NIRS-based On-tree Mango Fruit Maturity and Quality Estimation

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Declaration

I certify that this research work titled "*NIRS-based on-tree mango fruit maturity and quality estimation"* is my own work. The work has been published in following two journals:

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The material that has been used from other sources it has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

Dedicated to my exceptional parents and adored siblings whose tremendous support and cooperation led me to this wonderful accomplishment

Abstract

Estimation of on tree mango maturity is essential for the prediction of harvest time. Dry matter (DM) is a useful index in deciding mango maturity, and post-harvest quality. Existing NIR based maturity meters employ machine learning regressors to predict a particular maturity index value (such as DM, oBrix, or etc.) and then impose a hard threshold on predicted value to estimate maturity state of the fruit. In this paper, a new non-destructive handheld maturity meter is developed for on-tree harvest maturity estimation. The developed maturity meter directly estimates the maturity state (mature/immature) using a classifier trained on maturity labels assigned through standard DM thresholds for investigated mango varieties. To develop the hardware of the device, a commercial-off-the-shelf development kit of NIR micro-spectrometer in the spectral range of 400 - 1100 nm was employed with an intel compute stick, a micro-halogen lamp, a lithium battery, and a display. The application software (developed in C++) is designed to collect interactance spectra, noise removal, dimensionality reduction, and classification of maturity state. Performance of the developed device is evaluated by on tree test samples of mango fruit of different season. Comparison of both the literature reported indirect maturity estimation and proposed direct maturity classification is conducted. The test results show that the maximum accuracy achieved using indirect maturity estimation using hard thresholds is 55.9%. Whereas, direct maturity classification using KNN achieved 88.2% accuracy in predicting the maturity state (mature/immature) of the test mangoes. Overall results show that the developed DM mango maturity method has considerable potential to detect maturity state of mangoes in practical situations.

Key Words: *NIR Spectroscopy, Dry matter, Maturity Estimation, Maturity meter, Classification*

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CHAPTER 1: INTRODUCTION

1.1 Motivation

Pakistan produces approximately 1.8 million tons of mango (*Mangifera indica* L.) fruit per year, equivalent to about 8.5 percent of the world's total mango production. Indeed, Pakistan is the fourth largest mango producer of the world. In years 2012-13 Pakistan exported 103,487 tons of mangos, decreasing to around 65,000 tons in 2014-15. In 2014, Ministry of National Food Security and Research received warning from European Union for imposing ban on export of mango fruit due to poor quality mango fruit. The ministry then restricted the fruit export and only allowed registered user to export mango fruit that passed certain criteria. This helped to increase the export to approximately 84,000 tons in 2015-16 and more than 140,000 tons in this year. With this scale of activity in export markets comes a need to forward predict harvest volumes, to better co-ordinate harvest and market logistics. Harvest timing for mangos is critical, with longer time on tree giving more carbohydrate accumulation and better eating quality, but at the expense of post-harvest life which is critical for long distance export markets. Harvest timing and load information is also critical to farm management (of labor and packing consumables). Another important factor is the time duration of harvest, which occurs within a few short weeks, at the height of summer. Further, the sap that spurts from a harvested mango is acidic and damaging to skin. These factors drive the need for automation of testing of fruit quality. Harvest time is very important for mango fruit quality, early harvest brings poor eating quality fruit to the market, while late harvest will bring over ripen fruit to the market. Standard optical tools are available in the precision agriculture domain that are used to quantify fruit quality, age and health by measuring dry matter content, chlorophyll, soluble solid contents, starch, and sugar levels. However, these tools are expensive and lack a decision support system that predicts fruit harvest time.

Fruits are wellspring of nutrients, cancer prevention agents, polyphenols, and minerals, which have direct advantageous consequences for human wellbeing. It is significant to understand maturity-related biochemical, physiological, and structural processes to produce high-quality and healthy fruits. Such improved fruits ought to taste better and be outwardly appealing, however they should likewise contain bioactive compounds advantageous for consumers. The visual presentation of fresh fruits is one of the principal factors assessing the quality by a buyer whether he is a distributor, supplier, or consumer. Fruits are extremely perishable, with about 20%-40% of fruits being wasted before they reach the customer. Roughly 2% are utilized for testing and production, while more than 25% is wasted on bad management and storage. [1]. Regularly, the fruit's appearance is the most basic factor in the underlying purchase (despite cost) whereas the subsequent purchases may be progressively more associated with taste and texture. [2].

1.2 Fruit Maturity Estimation Parameters

Mango (*Mangifera indica* L.) is one of the highly consumed fruits world-wide and is known as the 'King of Fruits'. Its taste and quality cannot be assured by proper cultivation practices only, but also by deciding its optimal harvest time [3]. Estimation of mango fruit maturity on-tree is essential for the prediction of harvest time. During maturation on the tree, mango fruit accumulates starch. This starch is converted into soluble sugars during ripening, whether the fruit is on or off the tree.

Fresh fruit is often manually harvested. The picker is responsible for determining if the fruit is sufficiently ripe. Storage life and quality of perishable fruits is highly dependent on the maturity stage at which it is harvested, which can affect the way they are cared for, marketed and transported [4]. Many fruits are differentiated from vegetables by a qualitative difference in the relationship between maturity and edibility. The eating quality of many fruits, such as mature (but green) bananas [5], will be much lower than optimal at maturity. Only after sufficient ripening has taken place does the fruit become edible. In comparison, optimal maturity correlates with optimal eating efficiency for most vegetables.

1.2.1 Maturity Indices

To identify whether a specific sample of fruit is mature, different measurements as maturity indices can be used. These indicators are important for selling fresh vegetables and fruits for many reasons.

Trade regulations: A declaration of the minimum (and sometimes maximum) maturity appropriate for a given product is often included in the regulations published by the state departments of agriculture.

Marketing strategy: The laws of supply and demand in most markets establish price incentives for the earliest (or even the latest) shipments of specific goods. This allows farmers and shippers to speed up or postpone harvesting their crops to take advantage of premium rates. In order to avoid the selling of immature or overmatured goods and the consequent loss of consumer trust, the minimum maturity statements in the grade requirements exist. Objective maturity indices allow growers to know if when the demand is buoyant, their product can be harvested.

Efficient use of labor resources: For many crops, the need for labor and harvesting and handling equipment is seasonal. Growers need to forecast the expected start and completion dates for each commodity's harvest in order to schedule operations effectively. For accurate prediction of harvest dates, objective maturity indices are important.

1.2.2 Maturity Index Characteristics

Producers, exporters, and reseller requires maturity measures to be straightforward, promptly performed in the field or orchard, and requires generally cheap equipment keeping maturity index nondestructive.

There will be two very distinct concerns discussed here. The first issue is how maturity can be assessed at the harvest or at a subsequent checkpoint. How to predict the time at which a fruit will mature is the second and more complex problem. Similar methods may be ideal for both problems, but the ways in which they are implemented vary.

1.2.3 Maturity Index Development

Acceptable maturity estimation has used number of different fruits' features. Table 1 provides examples of those that have been suggested or that are in use. Table 2 summarizes the broad variety of methods that have been designed to quantify these attributes. During Maturity index development, following strategies can be adopted:

- Identify the changes in the fruit during its development.
- Identify the features (firmness, color, size, etc.) whose changes associated with the development stages of the commodity.
- Using taste panels and storage trials to decide the value (or level) of the maturity index that defines minimum acceptable maturity.
- Assign an index value to the minimum appropriate maturity when the relationship between changes in the quantity of the maturity index and the product's quality and storage life has been identified.

- Ensure that the index value consistently reflects the quality of the harvested product, test it over a few years and in a few growing areas.

1.2.4 Features used as Maturity Indices

1.2.4.1 Chronological features

Maturity may be described chronologically as days from plantation or as days from flowering in certain crops. Chronologic indexes are widely used for planning plantation, but they are barely ideal. The chronological method is refined for certain crops by measuring heat units that modulate the chronological index in accordance with the weather conditions of the growing season obtained during the growing period [6]. A variable whose changes during the creation of the product can be mathematically modeled to reveal a trend or pattern of change is a basic requirement for prediction. Once the measurement pattern is established, measurements taken at the early stage of the season can be compared with the pattern so that the minimum acceptable maturity of the commodity should be predicted. There are several requirements for the selection of the fruit to be harvested, [7] such as fruit size, dry matter, heat sum from blossom, exterior shape and colour and internal flesh colour.

1.2.4.2 Physical features

To test the maturity of different commodities, a wide variety of physical features are used.

1.2.4.2.1 Shape, skin, and size characteristics

Changes in fruit and vegetables' shape, skin and size characteristics are also used as maturity indices [7]. When vegetables, for example, exceed a marketable size and become too large, they are harvested in particular. In bananas, fingers' diameter is measured in order to evaluate its maturity [5], whereas, surface gloss or waxiness changes are used as a handy method for harvesting few melons, such as hybrid honeydew [8].

Table 1: Different Indices of maturity of the selected fruit

Fruit	Indices of maturity
Apple, Pear	Elapsed days from full bloom to harvest, Size, Firmness, External color, Starch content, Sugar content, Internal ethylene concentration

Mango	Shape, Pulp color, External color, Dry Matter, Sugar content, Firmness
Grape	Sugar Content, Surface morphology and structure
Avocado	Oil Content
Citrus fruit	Juice content, Acid content, sugar/acid ratio
Kiwifruit	Acid content, sugar/acid ratio
Pomegranate	Acid content, sugar/acid ratio
Melon	Acid content, sugar/acid ratio, Development of abscission layer, Shape
Date, Persimmon	Astringency (tannin content)
Cherries	Specific gravity

1.2.4.2.2 Abscission

On the pedicel, which bonds the fruit with the plant, a specific band of cells, the abscission zone [9] develops in many fruit during the later maturation and the beginning of maturation. The zone of abscission allows to separate the fruit from the plant. This zone (separation level) is possibly the oldest of all maturity indicators to measure progress. The force of abscission (force needed to pull fruit from the tree) is generally not a formal maturity index, but is used to assess maturity by the evolution of the abscess zone or slip in netted hybrid muskmelons [8].

1.2.4.2.3 Color

A widely used maturity indicator is the color transition following ripening of several fruits. Expensive equipment are required for objective color analysis (Fig. 1) and even though the human eye cannot provide a reasonable one-color assessment, it is highly sensitive to color variations. Thus, techniques of color comparison are commonly used for fruit ripeness evaluation [10]. To assess external or internal color, color swatches can be used. Precise devices using cutting-edge electronics and optics now require objective color measurements. Since the price of such devices has dropped, comparison techniques have often been replaced. In the mechanically harvested production of tomatoes, for example, automated color analysis is being used [9].

Figure 1: Colorimeter used to measure surface color of apples

Figure 2: UC firmness tester

Figure 3: Measuring soluble solid content with refractometer

1.2.4.2.4 Texture

Fruits are often matured with softening; fibrous or hardy are often over ripe vegetables. For maturity determination [11], these textural characteristics can be used. They are measured using instruments that calculate the force required to shoot the sample through the flesh of the fruit or vegetable with a known diameter (Fig. 2). The authors [12] note that through the stages of senescence, growth and maturation, the textural properties of fruits and vegetables can be determined by the biochemical, physiological, and structural characteristics of the living cells and their changes over time. To test the textural properties of fruits and vegetables, destructive instrumental techniques were used [13], [14].

1.2.4.2.5 Chemical changes

Fruit and vegetable maturation is often accompanied by drastic changes in its chemical composition. In maturity studies, many of these changes were utilized, but relatively few provided satisfactory maturity indicators as complex chemical analysis and destructive sampling typically are needed. A change in total soluble solids, calculated by refractometer (Fig. 3), a change in starch distribution of the product in flesh by calculating the reaction of starch-iodine is the chemical changes used for the measurement of maturity and is based on the titration of acidity and sugar-acid ratio, which are used in the legal maturity index of citrus. Avocados' oil contents calculation, which was superseded by the determination of dry weight percentage due to the time-consuming and complexity in determination of oil, show the unsatisfactory existence of the testing for maturity.

A fascinating method has been developed by French scientists to evaluate the maturity and quality of harvested melons. They extract slender fleshy cylinders from each melon and assess quickly their sugar content by calculating the juice refractive index [15]. The exterior of the cylinder is removed and on the basis of sugar reading, the melon may be accepted or refused.

The development of near-infrared (NIR) techniques to investigate fruit and vegetables composition and of rapid sensor technology in order to determine volatile profiles in harvested products is examples of new opportunities in chemical analysis [16]. The former will evaluate SSC and DM in commodities in a non-destructive manner, and the latter will assess the in-field melon maturity rapidly. For example, researchers used NIR procedures to measure SSC in peaches accurately [17]. The volatile aromas production increases dramatically as the melons mature. To make this rise in production an indicator of harvest readiness in melons, Allwood et al. [18] has developed an instrument.

1.2.4.2.6 Physiological changes

As calculated by changing patterns of respiration and ethylene production, the maturation of commodities is correlated with changes in their physiology. The problem with the use of these characteristics in maturity evaluation is the inconsistency between similar individuals of the same commodity in absolute rates of ethylene development and respiration. The approaches are often difficult and costly to execute on a commercial scale. Nonetheless the ethylene output rate of a sample of apples is used by some manufacturers to assess the maturity of the apples [19], and is used in particular to classify those appropriate for long-term managed atmospheric storage.

1.2.5 Predicting maturity

It is more difficult to predict when a product will mature than to determine its maturity at or after harvest. A measurement hose shift during the production of the product can be mathematically modelled to display a trend or patterns of change is the fundamental prerequisite for prediction. Once the pattern of change for the measurement is established, measurements made early in the season can be compared with the pattern in order to predict the date on which the minimum appropriate maturity should be reached for the product [2].

The dry matter (DM) is considered as the most critical parameter in deciding fruit maturity, and post-harvest quality [20]. At maturity, most mango varieties are green, but external colour and firmness alone are not sufficient to suggest maturity. According to recent studies, DM content is a valid index for mango maturity classification, the DM percentage rises at a rate of 0.72 percent DM/week during maturity. In large and mature fruits, most of its weight is contributed by its pulp (pulp is 60% - 70% of total DM of mango fruit) [3]. This makes DM of pulp a strong maturity indicator for mango maturity classification.

1.3 Techniques of Maturity Estimation

1.3.1 Destructive techniques

It is possible to determine texture / firmness by determining the force needed to compress, penetrate, shear, or deform the product. The compression method measures the force required to compress a commodity a few millimeters. A Magness-Taylor firmness meter or other similar instruments [21] measure the force required for small diameter probe to penetrate a commodity a given distance. A cell such as the Kramer shear cell is used to measure the force required to shear a product.

Sensory attributes which include taste, flavor or smell are difficult to determine objectively because of the poor understanding of how chemical components and their interactions affects these attributes. Sweetness is based on soluble solids or the brix content using a refractometer [22] and sourness is based on the standard base amount required to titrate juice of a sample to a given pH. However, because sourness and sweetness mask each other, in several products, the sourness and sweetness intensity are reliant on the sugar to acid ratio, or on the total content of sugars or acid in other products such as the tomatoes [23]. Distinctive aroma of the commodity is due to volatile compounds and in combination with taste sensation i.e. sweetness, sourness and bitterness, these compounds form the characteristic flavor of the commodity. Volatile compounds can be measured by a gas chromatograph combined with a mass spectra detector. In grapes, as many as 225 volatile components were separated with the gas chromatograph / mass spectrometer [24].

1.3.2 Non-Destructive techniques

With the advancement of electronics technology, nondestructive methods are being developed to measure quality. To calculate quality attributes, these methods use techniques such as optical, electrical, vibrational, gas analysis and nuclear magnetic resonant [21]. Optical characteristics can be calculated by diffuse reflectance, light transmittance, light reflectance and method of delayed light emission. It is currently used commercially to automatically sort oranges, apples, lemons and tomatoes for color, shape, and limited defects [25]. The method diffuse reflectance estimate the light reflected beneath the fruit skin. Upon illumination, light penetrates a few millimeters into the surface tissue, where a small portion of the energy is reflected. Fiber optics are used for these measurements and many of the measurements are now made in the near infrared

(NIR) region. The delayed light emission method measures the energy reradiated by a sample when illuminated briefly [26]. The reradiated energy is in the nanowatt range and persists only for 3 to 5 seconds. Several factors such as wavelength and intensity of excitation, dark exposure prior to excitation, temperature and chlorophyll content affect the reradiated energy. Chlorophyll pigment is the main source of reradiated energy.

In the past fifty years, the fruit maturity has been measured in a non-destructive method with the light transmittance techniques evolution. From that day forward, numerous non-destructive techniques have been developed including visible imaging [25], colorimetry [26], VNIR spectroscopy [27], Computed Tomography (CT) scan [28], hyperspectral imaging [29], fluorescence imaging [30], multispectral imaging [31], acoustic impulse technique [32], Magnetic resonance imaging (MRI) [33], the electronic nose technique [34] and the acoustical vibration technique [35]. For estimation of maturity indices, these techniques has been applied by a number of researchers, as illustrated in Table 2.

1.3.2.1 Color Measurement

As the initial quality valuation, consumers use color and appearance of a fruit to critic the fruits acceptability. During fruits ripening, these criteria are identified with chemical and physical changes in a fruit [36], [37]. Chlorophyll degradation as well as increase in pigments' concentration, are responsible for color change during ripeness of many fruits. For the relationship between color and maturity, few fruits have been studied including blueberries [38], cherries [38], guavas [39], mangoes [40], [41], nectarines [10], oranges [42], peaches [43], [44], pineapple [45], and tomatoes [46].

1.3.2.1.1 Colorimeter

In the fruit industry, fruit color is measure by using traditional non-destructive instruments such as colorimeters [46]. Colorimeters use CIELAB color space, which has better precision than visual appraisal of humans and gives unified estimations. CIELAB have three coordinates, a*, b*, and L*, which represents, values of green to red, blue to yellow ratios and lightness, correspondingly. Because of the uniform color distribution, CIELAB is nearby human color acuity, moreover, on its three-color coordinates, all the colors can be located that can be seen by human eye [95]. As the indicator of ripeness of fruits, few color indices have been developed.

Table 2: Summary of techniques used for non-destructively fruit maturity estimation

Techniques	Maturity Indices	Fruits
Colorimetry	Color	Apple [47], Peach [48], Nectarine [43], Mango [10], Banana [49]
Visible Imaging	Color	Apple [50], Banana [49], Pineapple [45]
Spectroscopy	Color	Peach [48], Mango [10], Strawberry [51]
	Firmness	Apple [52], Pear [53], Peach [54], Nectarine [55], Mango [56], Mandarin [57], Strawberry [51], Apricot [58], Kiwifruit [59]
	SSC	Apple [60], Pear [61], Nectarine [55], Mango [62], Banana [63], Melon [64], Mandarin [65], Strawberry [66], Apricot [58], Kiwifruit [67], Persimmon [68], Grape [69], Pineapple [70],
	Dry Matter	Avocado [71], Mango [62], Mandarin [72], Kiwifruit [73], Pineapple [74]
	Chlorophyll	Apple [75], Peach [76], Banana [77]
	Starch	Mango [78], Kiwifruit [67],
	Titratable Acidity	Mandarin [79], Strawberry [66], Apricot [58]
Fluorescence	Firmness	Apple [80], Peach [81], Nectarine [81],
	SSC	Apple [80],
	Chlorophyll	Apple [82], Grape [83]
Hyperspectral Imaging	Firmness	Apple [84], Peach [85], Mango [29], Banana [5], Strawberry [32], Persimmon [86]
	SSC	Apple [87], Pear [88], Mango [29], Banana [5], Grape [89], Strawberry [90],
	Dry Matter	Avocado [91]
	Titratable Acidity	Strawberry [90], Grape [89]
Multispectral Imaging	Firmness	Apple [92], Peach [31], Strawberry [93]
	SSC	Apple [94], Peach, Strawberry [93]

In specific experiments, color change in fruits is correlated with only the a* value [39], [96], while it is reported that B* ripeness in peaches is correlated with b* value only [97]. To improves the evaluation of ripeness, more than one of the color components must be used. For tomatoes [98] and citrus [48], L* value along with a* and b* was correlated with the color models. Commercially available portable [41] colorimeters can be used in the field. Nevertheless, single fruit calculation is limited in its application to map the fruit ripeness in the entire region.

1.3.2.1.2 Visible Imaging

The sampling area of the colorimeters is limited as compared to the size of fruit, due to which they are not enough capable to get illustrative color values [99]. 2D color imaging can overcome this constraint by converting photons to electrical signals, which are reflected from fruit skin and then captured by a camera having CMOS or CCD sensors, in it. Usually, light is received by a sensor and then convert it to three channels, B (blue), R (red), and G (green). Whereas, illumination, internal characteristics of the camera and fruit samples are used to determined intensity values [100].

It is conceivable to break down fruit ripeness in RGB color space, because of its similarity with L*a*b* color space. According to Schouten et al., R values can be used at different stages of ripeness to explain the progressive color shift of tomatoes, and shifts in fruit firmness are often associated with R values [101]. Due to the constantly evolving ripeness phase, it is difficult to define the exact color boundaries between different ripeness stages, otherwise arbitrary thresholds must be given for each color channel. Klir and Yaun [102] reviewed and implemented fuzzy logic, which is a statistical analysis approach, on the ripeness evaluation of apples and mangoes [50], [103], to overcome the need for discrete thresholds. Whereas, by using the difference between B and R values, Goel et al. [104] achieved a precision of 94.3 percent in order to improve the classification of the different ripeness stages of tomatoes.

1.3.2.2 Spectral Imaging

1.3.2.2.1 Hyperspectral Imaging

To obtain both spectral and spatial information of samples competently, the principles of computer vision and spectroscopy can be combined in the form of Hyperspectral Imaging (HI) [105], [106]. The spectroscopy shows plentiful spectral information while the imaging delivers rich spatial data. The spectral data acquired from each pixel sampling attributes on requisite pixel and spatial region. There are two types of wavelength scattering devices for the image acquisition of HSI, that are normally used for fruit quality assessment such as area scanning, and line scanning coupled with image sensor. Hyperspectral imaging can be implemented by using fluorescence, reflectance, scattering or transmittance modes [107].

For the far-reaching analysis of food safety and quality, HSI has been recognized as an incredible technique [108]. Most as of late, Hyperspectral imaging was misused by applying Partial Least Square Regression (PLSR) approach in 450-998 nm spectral region to identify the mangoes' quality attributes such as titratable acidity (TA), firmness, and total soluble solids (TSS). RMSE, R^2 and bias have been analyzed to test the prediction models' performance. A model with low RMSE and bias while high R^2 values, is considered as best model. The best prediction model achieved R^2 of 0.81, RMSEV of 2.85N and bias of 0.20N for firmness, whereas, for TA, R^2 of 0.81, RMSE of 0.24%, and bias of -0.00% were recorded. Whereas, for TSS shows low prediction performance with R^2 of 0.5, RMSEV of 2.0%, and bias of -0.0% [109]. Correspondingly, phenolic content in grapes, was analyzed with Support vector regression (SVR), PLSR, and principal component regression models, in the spectral range 865 – 1711 nm to confirm the ripeness of grapes. SVR model is the one who displayed the best performance except for tannins content analysis. For skin sample of grapes, SVR model attained R^2 of 0.8960, RMSE of 0.1069 g/L for tannins, R^2 of 0.8789, RMSE of 0.1442 g/L glucoside for anthocyanins, and for total iron-reactive phenolics (TIRP), achieved R^2 of 0.9065, RMSE of 0.1776 g/L, although for seeds, RMSE and R^2 were 0.5190 g/L and 0.8790 for TIRP, whereas, 0.2401 g/L and 0.9243 for tannins, correspondingly [110].

1.3.2.2.2 Multispectral Imaging

As a form of HSI, multispectral imaging is a technique that, instead of scanning whole wavelength range, it only gathers data at explicit wavelengths. MSI scanning system uses CMOS or CCD sensors, coupled with Liquid Crystal Tunable Filter (LCTF). Based on preceding papers, Lu et al. [92] used ANN model to correlate the scattering profiles of five wavelengths, with the SSC and firmness of apples. For both quality traits, they attained a reasonably high correlation; R^2 = 0.77 and 0.87, correspondingly [92]. Instead of LCTF, a rotating filter wheel including some band pass filter, while having lower tuning speed than LCTF, is used by another low-cost MSI system. To predict the SSC and firmness of peaches, the above-mentioned device has been used, with the best combination of four wavelengths, and achieve high correlation coefficients; 0.97 and 0.94, correspondingly [85]. The prediction by HSI was lower than the prediction for firmness [85]. Likewise, Liu et al., predict TSS and firmness of strawberries by using MSI with nineteen wavelengths. The best R values 0.83 and 0.94 were equated with ANN, PLS and SVM, correspondingly [111], with which HSI can be compared for prediction of TSS of strawberries [90].

For in-field measurements, MSI is one of the most favorable techniques that are mentioned above, for instance, it can be used to record high resolution images for the prediction of specific quality attributes, at most significant wavelengths. MSI imaging is low-cost and easy to convert into handheld devices, with a smaller output imaging dataset compared to HSI. A portable MSI device has been developed, having four different wavelength sensors at 870, 750, 670 and 570 nm, along with four narrow-band light sources [112]. This device has achieved correct classification rate greater than 85% by using linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), to classify different stages of oil palm ripeness with Mahalanobis distance classifiers [113].

1.3.2.3 Visible and Infrared Spectroscopy

Light can be absorbed, reflected, or dispersed when it reaches the skin of the fruit. They depend on their chemical and physical properties and consequently on the fruit maturity. The reflected light measured by VNIR reflectance spectroscopy, is ranging from 380 nm to 2500 nm, which depends on fruit’s light absorption and can be used to evaluate mostly organic compounds. VNIR spectroscopy, as a non- destructive rapid evaluation technique, has been utilized for estimation of several maturity indices [65]. The fruits NIR absorption spectrum is not conclusive, so it is challenging to choose the best wavelength associated with a particular maturity index. In order to solve this problem, multiple regression technique is applied on a spectrum pre-treated with first or second derivative. The wavelengths are not generally absorbed by the interest portion.

As like colorimeter method [114], change in concentration of peel pigment can also be describe by spectral indices, nevertheless ripeness is not only be estimated by peel color. In VNIR spectroscopy, PLSR model has been widely used for fruit maturity prediction. An orthogonal factor set is extracted from latent variable, having the best predictive power, in order to achieve prediction. Similarly, as the second most regression model used for fruit maturity estimation, Principal Component Regression (PCR) correlates the quality parameters with the scores of principal components extracted from the latent variables [115]–[117]. In contrast with PLSR, PCR has a drawback of collecting the principal components without considering the dependent variables.

In spectroscopic methods, the correlation for SSC prediction, is always higher than of the firmness of fruits. The prediction of SSC was easier than firmness, showed by Park et al. [118], because firmness was not identified by a single analyte. For the single fruit cultivar, the correlation of calibration model trained for both DM and SSC prediction, is higher than the use of mixed fruit cultivars, because the efficiency of the model is always cultivar dependent. Spectroscopic methods, as compared to visible imaging and colorimeter, employ longer wavelengths, but like colorimeter, they cannot be employed as high-throughput tools for ripening estimation because of low spatial resolution. The sample temperature predisposed the internal quality measurement accuracy, which needs an extra calibration model to compensate it [119]. In the quality assessment of a large fruit variety, spectroscopy was used and portable commercial spectrometers were developed [52], [120], but research studies mostly concentrated on the indoor, and post-harvest fruit quality estimation. There have been erroneous performances with the models established with on-tree and indoor spectroscopy. For both firmness and SSC prediction, on-tree PLS model showed the best correlation as compared to indoor spectroscopy [121]. Though, indoor spectroscop post-harvest model for nectarines showed best results than that of on-tree [122]. Consequently, a statistical model for the on-tree maturity evaluation of in-field spectroscopy should be established and environmental variables for spectral efficiency examined.

1.4 Chemometrics

Fruit maturity indices are generally measured by using spectroscopy in the Vis-NIR region because spectra in this range contains abundant information about C-H, N-H and O-H, vibration absorptions [123]. In this region, however, the spectrum is effectively regulated by water, as it highly absorbs NIR radiations [124]. In addition, there is a low signal-to-noise ratio (SNR) and high overlap of combination bands in the Vis-NIR range, complex fruit structure, instrumental noise and scattering of wavelength-dependent light. These all factors cause Vis-NIR spectrum convolution. Chemometrics are then applied to derive information from the spectral data concerning those quality attributes [125].

1.4.1 Pre-Processing Techniques

1.4.1.1 Smoothing

Smoothing is an efficient way to eliminate a spectrum of high-frequency noise and increase the SNR. Via the "averaging" or "fitting" of multiple points in a window, the basic concept is to obtain an optimum estimated value. The wider the frame, the smaller the spectral resolution. Therefore it is necessary to correctly select the window width. Sun et al. [126] showed that the most feasible pre-treatment approach for SSC prediction of navel oranges was moving average smoothing, and Roger and Bellon-Maurel [127] applied NIR spectra pre-treated by using moving average smoothing for measuring SSC in cherry fruit. Though, in conjunction with other types of pre-treatment, such as Multiplicative Scatter Correction (MSC), smoothing is typically used. Liu and Zhou [128] reported that for predicting SSC in apples, the application of smoothing technique along with MSC and 1st derivative, was feasible to process NIR spectra in transmittance mode.

1.4.1.2 Standard Normal Variate (SNV)

The purpose of SNV, essentially the same as MSC, is to remove the deviations induced by scattering and particle size [129]. The strategy assumes that some unique distribution suits the absorption of each wavelength point in the spectrum, such as a Gaussian distribution. Each spectrum is calibrated based on this hypothesis. Firstly, the average value of a spectrum is subtracted from the original spectrum and then the effect is divided by the standard deviation (SD). For SNV effects on each spectrum alone the correction potential of SNV is typically larger than that of MSC. After SNV pre-treatment in the model developed by Shi et al, the relative standard deviation of prediction (RSDP) was reduced from 16.65 percent to 14.82 percent [130] to assess the apples' firmness.

1.4.1.3 Derivative Correction

The 1st and 2nd derivatives are implemented as a normally used pretreatment method to prevent scattering and drifting. Both derivatives can reduce intrusion in the background, differentiate superimposed peaks and increase spectral resolution and sensitivity. Direct finite difference and Savitzky-Golay (S-G) derivatives are two commonly used spectral derivative approaches. Smoothing should be applied prior to derivatization, as derivatives can extract differences from adjacent wavelength points and amplify spectral noise. Pissard et al. [123] proved that the best pretreatment technique was S-G 1st derivative processing, whereas Liu et al. [131] stated that the best was the 2nd derivative.

1.4.2 Discriminant Methods

1.4.2.1 Principal Component Analysis (PCA)

A number of principal components (PCs) are obtained with the implementation of the PCA. The first PC includes the highest percentage of variance in data and in the subsequent PCs, the variance decreases. These PCs are linear combinations, but not correlated with each other, of the original spectral data, endowing their ability to handle multicollinearity. In conjunction with other discriminating approaches, PCA is also used [132].

1.4.3 Calibration Methods

1.4.3.1 Multiple Linear Regressions (MLR)

MLR, at each wavelength level, predicts the dependent variables through spectral values' linear combination. In the minimal square sense, the error between calculated and predicted values is minimized. Multicollinearity between the variables degrades the performance of MLR algorithms in spectral analysis. ElMasry et al. [90] and Peiris et al. [133] have used MLR successfully. However, Jaiswal et al. [63] documented a large gap between Rc and Rp in the MLR model they created, indicating unstable predictions.

1.4.3.2 Partial Least Squares Regression (PLS)

PLS regression predicts the dependent variables by extracting from the variables the smallest possible number of orthogonal factors with the greatest predictive capabilities. These orthogonal variables were grouped according to the value of the dependent variables to be predicted, called latent variables (LVs). PLS regression is particularly feasible in situations where there is multicollinearity between the variables and has usually less LVs than PCR regression, synthesizing the PCA background and MLR. Lu et al. [134] and Liu et al. [58] have been confirmed the PCA gain. Several researchers including Bureau et al. [135] and Shan et al. [136], have implemented PLS regression in their studies.

1.4.3.3 Least Squares Support Vector Machine (LS-SVM)

LS-SVM is an emerging statistical learning algorithm which enhances the generalization capacity of the learning machine based on the principle of structural risk minimization [137]. The input data dimension is not directly dependent on the support vector machine's computational complexity and performance. Thus, LS-SVM is extensively implemented in feature regression and pattern recognition for the benefit of feature regression, minimal over-fitting, strong generalization performance, high predictive reliability. For limited sample space modelling conditions, the LS-

SVM is especially feasible. In the studies of Zhang et al. [138], Suykens and Vanderwalle [139], Liu et al. [140], and Pissard et al. [128], as best calibration model, LS-SVM has been applied.

1.4.3.4 Artificial Neural Network (ANN)

ANN, in NIR Spectroscopy, has been extensively implemented. Three neuron layers, which are the input layer, the hidden layer, and the output layer, are typically composed of an ANN model. Each neuron in the previous layer is connected to each neuron in the latter layer and there is a weight factor for each connecting line, the value of which is calculated using cross-validation based on a calibration set and continues to adjust with the flow of new information. The value of the neurons in the hidden layer is determined by means of a nonlinear equation using the weighted sum of the neuron values in the input layer, and the value output layer's neurons is similarly calculated using the hidden layer's neuron values. ANN model's predictive performance, in some cases, may be excellent, but it also has few drawbacks including visualization difficulty, slow training speed, and over-fitting. ANN shown best results according to the experiments of Zhang et al. [141], He et al. [94] and Liu et al. [142]. These all calibration techniques have been used in this study.

1.4.4 Classification

The classification consists of predicting the particular outcome on the basis of the input given. Construction of classification models from input data is a systematic approach [143]. Two stages are involved in the process i.e. learning stage and classification stage. In the learning process, the unknown results are generated by training data analyzed by the classification algorithm. To estimate the accuracy of classification, test data is used. The input to generate the prediction is evaluated by this algorithm. In fruit maturity and variety classification, various classification techniques are used.

1.4.4.1 Linear Discriminant Analysis (LDA)

LDA, also referred to as Fisher's LDA (FLDA) after its founder's name, uses hyperplanes to distinguish the data classes represented in more than one dimension [58],[59]. The hyperplane distinguishing two classes of data vectors with LDA.

LDA assumes the data is normally distributed and all groups have equal covariance. The hyperplane separating the classes is obtained in such a way that the projection of information onto the plane minimizes the variance within the class and maximizes the variance between classes. If the number of classes exceeds two, more than one hyperplane (N>2) will be used for class separation. The "one verse rest" method is used for this approach by separating one class from all others for multi-class problems. LDA is a robust classifier with very low computational complexity. A regularized Fisher's LDA (RFLDA) has been proposed by Blankertz et al. to improve classification accuracy and error reduction. This model contains a regularization parameter C that makes or penalizes a training dataset classification error. If outliers are present in the data and demonstrate better generalization capabilities [60], the regularized qualified classifier shows better results.

1.4.4.2 Support Vector Machine (SVM)

In order to classify the groups, Linear-SVM often constructs a discriminating plane, but the hyperplane is chosen such that the margin with the nearest data point is maximized. This margin maximization increases the classifier's generalization capacity [59]. The hyperplane separating the two types of data vectors with SVM.

1.4.4.3 K-Nearest Neighbours (KNN)

The method of assigning the feature vector (unseen data point) to a dominant class among its 'k nearest neighbours within the training set is used by the K-NN classifier. The method of measuring metric distance for the determination of the nearest neighbours is used for fruit maturity and variety classification. A higher value of k' with appropriate K-NN training samples is capable of generating a non-linear classification decision boundary. The classification based on neighbours is a type of lazy learning as it does not attempt to create a general internal model, but merely stores instances of training data. Classification is determined from the k closest neighbours of each point by a clear majority vote. This algorithm is easy to implement, resilient to noisy training information, and efficient if there is a large amount of training data. The value of K needs to be calculated and the cost of computation is high as the distance of each instance to all training samples needs to be computed.

1.4.4.4 Ensemble Classifier

Ensemble approaches use many learning algorithms in statistics and machine learning to achieve better predictive efficiency than could be achieved from any of the constituent learning algorithms alone [144]. A machine learning ensemble consists of only a concrete, finite set of alternative models, unlike a statistical ensemble in statistical mechanics, which is normally infinite, but generally allows for a much more versatile structure to exist among those alternatives [145].

As it can be trained and then used to make predictions, an ensemble is itself a supervised learning algorithm. Therefore the qualified ensemble reflects a single hypothesis. However, this hypothesis is not inherently included within the hypothesis space of the models from which it is constructed. Thus, in the roles they can represent, ensembles can be seen to have more versatility. In theory, this versatility can allow them to over-fit the training data more than a single model would, but in practice, some ensemble techniques (particularly bagging) tend to reduce issues related to over-fitting the training data.

1.4.4.5 Decision Tree Classifier

In several different application contexts, including energy-based applications, decision tree classifiers have a readable classification model that is theoretically accurate. By constructing a decision tree, the decision tree classifier constructs the classification model. Each node in the tree defines a test for an attribute, and each branch descending from that node corresponds to one of the attribute's possible values [146]. Each leaf reflects instance-related class labels. Instances in the training set are graded according to the results of the tests along the route, by navigating them from the root of the tree down to a leaf. Starting from the root node of the tree, according to an attribute test condition, each node splits the instance space into two or more sub-spaces. Then a new node is generated by moving down a tree branch corresponding to the attribute value.

CHAPTER 2: LITERATURE REVIEW

2.1 Estimation of Fruit Maturity

The physiological maturity of the fruits usually occurs before its harvest maturity. The commercial maturity of the fruits is the stage at which the fruit is consumed by the consumer. Fruit maturity is typically estimated using multiple indices such as TA, DM, SSC, chlorophyll, colour, and firmness. NIRS has been used for assessing the maturity indexes of various fruits, including peach, strawberries, plum, melon, apple, etc., in recent studies as one of the most sophisticated techniques. Some of the new research, against Mango fruits, have been discussed below.

The DM of the mango fruit is determined by carbohydrate content, such as soluble sugar and fruit starch. Thus, DM is an important measure of the amount of fruit starch and sugar [147]. DM content is also well correlated to ^{o}Brix of fully ripened fruit in which all starch has been converted to sugar [148]. In addition, the fruit's DM is usually stable after harvest until fully ripe and has correlation greater than 80% with Brix, in case of mango fruit [149]. Consequently, fruit DM at harvest (the amount of starch and sugar in the fruit) is therefore an index of the ^{o}Brix of ripped mango and its eating quality, as suggested by Subedi et al. [150]. Earlier harvesting exploits the storage and transport time. Moreover, the best DM percentage at harvest varies for different varieties and regions. In [151] authors, observed fruit harvest maturity indicators for Pakistani export mango varieties i.e. Samar Bahisht (SB) Chaunsa, White Chaunsa and Sindhri [151]. It is reported that significant interaction was found between panicle emergence and harvest maturity regarding fruit pulp DM contents in investigated cultivars. SB Chaunsa takes mean 114 days from fruit setting to reach physiological maturity with mean cumulative heat units of 1630.2-degree days and under such growing condition it has 18-21% DM at the time of harvest maturity. While, White Chaunsa has an extended harvest window, starting around 10th August with DM values 22-25% [152] under same growing conditions as of SB Chaunsa.

DM can be measured destructively, but recent advances have developed spectroscopic [147], [150], [153] and handheld portable devices that estimate on-tree DM of the fruit precisely. Many earlier studies have shown the potential, as suggested by (Greensill and Walsh) [154], of using NIR spectroscopy to estimate Mangos fruits DM and SSC. NIR spectroscopy can be precisely used for on-tree estimation of DM of intact fruit . Guthrie and Walsh confirmed the use of Multiple Linear Recession (MLR) with result of ($R2 = 0.96$ and RMSEP=0.79), whereas Saranwong et al. [155] reported that the single hard green mango cultivar can be predicted using PLSR predicted model with the results of ($R2 = 0.89$, SEP=0.41).

Intact mango fruit's diameter, length, and width can also be determined and correlated with weight of fruit without any grievance (R2=0.96, precision 0.1 g) [156]. On-tree fruit growth can be monitored continuously using these non-invasive techniques without any sampling errors associated with disruptive sampling. Nagle et al. [157] have however demonstrated a transition in Light Dissemination characteristics that would interrupt the measurement of fruit DM using NIR sprctroscopy by a shift in the intercellular spacing. The mango DM is estimated by a wavelength range (500 - 1050 nm), and a PLS regression during all maturity stages with ($R > 0.75$ and RMSECV > 0.70). For estimation of DM of mango fruit in the field and verification of harvest decision tool, handheld spectrometer has been used by Walsh and Subedi [147] with PLS Regression.

Recent studies have demonstrated that consumer preference has a positive relationship with high DM in fruits, as DM is indicated as a good predictor of Brix of post-storage in apple fruits [159], [160]. Traditional method for DM evaluation involves fruit harvesting, sampling, drying, and weighing slices of fruit to eliminate water. Traditional methods for DM and ^{o}Brix measurements provide precise results and can be used for sampling detection only as these methods are destructive, and laborious. To find the optimal harvest time, the DM of developing fruits must be constantly monitored. Moreover, fruit should be measured non-destructively, to prevent crop waste as many fruits are measured each time. Hence, the most common technology used to estimate DM is non-destructive near-infrared spectroscopy (NIRS), which can be integrated into small handheld devices [161]. Up till now, NIRS, multispectral imaging [10,11], dielectric spectroscopy [164], hyperspectral imaging [13,14], and nuclear magnetic resonance [167] have been developed to measure fruit quality attributes. However, the most used technology is NIRS. Applications for mango maturity measurement, NIR spectroscopy is summarized in table 4. DM and SSC are primarily used as maturity indexes in the literature for the calculation of mango maturity. PLS, MLR, PCR, SVM and ANN-designed models along with different pre-processing methods produce strong R2 performance.

Table 3: Summary of NIRS applications for estimation of maturity indices of Mango fruit varieties

Cultivar	Maturity Indices	Spectral Range (nm)	Mode	# Samples	Pre-processing	Prediction Model	R^2	Ref.
Tommy Atkins	SSC, firmness, Acidity	1200 – 2400	Reflectance	80	2nd derivative	MLR, PCA, PLS	0.93, 0.90, 0.95	[56]
Caraboa	SSC, Dry Matter	1100 – 2500	Reflectance	200	MSC, 2nd derivative	MLR, PLS	0.96, 0.97	[117]
Tommy Atkins	SSC, Dry Matter, TA, firmness	950 – 1650	Reflectance	400	SG smoothing, SNV, EMSC	PLS	0.92, 0.67, 0.50, 0.72	[168]
Osteen	SSC, TA, firmness	400 – 700	Reflectance	140	SG smoothing, EMSC	PLS	0.88	[169]
Palmer	SSC, Dry Matter	306 – 1140	Reflectance	149	SNV, 1st derivative	PLS	0.87, 0.84	[170]
Cogshall	SSC, Dry Matter, TA	800 – 2300	Reflectance	250	SG smoothing	PLS	-	[171]
Kensington Pride, Calypso	Dry Matter	300 – 1050	Reflectance	350	-	PLS	0.82	[148]
Palmer	Dry Matter	699 - 981	Reflectance	200	SNV, 1st derivative	PLS	0.75	[172]
Sunshine	pH	300 – 1000	Transmittance	120	SG smoothing, MSC	PLS	0.93	[173]
Nam Doc Mai	firmness	800 – 2500	Absorbance	85	SNV, 2nd derivative	PLS	0.71	[174]
Chokonan, Rainbow, Kai Te.	SSC	900 – 1700	Reflectance	80	EMSC	SVM, PLS	0.95, 0.86	[175]

Keitt	Internal Browning	400 – 1000	Reflectance	576	thresholding	PLS, ANN	0.53, 0.57	[158]
Harumanis	SSC	941 – 1685	Absorbance	30	UVN, MSC, MSCCA, MN, MSCCO,	PLS	0.98	[176]
Kent	SSC, TA, Ascorbic Acid	1000 – 2500	Reflectance	58	SNV, MSC, 2nd derivative	PLS, PCR	0.66, 0.95 0.61	[177]
Caraboa	SSC, Dry Matter	470 – 990	Reflectance	1200	derivative	PLS	0.84, 0.77	[178]

2.2 Fruit Maturity Instrumentation

Researchers have recently developed portable systems to track fruit maturity using non-invasive applications. Extensive study has been carried out in non-destructive calculation of fruit maturity using optical, acoustics, electrical, and ultrasonic properties, including image processing and analysis of response of impact force. Latest study has made non-destructive approaches considered the most effective tools to measure fruit maturity parameters efficiently and effectively [179]. A variety of NIRS prototypes have been developed in previous research using commercially accessible portable fruit quality assurance spectrometers. The following segment will address various established laboratory protypes and commercially available NIR-based spectrometer.

2.2.1 Laboratory prototypes

Dedicated instruments are normally lightweight and use filters with near-infrared (NIR) LEDs to calculate the quality parameters in specifically pre-selected wavelengths [180] of various commodities. Acceptable findings were found by researchers in non-destructive assessment of fruit maturity. The NIRS, as the most popular non-destructive technique, has been widely used for estimation of fruit maturity [181]. Although other methods are useful, like NIRS, farmers cannot use them easily. To use such non-destructive methods, it needs skills, experience, and expertise in application. Furthermore, farmers do not know fundamental methods of data processing. While these experiments can only be performed in laboratory. While this is costly and time-consuming, experiments of NIR must be performed in laboratory. In addition, the bench-top devices are not carried to fields or orchards due to their weight and large size [55]. Therefore, the demand for non-invasive, cost-efficient, precise, fast portable and/or handheld devices for estimation of fruit maturity in industry, producers and consumers has been increasing in recent years [182]. Consequently, modern handheld and/or compact instruments were progressively designed and developed to evaluate fruit maturity non-destructively [183].

Several portable non-destructive instruments for the quality detection of commodities were built on the basis of use of portable exchange spectrometers. It can be made much easier to create non-destructive mobile devices by using compact industrial spectrometers and merely incorporating additional components including processors, light sources, detectors and fibers. The biggest advantage of portable spectrometers is a wide spectrum range. Many items will also be subject to a range of calibration and experimental procedures. New prospects in chemical analysis have been opened up by developing rapid NIR sensor technology to determine the composition of fruits and volatile profiles [16]. The former will evaluate SSC and DM in commodities in a non-destructive manner, and the latter will assess the in-field melon maturity rapidly. For example, researchers used NIR procedures to measure SSC in peaches accurately [17].

An ultra-wireless handheld smartphone spectrometer for evaluation of apple maturity has been developed by Das et al. [186]. The spectrometer's key components were UV-LEDs with wavelengths of 360-380 nm that are used as a light source, along with an Arduino microcontroller, filters, mini-spectrometer, and Bluetooth. Using spectrometer prototype for apples authors have studied Chlorophyll UV fluorescence. The findings showed a strong correlation between chlorophyll and reflected light content. Sanchez et al. [121][51] has developed handheld microelectromechanical spectrometers in the 1,600 to 2,400 nm wavelength range in order to calculate the internal and external quality parameters of mandarins. Volume, color, and weight were external parameters, whereas the internal parameters include pH, Brix, and TA. The authors concluded that this spectrometer can improve the estimation of quality indexes of Mandarin and thus farmers can predict the harvest date.

Beghi et al. [187] used a handheld NIR spectrometer, worked in a range of 450 to 980 nm, on the Golden Delicious and Stark Red Delicious apples for evaluation of ascorbic acid , SSC, carotenoids, chlorophyll, and TA. The unit was focused on reflective properties of the material, with the most significant components being halogen, fibre-optic microscope, portable spectrometer, PC, batteries. It reveals in findings that the overall anthocyanin content of Stark Red Apples, complete flavonoids and non-anthocyanin flavonoids have been tested at a reasonable degree of accuracy on Golden Delicious apples, for TA, chlorophyll and SSC.

A handheld Near-infrared spectrometer was proposed by Yu et al. [188], that was designed explicitly for measurement of internal quality parameters of fruits . In particular, development of a linear variable filter (LVF) module was a main feature of this spectrometer. The gun-shaped portable spectrometer, operated in the NIR wavelength range from 620 to 1080 nm, in interactance mode. In interaction mode with the 620-1080 nm wavelength vs. NIR, the formed spectrometer device has a gun-shaped configuration. This device has been used on Crown Pear for the SSC measurement. The device can be operated wirelessly from tablet, laptop or a smartphone to analyze spectral data using the onboard prediction model. The findings have shown that this tool is very stable for the prediction of internal fruit quality.

2.2.2 Commercial products for in-field Spectroscopy

Many portable spectrometers, some of which are extremely compact, lightweight and cost effective, are being produced and commercialized over the past ten years, which turn the NIRS technology into in-field measuring tool, at packaging houses, production, distribution points, and markets [180]. While many small spectrophotometers need external sources of light and are handheld, their in-field use is limited, some of them has compact in size and weight. Many of these are based on micro-electro-mechanical systems (MEMSs) and all are fitted with sensors, light bulbs or LEDs, electronic control systems, displays and batteries necessary for the operation of self-sufficient equipment. Some vendors produce battery-operated handheld devices, have internal light sources and are compatible with Bluetooth-based communication technology. These devices are working independently and are known as "micro" instruments because of their light weight (about 100g) and compact scale.

Recently, the portable system built by Viavi Solutions has been specially evaluated. A linear variable-interference filter (LVF) with 124 InGaAs sensors on a chip with an optical resolution of between 15 and 20 nm, is the integrated in the portable system [189]. This lightweight device of approximately 100 g contains two small tungsten light sources which allow samples placed near the external window to reflectivity. Each sensor that LVF selects has spectral range between 950 and 1650. Commands can be sent by a laptop, tablet or even a mobile phone to the spectrometer and the spectral data is obtained through a Bluetooth or a USB port. The same spectral properties of the MicroNIR was developed for another micro-instrument called NanoNIR by Texas Instruments. However, the internal infrastructure varies significantly. This device includes two small filament lamps for reflective sample lighting. This system performs in standalone mode within the range of 900 – 1700 nm. Bluetooth, micro-SD card and a battery are included with this system. The Hadamard multiplexing method, as seen in the Phasir, the product of Thermo Scientific, also helps to increase the signal-to-noise ratio of the NanoNIR [190], [191].

The SCiO, developed by consumer physics, is a lightweight spectrometer with a palm size of 68 x 40 mm and a weight of 37 g [192]. It has a LED as a light source with a wavelength range of 740–1070 nm with a sampling interval of 1 nm. The system performs in mode of interactance that measures the light from the same side of the sample as the light enters. The Sunforest H-100C Instrument is a small, gun-shaped spectrometer and applies to kiwi and mandarins. With 2nm of delay, it can measure a range between 650 and 950 nm [193]. Its weight is around 420g without a head cap. The H-100C includes, as a light source, a small halogen lamp and an improved sensor CMOS spectrometer, designed for measuring the fruit on one side in interaction mode. A simple and convenient measurement tool for non-destructive quality estimation of fruit, developed by Felix Instruments is the F-750 Produce Quality Meter [194]. It is a spectrometer with a rectangular shape and the weight is around 1 kg. The F-750 is made up of diodes array (MMS1, Zeiss, VIS-NIR). It is dynamic where a lead-sulphide detector and light source are on the same side of the sample. A halogen lamp in the base of instruments assails the fruit skin through the sample window of the diameter 30 mm. The spectrometer has a specimen range of 3,3 nm and an optical resolution of 8 to 13 nm in the wave-length range. Around 5s, including comparison calculation, is the average time to register a spectrum. In contact with chemical analysis, the F-750 incorporates NIR spectroscopy to estimates quality indices, including DM, acidity , SSC or brix, and other fruit quality indices.

Over past decades, NIRS together with chemometrics, has been widely used as a reliable and rapid non-destructive technique for fruit quality estimation [195]. However, most of these studies have been performed using bench-top instruments used in laboratory. Although, these instruments are fast and precise, in-field research applications, for instance on-tree fruit maturity estimation, are limited because of large mass and size [196]. In contrast, portable and hand-held spectrometers, having compact size, high robustness, and low development cost, have been developed and marketed. Consequently, these devices allow on-site quality evaluation of on-tree fresh fruit, during storage, in packing houses and even in super stores [197]. Recently, NIRS based several prototypes have been developed using spectrometer development kits for fruits' DM and ^{o}Brix evaluation, including mango [198], apple [199], grape [200], apricot [58], and mandarin [201]. However, these devices are expensive, need calibration for local fruit varieties [202], and do not classify the fruit variety being tested. Moreover, these devices indirectly estimate the maturity state of fruits by predicting some maturity index value (e.g. ^{o}Brix, DM) using some regression technique and then applying hard thresholds on the predicted value.

To the best of our knowledge all previous literature review suggests indirect maturity classification using estimated maturity index value. We argue that, proposed direct maturity classification of fruit based on reference maturity index (DM) has better accuracy as compared to indirect classification using estimated maturity index (DM) value. This study presents a new handheld NIR maturity meter that acquires spectral data, process the data to remove noise, reduce data dimensionality, and directly classify on tree mango fruit maturity. Performance of the developed device is evaluated by on tree test samples of mango fruit of different seasons.

CHAPTER 3: HARWARE AND SOFTWARE DEVELOPMENT

3.1 Hardware development

The handheld device is composed of a spectrometer development kit, a light source, a LCD display screen, two USB data cables, a computational device (Intel Compute Stick), a Bluetooth based light controlling circuitry and a battery (see Fig. 5). The light source emits radiation, which then enters the spectrometer after interacted from the fruit sample (see Fig. 5(a)). Bluetooth based controller circuit is used to turn on/off the light source. The acquired spectral data is sent to computational device to remove noise, reduce dimensions, and direct maturity classification. The total development cost of the presented handheld device is approximately 3,500 US Dollars.

3.1.1 Micro-spectrometer

A Vis-NIR spectrometer (model BIM-6002A, Hangzhou Brolight Technology Co., Ltd., China) with the Vis-NIR spectrum range of 400 – 1100 nm, optical resolution of 1 nm, and integration time from 0.5 ms to 10s, was used for the collection of fruits spectra. The dimension of spectrometer is 91 mm × 60 mm × 34.5 mm and its weight is 300 g. This device supports windows-based operating system only and it is cost-effective as compared to micro-spectrometers, integrated in commercially available handheld NIR-based instruments. The cross Czerny-Turner optical system is used in this spectrometer. The system structure is simple and compact, as shown Fig. 4. The light transmitted from the fiber is collimated by the concave reflector M2 and reflects to the blazed grating G. The diffracted light beam will have different angles due to the wavelength difference. They are focused on the CCD by the concave reflector M1. The different wavelength light beam is converted into electric signals by the CCD and the spectrum information is shown in computer by the BSV software.

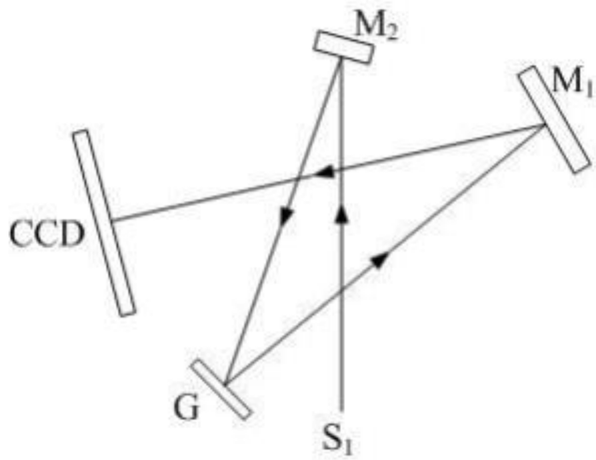
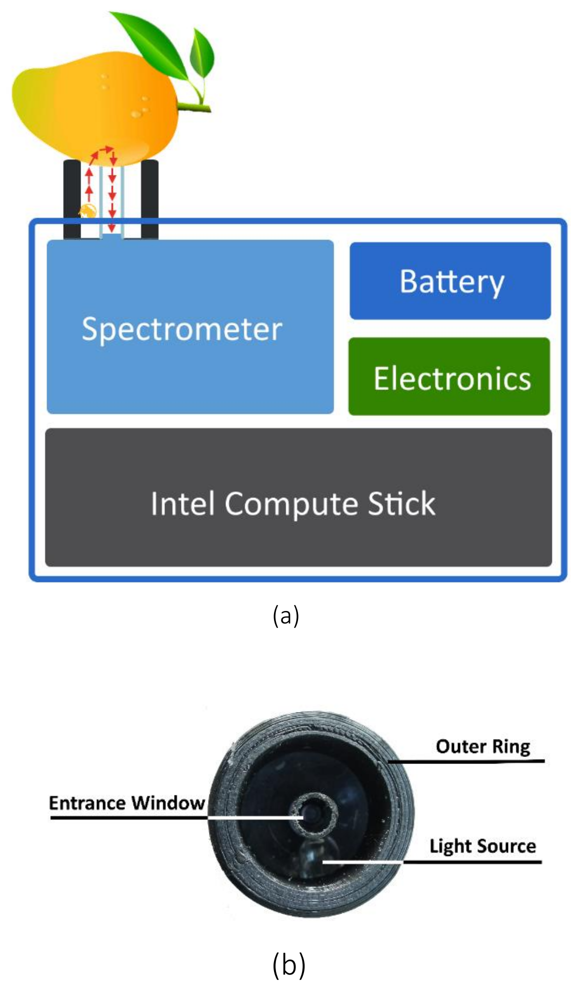


Figure 4: Working principle of the Brolight micro-spectrometer



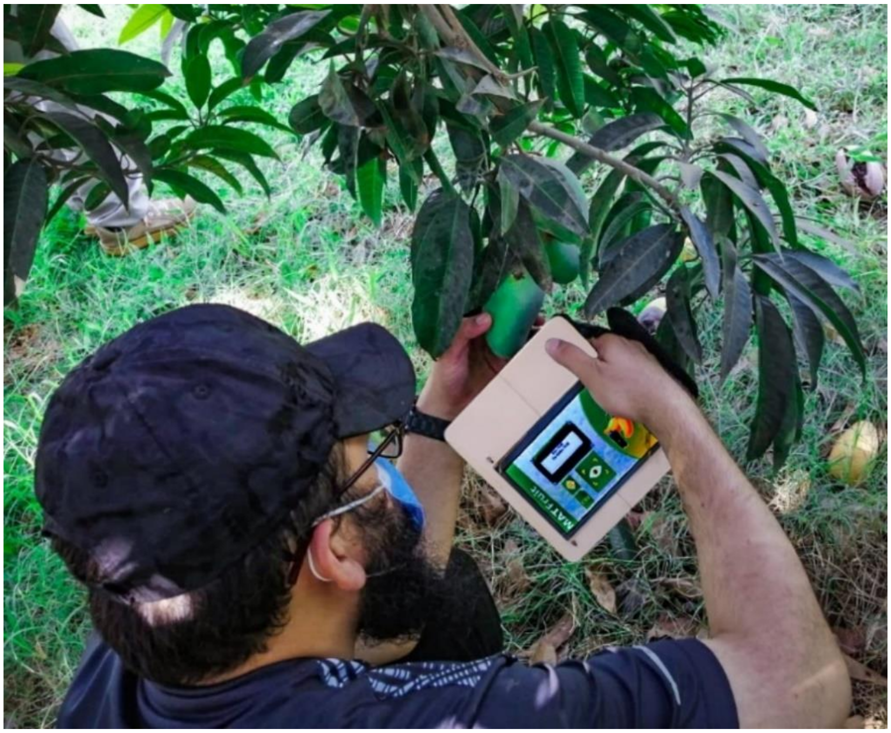


Figure 5: (a) optical geometry diagram of NIR maturity meter (b) top view of spectrometer scanning section (c) in field usage of developed product

3.1.2 Controller

In the proposed hardware the computational device used is the Intel-Compute-Stick® (model STK1AW32SC, Intel Corporation, USA), which have the dimensions of 122 mm x 38 mm x 13 mm, has two USB ports, supports high definition HDMI display, Bluetooth, Wi-Fi and comes with a pre-installed Windows-10 32-bit operating system. This small computer has enough computational power to implement machine learning algorithms.

3.1.3 Light source, Display, and battery

Light source also plays a key role in developing fruit maturity meter because it decides whether stable spectrums can be achieved. A 12V/5W micro-halogen lamp is used as a light source. Warm up time of the lamp is about 100ms as illustrated in Fig. 6. A 7-inch HDMI touch display is used in fruit maturity meter for user interface. The display is connected to the compute stick through HDMI port. A rechargeable lithium battery with 20000 mAh is used to power the NIR maturity meter.

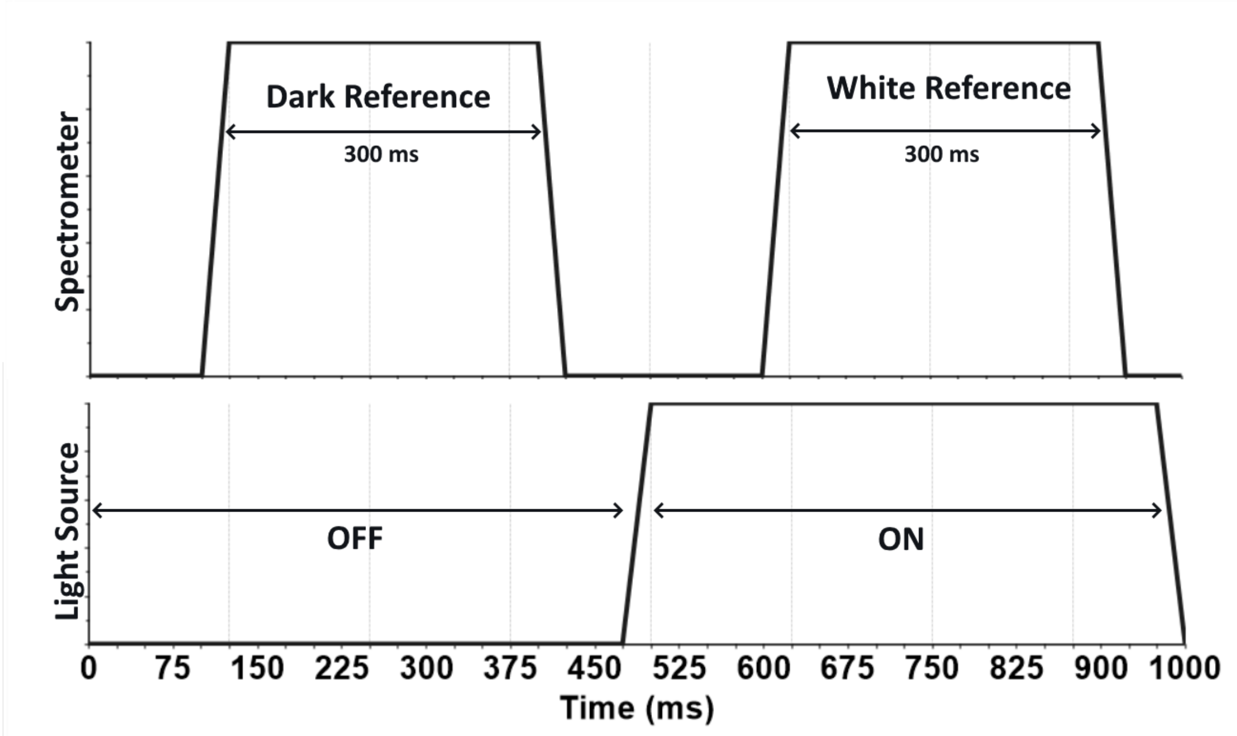


Figure 6: Timing diagram of calibration process

3.2 Software development

The graphical user interface (GUI) of custom software is developed for Windows operating system using Microsoft Visual C++. A system development kit (provided by Brolight) is used to control the spectrometer for parameter settings, calibration, and spectral data collection. The main function of device software is to get spectral information of each sample, convert it to absorbance spectra, remove noise, reduce dimensions, and direct maturity classification. It also saves the spectral data in CSV format. The main interface of the software is shown in Fig. 7).

"Calibration" button is used to calibrate the fruit maturity meter using white Teflon disc (having 99% reflection ratio). Calibration is done by measuring reflectance spectra of white Teflon disc by turning off and on the light source, and then used it as a dark and white reference, respectively. The total time for calibration is 1 second, as illustrated in timing diagram (see Fig. 6). For both dark and white reference, the integration time of the micro-spectrometer is about 300ms. "Scan" button is used to predict maturity and variety of sample. To improve the spectral stability, equation (1) is used to correct the spectrum of each fruit sample. "Generate CSV File" button is used to create a CSV file and then save current spectral data in CSV format at pre-defined directory.

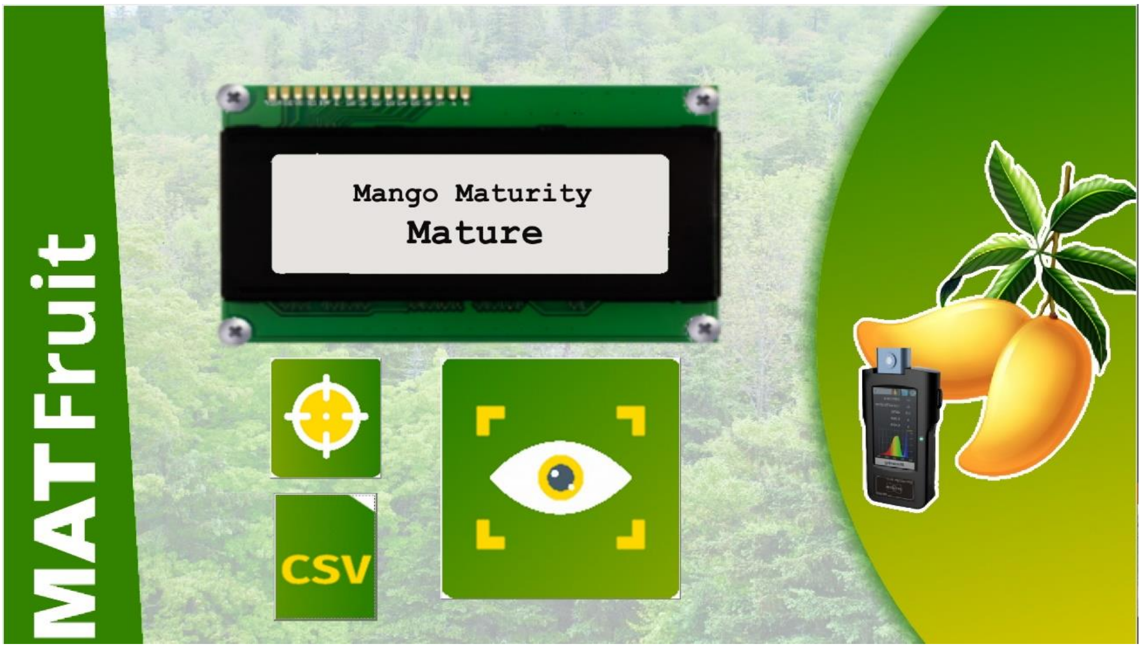


Figure 7: Main Graphical User Interface

$$Reflectance = \left(\frac{Sample-Dark}{White-Dark}\right) \tag{1}$$

$$Absorbace = log\left(\frac{1}{Reflectance}\right) \tag{2}$$

CHAPTER 4: MATERIALS AND METHOD

4.1 Fruit samples

In this study, 240 hard green matured mango fruits (Mangifera indica L. varieties 'Samar Bahisht (S.B.) Chaunsa' and 'White Chaunsa', each 120 fruits), were harvested from the Mango orchard located in Multan District, Punjab Province, Pakistan. In season 2019, 120 samples were harvested in three stages i.e. one week before estimated full maturity stage, on full maturity and one week after maturity stage (20 samples each variety for each stage). Likewise, in season 2020, 120 samples were harvested. Samples harvested in August 2019 named as batch-A, were used for model calibration and samples harvested in July 2020, named as batch-B, were used for on-tree validation (prediction). Batch-B mangoes were marked and scanned on tree and then harvested for destructive testing. Harvested fruits were transported on the same day to the laboratory, located in Muhammad Nawaz Shareef University of Agriculture (MNSUA), Multan.

4.2 Spectral acquisition and reference method

The NIR maturity meter was calibrated by measuring reflectance spectra of white teflon disc by turning off and on the light source, and then used it as a dark and white reference, respectively. For spectra acquisition and reference analysis, the equatorial region of the mango fruit was selected as representative of the whole fruit for DM. Fruits were marked at the equator of the fruit, and then acquired spectra and reference cores from these marked locations. The reflectance spectra of each sample were then obtained by placing fruit on the lens of the NIR maturity meter. Three measurements were performed on each sample, and further analysis was carried out using the mean spectrum of the three measurements. At the end, 500 spectra were obtained for each variety with 324 data points each, recorded from 400 – 1100 nm. Reference DM values were determined by sampling a portion of 27 mm in diameter and 10 mm in depth from marked locations after removing the mango epidermis (1–2 mm thick) using a fruit peeler. DM content in a fan forced oven set at 65°C after 48h was measured by following drying to constant weight [203]. Schematic diagram of labeled mango sample is illustrated as Fig. 8.

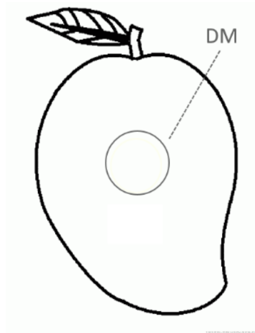


Figure 8: Schematic diagram of the labeled positions for NIR spectral acquisition in Mango sample

4.3 Chemometrics

Both the indirect and direct classification (Fig. 9) of fruit maturity have been compared. To test indirect method of regression-based thresholding represented in Fig. 9, both linear and nonlinear multivariate calibration methods have been implemented and compared to build DM prediction models. For regression, linear calibration models including PLSR and multiple linear regression (MLR) while nonlinear methods include support vector machine (SVM) and artificial neural network (ANN) have been employed using NIR spectroscopic data [202]. For building direct classification models to identify mango variety and decide on-tree mango maturity state (Fig.4), various classification techniques are implemented. These techniques include supervised and non-supervised approaches such as tree, ensemble, linear discriminant analysis (LDA), SVM, K-nearest neighbor (KNN), and ANN.

The Unscrambler software (version 11.0, CAMO, Oslo, Norway), chemometrics software package, was used for development of PSLR, MLR and SVM calibration model. In PLSR model development, the number of PLS factors, suggested by the Unscrambler chemometrics software, were used. For implementation of ANN calibration model and classification techniques, MATLAB (ver. R2018a) neural network toolbox and classification Learner toolbox was used, respectively. Results were compared in terms of correlation coefficient (R) and root mean squared error (RMSE) values. Cross-validation was performed using 10-fold with random selection of samples. The absorbance spectra, obtained by using equation (2), was further treated by different pre-processing techniques including smoothing using 3 point moving average filter, normalization by unit vector normalization, standard normal variate (SNV), Savitsky Golay (SG) first derivative and second derivative using 9 points and 21 points windows, one at a time and results were compared. These all pre-processing treatments were applied within the spectral range of 729 – 975nm. After preprocessing, principle component analysis (PCA) was then performed on the resulting transformed spectra for dimensionality reduction.

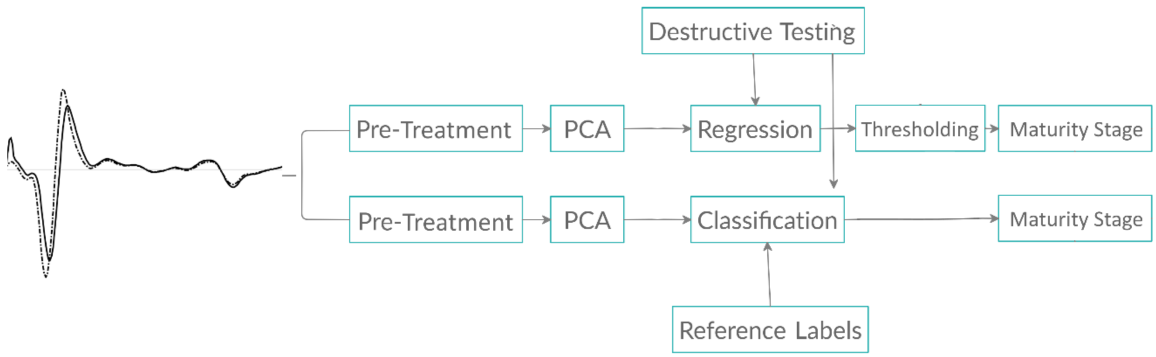


Figure 9: Block Diagram representing two different definitions of establishing maturity levels

CHAPTER 5: RESULTS AND DISCUSSION

5.1 DM statistics

Table-1 shows the statistics of DM for mango fruit samples of batch A1, A2, and A3 (calibration set) and batch B1, B2, and B3 (prediction set). It shows no. of samples in each batch, harvesting period, and Min and Max DM computed using destructive testing.

Table 4: Statistics of DM of Mango fruit in Batch-A and Batch-B

Fruit Batch	# of Sample	Maturity Stage	Min	Max	Mean ± Standard Deviation
A1	40	One week before estimated harvesting date	14.8	20.8	19.5 ± 1.9
A2	40	On estimated harvesting date	19.4	24.6	22.7 ± 1.2
A3	40	One week after estimated harvesting date	23.6	25.9	24.6 ± 1.6
B1	40	One week before estimated harvesting date	18.1	21.3	20.2 ± 0.9
B2	40	On estimated harvesting date	20.6	24.9	23.2 ± 1.8
B3	40	One week after estimated harvesting date	23.6	26.8	25.0 ± 2.3
Total	240	---	14.8	26.8	22.5 ± 1.5

5.2 Spectral overview

The mean absorbance spectra and the preprocessed spectra using SG smoothing second derivative of both mango fruit varieties are illustrated in Fig. 10. at 250 different wavelengths over the 500-1050 nm wavelength range. There are two high absorption peaks, located at around 680 nm and 970 nm, over the entire wavelength spectrum of the raw absorbance spectra (Fig. 10). The first one is correlated with chlorophyll absorption, which was also found in the spectra of apricot, nectarine [204], apple [205], and kiwifruit [206], [207]. The second one occurs in the second overtone of O-H bands, especially those presented in water, and the second overtone of N-H [208]. On Several fruits, such as persimmon [183], apples [209], and pears [210], have also seen an absorption peak at around 960 nm.

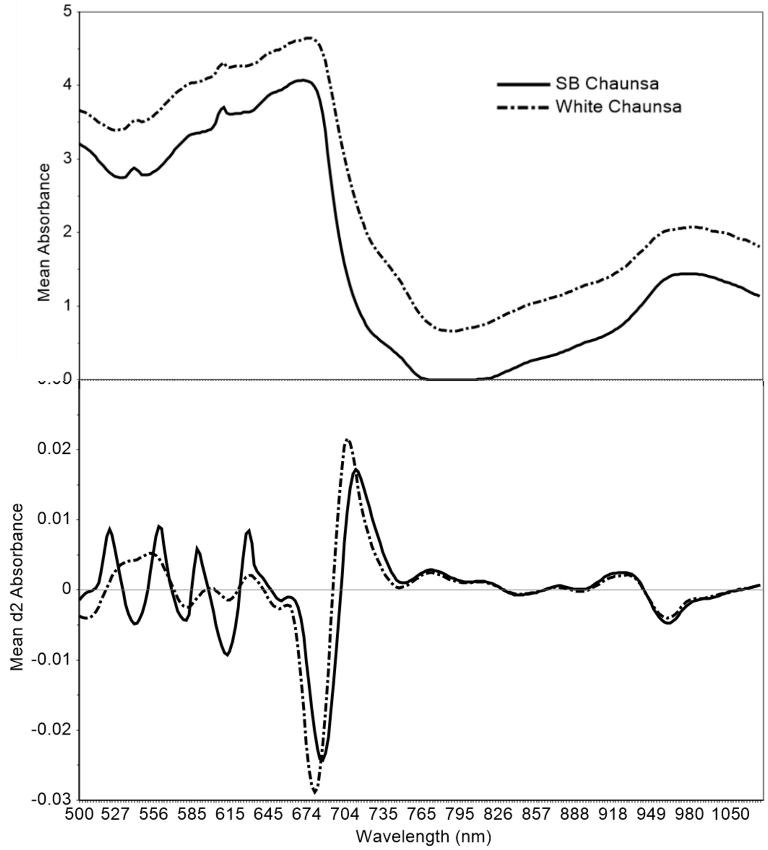


Figure 10: Mean Absorbance and 2nd Derivative pre-processed Absorbance spectra of mango fruit Varieties.

5.3 Modeling results

5.3.1 Model Robustness – Indirect maturity estimation

In calibration models, inclusion of non-informative wavelengths may reduce predictive efficiency. Previous research simply used a fixed spectrum, or compared two or three ranges of wavelengths at most [150]. The optimal wavelength range used for DM was 729 - 975 nm [148]. Performance comparison of DM prediction model built with PLSR, MLR, SVM and ANN regressors is presented in table 2. PCA is a fundamental part of PLS regression though, for other applied regression techniques, their performances have been compared using PCA enabled preprocessed spectral inputs. For all prediction models, first 15 principal components (PCs) were used. SVM and MLR models were built using linear kernel while ANN architecture had input layer of 15 inputs, one hidden layer with 15 neurons and output layer having single output. Number of neurons and hidden layers are chosen heuristically. Overall, all investigated models gave better performance while predicting independent test data. With prediction set, MLR performed relatively better with SG second derivative pre-processed spectral inputs with R = 0.92 and RMSE = 1.48, as compared to other pre-processing techniques. In contrast, with SG first derivative pre-processed spectral inputs, PLSR have best performance for DM with R = 0.87 and RMSE = 1.25. Other prediction models also performed well. Such as SVM and ANN also shown good performance using PCA enabled spectral data with SG 2nd derivative treatment (R = 0.83 and RMSEP = 1.46) and (R = 0.80 and RMSEP = 1.58), respectively. Since, MLR model with SG second derivative preprocessed data has the best correlation coefficient among other models, we have embedded this model as DM estimation model in our developed device.

Table 5: DM prediction model comparison for the input spectral range 729-975 nm

Preprocessing	Regression Model															
	Calibration set								Prediction set							
	PLSR		MLR		SVM		ANN		PSLR		MLR		SVM		ANN	
	R	RMSE	R	RMSE	R	RMSE	R	RMSE	R	RMSE	R	RMSE	R	RMSE	R	RMSE
None	0.94	0.89	0.85	1.52	0.88	1.33	0.89	1.32	0.85	1.33	0.86	1.95	0.81	1.56	0.76	1.63
Smoothing	0.93	0.96	0.85	1.53	0.86	1.39	0.87	1.33	0.85	1.36	0.86	1.96	0.80	1.59	0.74	1.70
Normalization	0.95	0.80	0.88	1.40	0.89	1.25	0.84	1.40	0.84	1.39	0.85	2.00	0.81	1.57	0.71	1.80
SNV	0.94	0.88	0.84	1.58	0.85	1.40	0.86	1.35	0.83	1.41	0.83	2.09	0.76	1.69	0.75	1.67
SG 1st derivative	0.94	0.92	0.84	1.59	0.86	1.39	0.89	1.25	**0.87**	**1.25**	0.87	1.89	0.75	1.72	0.79	1.59
SG 2nd derivative	0.91	1.22	0.90	1.29	0.91	1.14	0.91	1.19	0.85	1.33	**0.92**	**1.48**	**0.83**	**1.46**	**0.80**	**1.58**

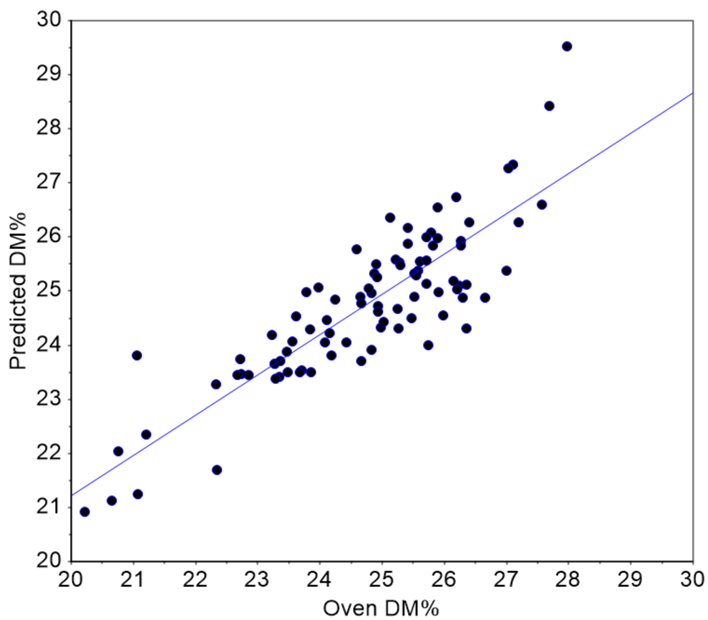


Figure 11: Prediction results for a MLR based DM model using 2nd derivative spectra.

Table 6: Performance comparison in terms of accuracy of different classifiers for binary class classification

Preprocessing	Classification Models											
	Calibration set						Prediction set					
	Tree	LDA	SVM	KNN	Ensemble	ANN	Tree	LDA	SVM	KNN	Ensemble	ANN
None	72.2	76.5	81.7	77.4	83.5	81.2	73.5	67.6	70.6	70.6	73.5	70.3
Smoothing	78.3	80.0	84.3	80.0	79.1	79.5	**79.4**	70.0	**88.2***	**88.2***	85.3	**84.6**
Normalization	73.9	79.1	84.3	76.5	80.9	79.2	**79.4**	76.5	82.4	85.3	**88.2***	81.1
SNV	79.1	78.3	83.8	76.5	80.0	81.4	73.5	70.6	79.4	82.4	85.3	83.2
SG 1st Deriv	68.7	79.1	82.6	80.0	80.0	79.0	67.6	**79.4**	79.4	76.5	79.4	79.1
SG 2nd Deriv	74.8	76.5	80.9	80.0	80.0	78.4	75.0	77.5	85.3	79.4	85.3	82.2

5.3.2 Model Robustness – Direct maturity estimation

To predict mango maturity in terms of DM at harvest, binary class classification techniques were implemented. Classifier predictor inputs were PCA enable spectral absorbance values within range of 726 – 975 nm whereas the reference labels were based on DM values, provided as mango destructive maturity indices for investigated varieties [151]. The DM values at maturity for SB Chaunsa and White Chaunsa is 21-22%DM and 24-25%DM, respectively. The spectra of mango above 21% DM were labeled as mature for SB Chaunsa and below 21%DM were labelled as immature. Similarly, for White Chaunsa, below 24% DM was labeled as immature and above 24%DM was labelled as mature mango. It is to be noted here that the labels were assigned based on DM values measured using standard destructive procedure to get precise and accurate labels. This maturity classification is totally independent of the predicted DM values by regression model of the developed device. PCA is applied on preprocessed spectra for performance optimization and first 15 PCs were selected. Several classifiers were implemented such as tree, LDA, SVM, KNN, and ensemble, using 10-fold cross validation for calibration sets. ANN architecture was implemented with input layer of 15 inputs, one hidden layer with 15 neurons and output layer having single output. Performance comparison of the explored classifiers in terms of accuracy is presented in Table 4. Among all classifiers, SVM, KNN and ensemble classifier have best performance i.e. 88.2% accuracy, with PCA enabled input spectra treated with 3-point moving average filter and unit vector normalization, respectively (Table 4.). ANN and tree classifier have depicted their best accuracies of 84.6% and 79.4% with 3-point moving average filter treatment and PCA enabled spectral input data, respectively. Using PCA enable spectra treated with SG 1st derivative as input data, LDA shown its best performance with an accuracy of 79.4%. From these results, we have embedded KNN classifier model for maturity state classification in our developed maturity meter.

5.3.3 Model Robustness – Fruit variety estimation

In recent studies, NIRS has been employed for non-destructive discrimination of various fruit varieties such as apple [211],mango [212], pears [213], and peach [214]. Developed NIR maturity meter can also distinguish between the investigated varieties of mango. PCA enabled spectral input data has been used to investigate the performance of all classifiers for the identification of mango fruit varieties. Among all classifiers, LDA, SVM, ensemble and KNN depicted best performance with 100% accuracy with SG second derivative smoothed data as input. Therefore, our developed maturity meter employed KNN classifier model to identify the variety of mango sample being tested.

Table 7: Performance comparison in terms of accuracy of different classifiers for mango fruit variety classification

Preprocessing	Classification Models											
	Calibration set						Prediction set					
	Tree	LDA	SVM	KNN	Ensemble	ANN	Tree	LDA	SVM	KNN	Ensemble	ANN
None	82.6	97.4	98.3	95.7	95.7	89.5	76.5	91.2	94.1	85.3	85.3	91.6
Smoothing	84.3	98.3	98.3	97.4	98.3	91.5	82.5	97.5	97.5	**100.0**	**100.0**	92.4
Normalization	79.1	96.5	97.4	98.3	91.3	88.4	82.4	76.5	94.1	94.1	88.2	86.1
SNV	94.8	98.3	99.1	96.5	99.1	91.2	76.5	**100.0**	**100.0**	94.1	100.0	93.1
SG 1st Derivative	87.0	98.3	98.3	91.3	98.3	91.1	82.4	**94.1**	97.1	91.2	100.0	**94.6**
SG 2nd Derivative	93.5	99.1	99.1	98.3	96.5	88.7	**88.2**	**100.0**	**100.0**	**100.0**	**100.0**	90.4

5.4 Discussion

5.4.1 Indirect vs direct maturity classification

To quantify harvest maturity state, certain minimum, and maximum threshold levels for maturity indices of many fruits are locally known amongst the fruit cultivars and defined in literature[151]. It is observed that all existing NIR based spectroscopic devices use machine learning regression algorithms to estimate relevant maturity indices (e.g soluble solid content (^{o}Brix), DM etc) of fruits [188], [198], [201], [204]. To further classify the sample based on harvest maturity, the predicted value of maturity index using NIRS is compared with the standard threshold value of maturity index. Which means that class labels are assigned based on 'predicted' value of maturity index. This procedure is termed as indirect maturity classification. All regression algorithms have a certain prediction error associated with them hence the predicted value might be slightly different than the actual value of maturity index [125]. And defining maturity class of sample based on predicted values may result in wrong judgement.

On the other hand, instead of predicting the maturity index value, direct maturity classification can be performed as proposed in this paper. In direct maturity classification, classification algorithm is trained by a set of spectra, where each spectra is assigned a class label by comparing actual value of maturity index (observed using destructive testing standard procedure) and the standard threshold value of the maturity index. The job of the classifier is to identify that the test sample belongs to which class using the trained classification model. Binary classification is relatively simple problem than multi class classification and normally gives good accuracy (unless there is significant overlap between the two classes in terms of features) [215].

The quantitative results presented in the paper support these arguments that direct maturity classification (88.2% accuracy) is a better approach than indirect maturity classification (55.9% accuracy) to classify mango fruit in mature/immature fruits using DM as maturity index.

5.4.2 DM as an index of mango maturity

DM, which is a measure of fruit starch and sugar content, is considered a valid maturity index for mango fruit [20]. Moreover, optimum DM value at the time of harvest depends on mango variety and growing conditions. For the investigated mango varieties, optimum DM values as an indicator of harvest maturity have been reported by Amin et. al. [151] along with their growing conditions (e.g. daily heat units). The reported DM values [151]at the time of harvest have been used as DM thresholds to assign class labels in our classification model. Also, the proposed maturity meter has been trained under the same growing conditions as reported in [151].

Our proposed device and direct maturity classification method can also be trained for other fruits. However, while training for other fruits, the class labels for training set can be assigned using any maturity index that is valid to estimate harvest maturity for that fruit. As each fruit has its own set of valid maturity indices e.g. for grapes ^{o}Brix and total acidity are used as maturity indices [202]. DM is used as maturity index in this research with reference to mango maturity classification.

5.4.3 Comparison of different classifiers

Classification is a process of grouping objects into pre-defined categories based on by analyzing training data sets. There exist several types of classification algorithms and their application depends upon the dataset under consideration and desired output [216], [217]. For mango maturity classification, multiple classification algorithms i.e. ensemble, tree, LDA, SVM, KNN and ANN were tested in this work. Ensemble classifiers are very effective generally when large amount of training data set is available [215]. Tree classifiers require less effort for data preprocessing, they do not require normalization and scaling of data, however, sometimes calculations can be far complex than other classifiers and there training is more expensive in terms of complexity and time. LDA is a simple and fast statistical method for binary classification. SVM is amongst the best classifiers with limited amount of training data however, if large training data sets are available ensemble and tree classifiers outperform SVM. KNN is the simplest, robust, and non-parametric classifier which does not explicitly build any model and tags new sample based on learning from historical data. Given its instance-based learning KNN adapts itself as new data is collected. Neural networks are slow to train but very fast to run and often perform very well [215], [216].

For data set collected from investigated mango varieties, KNN, SVM and ensemble performed equally good with 88.2% accuracy each. Keeping in view the advantages of KNN over SVM and ensemble, KNN was chosen among all investigated classifiers for mango maturity classification. However, while training the device for other fruit’s maturity classification, KNN may not be the best one. Depending upon data set, other classifiers may outperform KNN in terms of classification accuracy.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

A new non-destructive handheld near infrared spectroscopy-based maturity meter was presented for mango maturity classification. The presented maturity meter employs classification algorithm to directly classify maturity of mango fruit as opposed to literature reported maturity meters which employ regression algorithms to estimate the maturity index value of fruits. To develop the hardware of the device, a commercial-off-the-shelf development kit of NIR micro-spectrometer in the spectral range of 400 - 1100 nm was employed with an intel compute stick, a micro-halogen lamp, a lithium battery, and a display. Device software was developed to collect spectra (features), pre-process the spectra by smoothing, reduce dimensionality of features and perform classification.

To perform classification, labels were assigned to training data set using actual dry matter (DM) content measured by destructive testing procedure and comparing it with reference DM value reported at harvest maturity. The developed maturity meter was trained for two local varieties of mango i.e. Samar Bahisht Chaunsa and White Chaunsa. Data was collected on two seasons i.e. summer 2019 data was used to train model and summer 2020 data was used as test data to validate model. Various classification algorithms were compared i.e. tree, ensemble, linear discriminant analysis, support vector machine (SVM), K nearest neighbor (KNN) and artificial neural networks (ANN). SVM, KNN and ensemble outperformed other classifiers with 88.2% accuracy on independent test data (samples of different season). Considering simple and robust nature of KNN classifier, it was selected to be used in our developed maturity meter. The proposed direct maturity classification was also compared with literature reported indirect maturity estimation method. For that, multiple linear regression (MLR), SVM, partial least squares regression and ANN regressors were compared to estimate DM value of mango samples. MLR performed better than other investigated regressors with correlation coefficient 0.92 and root mean square error 1.48 on independent test data. The estimated values of DM given by MLR model for test data were then compared with standard DM maturity value to classify the mangoes, which resulted in 55.9% correct classification. Hence, direct maturity classification was proven to be a better non-destructive quantitative measure as compared to indirect maturity estimation.

6.2 Future work

Further work will be concentrated on validating the accuracy of the developed mango maturity meter for other commodities as well as to analyze the different factors that effects the performance of the developed maturity meter.

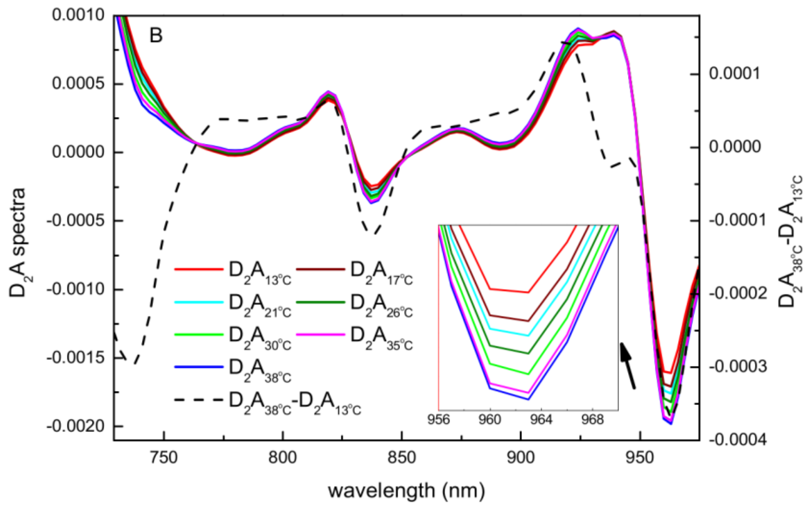


Figure 12: Average second derivative spectra (725–975 nm) of mango fruit for fruit temperatures of 13, 17, 21, 26, 30, and 38 °C, and the difference spectrum between 13 and 38 °C *[219]*

Sample, instrument, and environmental factors i.e., temperature and humidity, can influence the prediction accuracy of an NIR system [125], [218]. In NIR spectroscopy fruit evaluation, the temperature of the samples varies greatly, as a fruit's spectrum is dominated by water features, and in DM evaluations the water content is mostly evaluated [219]. Temperature influences the water spectra due to changes in degree of H bond and an apparent transition to a shorter wavelength in the direction of water peaks with decreases of the temperature [220]. In order to compensate the influence of temperature, sample spectra at multiple temperatures are recommended during the development of training models. The program can ignore spectral shifts and changes that are not related to the desired feature when scanning the same fruit at 2-3 temperatures. The model will autocorrect for temperature if the temperature variation for the same fruit is included in the model. The need for temperature compensation is minimal for certain applications, for example in controlled environment having constant temperature, but if the developed maturity meter is used for on-tree fruit maturity estimation with several types of variations, a training set needs to be built to accommodate the possible temperature range. These variations might be in temperature, fruit variety, climate growth as well as season-to-season variation.

Furthermore, if the calibration model is transferred to another developed maturity meter, it would introduce an error, which reduce the prediction acceptability. In order to cater this problem, the existing model will require to be tailored with 20% of the population of original samples. These 20% samples will be collected using newly developed maturity meter and then the resulting model should be validated with additional samples.

Acknowledgement

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Completion Certificate

It is certified that the thesis titled **"NIRS-based On-tree Mango Fruit Maturity and Quality Estimation"** submitted by CMS ID. 00000206594, NS Syed Sohaib Ali Shah of MS-17 Mechatronics Engineering is completed in all respects as per the requirements of Main Office, NUST (Exam branch).

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