non-linear data modelling such as ANN, can be used for non-destructive classification of the internal quality of mango. Reliable non-destructive measurements of internal quality are crucial to allow proper

decision making in the mango chain and will increase profit and decrease waste. Future work will involve testing the performance of the model on mangoes in other production circumstances and in different cultivars.

## CRediT authorship contribution statement

**Suzan H.E.J. Gabriëls:** Conceptualization, Data curation, Investigation. **Puneet Mishra:** Formal analysis, Software, Visualization, Writing - original draft. **Manon G.J. Mensink:** Formal analysis, Methodology, Software. **Patrick Spoelstra:** Methodology, Formal analysis, Resources. **Ernst J. Woltering:** Writing - review & editing.

## Declaration of Competing Interest

None.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.postharvbio.2020.111206.

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