Design, Implement and Benchmark a Low-Cost Optical Device for Measuring Brix and Dry Matter in Fruits

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JUNE, 2021

Declaration

I certify that this research work titled "*Design, Implement and Benchmark a Low-Cost Optical Device for Measuring Brix and Dry Matter in Fruits"* is my own work. The work has not been presented elsewhere for assessment. 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

A low-cost sensor is developed for non-destructive fruit quality estimation which switches light-emitting diodes sequentially on at 4 various wavelengths and measures the reflection in the interactive mode. The detector is tested on Apple samples for a non-destructive estimation of soluble sugar content (SSC), and dry matter (DM). A total of 240 apple samples were determined for SSC and DM measurements. The developed handheld device is composed of a Raspberry Pi, analog to digital converter ADS1115, light emitting diodes (LEDs), a liquid crystal display (LCD) screen, a photodetector, resistors, PCBs, buttons, headers, jumper wires, batteries and 18650 batteries shield. The photodetector was used for linear regression i.e., partial least square (PLS) regression and multiple linear regression (MLR) and support vector machine (SVM) as non-linear regression while the benchmark spectrometer i.e., Felix F-750, was fitted with a partial least square (PLS) regression model. The best estimate for the two different measurements were employed in different regression techniques. A LED detector was observed for SSC measurements with correlation coefficient (R) of 0.82 and 1.51% of root mean square error for prediction (RMSEP). whereas SSC values were 0.95 and 0.76%, respectively with the benchmark spectrometer. The LED detector prototype achieved DM values of R = 0.85 and RMSEP =1.59%, while for benchmark spectrometer, R and RMSEP of DM was 0.93 and 0.69%, respectively.

Key Words: *near-infrared, light emitting diode, photodetector, handheld optical device, soluble solid content, dry matter*

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CHAPTER 1: INTRODUCTION

1.1 Motivation

A main challenge for food processors and retailers is the supply of superior food to a increasing population while curtailing losses. A total of 1.3 billion tons of food, which is about 30% of the total food production, is wasted annually [1]. Wasted food contributes to useful chemicals such as fertilizers, pesticides, transport fuel, and the output of methane from decay. Fruits and vegetables are a big part of the food waste [2] and it is avoidable if it were better managed [3]. For the prediction of shelf-life and calculation of fruit quality constraints, food retailers need non-destructive portable instruments. Concept of a "first-in, first-out" has been followed by retailers in the absence of these instruments (fruits come in first, go first to the supermarket shelves). However, due to abuse of fruits during shipping, shelf life may be drastically shortened. Exposure to volatile organic chemicals, for example [4], breakdown in Cooling during shipping, and inappropriate packaging. Retail food is currently evaluated using destructive methods in terms of firmness, color, shape, size, and content of soluble solids (measured as %). Although the tests assess the quality at the time of testing, shelf-life estimation and quality in retail stores are not achieved until the fruit hits the customers. Since retailers are unsure of the exact shelf life, fruits and vegetables are delivered in greater quantities than required to ensure that the store meets the demand. Increased demand forecasting, dynamic routing and better inventory management are needed to minimize food wastage during retail [5] and the fruit quality can only be achieved by quantifiable parameters. The characteristics of fruit quality are also significant considerations in the transport and storage of various batches for retailers [6]. With low-cost, compact, non-destructive sensors that quantify efficiency, predict shelf life, and predict consumer loyalty, these targets can be accomplished.

1.2 Quality of fruit

A summary of the notion of quality of fruit, its significance in production of fruit, and the criteria will be given in this chapter

1.2.1 Concept of Fruit Quality

A highly mutable definition is consistency. Its meaning is rather contingent on the product in question; it is meant to be used and the needs of scholars, producers, manufacturers or customers are meant to describe it [7]. In general, the concept means a superiority and suitability in a fruit for its proposed use [8]. To promote foreign trade, quality may belong to a collection of legitimate requirements developed for fresh food [9][10]. It may also be highly subjective, or based on a set of observable attributes [8], based on general, cultural and sensory preferences [11].

Indeed, quality definitions differ according to context. When a product travels down the supply chain, from the plant to the cold shop, to the manufacturer and eventually to the customer, they shift and combine [12]. For example, on quantifiable factors such as height, firmness and color, a customer may judge a product, although other less valuable principles such as visual appeal, texture, and taste are also very important in defining and meeting quality standards.

1.2.2 Maturity of Fruit

For scrutinizing the growth of a commodity or a crop, their pre-harvest quality assessment is crucial. Probably the most important reason for doing so is for the prediction of maximum physiological maturity of the fruit for improved production after harvest and to minimize the loss of storage.

In dictating postharvest storage life and potential eating efficiency, fruit maturity at harvest is critical [13]. The stage of maturity when fruit can mature successfully after harvesting or is at its peak for storage, however, does not invariably correspond with the time when fruit has the most commercial appeal [14]. Maturation can also be seen as a period of growth heading to two associated, but different, maturity categories: physiological maturity and commercial maturity.

Commercial ripeness is the period at which the fruit has the preferred characteristics for market use [13], and this follows physiological maturity for most fruits. This suggests that fruit intended for storage needs a particular stage of maturity, comparative to immediate consumption of fruit.

Physiological ripeness is described as the development stage of fruit where it can persist to ripeness even after harvest and where storage potential is optimal [13]. Ripening involves a succession of physiological changes occurring from the late growth and development phases through the early stages of senescence, which culminate in the characteristic consistency of eating of fruit. [13]. Some climatic fruits, such as apples and pears, require some time in cold storage following harvest, in order to promote production of enzymes involved in ethylene generation before appropriate maturation at ambient temperature [15]. Other fruits are an exception to these general rules, such as 'Clara Frijs' pears. When picked, these pears do need to be physiologically mature, so when they are do firm and green not long after selection, their organoleptic consistency is highest.

Defining maturity assumes that it is observable and that there are methods for quantifying it. The maturity indices are based on features known to change when the fruits ripen. Most of them are twofold markers of quality and represent the balance between physiologically but not commercially mature fruit harvesting requirements, yet still guaranteeing the greatest possible eating quality for the consumer [13].

1.2.3 Preharvest fruit quality

By its own meaning, in order to pre-empt an optimal harvest date, assessing physiological maturity involves a certain degree of pre-harvest quality evaluation. Preharvest can be described as the time between fruits set until just before harvesting in fruit production. Quality of fruit is inseparably related to its composition, hence the mechanism of production of fruits, and the external parameters, can be used for the estimation of quality of harvest and storage [13]. This also ensures that some characteristics of preharvest consistency and unique internal fruit production processes are compatible. It will enhance orchard management and overall fruit quality to consider the relationship between preharvest production and harvest and post-harvest quality. In addition, early quality estimates can be helpful in preparing harvests and modifying inputs including fertilizers and water. Field activities are important quality determinants as only quality characteristics specified in the field can be preserved by post-harvest treatments and storage [16]. The assessment of the consistency of the pre-harvest fruit relies primarily on the calculation of the soluble sugar content, starch content and firmness, which are likewise used to monitor fruit quality during cold storage as well as at harvest.

1.2.4 Pre-harvest factors that affect the fruit quality of post-harvest

Several factors affect the preharvest fruit production and also have an effect on post-harvest quality and during cold storage. Environment conditions for example light strength, precipitation and surrounding temperature are included; similarly cultural aspects including diet, training and pruning methods, seed loading and plant growth regulators (PGRs) usage; and whereas genetic effects are due to the choice of rootstock and cultivars [17][18][19][20][21]. Awareness of the influence of environmental influences on crop growth and fruit quality enables crop and fruit production to be exploited for the benefit of growers and customers. Root pruning in conjunction with supplementary irrigation are two variables that have been established after an extensive experimental study. Technique of Root pruning has been introduced to supplant the utilization of chemical PGRs to control the vegetative growth in the cultivation of orchard fruit. Growth of vegetation can also be reduced by a reduced availability of water [22] and both can decrease fruit size and change consistency.

1.2.5 Parameters of Fruit Quality

A core aspect of this study is the 'measured standards' for fruit quality, which are how samples of apple have been tested by experimentation. Measuring these indexes takes time and is dependent on sample’s number, selected for testing, but quality of fruits is usually measured by this method. Such metrics, while calculated separately, make more sense when interpreted holistically. Undeniably, many parameters are interlinked, either physiologically, for instance by the interaction between soluble solids content (SSC) and dry matter (DM) [23] or by customer desire for sweetest apples, having suitable firmness [10].

1.2.5.1 Size of Fruit

In the marketing of fruit, size is a critical parameter as it can greatly impact its customer appeal [20]. The size of the fruit is therefore related to the average tree's yield and hence has an effect on the crop's commercial value. An initial period of cell division and expansion is characterized by fruit development, followed by continued cell expansion until harvest [24][25][26]. The number of cells (division) and volume (expansion) at harvest, as well as the size and weight of the fruit, are affected by the pace and length of these stages [27][28]. Other factors affecting fruit size are field conditions, crop load and seed growth. Fruit size influences other consistency properties, including firmness, dry matter, and the volume of soluble solids.

1.2.5.2 Color of Fruit

In terms of customer choice and quality evaluation, color is hugely significant. A decrease in the quality of skin chlorophyll is associated with advancing maturity [8] and it is always the most visible indicator of maturity depending on the fruit [29]. Apples have an unevenly spaced skin flush, rendering color measures an unreliable predictor of maturity dependent on single points on the fruit surface.

1.2.5.3 Firmness of Fruit

Firmness is one of the good maturity parameters and it is often used as an indicator of food consistency for many fruits, including apples [30]. In the laboratory, though, firmness does not invariably translate into a strong quality. Its dynamic phenomenon is built on [31] cell physical properties, but also linked to other parameters, such as SSC [10].

The composition of apple flesh cell walls is based on cellulose which is a great source of pectic substances and strength that touch and provide versatility to adjacent cells [31]. During fruit growth, this versatility is important because fruit growth is due to expansion of wall cells. When fruit ripens, the pectic compounds are solubilized causing a lack of cell-to - cell cohesion and thereby affecting general fruit juiciness and firmness.

1.2.5.4 Dry Matter (DM) of Fruit

The internal consistency of apples and pears depends on their flesh components and their concentration. Water, with phenolic compounds, proteins, nutrients, organic acids, lipids and vitamins, is the dominant portion of fruit [32][33][34]. These constituents may be regarded collectively as 'dry matter' until water is omitted. The ratio of fruit dry weight (DW) to fresh weight (FW) can be specified as DM and it is stated in the form of percentage. The word DM is also used for other meanings, for instance, the concentration of dry matter (DM, dry matter per volume of plant organ) and the content of dry matter (DMC, dry matter per fresh mass) [35].

1.2.5.5 Soluble Solid Content (SSC) of Fruit

Starch is processed into sugars as apples are mature, thereby fruit taste become sweeter with increase in SSC. Soluble compounds include organic acids, sucrose, inorganic salts, fructose, sorbitol and glucose, are found in extractable juice in apples [30][29]. Depending on the fruit and the variety, the proportion of sugars varies [36] and affects taste. Glucose is less sweet then sucrose, which is less sweet than Fructose [34].

1.2.6 Assessment of Non-destructive Fruit Quality

Standard technique within the fruit industry is all the above quality analysis techniques. Many of them, though, have one big drawback, all of which are destructive measurements. There has been a shift in recent years towards the production of alternative non-destructive fruit quality analysis approaches with special attention given to near-infrared (NIR) spectroscopy [37][38][39]. Dry matter is of concern, apart from its usefulness as a consistency parameter, as NIR spectroscopy is particularly useful for predicting the constituents present in carbohydrates.

1.3 Chemometrics

1.3.1 Principles

Via multivariate computer science, applied mathematics and statistics, chemometrics attempts to model and investigate the fundamental relationships in different chemical processes [40]. In chemometrics, multivariate approaches are basically instruments that simultaneously contemplate several variable quantities and consequently holistically perceive a chemical query. Chemometric models can show unexplained trends in the data by considering all variables [41]. Posteriori data has been used by chemometrics uses a for production of new assumptions by using novel data interpretations, but all hypotheses are not considered a priori [41]. It is also extremely graphical in its method, thereby allowing the inner framework of massive databases to be visually defined.

1.3.1.1 Model Importance

Chemometric modeling links variables to each other that are experimentally defined. Two primary model types exist: one for the prediction and other for the exploratory analysis. Exploratory models of spectroscopic data, illustrate in what manner specific spectra, which are identical or different, relate to each other, patterns in spectral activity, along with the supply of knowledge on extreme or outliers spectra. The most common approach for exploratory data analysis in chemometrics is principal component analysis.

The development of a regression model is necessary for the prediction of fruit quality. The tool is trained by using this model for the prediction of future samples. A regression model is therefore a quantitative means of associating spectral data with sample components. The success of a model clearly relies on the consistency and depth of knowledge used to create it. In order to optimize model performance by removing outliers and reducing noise and scatter, preliminary data discovery and preprocessing are therefore vital.

1.3.1.2 Noise

In a dataset or calculation, uncertainty or noise is usually present. Three big things can be related to the deviation between a calculated value and a model. First, the loss of full control over laboratory parameters (Sample concentration, Temperature etc.) makes it difficult for the next time the experiment is performed to retain precisely the same parameters. The biological heterogeneity of samples, within the identical fruit, from the similar cultivar, or even from the identical tree, is a constant source of noise with regard to fruit [42]. In addition, fruits are complex entities; either during tree growth or in post-harvest storage, they alter over time. Second, since it is affected by variables such as temperature and humidity, the spectrometer is not purely stable. Finally, as a result of approximation and the inherent simplification needed to construct the model, modeling errors. [41] concludes that noise is polluted by all chemical data, whether spontaneous (environmental) or systemic (due to model restrictions).

1.3.2 Processing of Data

The performance of a model, as stated, hinge on the data quality used to create it. Any appropriate preprocessing must be done before modeling takes place to ensure optimum retrieval of the relevant information. Spectra can need to be converted from reflectance or transmission to absorbance, based on the process of acquisition. A major cause of variation in the spectrum is radiation dispersion attributable to the size of particle, particularly in fruit. The effect of particle size and scattering can be minimized by such transformations by eliminating the slope changes and shifts of spectral baseline. Other methods support separate overlapping spectral characteristics.

1.3.2.1 Spectral Transformation

The Beer-Lambert Law can be used to calculate transmission spectra (where reflectance is approximated as log (1 / R) and concentration measurements are usually translated into log (1 / T). however, interaction of samples are not pure, and spectral data is byzantine by differences in temperature and morphology of the sample. The transformation of Kubelka-Munck accounts for dispersion, but transformation using log (1 / R) is well-thought-out preferred for agronomic goods. [43], nevertheless, suggest that there does not appear to be any significant benefit in spectral transformation.

1.3.2.2 Mean Centering

In data preprocessing, this is a very significant step which involves the mean value subtraction from each variable value. Resemblances and discrepancies between samples are illustrated. The data cloud is centered in a variable space and thus illustrates resemblances and discrepancies between samples. For most chemometric techniques, centering is a critical move.

1.3.2.3 Weighting or Auto scaling

This distinguishes every vector by considering its standard deviation and considered as important as separate units (mg, g, percent, ° Brix, etc.) calculate results. As no one variable is able to dominate or distort the formula, variables become more comparable. Principle Component Analysis (PCA) and PLS regression, attempt systemic variance, while like larger variation, subtle variations can also plays the same function as allowed by auto scaling. Though, for spectra, it is not needed or suggested as it have same units and substantial data may be lost or noise overemphasized by scaling [44].

1.3.2.4 Spectral Smoothing

For optimization of signal amplitude, signal to noise ratio is increased by using spectral smoothing functions. In order to eliminate noise and scattering effect, without effecting the true signal accountable for the observed intensities, transformation suggested by Savitzky-Golay is often used when using derivative spectra. The transformation eliminates noise while still maintaining the spectrum 's character [45]. Although others disagree to use this smoothing technique, as it eliminates data before it becomes clear if it is beneficial [38].

1.3.2.5 Minimizing scatter

There may be additive and multiplicative effects in cases of strong scatter, where both baseline change and slope are visible in the continuum. In reference spectrums, none of these effects are present. Both phenomena are efficiently addressed by using these transformations. Standard normal variate (SNV) prevents scatter-induced intrusion, while baseline changes can be rectified by multiplicative scatter correction (MSC) alongwith pathlength variations that influence absorption. SNV concentrates and weights each continuum by its own standard deviation [46]. The slope of the spectra is not changed by treating each spectrum separately, without shifting their baseline (offset correction). Based on the assumption, MSC considered that all samples have the same scatter coefficient at all wavelengths. The scatter amount is corrected to that of the spectrum of a 'ideal' set, which is normally the typical spectrum (Geladi et al., 1985). The initial spectral orientation is retained for both techniques.

1.3.3 Principal Component Analysis (PCA)

The center of chemometric analysis lies in theory component analysis (PCA). It is a way of squeezing vast volumes of spectral data into a little components without omitting any useful details that explains differences in the dataset / data matrix. In multivariate analysis, PCA is an unsupervised step which allows simulation of the latent dataset structure which trend and allows early detection of outliers [44]. It is possible to express it as:

$$X = TP' \text{ (explained variance)} + E \text{ (residual variance)}$$

A potentially correlated variables data matrix (X) is converted by PCA into principle components (PCs) also known latent variables, (LVs), which are basically the fresh set of orthogonal variables [44]. The number of PCs is equivalent to or less than the number of initial variables. PCs are related through a score matrix (T) to the original data matrix, containing sample quantitative information, and a loading matrix (P), containing variable quantitative information. PCA is carried out before all that remains is unsystematic or unknown [44] by repetitive subtraction of the largest difference in the results. Therefore, with each successive variable including the highest remaining variance available, the 1st PC accounts for the greatest difference in the data, providing that it is unrelated to the previous one.

1.3.4 Partial Least Square Regression (PLSR)

A supervised learning approach widely used in NIR spectroscopy to compare chemical reference data (Y), usually acquired using destructive methods with spectral data (X). Latent variables have been used by PLS regression, which is similar to PCA. Nevertheless, variation in Y drives the decomposition of X in such a way that maximum co-variance between X and Y is achieved) in PLS regression, so variation in X is derived directly associated to Y. A major advantage of PLSR is that it has a capacity to analyze highly noisy, correlated data with multiple input variables (as opposed to Y), while at the same time modeling multiple response variables [47]. Its main aim is to create a prediction model, which can predict y (a chemical component) from X (a spectrum). The model has to be calibrated on different samples that cover the spectrum of potential Y samples in order to achieve a reasonable forecast, as the model does not extrapolate [47]. Once again, residuals are added to parts of the data not clarified by the model.

1.3.5 Multiple Linear (MLR) Regression

In order to predict the outcome of a dependent variable, multiple linear regression refers to a mathematical method using two or more independent variables. The methodology helps analysts to assess the model deviation and the relative contribution of the overall variance of each independent variable. There can be two types of multiple regression, i.e., linear regression and non-linear regression. Easy linear regression helps statisticians to use the information available about another variable to estimate the value of one variable. Linear regression tries to determine the relationship in a straight line between the two variables. Multiple regression is a type of regression where a linear relationship between two or more independent variables is displayed by the dependent variable. It may also be non-linear, where a continuous line doesn't obey the dependent and independent variables. Using two or more variables graphically, both linear and non-linear regression trace a given answer. However, because it is generated from hypotheses obtained from trial and error, non-linear regression is typically difficult to implement.

CHAPTER 2: LITERATURE REVIEW

For the fruit industry, poor and inconsistent fruit quality is of critical significance. A major concern for food processors and retailers is the provision of high-quality food to a growing population while reducing losses. Approximately 30% of food, mostly fruits and vegetables, being wasted worldwide [2]. Around 25% of fruits are wasted by inadequate storage procedures and handling while only 2% are utilized in food processing [48]. Fruits and vegetables are a big part of the food waste and it is avoidable if it were better managed [3]. To predict shelf-life and calculate internal quality parameters, food retailers need non-destructive sensors. Retailers follow a "first-in, first-out" concept in the absence of these sensors (fruits come in first, go first to the supermarket shelves). However, due to exploitation of fruits during shipping, such as improper packaging and exposure to volatile organic compounds [4], shelf life may be drastically reduced. Retail food is usually evaluated destructively in terms of firmness, color, shape, soluble sugar content (SSC) size, and dry matter (DM) .To ensure fruit quality and avoid fruit wastage, fruit quality estimation needs to be done before delivering them to the market [49]. Soluble sugar content (SSC) and dry matter (DM) are the most important among many traits in deciding the overall quality of the apple fruit. Traditional method for DM evaluation is drying and weighing slices of fruit to eliminate water [50], whereas, for SSC evaluation, it is to measure the extracted juice of fruit using a refractometer [51]. By using these traditional methods for DM and SSC, fruit quality traits can be measured accurately. However as the samples would be damaged, these procedures are arduous and cannot be carried out on a large number of samples [48]. In recent years, to overcome these issues, various non-destructive techniques have been developed for fruit quality estimation. Among these non-destructive techniques, near-infrared (NIR) spectroscopy have been extensively used for quality estimation of apple fruit [52], [53].

For decades, the use of NIR spectroscopy (NIRS) has been shown in measurements of quality of fruit [52], [53]. NIR is most appropriate for the detection of organic compounds because wavelengths falling within the near infrared range are absorbed by bonds between nitrogen and hydrogen (N-H), oxygen and hydrogen (O-H), and carbon and hydrogen (C-H) [54]. The key components present in living tissues, including fruits, are organic compounds, making NIR suitable for use in fruits. In addition, NIR can penetrate into a sample more deeply than any other component of the infrared spectrum [55]. In NIRS, the fruit is illuminated with light ranging from

400 nm to 2500 nm of radiation spectrum and then measured the absorption fingerprint of active chemical groups [56]. Fruits have a significant number of C-H, O-H, and N-H bonds linked to those chemical groups [57]. For instance, in measurement of SSC of grapes, O-H bands have absorption peaks at 1190 and 1400 nm [58], while for SSC estimation of jujube fruit, O-H and C-H bands have peaks at 960, 1180, 1450 and 2000 nm [59]. To measure acidity, absorption peaks of O-H bands at 1127 nm was used [60], and at 768 nm, absorption peak of C-H bands was used to calculate pH [61]. The quality characteristics of various fruits have been determined using all these absorptions.

In recent research, spectral data between 940 and 1400 nm, have been used for estimation of SSC in oranges [62]. Similarly, SSC was predicted with excellent precision in gala apples (determination coefficient (R2) = 0.94 and root mean square error of prediction (RMSEP) = 0.34%) using spectral wavelengths of 800-1100 nm [39]. For estimation of SSC in kiwifruits, [63] interactance mode has been used in spectral range from 800 to 1100 nm (R2 = 0.90, RMSEP = 0.39%), while SSC for kiwifruits has been estimated using spectral wavelength range of 408–2492 nm (R2 = 0.98, RMSEP = 0.49%) [64]. In many fruit, chlorophyll has an absorption peak at 670-690 nm [65]. As the fruit ages, chlorophyll degrades and shelf life can be predicted using spectral information at 680 nm [66][67].

NIR was used to measure the quality of fruit easily [63][64][68][69][70] and to forecast future quality [71][72][73]. Today, with many commercial systems offered, NIRS is commonly used in packing line operations [74], such as Aweta, Maf Roda Agrobotic, and Compac Sorting Equipment Ltd.. Commercial products for instance the FieldSpec Pro (PA Nalytical, B.V.) and the Produce Quality Meter F-750 from Felix Instruments Inc., have also been produced for retail. However, due to the high cost of these instruments, which range to thousands of dollars, the permeation of NIRS in the marketing sector has been constrained and is still in its early stages. In recent years, the use of low-cost, compact smartphone-connected spectrometers such as Tell Spec Food Sensor (Tell Spec) and SCiO (Consumer Physics Inc.) for food applications has been of significant interest [75][50][76]. Many of these spectrometers attach to a smartphone, where they interpret and visualize the spectral data. SCiO, having spectral resolution of 1nm, in the 740 to 1070 nm wavelength band, while a micro-spectrometer from Texas Instruments, has been used by TellSpec, having (900 - 1700 nm) of operating range. SCiO, was utilized for DM and SSC estimation (R2 = 0.85, RMSEP = 0.66%) for kiwifruits, whereas for firmness, it showed poor results [50].

Several portable spectrometer devices based on NIR have been developed and commercialized over the last decade. Using these non-destructive devices requires training, knowledge and expertise in implementation. For several fruits, including grape, apple, peach, mango, peach, grape, pear, kiwi, and persimmon, these handheld portable devices have integrated prediction models. Various varieties of each fruit, however, required the creation of distinct prediction models. However, the equipment available is costly for the estimation of shelf-life and quality traits, which limits their widespread use in developing countries. Democratization of NIR spectroscopy for the estimation of fruit quality requires the focus to be changed from a costly handheld NIR system covering a wide range of fruits to a relatively low-cost photodiode-based fruit maturity estimation device calibrated for a single fruit variety [48].

The purpose of this study is to develop a small, easy-to-use and cost-effective handheld device for less than $750. The prototype should be in a position to estimate shelf life and quantify the quality characteristics, so that dealers can execute competitive pricing and better demand forecasting. Therefore, the focus was on two parameters for predicting fruit quality i.e., DM and SSC. This study illustrates the design and assessment carried out to assess the efficiency of LED based fruit quality meter.

CHAPTER 3: HARDWARE AND SOFTWARE DEVELOPMENT

3.1 Hardware Development

The optical device is composed of a Raspberry Pi, Analog to Digital converter ADS1115, an Optical devices Light Emitting Diodes (LEDs), a Liquid Crystal Display (LCD) screen, a Photodetector, resistors, PCBs, buttons, headers, jumper wires, batteries and 18650 batteries shield. When the power button on controller takes a few second to stable, when it is stable press the reading button there are four types of LEDs in this device which takes the reading of the sample one by one and reflect to the photodetector. Photodetector passes the analog readings through ADC where analog readings are converted to digital and sent to the controller. The spectra from photodetector were obtained and preprocessed by using controller through USB data cable and then calculate the SSC and DM of fruit based on obtained spectra.

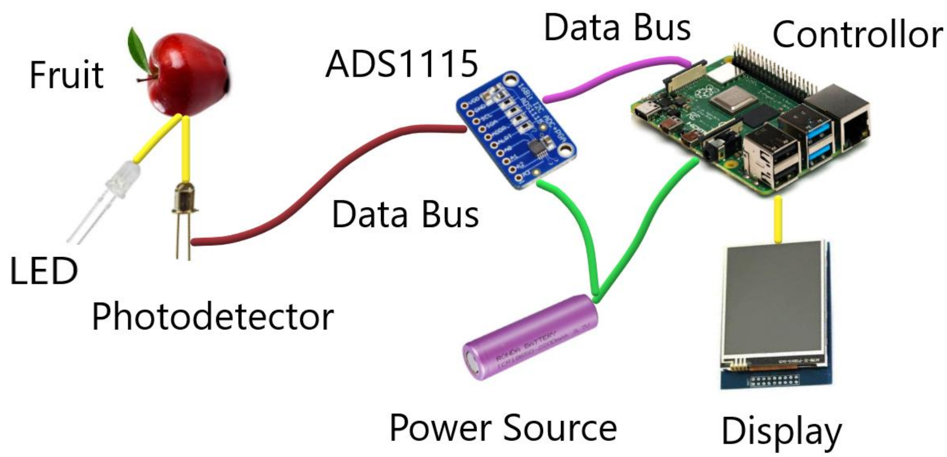

Figure 1: Block Diagram of LED Meter

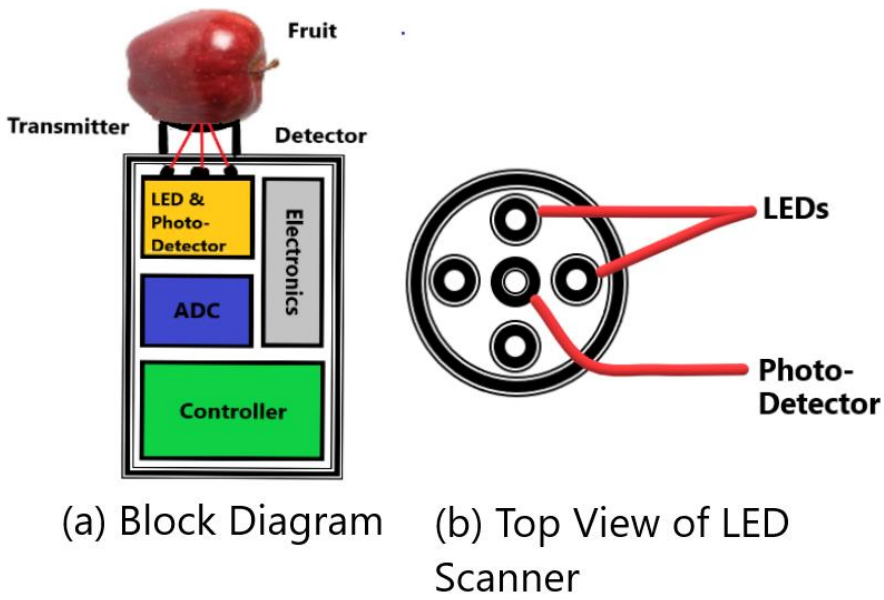

Figure 2: (a) Block Diagram (b) Top View of LED scanner

3.1.1 Controller

The Raspberry Pi 4 Model B is the newest update to the famous range of Raspberry Pi computers. It provides revolutionary improvements in processing power, connectivity, output of multimedia, and memory as compared to the previous product. For pre-processing of detector readings and analysis Raspberry Pi 4 (UK), with size of 85.6mm × 56.5mm was used. The Raspberry Pi 4 board include RAM of 4GB, 2x ports of USB 3.0, 2x ports of USB 2.0, Bluetooth 5.0, dual pair of micro-HDMI ports at resolutions up to 4k for display, high performance 64-bit quad core processor and Gigabit Ethernet port. The 5V/3A via Type-C was needed to operate the Raspberry Pi 4 and GPIO header also gave 5V.

3.1.2 Analog-to-digital Converter

The ADS1115 delivers 16-bit precision at 860 samples/second over I2C for microcontrollers without an analog-to-digital converter or when you choose a higher-precision ADC. The chip can be programmed as either 4 single-ended or two differential input channels. As a cool extra, to further improve smaller single/differential signals to the maximum spectrum, it also provides a programmable gain amplifier, up to x16. We like this ADC because it can calculate a wide variety of signals and it is super easy to use because it can operate from 2V to 5V power/logic. It is a decent 16-bit translator for general purposes.

3.1.3 Light Emitting Diode (LEDs)

Light Emitting Diodes was played an important role to developed handheld optical device. The main task to select the LEDs for measuring Brix and Dry Matter of fruit. There were four types of different LEDs used with different wavelength such as 780 nm, 810 nm, 880 nm, and 940 nm. These were different voltages and current for operating.

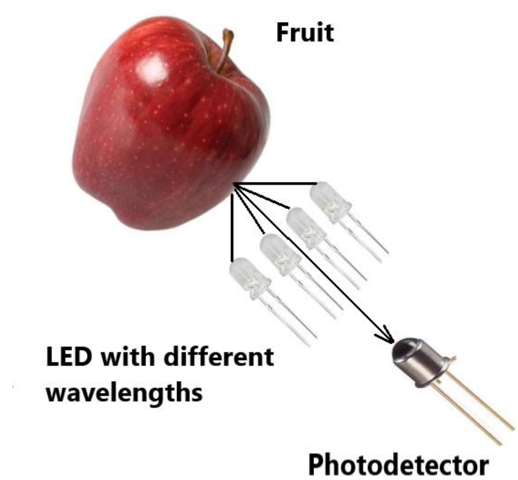

Figure 3: LEDs with different wavelength and Photodetector

3.1.4 Photodetector and Resistors

Using ST-1KL3A NPN Silicon phototransistor which are highly reliable and better used for outdoor equipment. It has two lead (collector, Emitter) and narrow angular response, which will give durable response yearly. Spectral sensitivity of phototransistor is from 500 nm to 1050 nm and the peak wavelength is 880 nm. For the reduction of the current flow, changing signal speeds, separate voltages, bias active components and terminating transmission lines, resistors are employed in electronic circuit applications. There are five resistors was used in this device, four resistors were same values, and one resistor was different value with different tolerances.

3.1.5 LCD, Batteries and Batteries shield

Display was played an important role to develop a handheld optical device. The 1.8-inch TFT LCD was used for user interface. The LCD was connected with controller Raspberry Pi 4 through jumper wires. Using 18650 battery lithium-ion cell for device. As compared with AA cell it is slightly large, dimension of this cell is 18 mm x 65 mm in size. Each cell has max 3.7 voltage and max current 3000mAh. Portable power 18650 V8 shield used for Raspberry Pi. It has on/off button, USB port, dual charging ports type-B and type-C. Besides there are two types of outputs such as 5V/3A and 3V/1A also available. The benefit of those outputs was used to multiple devices in one module. The main purpose to use the V8 18650 shield was to recharge the cell and take the different outputs from that.

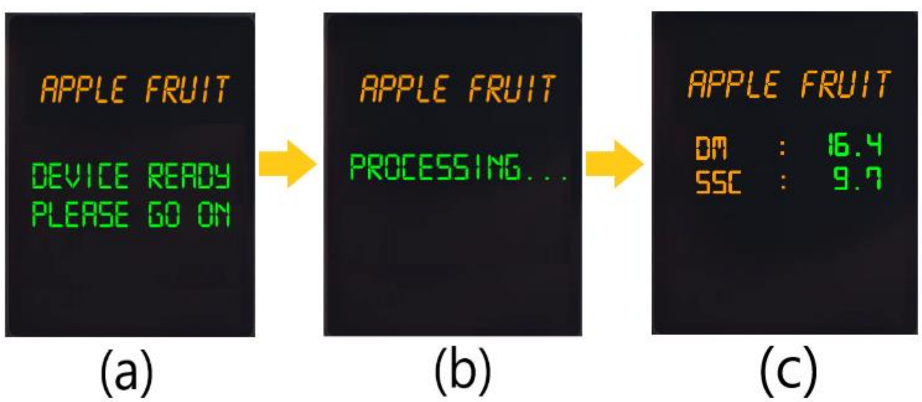

Figure 4: (a) main display (b) Show that by pressing the reading button data being process (C) Display data of Dry matter and SSC

3.2 Software Development

On the Raspbian operating system and the integrated development environment (IDLE), the software was built with the aid of the Python language (Version 3.7). Following are the key functions of the established software.

Calibration: The calibration is achieved by switching on and off the light source, collect the reflection light from the white Teflon disc and saved it as white and dark reference, correspondingly. The calibration time of the device in only 1500 millisecond, as illustrated in timing diagram (see Fig. 5). For each LED of specific wavelength, the integration time is about 200ms.

Measurement: The fruit quality could be calculated after calibration. After pressing a scan button, "Processing…" is being displayed on screen while taking reading from the fruit and then SSC and DM are calculated and at the end the SSC and DM values are appeared on the 1.8-inch TFT LCD.

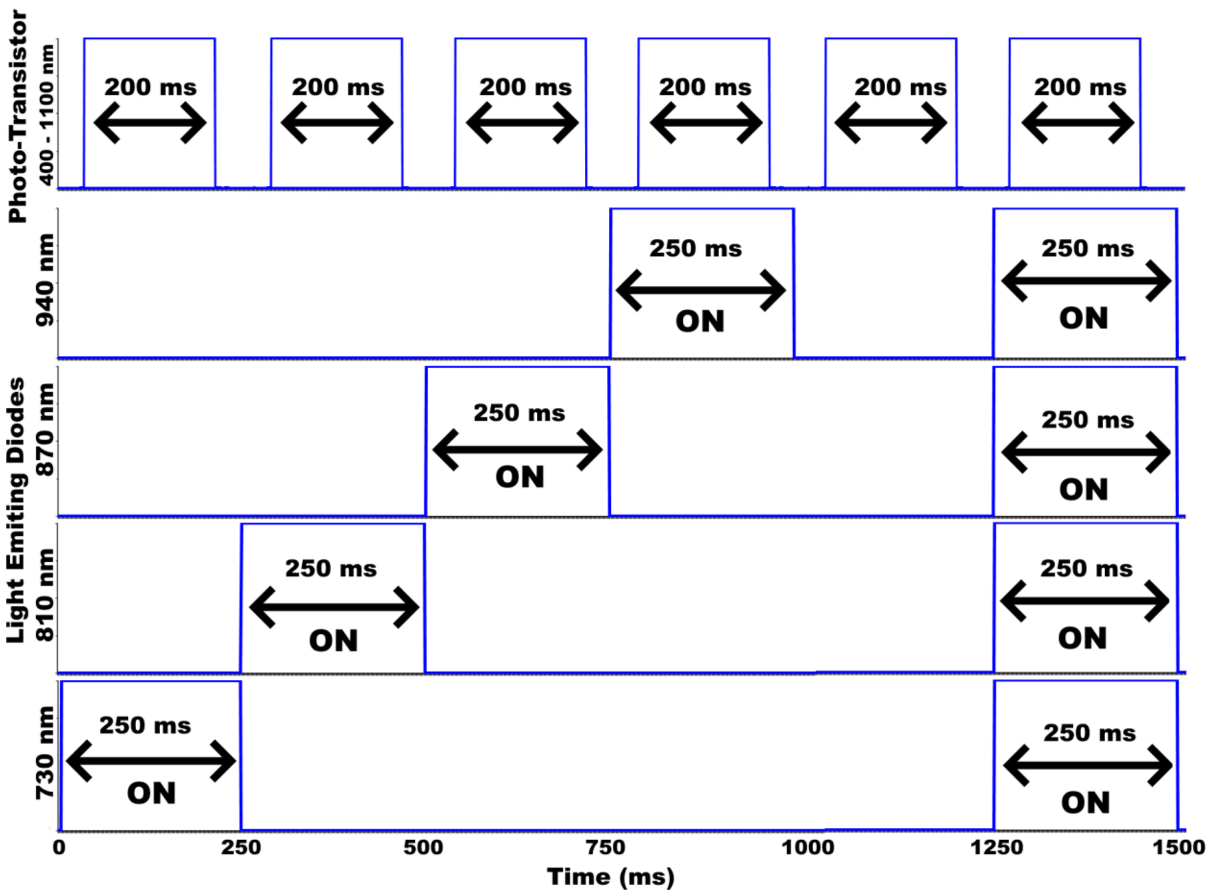

Figure 5: Timing diagram of calibration process

CHAPTER 4: MATERIALS AND METHODS

4.1 Fruit Samples

In this study, 240 ripe Apples (Malus Domestica varieties ‘Golden Delicious’, ‘Red Delicious-Pak’ and ‘Red Delicious-Turk’, each 80 fruits), were bought from a local Superstore. At the same day fruit were transported in the laboratory, Agriculture Robotics Lab, Robot Design and Development Lab (RDDL), NCRA, Rawalpindi. 80 samples of each variety were segregated and placed on table for difference from one another. Each fruit was marked rounded circle with black marker from two sides for destructive and non-destructive testing. All fruits sample were divided into two batches such as batch-A and batch-B. In batch-A there are total 180 training samples, and in batch-B there are total 60 test samples, which were tested by using developed handheld optical device.

4.2 Spectral Acquisition and reference method

The LED fruit quality metre was calibrated by measuring the reflectance spectra of each LED with a white Teflon disc when the light source was turned off and on, and then using it as a dark and white reference, respectively. The equatorial part of the apple fruit was chosen as a representation of the entire fruit for DM spectra collection and reference analysis. Fruits were marked at the fruit's equator, and spectra and reference cores were obtained from these designated sites. By putting the fruit on the lens of the LED fruit quality metre, the reflectance spectra of each sample were collected. On each sample, two measurements were taken, and the mean spectrum of the two measurements was used for further investigation. Finally, four spectra were acquired for each variety, each with three data points, recorded from LEDs with varied wavelengths of 730 nm, 810 nm, 870 nm, and 940 nm. After peeling the apple skin (1–2 mm thick) using a fruit peeler, a section measuring 27 mm in diameter and 10 mm in depth was sampled from indicated sites. The DM content of the apple sample was measured using a fan forced oven which was set at 65°C for about 48h [77]. Figure 6 shows a schematic design of a labelled Apple sample.

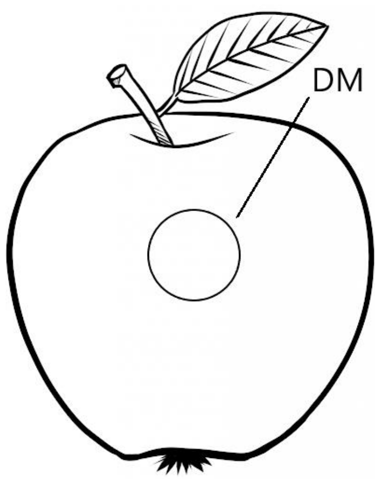

Figure 6: Schematic diagram of the labeled position for LED spectral acquisition in Apple sample

4.3 Chemometrics

The reflectance at each wavelength is converted into absorbance by removing dark and white reference values. Cross-validation approaches have been used for data analysis. The 240 Apple samples data has been randomly divided into 10 folds for both SSC and DM measurements. Every fold consisted of 168 samples for model calibration and 72 separate predictive samples. The samples were sorted first by SSC values and then classified into 10 subgroups. A sample was allocated to a fold from the subgroup. This allows the calibration and prediction data sets to contain identical SSC profiles. Each calibration model was calibrated autonomously with168 calibration samples and then validated on 72 prediction samples.

Different linear regression models to select the wavelengths for the calibration template was developed in order to detect the wavelengths which contribute statistically to the SSC or DM prediction. Calibration models have been built using the chemometrics analysis software package of Unscrambler (version 11.0, CAMO, Oslo, Norway). The absorbance has been pre-treated using smoothing, normalization (SNV), first derivative Savitsky Golay (SG) and second derivative SG, similar to that for navel oranges [78]. The software of Unscrambler was used to build the calibration model PSLR, MLR and SVM. The number of PLS factors recommended by the Unscrambler chemometrics was used during the development of the PLSR model. The machine-learning algorithm goes through a combination of different pre-processing and regression techniques and predicts the best combination. To achieve the highest validation accuracy, the model predicted a combination of second derivative along with and MLR for SSC prediction whereas combination of normalization along with MLR for DM prediction. The prediction model was constructed in Anaconda deep learning framework of Python with a self-developed code.

The efficiency of the LED meter was calculated with the observation of the root mean square error for calibration (RMSEC), prediction (RMSEP) and the determination coefficient (R2). The findings of this analysis are also correlated with previously published low-cost and portable spectrometer data to measure the LED system output. When the paper to be compared has both calibration and validation models, it was compared with RMSEP because it is a rigorous calculation of the calibration model's prediction capacity. However, only calibration versions were available for certain records, in which case RMSEC was compared.

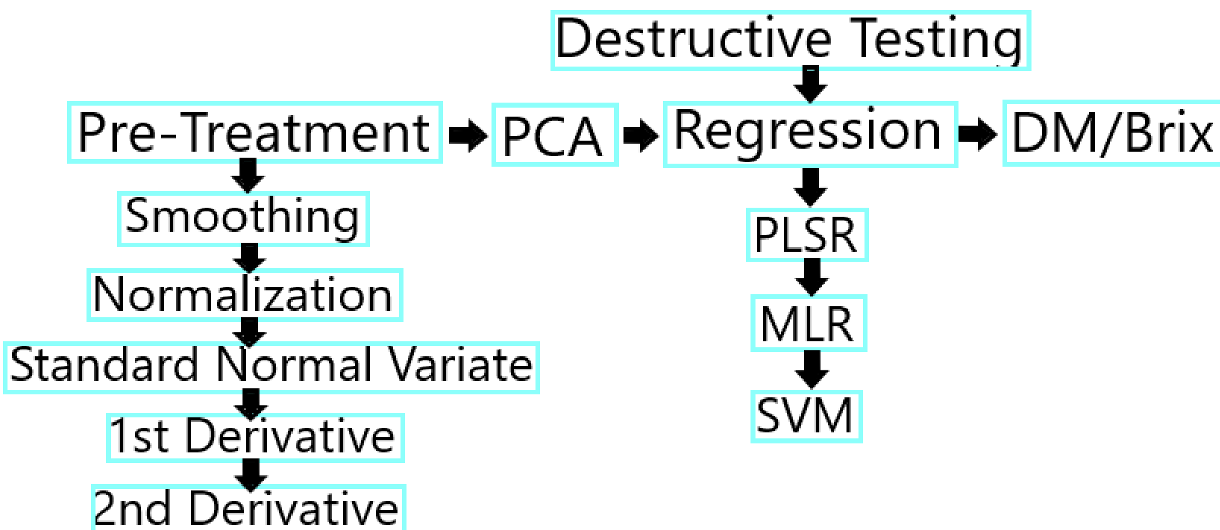

Figure 7: Block Diagram representing different techniques and methods of quality indices

CHAPTER 5: RESULTS AND DISCUSSION

5.1 DM Statistics

In Table 1., the statistics of Apple fruit samples in Batch-I (calibration set) and Batch-II (prediction set) on DM are illustrated. Table 1. Shows that there is total 240 no of samples of three different varieties of apples fruit such as Golden Delicious, Red Delicious Pak and Red Delicious Turk. In Batch-I (calibration set) there are total 180 no of samples of apples fruit each variety has 60 no of apples fruit. DM values have min and max range of 13.5 – 17.4, 12.5 – 16.4, and 12.8 – 15.3. In Batch-II (prediction set) there are total 60 no of samples of apples fruit each variety has 20 no of apples fruit. DM values have min and max range of 12.8 – 18.1, 12.9 – 16.8, and 12.4 – 15.7. DM have small distribution range of 12.4 – 18.1.

Table 1: Statistics on DM of Apple fruit in Batch-I and Batch-II

Fruit Batch	# of Sample	Fruit Variety	Min DM	Max DM	Mean ± Standard Deviation
	60	Golden Delicious	13.5	17.4	15.5 ± 2.0
I	60	Red-Delicious	12.5	16.4	14.5 ± 2.0
	60	Red-Delicious	12.8	15.3	14.1 ± 1.3
	20	Golden Delicious	12.8	18.1	15.5 ± 2.7
II	20	Red-Delicious	12.9	16.8	14.9 ± 1.9
	20	Red-Delicious	12.4	15.7	14.1 ± 1.6
Total	240	---	12.4	18.1	15.3 ± 2.9

Table 2: Statistics on SSC of Apple fruit in Batch-I and Batch-II

Fruit Batch	# of Sample	Fruit Variety	Min SSC	Max SSC	Mean ± Standard Deviation
I	60	Golden Delicious	11.0	14.7	12.9 ± 1.9
	60	Red-Delicious	9.7	13.5	11.6 ± 1.9
	60	Red-Delicious	9.7	12.6	11.2 ± 1.5
II	20	Golden Delicious	10.4	15.0	12.7 ± 2.3
	20	Red-Delicious	9.8	13.1	11.5 ± 1.7
	20	Red-Delicious	9.1	11.9	10.5 ± 1.4
Total	240	---	9.1	15.0	12.1 ± 3.0

5.2 SSC Statistics

In Table 2., the statistics of Apple fruit samples in Batch-I (calibration set) and Batch-II (prediction set) on SSC are illustrated. Table 2. Shows that there is total 240 no of samples of three different varieties of apples fruit such as Golden Delicious, Red Delicious Pak and Red Delicious Turk. In Batch-I (calibration set) there are total 180 no of samples of apples fruit each variety has 60 no of apples fruit. SSC values have min and max range of 11.0 – 14.7, 9.7 – 13.5, and 9.7 – 12.6. In Batch-II (prediction set) there are total 60 no of samples of apples fruit each variety has 20 no of apples fruit. SSC values have min and max range of 10.4 – 13.1, 9.8 – 13.1, and 9.1 – 11.9. DM have small distribution range of 19.1 – 15.0.

5.3 Spectral Overview

5.3.1 Felix F-750

Felix F-750 spectrometer is the fruit measurement device, which we have used as a benchmark device. we have trained different varieties of apple fruits in this device and the graph shows that the full absorbance spectra of three different varieties of apple fruits i.e., Red delicious Pak, Red delicious Turkey and Golden delicious. Different color shows different varieties of apple absorbance spectra with a wavelength range of 400 nm – 1100 nm. Which is shown in Fig 8. But in my research, I have required the wavelength range from 725 nm – 976 nm which is for the measurement of fruit quality indices i.e., soluble sugar content (SSC) and dry matter (DM) as shown in Fig 9. It is shown that the validated model of three different varieties of apple which has an accuracy of 96 %.

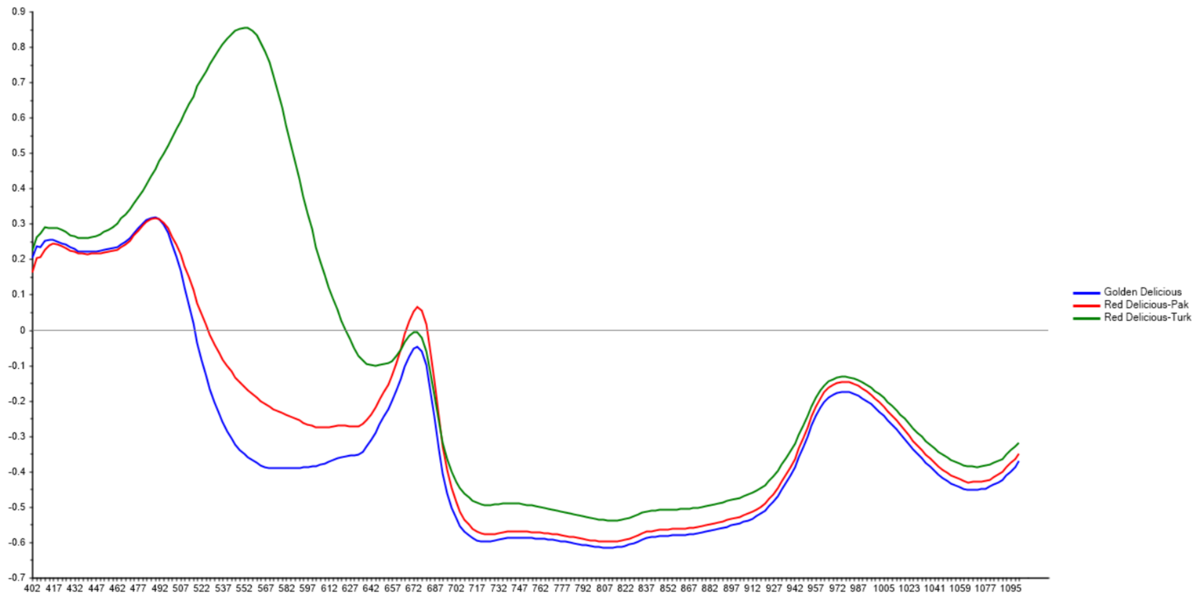

Figure 8: Felix F-750 Full absorbance Spectra of 3x Apples varieties

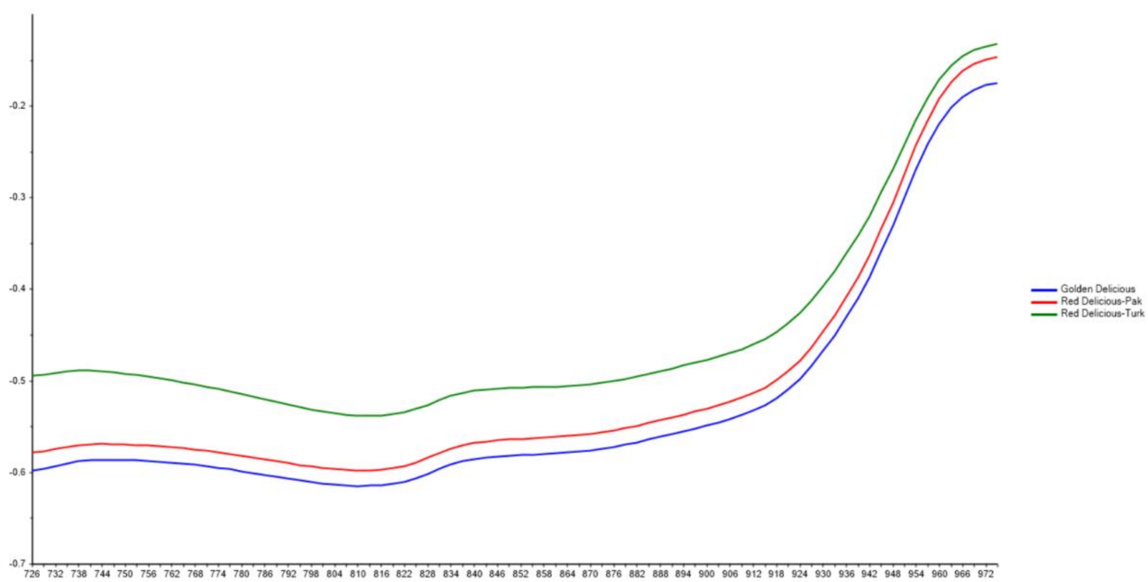

Figure 9: Felix F-750 Absorbance spectra of 3x Apples varieties of quality indices range

5.3.2 LED Quality Meter

LED Quality Meter is a handheld device which is developed for the measurement of fruit quality indices i.e., Soluble sugar content and Dry matter. The main purpose of the development of this device was cost minimization because there are different devices available in the market, but their cost is too high. So, I was used four different types of wavelengths of LED light which had a range from 700 nm – 1000 nm and a range to measure the quality indices. I was trained my dataset with these range of wavelength with three different varieties of apple fruits and in the graph golden delicious shown in blue color, red delicious-Pak shown in red color and red delicious-Turk shown in green color. The mean absorbance spectra of each variety of apple fruit as shown in Figure 10.

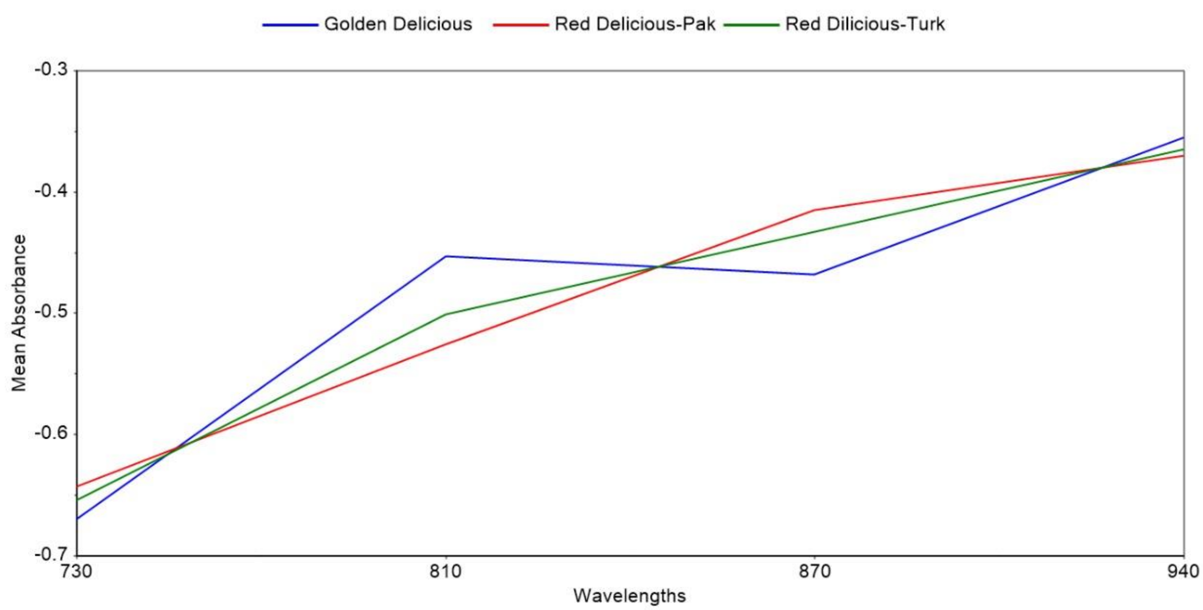

Figure 10: Mean Absorbance spectra of three different varieties of apple fruit from Led quality meter

5.4 Modeling Results

5.4.1 Dry Matter

For dry matter (DM) multi-linear regression (MLR) techniques shows best result followed by support vector machine (SVM), where is partial least square regression (PLSR) shows poor results, with in multi-linear regression techniques (MLR) normalization pre-processing technique shown best result correlation coefficient (R). correlation coefficient R = 0.85 and root mean square error

RMSE = 1.59. In PLSR regression techniques standard normal variate (SNV) shows maximum value of R = 0.52 and RMSE = 1.68 and SVM regression techniques smoothing shows maximum value of R = 0.59 and RMSE = 1.58. overall regression techniques multi-linear regression (MLR) shows a best result as shown in table 3.

Table 3: Prediction model of DM with different regression techniques

Preprocessing	Prediction Set					
	PLSR		MLR		SVM	
	R	RMSE	R	RMSE	R	RMSE
None	0.49	1.76	0.80	1.83	0.59	1.59
Smoothing	0.49	1.73	0.80	1.83	0.59	1.58
Normalization	0.51	1.71	0.85	1.59	0.57	1.61
SNV	0.52	1.68	0.79	1.85	0.52	1.70
1st derivative	0.48	1.72	0.81	1.78	0.55	1.65
2nd derivative	0.40	1.80	0.83	1.67	0.47	1.72

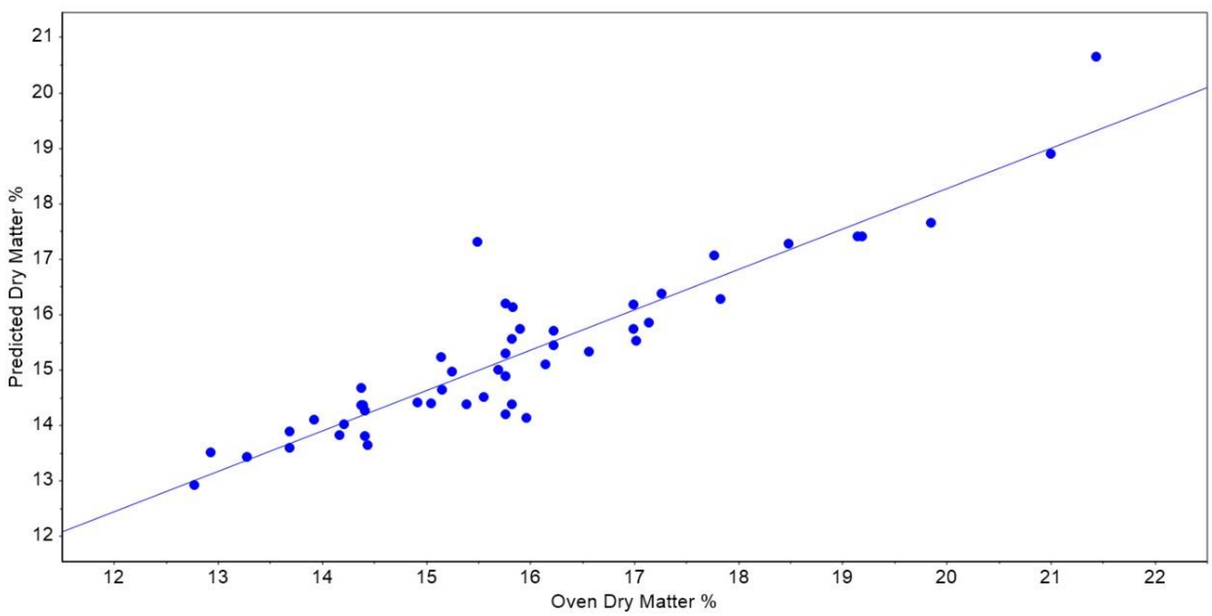

Figure 11: Prediction results for a MLR based DM model using normalization Spectra

5.4.2 Soluble Sugar Content

For soluble sugar content (SSC) multi-linear regression (MLR) techniques shows best result followed by support vector machine (SVM), where is partial least square regression (PLSR) shows poor results, with in multi-linear regression techniques (MLR) second derivatives pre-processing technique shown best result correlation coefficient (R). correlation coefficient R = 0.82 and root mean square error RMSE = 1.51. In PLSR regression techniques standard normal variate (SNV) shows maximum value of R = 0.40 and RMSE = 1.56 and SVM regression techniques smoothing shows maximum value of R = 0.46 and RMSE = 1.52. overall regression techniques multi-linear regression (MLR) shows a best result as shown in table 4.

Table 4: Prediction model of SSC with different regression techniques

Preprocessing	Prediction Set					
	PLSR		MLR		SVM	
	R	RMSE	R	RMSE	R	RMSE
None	0.33	1.63	0.73	1.81	0.46	1.52
Smoothing	0.36	1.59	0.73	1.81	0.46	1.52
Normalization	0.37	1.60	0.79	1.63	0.44	1.54
SNV	0.40	1.56	0.76	1.73	0.41	1.57
1st derivative	0.38	1.54	0.74	1.77	0.44	1.53
2nd derivative	0.32	1.62	0.82	1.51	0.40	1.56

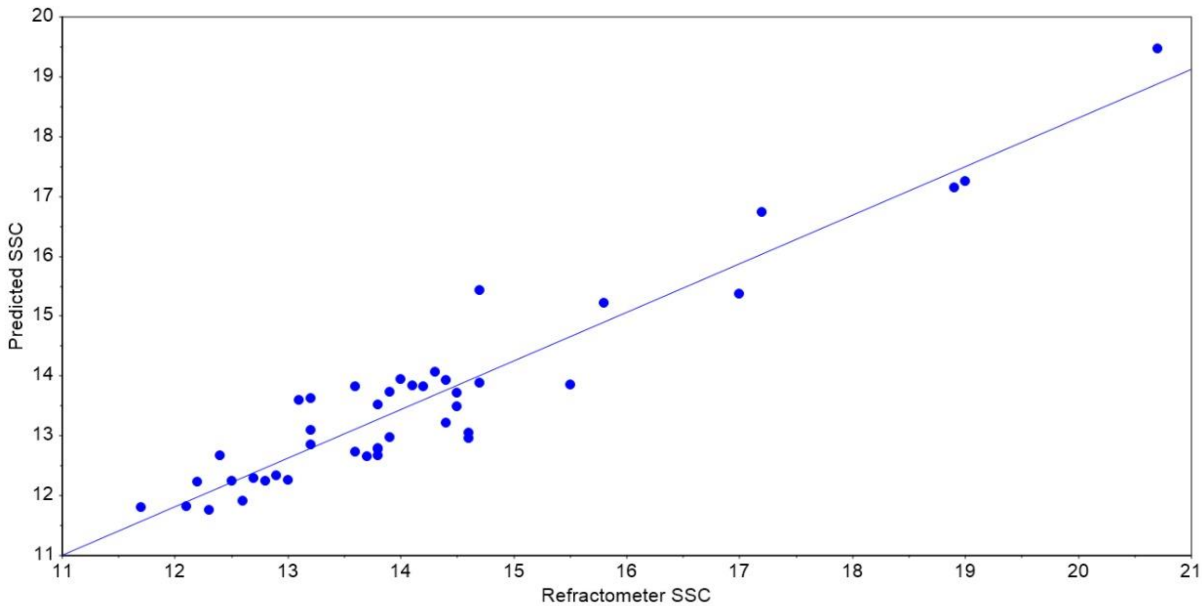

Figure 12: Prediction results for a MLR based SSC model using 2nd derivative spectra

5.5 Discussion

5.5.1 Temperature effect on LED

Performance of LED was evaluated on temperature change. In ambient temperature at 25 ^{o} C, the wavelength of led shows response as per its datasheet with the increased in temperature at 10 ^{o} C interval from 35^{o} C to 65^{o} C. The wavelength shifted towards right as shown in Figure 13. The peak was clipped due to larger distance between the LED and spectrometer in the experiment. As per LED datasheet, the relative radiant power will decrease in response to increase in temperature.

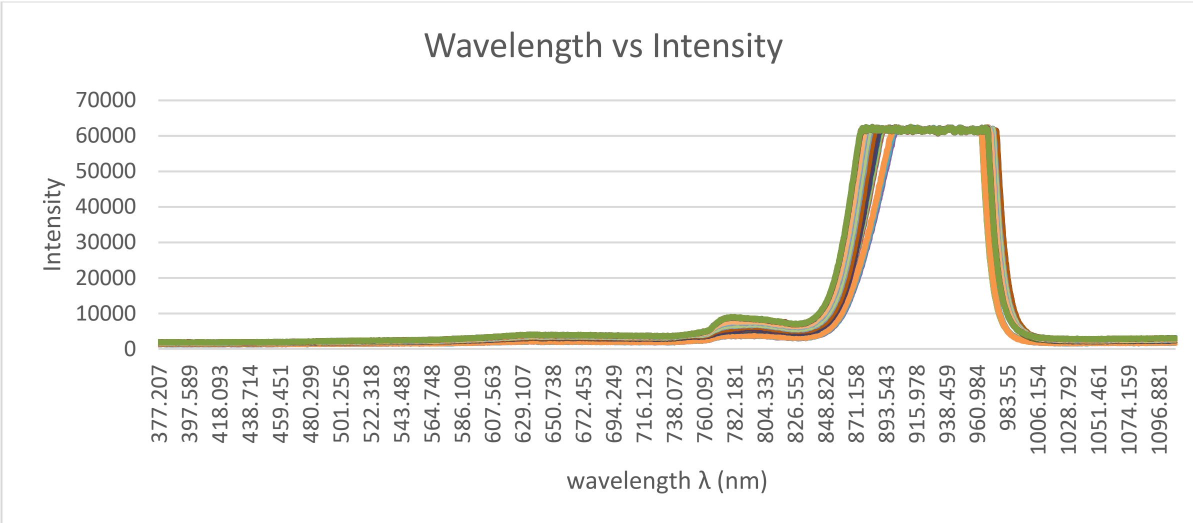

Figure 13: Wavelength vs Intensity graph

To validate the temperature reading display of temperature chamber. An additional thermocouple was used. In Figure 14 and Figure 15 show that the graph of chamber display temperature vs thermocouple (mv) and temperature vs thermocouple temperature (^{0} C) graph. In Figure 2 show that with the increases in temperature of chamber, thermocouple values also increase linearly and vice versa.

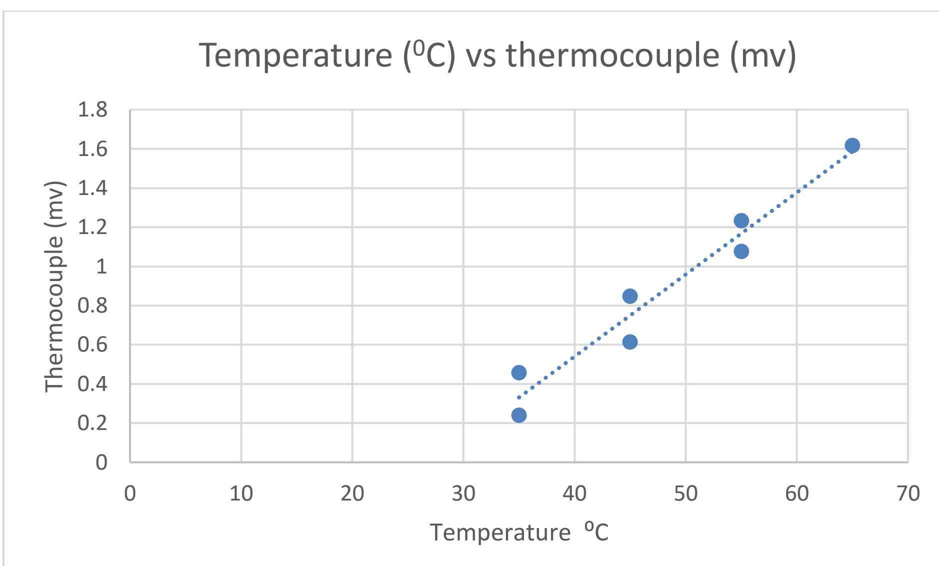

Figure 14: Temperature vs Thermocouple graph

To find out the error between temperature with thermocouple convert mv into ^{0}C. For this we use interpolation formula to convert mv to ^{0}C. Interpolation formula as shown below.

$$T_M = T_L + [(V_M - V_L)/(V_H - V_L)](T_H - T_L)$$

Where

v_M is the measured voltage

v_H is the higher voltage read from the table

v_L is the lower voltage read from the table

T_M is the calculated temperature

T_H is the higher temperature read from the table (corresponding to v_H)

T_L is the lower temperature read from the table (corresponding to v_L)

Figure 15: Interpolation formula for calculating thermocouple temperature

In Figure 15 show that with the increase in temperature thermocouple temperature increases linearly and vice versa.

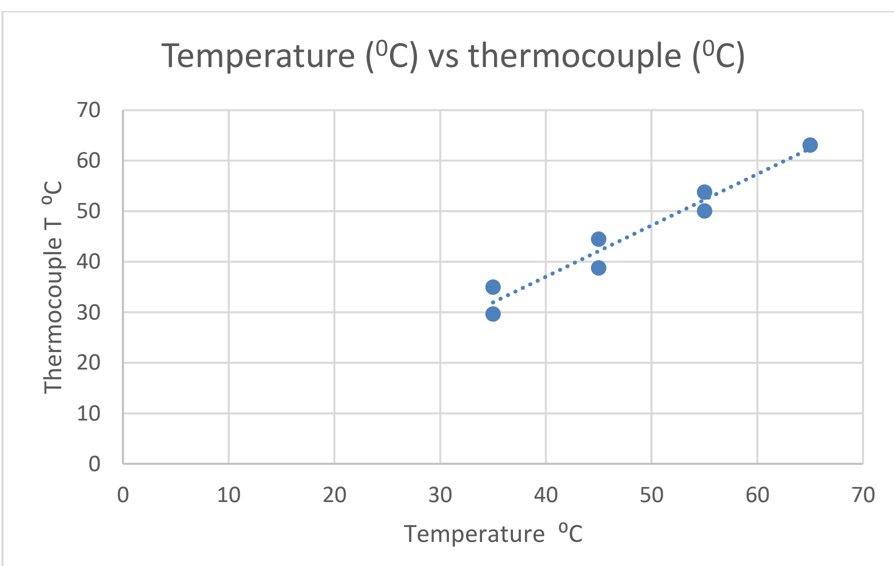

Figure 16: Temperature vs Thermocouple temperature graph

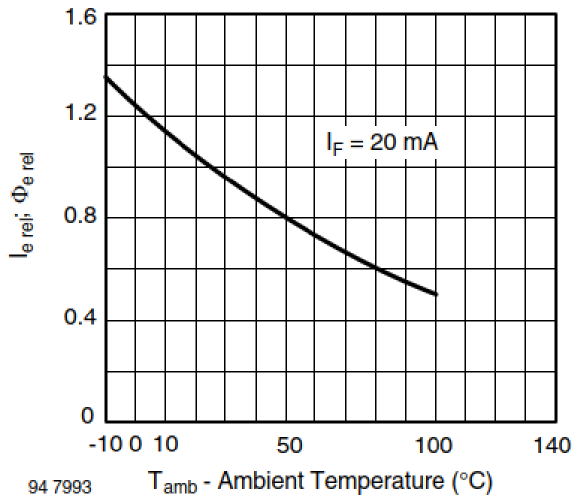

Figure 17: Relative Radiant intensity/power vs ambient Temperature

In data sheets, graph shows that with the increase of temperature the power of light decreases which mean as we increase the temperature the intensity of light decreases and shift to longer wavelength as shown in Figure 16 and 17. In our results show that there are four parameters are important i.e., temperature, distance, Intensity of light and angle because temperature effect the intensity of light and distance between led and photo transistor disturb the peak of the wavelength. The angle between LED fruit and phototransistor (receiver) is important as in Figure 18 of datasheet, LED intensity variable with angle. At ^{0}C LED light intensity is high but as we increase the temperature (^{0}C), the intensity of light decreases.

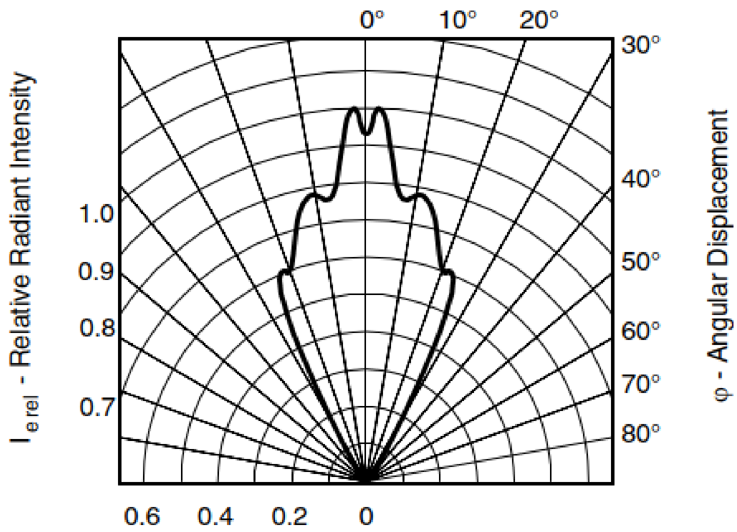

Figure 18: Relative Radiant Intensity vs Angular Displacement

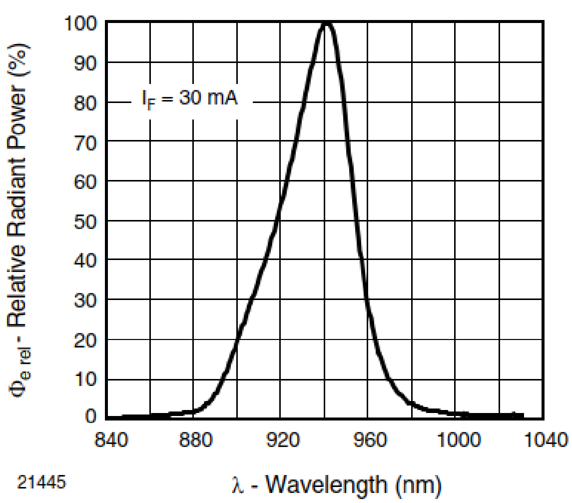

Figure 19: Relative Radiant power vs wavelength

We used photo transistor which has receive the range of 500 – 1050 nm wavelength as shown in Figure 20 of datasheet. In photo transistor (receiver) angle is important parameter which is directly linked with relative sensitivity. Wide rage of angle shows that changing the angle direction there is change in relative sensitivity percentage as shown in Figure 19.

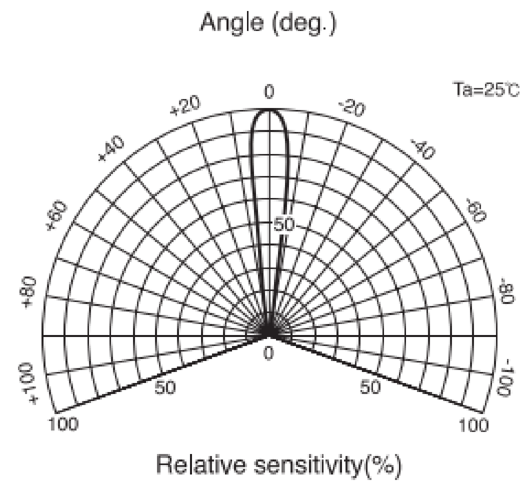

Figure 20: Radiant pattern

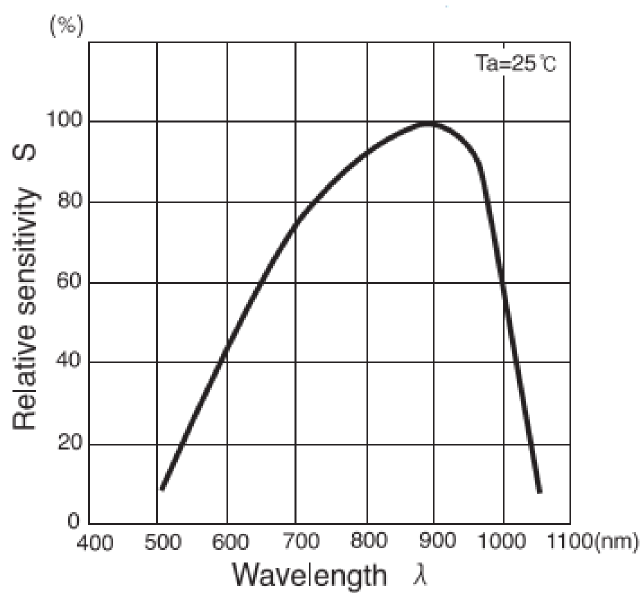

Figure 21: Relative sensitivity vs wavelength

5.5.2 Angle measurement with photodetector

Development of the LED device their geometry played an important role, but most important parameter is the angle between fruit and photodetector. So, I have performed an experiment for the measurement of angle, for this I have used servo motor MG 699R with their 16-channel driver module PCA 9685 and Arduino mega 2560 for processing the code. To check the angle at the difference of 5 degree start from 0 to 30 degree. So, experiment was started and moved step by step, in each step there is a different angle. I was visualized and measure each step and their behavior while LED light interact from the apple fruit sample and show a peak high, I had seen a maximum peak at 30 degrees in my experiment. In my PCB circuit I was used four different wavelengths of LEDs i.e., 730 nm, 810 nm ,870 nm and 940 nm. Each LED placed at 30 degree and distance between each LEDs was 2 cm from detector and detector and fruit sample distance is same as 2 cm as shown in Figure 21.

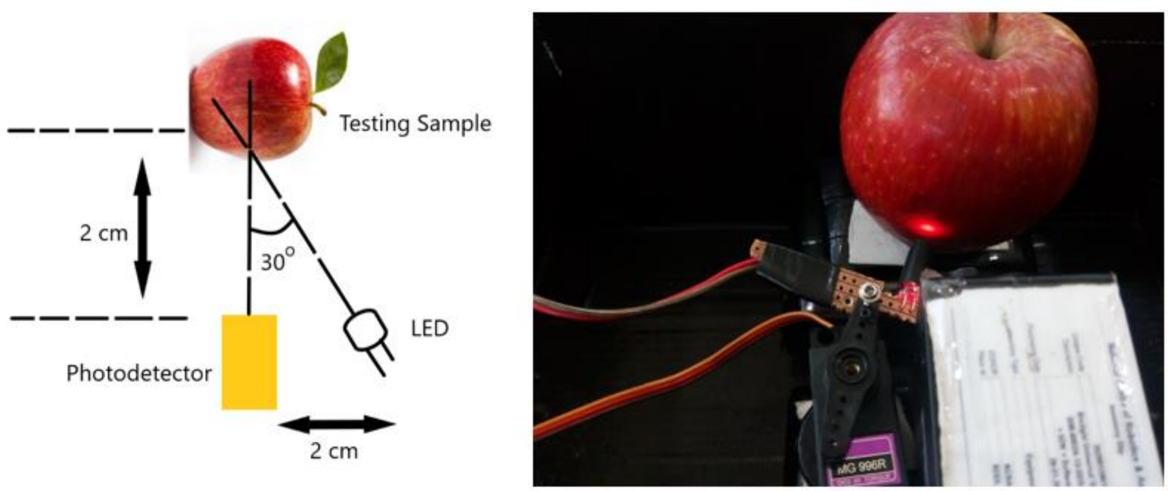

Figure 22: Angle measurement Test bench

In the above experiment, the result shown in software Bro-Light spectral viewer BSV_V2.0.8. There are two axes in the screen X-axis and Y-axis. In X-axis there is a wavelength measurement and in Y-axis there is an intensity measurement, so the graph is measured between wavelength vs intensity. The range of wavelength from 0 nm – 1100 nm and range of intensity from 0 – 5000. It

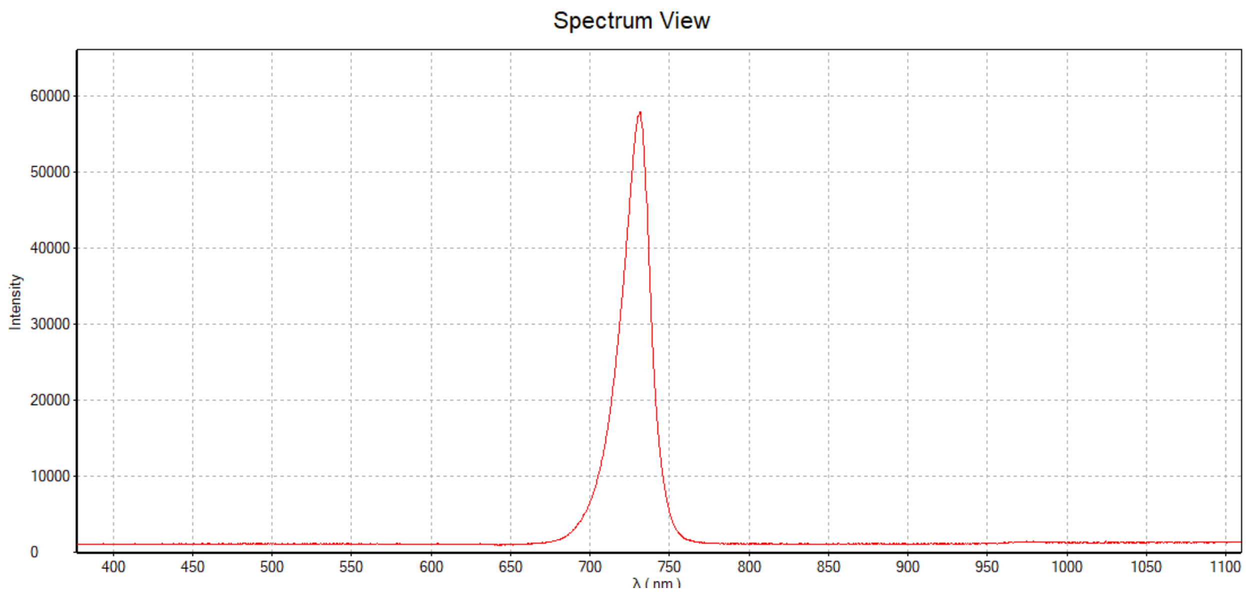

Figure 23: Angle measurement of peak value at 30 degree

is used for measurement of different spectrum of the lights, and I had used it for the measurement of the accuracy of angle with different wavelength of LED light. Integration time of the spectrum was 200 millisecond and the maximum peak show at 30-degree angle of 730 nm wavelength of LED as shown in Figure 22.

5.5.3 Design Optimization

Prototype handheld device has been trained and tested with different varieties of apple samples and results showed that MLR gave best result for both SSC and DM as compared to PLSR and SVM. The results were satisfactory, but in order to improve the results, several experimental exercises have been conducted. In consideration of these experimental results, the design of the prototype has been reviewed. During design optimization, four main parameters were considered i.e., distance, temperature, intensity of light and interactance angle. These parameters are already being discussed above in detail.

After implementing these revisions, a new prototype has been designed and fabricated as depicted in Fig. 24. Then again, final prototype has been trained and tested on different varieties of Apple fruit samples. For both SSC and DM, MLR technique shows best result followed by SVM and PLSR, with in multi-linear regression techniques (MLR) normalization pre-processing technique shown best result for DM with an improvement of R from 0.75 to 0.85 but with cost of RMSE from 1.32 to 1.59. Whereas for SSC, the results show improvement in R from 0.65 to 0.79 with the same RMSE of 1.51.

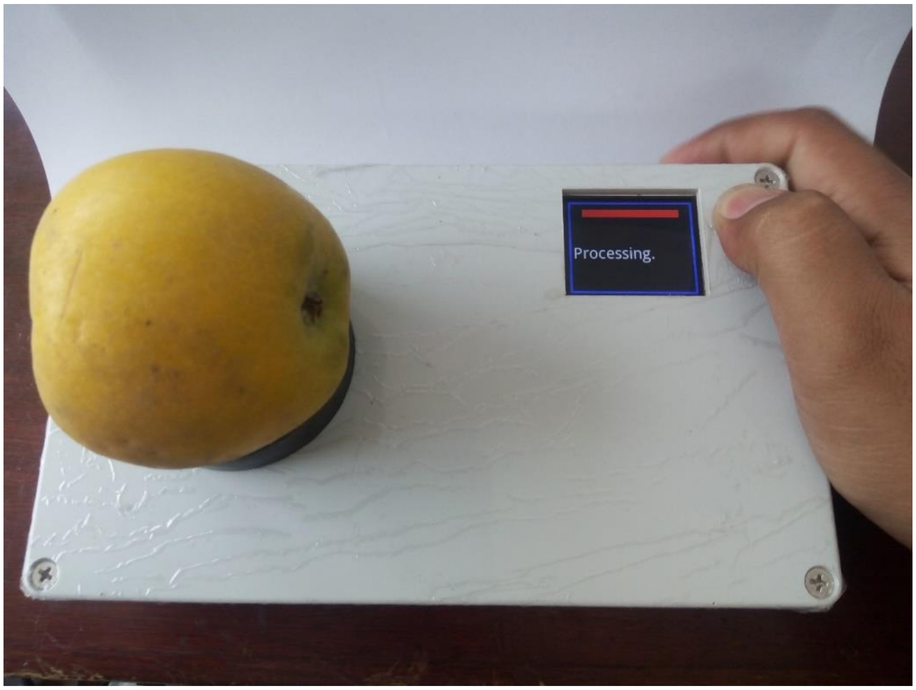

Figure 24: New Prototype of Fruit Quality Meter

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

A new low cost, handheld and easy to use optical device was presented for measuring apple fruit quality indices such as soluble sugar content (SSC) and dry matter (DM). The developed handheld device trained by different regression method using different preprocessing techniques to predict different varieties of apple fruit. To develop the handheld optical device, it was composed of four different wavelengths of NIR LED light i.e., 730 nm, 810 nm, 870 nm, and 940 nm, photodetector, analog to digital converter ADS 1115, Raspberry pi 4 controller for processing the data, rechargeable lithium-ion battery 18650 with charging battery shield v3 and 1.7-inch Lcd display for displaying the reading. Embedded a Raspberry pi software in Raspberry pi and run a code which was wrote in python. The handheld optical device was collected the spectra of each LED and compare the data with trained regression model and destructive testing measurement of dry matter and soluble sugar content was compare with the reference dry matter and soluble sugar content was shown in the display as in the form of dry matter and soluble sugar content. The total time was collected each spectrum 1.5 sec and the integrated time of photodetector sensor was 200 ms. The developed handheld optical device was trained by three different varieties of apple i.e., golden delicious, red delicious Pak and red delicious Turkey. In 2019, I was visited in Faisalabad to validate a model which was built in model of Felix F-750 spectrometer instrument with three different varieties of apple fruit. So, the built-in model was shown a satisfactory result, I was used these result and destructive testing results as a benchmark. Different regression methods were used for trained the dataset such as partial least square regression (PLSR), multi-linear regression (MLR) and support vector machine (SVM) using preprocessing techniques such as smoothing, normalization, standard normal variate (SNV), 1st Derivatives and 2nd Derivatives. These was the different methods and techniques which were used to trained and test our dataset. After that principal component analysis (PCA) for computing to change the basis of data and predicted the data with correlation coefficient (R) and root mean square error (RMSE). Predicted set for dry matter showed that multi-linear regression using normalization techniques best result. The correlation coefficient R = 0.85 and root mean square error RMSE = 1.59 and partial least square regression and support vector machine showed poor result whereas in PLSR, R = 0.52 and RMSE = 1.68 and in SVM, R = 0.59 and RMSE = 1.58. Predicted set for soluble sugar content showed that multi-linear regression using second Derivatives techniques best result. The correlation coefficient R = 0.82 and root mean square error RMSE = 1.51 and partial least square regression and support vector machine showed poor result whereas in PLSR, R = 0.40 and RMSE = 1.56 and in SVM, R = 0.46 and RMSE = 1.52. Hence, non-destructive result compared with the benchmark device and destructive testing for the measurement of quality indices. Performance of low-cost handheld optical device evaluated by three different varieties of local apples fruits. Developed device show good performance in comparison of Felix F-750 handheld spectrometer instrument. In future with the improvement of hardware and concentrated the validation of accuracy and the measurement of quality indices of different fruits it will compete with other handheld devices.

6.2 Future work

Future work will be concentrated on further design optimization and validating the accuracy of the developed quality meter for other commodities as well as to analyse the different factors that effects the performance of the developed fruit quality meter. Currently, handheld device has only four LEDs of different wavelength. In order to improve the hardware and performance of the device, quantity of LEDs need to be increased up to at least 12 LEDS of different wavelength range from 725 nm – 975 nm which is used for measuring SSC and DM in fruits.

Furthermore, if the calibration model is transferred to another developed fruit quality 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 fruit quality meter and then the resulting model should be validated with additional samples.

REFERENCES

[1] *Characterization and Management of Food Loss and Waste in North America*, vol. Foundation. 2017.

[2] K. Foster, “Spoiled, Rotten, and Left Behind,” in *How to Feed the World*, 2018.

[3] A. Knight, “Food Climate Research Network (FCRN) | Knowledge for better food systems,” *Food Clim. Res. Netw.*, 2010.

[4] M. Mari, S. Bautista-Baños, and D. Sivakumar, “Decay control in the postharvest system: Role of microbial and plant volatile organic compounds,” *Postharvest Biol. Technol.*, 2016, doi: 10.1016/j.postharvbio.2016.04.014.

[5] R. Kaipia, I. Dukovska-Popovska, and L. Loikkanen, “Creating sustainable fresh food supply chains through waste reduction,” *Int. J. Phys. Distrib. Logist. Manag.*, 2013, doi: 10.1108/IJPDLM-11-2011-0200.

[6] M. S. Ahmad, M. W. Siddiqui, M. S. Ahmad, and M. W. Siddiqui, “Factors Affecting Postharvest Quality of Fresh Fruits,” in *Postharvest Quality Assurance of Fruits*, 2015.

[7] A. A. Kader, “FRUIT MATURITY, RIPENING, AND QUALITY RELATIONSHIPS,” *Acta Hortic.*, vol. 485, no. 485, pp. 203–208, Mar. 1999, doi: 10.17660/ActaHortic.1999.485.27.

[8] J. A. Abbott, “Quality measurement of fruits and vegetables,” *Postharvest Biol. Technol.*, vol. 15, no. 3, pp. 207–225, Mar. 1999, doi: 10.1016/S0925-5214(98)00086-6.

[9] P. Barreiro, M. Ruiz-Altisent, C. Valero, and J. García-Ramos, “Fruit Postharvest Technology: Instrumental Measurement of Ripeness and Quality,” in *Production Practices and Quality Assessment of Food Crops*, Kluwer Academic Publishers, 2006, pp. 321–340.

[10] F. R. Harker, E. M. Kupferman, A. B. Marin, F. A. Gunson, and C. M. Triggs, “Eating quality standards for apples based on consumer preferences,” *Postharvest Biol. Technol.*, vol. 50, no. 1, pp. 70–78, Oct. 2008, doi: 10.1016/j.postharvbio.2008.03.020.

[11] R. L. Shewfelt, “What is quality?,” *Postharvest Biol. Technol.*, vol. 15, no. 3, pp. 197–200, Mar. 1999, doi: 10.1016/S0925-5214(98)00084-2.

[12] C. H. Crisosto and G. Costa, “Preharvest factors affecting peach quality,” in *The Peach: Botany, Production and Uses*, CABI Publishing, 2008, pp. 536–549.

[13] A. E. Watada, R. C. Herner, A. A. Kader, R. J. Roman!, and G. L. Staby, “Terminology for the Description of Developmental Stages of Horticultural Crops,” 1984.

[14] C. M. Kingston, “Maturity Indices for Apple and Pear,” in *Horticultural Reviews*, Oxford, UK: John Wiley & Sons, Inc., 2010, pp. 407–432.

[15] M. G. Villalobos-Acuña *et al.*, “Effect of maturity and cold storage on ethylene biosynthesis and ripening in ‘Bartlett’ pears treated after harvest with 1-MCP,”

Postharvest Biol. Technol., vol. 59, no. 1, pp. 1–9, Jan. 2011, doi: 10.1016/j.postharvbio.2010.08.001.

[16] G. A. Manganaris, A. R. Vicente, and C. H. Crisosto, "Effect of pre-harvest and post-harvest conditions and treatments on plum fruit quality," *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, vol. 3. Jan. 2008, doi: 10.1079/PAVSNNR20083009.

[17] L. Asín, S. Alegre, and R. Montserrat, "Effect of paclobutrazol, prohexadione-Ca, deficit irrigation, summer pruning and root pruning on shoot growth, yield, and return bloom, in a 'Blanquilla' pear orchard," *Sci. Hortic. (Amsterdam).*, vol. 113, no. 2, pp. 142–148, Jun. 2007, doi: 10.1016/j.scienta.2007.02.008.

[18] M. H. Behboudian, J. Marsal, J. Girona, and G. Lopez, "Quality and Yield Responses of Deciduous Fruits to Reduce Irrigation," in *Horticultural Reviews*, vol. 38, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2011, pp. 149–189.

[19] J. W. Johnston, E. W. Hewett, and M. L. A. T. M. Hertog, "Postharvest softening of apple (Malus domestica) fruit: A review," *New Zealand Journal of Crop and Horticultural Science*, vol. 30, no. 3. Taylor & Francis Group , pp. 145–160, 2002, doi: 10.1080/01140671.2002.9514210.

[20] S. J. Kays, "Preharvest factors affecting appearance," 1999.

[21] C. E. Sams, "Preharvest factors affecting postharvest texture," *Postharvest Biol. Technol.*, vol. 15, no. 3, pp. 249–254, Mar. 1999, doi: 10.1016/S0925-5214(98)00098-2.

[22] "Deficit Irrigation to Control Vegetative Growth in Apple and Monitoring Fruit Growth to Schedule Irrigation in: HortScience Volume 30 Issue 6 (1995)." .

[23] J. W. Palmer, F. R. Harker, D. S. Tustin, and J. Johnston, "Fruit dry matter concentration: A new quality metric for apples," *J. Sci. Food Agric.*, 2010, doi: 10.1002/jsfa.4125.

[24] J. M. BAIN and R. N. ROBERTSON, "The physiology of growth in apple fruits. I. Cell size, cell number, and fruit development.," *Aust. J. Sci. Res. B.*, vol. 4, no. 2, pp. 75–107, May 1951, doi: 10.1071/BI9510075.

[25] M. Patricia Denne, "Fruit development and some tree factors affecting it," *New Zeal. J. Bot.*, vol. 1, no. 3, pp. 265–294, 1963, doi: 10.1080/0028825X.1963.10428999.

[26] A. Malladi and P. M. Hirst, "Increase in fruit size of a spontaneous mutant of 'Gala' apple (Malus×domestica Borkh.) is facilitated by altered cell production and enhanced cell size," *J. Exp. Bot.*, vol. 61, no. 11, pp. 3003–3013, 2010, doi: 10.1093/jxb/erq134.

[27] B. G. Coombe, "The Development of Fleshy Fruits," *Annu. Rev. Plant Physiol.*, vol. 27, no. 1, pp. 207–228, Jun. 1976, doi: 10.1146/annurev.pp.27.060176.001231.

[28] C. Pratt, "Apple Flower and Fruit: Morphology and Anatomy," in *Horticultural Reviews*, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2011, pp. 273–308.

[29] R. . M. B. . G. D. and J. D. Wills, "Postharvest An Introduction to the Physiology and Handling of Fruit, Vegetables and Ornamentals.," vol. 2, 2007.

[30] *Horticultural Reviews*. John Wiley & Sons, Inc., 1992.
[31] F. R. . R. R. J. . H. I. C. . M. S. H. Harker, *Texture of fresh fruit*. 1997.
[32] J. Ackermann, M. Fischer, and R. Amadò, "Changes in Sugars, Acids, and Amino Acids during Ripening and Storage of Apples (cv. Glockenapfel)," *J. Agric. Food Chem.*, vol. 40, no. 7, pp. 1131–1134, Jul. 1992, doi: 10.1021/jf00019a008.
[33] M. Colaric, F. Stampar, and M. Hudina, "Content levels of various fruit metabolites in the 'Conference' pear response to branch bending," *Sci. Hortic. (Amsterdam).*, vol. 113, no. 3, pp. 261–266, Jul. 2007, doi: 10.1016/j.scienta.2007.03.016.
[34] A. A. Kader, "Fruits in the global market. In Knee, M. (Ed.) Fruit Quality and Its Biological Basis ," 2002.
[35] B. Shipley and T.-T. Vu, "Dry matter content as a measure of dry matter concentration in plants and their parts," *New Phytol.*, vol. 153, no. 2, pp. 359–364, Feb. 2002, doi: 10.1046/j.0028-646X.2001.00320.x.
[36] J. Wu *et al.*, "Chemical compositional characterization of some apple cultivars," *Food Chem.*, vol. 103, no. 1, pp. 88–93, Jan. 2007, doi: 10.1016/j.foodchem.2006.07.030.
[37] V. A. McGlone, D. G. Fraser, R. B. Jordan, and R. Künnemeyer, "Internal quality assessment of mandarin fruit by vis/NIR spectroscopy," *J. Near Infrared Spectrosc.*, 2003, doi: 10.1255/jnirs.383.
[38] B. M. Nicolaï *et al.*, "Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review," *Postharvest Biol. Technol.*, vol. 46, no. 2, pp. 99–118, Nov. 2007, doi: 10.1016/j.postharvbio.2007.06.024.
[39] B. Park, J. A. Abbott, K. J. Lee, C. H. Choi, and K. H. Choi, "Near-infrared diffuse reflectance for quantitative and qualitative measurement of soluble solids and firmness of Delicious and Gala apples," *Trans. Am. Soc. Agric. Eng.*, 2003, doi: 10.13031/2013.15628.
[40] P. Geladi and E. Dåbakk, "An Overview of Chemometrics Applications in near Infrared Spectrometry," *J. Near Infrared Spectrosc.*, vol. 3, no. 3, pp. 119–132, Jun. 1995, doi: 10.1255/jnirs.63.
[41] S. Wold, "Chemometrics; what do we mean with it, and what do we want from it?," *Chemom. Intell. Lab. Syst.*, vol. 30, no. 1, pp. 109–115, 1995, doi: 10.1016/0169-7439(95)00042-9.
[42] E. Bobelyn, A.-S. Serban, M. Nicu, J. Lammertyn, B. M. Nicolai, and W. Saeys, "Postharvest quality of apple predicted by NIR-spectroscopy: Study of the effect of biological variability on spectra and model performance," *Postharvest Biol. Technol.*, vol. 55, no. 3, pp. 133–143.
[43] B. M. Nicolaï, K. I. Theron, and J. Lammertyn, "Kernel PLS regression on wavelet transformed NIR spectra for prediction of sugar content of apple," *Chemom. Intell. Lab. Syst.*, vol. 85, no. 2, pp. 243–252, Feb. 2007, doi: 10.1016/j.chemolab.2006.07.001.
[44] S. Wold, K. Esbensen, and P. Geladi, "Principal component analysis," *Chemom.*

Intell. Lab. Syst., vol. 2, no. 1–3, pp. 37–52, Aug. 1987, doi: 10.1016/0169-7439(87)80084-9.
[45] R. L. King, C. Ruffin, F. E. LaMastus, and D. R. Shaw, “The analysis of hyperspectral data using Savitzky-Golay filtering-practical issues. 2,” Jan. 2003, pp. 398–400, doi: 10.1109/igarss.1999.773512.
[46] A. Candolfi, R. De Maesschalck, D. Jouan-Rimbaud, P. A. Hailey, and D. L. Massart, “The influence of data pre-processing in the pattern recognition of excipients near-infrared spectra,” *J. Pharm. Biomed. Anal.*, vol. 21, no. 1, pp. 115–132, Oct. 1999, doi: 10.1016/S0731-7085(99)00125-9.
[47] S. Wold, M. Sjöström, and L. Eriksson, “PLS-regression: A basic tool of chemometrics,” in *Chemometrics and Intelligent Laboratory Systems*, 2001, doi: 10.1016/S0169-7439(01)00155-1.
[48] S. Sohaib Ali Shah *et al.*, “Towards Fruit Maturity Estimation Using NIR Spectroscopy,” *Infrared Phys. Technol.*, p. 103479, Sep. 2020, doi: 10.1016/j.infrared.2020.103479.
[49] R. Lu and D. Ariana, “A near-infrared sensing technique for measuring internal quality of apple fruit,” *Appl. Eng. Agric.*, 2002.
[50] H. Kaur, R. Künnemeyer, and A. McGlone, “Comparison of hand-held near infrared spectrophotometers for fruit dry matter assessment,” *J. Near Infrared Spectrosc.*, 2017, doi: 10.1177/0967033517725530.
[51] W. Guo, W. Li, B. Yang, Z. Z. Zhu, D. Liu, and X. Zhu, “A novel noninvasive and cost-effective handheld detector on soluble solids content of fruits,” *J. Food Eng.*, 2019, doi: 10.1016/j.jfoodeng.2019.03.022.
[52] P. S. Bhunase M, “Near infrared spectroscopy for fruit quality analysis. ,” *Int J Eng Res Technol* , 1998.
[53] H. Wang, J. Peng, C. Xie, Y. Bao, and Y. He, “Fruit quality evaluation using spectroscopy technology: A review,” *Sensors (Switzerland)*. 2015, doi: 10.3390/s150511889.
[54] F. García-Sánchez, L. Galvez-Sola, J. J. Martínez-Nicolás, R. Muelas-Domingo, and M. Nieves, “Using Near-Infrared Spectroscopy in Agricultural Systems,” in *Developments in Near-Infrared Spectroscopy*, InTech, 2017.
[55] T. J. Yeong, K. P. Jern, L. K. Yao, M. A. Hannan, and S. T. G. Hoon, “Applications of photonics in agriculture sector: A review,” *Molecules*, vol. 24, no. 10, 2019, doi: 10.3390/molecules24102025.
[56] Dufour É, “ Principles of infrared spectroscopy. In: Sun DW (ed) Infrared spectroscopy for food quality analysis and control. Academic Press, San Diego,” 2009.
[57] N. Zealand and J. Feng, “Segregation of ‘Hayward’ kiwifruit for storage potential,” Massey University, 2003.
[58] B. Kemps, L. Leon, S. Best, J. De Baerdemaeker, and B. De Ketelaere, “Assessment of the quality parameters in grapes using VIS/NIR spectroscopy,” *Biosyst. Eng.*, 2010, doi: 10.1016/j.biosystemseng.2010.02.002.

[59] S. Zhang, H. Zhang, Y. Zhao, and H. Zhao, “Comparison of modeling methods of fresh jujube soluble solids measurement by NIR spectroscopy,” *Nongye Jixie Xuebao/Transactions Chinese Soc. Agric. Mach.*, 2012, doi: 10.6041/j.issn.1000-1298.2012.03.021.

[60] B. S. . C. Y. R. . M. G. E. . S. Bennedsen, “Appli3 peaches. In: Monitoring food safety, agriculture, and plant health. ,” vol. 5271, pp. 347–355, 2004.

[61] V. González-Caballero, M. T. Sánchez, M. I. López, and D. Pérez-Marín, “First steps towards the development of a non-destructive technique for the quality control of wine grapes during on-vine ripening and on arrival at the winery,” *J. Food Eng.*, vol. 101, no. 2, pp. 158–165, Nov. 2010, doi: 10.1016/j.jfoodeng.2010.06.016.

[62] O. A. L. J. C. X. Liu YD, Ed., “Near infrared diffuse reflectance spectroscopy for rapid analysis of soluble solids content in navel orange. ,” 2007, pp. 2190–2192.

[63] V. A. McGlone and S. Kawano, “Firmness, dry-matter and soluble-solids assessment of postharvest kiwifruit by NIR spectroscopy,” *Postharvest Biol. Technol.*, 1998, doi: 10.1016/S0925-5214(98)00007-6.

[64] P. N. Schaare and D. G. Fraser, “Comparison of reflectance, interactance and transmission modes of visible-near infrared spectroscopy for measuring internal properties of kiwifruit (Actinidia chinensis),” *Postharvest Biol. Technol.*, vol. 20, no. 2, pp. 175–184, Sep. 2000, doi: 10.1016/S0925-5214(00)00130-7.

[65] B. Greg Mitchell and D. A. Kiefer, “Chlorophyll α specific absorption and fluorescence excitation spectra for light-limited phytoplankton,” *Deep Sea Res. Part A, Oceanogr. Res. Pap.*, vol. 35, no. 5, pp. 639–663, May 1988, doi: 10.1016/0198-0149(88)90024-6.

[66] M. Zude-Sasse, I. Truppel, and B. Herold, “An approach to non-destructive apple fruit chlorophyll determination,” *Postharvest Biol. Technol.*, 2002, doi: 10.1016/S0925-5214(01)00173-9.

[67] R. Van Beers, B. Aernouts, R. Watté, A. Schenk, B. Nicolaï, and W. Saeys, “Evolution of Vis/NIR bulk optical properties of apple skin and flesh during fruit maturation,” in *Near Infrared Spectroscopy: Proceedings of the International Conference*, Sep. 2015, vol. I, doi: 10.17648/nir-2015-34270.

[68] S. S. K. S. I. T. S. V. Williams PC, “Applications to agricultural and marine products. In: Ozaki Y, McClure WF, Christy AA (eds) Near-infrared spectroscopy in food science and technology.,” *2006*, pp. 163–277.

[69] S. N. Jha, “Food quality and safety: An overview,” in *Nondestructive Evaluation of Food Quality: Theory and Practice*, Springer Berlin Heidelberg, 2010, pp. 1–16.

[70] A. Moghimi, M. H. Aghkhani, A. Sazgarnia, and M. Sarmad, “Vis/NIR spectroscopy and chemometrics for the prediction of soluble solids content and acidity (pH) of kiwifruit,” *Biosyst. Eng.*, 2010, doi: 10.1016/j.biosystemseng.2010.04.002.

[71] V. A. McGlone, C. J. Clark, and R. B. Jordan, “Comparing density and VNIR methods for predicting quality parameters of yellow-fleshed kiwifruit (Actinidia

chinensis)," *Postharvest Biol. Technol.*, vol. 46, no. 1, pp. 1–9, Oct. 2007, doi: 10.1016/j.postharvbio.2007.04.003.

[72] T. Ignat *et al.*, "Forecast of Apple Internal Quality Indices at Harvest and During Storage by VIS-NIR Spectroscopy," *Food Bioprocess Technol.*, vol. 7, no. 10, pp. 2951–2961, Sep. 2014, doi: 10.1007/s11947-014-1297-7.

[73] M. Li, R. R. Pullanagari, T. Pranamornkith, I. J. Yule, and A. R. East, "Quantitative prediction of post storage 'Hayward' kiwifruit attributes using at harvest Vis-NIR spectroscopy," *J. Food Eng.*, vol. 202, pp. 46–55, Jun. 2017, doi: 10.1016/j.jfoodeng.2017.01.002.

[74] S. Kawano, "Present Condition of Nondestructive Quality Evaluation of Fruits and Vegetables in Japan," *undefined*, 1994.

[75] G. Rateni, P. Dario, and F. Cavallo, "Smartphone-based food diagnostic technologies: A review," *Sensors (Switzerland)*, vol. 17, no. 6. MDPI AG, Jun. 2017, doi: 10.3390/s17061453.

[76] M. Li, Z. Qian, B. Shi, J. Medlicott, and A. East, "Evaluating the performance of a consumer scale SCiO^{TM} molecular sensor to predict quality of horticultural products," *Postharvest Biol. Technol.*, vol. 145, pp. 183–192, Nov. 2018, doi: 10.1016/j.postharvbio.2018.07.009.

[77] P. P. Subedi and K. B. Walsh, "Assessment of avocado fruit dry matter content using portable near infrared spectroscopy: Method and instrumentation optimisation," *Postharvest Biol. Technol.*, vol. 161, p. 111078, 2020, doi: https://doi.org/10.1016/j.postharvbio.2019.111078.

[78] Y. Liu, R. Gao, Y. Hao, X. Sun, and A. Ouyang, "Improvement of Near-Infrared Spectral Calibration Models for Brix Prediction in 'Gannan' Navel Oranges by a Portable Near-Infrared Device," *Food Bioprocess Technol.*, vol. 5, no. 3, pp. 1106–1112, 2012, doi: 10.1007/s11947-010-0449-7.

Completion Certificate

It is certified that the thesis titled **"Design, Implement and Benchmark a Low-Cost Optical Device for Measuring Brix and Dry Matter in Fruits"** submitted by CMS ID. 00000206752, NS Syed Irfan Shah of MS-17 Mechatronics Engineering is completed in all respects as per the requirements of Main Office, NUST (Exam branch).

Supervisor: ________________

Dr. Waqar Shahid Qureshi

Date: ________ June, 2021