DEVELOPMENT AND EVALUATION OF A WOOD CLASSIFICATION SYSTEM USING A LOW-COST MINIATURE NIR SENSOR

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Mechatronics Engineering

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May 2023

DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"DEVELOPMENT AND EVALUATION OF A WOOD CLASSIFICATION SYSTEM USING A LOW-COST MINIATURE NIR SENSOR"** was prepared by **LEONG POU YEE** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Mechatronics Engineering at Universiti Tunku Abdul Rahman.

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ABSTRACT

Wood classification is a pivotal stage in wood processing, as a significant portion of commercially utilized wood species, known as "lesser-known", lack adequate visual characteristics based on anatomical features. NIRS has emerged as an effective and non-destructive technique for classifying wood species, surpassing the limitations of conventional methods. NIRS measures the absorption or emission of spectroscopic signals within the electromagnetic wave range of 800 nm to 2500 nm. In this study, the feasibility of employing NIRS for discriminating diverse wood species was assessed. A meticulously calibrated sensory system incorporating a sophisticated NIR sensor modeled AS7263 was constructed to capture and analyze spectral data, facilitating the identification of three wood species: Hevea, Jelutong, and Chengal. The data were acquired using the mode of diffuse reflectance, laying the foundation for subsequent comprehensive analysis and classification. The findings have proven that NIRS is a highly effective method for accurately categorizing various wood species based on the analysis of their distinct spectral data, irrespective of ambient conditions. Nonetheless, it is imperative to acknowledge that potential alterations in the wood surface may impact the reliability of the results.

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LIST OF SYMBOLS / ABBREVIATIONS

ADC	Analog-to-digital converter
ANN	Artificial Neural Networks
BPNN	Backpropagation neural network
CCI	Chlorophyll Content Index
CH	Carbon-hydrogen bond
CLE-PLS	Correlation linear embedding model
CNN	Convolutional Neural Network
CO	Carbon-oxygen bond
CT	Computed tomography
D-CNN	Deep Convolutional Neural Network
FT-NIR	Fourier Transform based near infrared spectroscopy
I2C	Inter-Integrated Circuit
IR	Infrared
KNN	K-nearest neighbors
MAPE	Mean absolute percentage error
MC	Moisture content
MOE	Modulus of elasticity (MOE)
MOR	Modulus of rupture
NH	Nitrogen-hydrogen bond
NIR	Near infrared
NIRS	Near infrared spectroscopy
OH	Hydroxyl group
PCA	Principal Component Analysis
PCR	Principal Component Regression
PLS	Partial Least Squares
PLS-DA	Partial least squares-discriminant analysis
PLSR	Partial Least Square Regression
R^2	Coefficient of determination
RMSECV	Root mean standard error for cross-validation
RMSEP	Root mean square error of prediction
Rp^2/R^2p	Determination of prediction coefficient

RPD	Ratio of performance to deviation
SEC	Standard error of calibration
SECV	Standard error of cross validation
SH	Thiol group
SPAD	Soil Plant Analysis Development
SSC	Soluble solids content
UART	Universal Asynchronous Receiver

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

Near infrared spectroscopy (NIRS) stands for absorption or emission of spectroscopy at NIR range. Near infrared region is the electromagnetic wave range between 800 nm and 2500 nm, which is in between visible range the infrared range (Ozaki, Huck and Beć, 2018). The application of chemometrics in near infrared spectroscopy allows researchers to determine how near-infrared radiation, regardless of its physical state as a solid, liquid, or gas transmits and reflects. In the 1980s, the first NIR spectrometers were developed for industrial applications and chemical analysis. Dispersive NIR (scanning) and Fourier Transform based (FT-NIR) are the two primary forms of NIR analyzers. Over the past decades, NIR spectroscopy has been applied in many industries and fields such as food, agriculture, polymer, textile, pharmaceutical and even applied sciences (Ozaki, Huck and Beć, 2018).

In NIRS, overtones and combination vibrations of molecules containing CH, NH, or OH groups make up the recorded NIR spectrum. For the analysis of organic compounds in the chemical and pharmaceutical industries, as well as in the food, feed, and agricultural industries, NIR spectroscopy is the preferred method. However, for most applications on solid wood, reflectance mode is used to acquire NIR spectra as reflectance mode can reflect and retain most of the information such as spectra data (Wang, et al., 2022).

NIRS is a powerful technique as it can evaluate chemical compositions of a substance within minutes, which is faster than the conventional detection approach. Besides it is a non-destructive method, NIRS is also environmentally friendly as no waste will be generated during the process. In addition to that, NIRS is cheaper due to its simple sample pretreatment processes. In contrast to that, there are also disadvantages in the NIRS technique. It has low sensitivity which results in higher detection limit due to low absorption coefficients. NIRS requires the use of multivariate calibration model for data analysis. The development of the model can be time-consuming as it requires a lot of samples whereby all sources of variability in the spectra must be included (Lanciki, 2020).

1.2 Importance of the Study

Wood is significant in wood industries to produce desired products. Before processing, different classes of wood must be categorized since they will reflect the wood quality. Even though some wood species that have different qualities and prices can be easily identified by skilled inspectors or workers in the wood industries, the details of wood identification might not be known by the online operators. Because different kinds of wood have distinct properties and features, they must be treated differently and separately during the process stage. It all depends on the wood mechanical and machining properties and by referring to the finished wood product. By doing so, wood species can be utilized optimally. Wood classification is therefore crucial for industrial utilization and in quality monitoring (Yang, et al., 2015). Wood classification also helps to increase the productivity in wood industries.

Observing the anatomical characteristics is one of the approaches to identify wood species in the industry. The harvested wood will normally be sent to a sawmill or dispersal area for processing. There will be various wood species to be processed at the same time, by just separating the wood species based on their anatomical features such as color, grain structure and density might mix up some of the timber when they are having the same secondary visual characteristics. This is because in some cases, certain wood species cannot be identified to the 'species' level. In contrast, some wood species can only be classified at a higher hierarchical level such as ‘Family’ and ‘genus’. In practice, anatomical characteristics of wood species are not distinctive enough in wood classification, therefore, it is often hard to tell the origin of a timber through its anatomical features, especially for those ‘lesser-known’ wood species. Almost 80 % of the commercially used wood species are of the ‘lesser-known’ species, whereby these kind of wood species might mix up with other wood species that are defined, the wood features and properties are thereby less known by the participants in the market (Kuilen, Ravenshorst and Gard, 2013).

Hence, by utilizing NIR spectroscopy as a non-destructive wood classification approach to separate various kinds of wood can boost the speed and efficiency in wood production.

1.3 Problem Statement

An essential component of wood processing and commerce is species classification. The conventional techniques for identifying wood species include microscopic detection, the use of physical, anatomical, and visual characteristics of wood species, as well as the recognition of wood texture, all of which are difficult, expensive and used up a lot of time (Kuilen, Ravenshorst and Gard, 2013). Hence, they cannot satisfy the present demands, especially for industries that require a high volume of classification processes. There are also some advancements that have appeared in wood classification technology to improve the identification processes, which includes DNA markers and chemical isotope approaches (Degen and Fladung, 2007). In 2007, it was proved that the DNA markers approach can identify six different wood species by determining the DNA fragments of these wood species. Whereas the chemical isotope approach is also able to classify wood species at high accuracy through stable isotope analysis (Yang, et al., 2015). However, despite their high capability in determining wood species, these two approaches are time-consuming where they take a long time in sample preparation and are not practical to be used in industries. To improve the classification process of wood species at lower cost, higher speed and higher accuracy, a non-destructive method, NIR spectroscopy can be used as an alternative in wood industries which requires little or no sample preparation.

Illegal logging involves the acts of harvest, transport, process, purchase, and sale of wood without authorization or in contravention of the law. Harvesting timber without permission or from a protected area itself is illegal. Besides, cutting down protected wood species and extracting timber beyond the agreed limits are also considered illegal logging. Wood laundering often happens all around the world including Malaysia, especially during transporting and exporting of timber through customs to avoid taxes and other charges (Loh and Yeo, 2022). Some companies even make fraudulent declarations to customs. Due to lack of classification and verification technology at customs, export inspections are only able to do verification on the quantity as well as the description of the timber until the taxes have been paid. The harvested timber has now become legal once it is loaded on a ship, provided that the local customs has endorsed shipping documents, even though the legality is obtained through fraudulent certification. It is important to know what species of wood is being transported through customs and its origin. Hence, without verification technology, there is no way to check on the illicit timber trade. Much effort must be put into this situation to tackle any illegal logging. One of them would be implementing NIR spectroscopy technology, which is a non-destructive and uncomplicated way to verify the wood species and its origin in a quick manner.

1.4 Aim and Objectives

This project aims to evaluate the feasibility of classifying several types of wood by using spectroscopic methods with a low-cost and portable NIR sensor. The NIR sensor should be able to classify different types of wood species, namely Hevea, Jelutong and Chengal.

Objectives:

1. To design and set up a properly calibrated sensory system with an NIR sensor to collect data from wood samples. Data collected from the system will be analyzed and the results will show the types of wood each specimen belongs to.
2. To tabulate the spectra data collected from the sensor and perform analysis on the data.
3. To evaluate the feasibility and accuracy of wood classification using the NIR sensor. The higher the accuracy of wood classification, the higher the feasibility of the NIR sensor.

1.5 Scope and Limitation of the Study

One of the requirements in this project is to build a wood classification system using a NIR sensor. The available wood samples, namely Hevea, Jelutong, and Chengal, are limited in number, and thus the database of wavelength readings from these types of wood may not be sufficient for the analysis. The data collection and analysis may be limited by the availability of only three types of wood, which may not be representative of the entire population of interest. This lack of information could make it difficult to evaluate the feasibility of the system being studied.

Another limitation in this study would be only the limited range of wavelengths available in the NIR sensor modeled AS7263. The spectrometer AS7263 is only able to detect NIR wavelengths ranging from 600 nm to 870 nm. The wavelengths that are out of the preset range will not be detected, in other words, the NIR sensor will not receive reflected wavelengths that are out of the range from the wood specimens when the system is operating in reflectance mode. This lowers the accuracy in wood identification processes as the number of spectra data collected from each wood species for analysis purposes will be reduced as well. The wood species can only be classified using the six channels multispectral sensing in the NIR sensor, whereby each channel represents one specific wavelength.

For most of the wood classification systems, NIRS is commonly used in diffuse reflectance mode. Therefore, even though NIRS can be measured in different modes such as transmittance and transflections mode to obtain spectra data, but in this study, only diffuse reflectance mode is suitable to be implemented in the data acquisition process of NIRS.

Lastly, NIRS technology's capability to differentiate between wood species that have similar chemical compositions may be limited in wood classification. Moreover, the accuracy of NIRS-based wood classification can be influenced by various factors, including wood age, growth conditions, and processing methods.

CHAPTER 2

LITERATURE REVIEW

2.1 Near Infrared Spectroscopy (NIRS)

Most of the studies that focus on the applications of NIRS in forestry stated that chemometric analysis was performed to estimate the physical, mechanical and chemical properties of solid wood from near infrared spectra, which mostly collected in reflectance mode. Application of NIRS in wood classification can be an accurate and useful way based on the research found. According to Tsuchikawa and Kobori (2015), Batista and team used a fiber optic NIR scan on different solid wood surfaces in order to identify the probability of wood classification. Only a small error was found in each classification of wood species, which indicates the reliability of NIRS in identifying solid wood. In the research done by Tsuchikawa and Kobori (2015), Espinoza and team showed the effectiveness of NIRS in distinguishing between pure pine species as well as the hybrids species. NIR was proved that it can identify softwood and hardwood species accurately and rapidly by a study conducted by Yang and team (2015). The research showed that NIRS can be used to classify eight rosewood samples by using Principal Component Analysis (PCA) through the Unscrambler software. Russ and Fiserova (2011) performed classification on 10 hardwood species by NIRS and the results obtained from PCA of hardwood NIR spectra showed high classification capability. Based on Tsuchikawa and Kobori (2015), Cooper and team stated that there were still weakness exists on wood classification by NIRS which may be due to factors like localized density variations of wood species and surface roughness, when they were trying to extract information from the wood samples such as moisture content.

The applications of NIR technology and instrumentation in forestry have been expanded due to recent advances in this field where wood classification can be performed through predictions of properties of wood samples as well as its feasibility and accuracy in classifying various wood species.

2.2 Traditional Alternatives in Wood Classification

Wood classification is one of the important parts in wood processing and commerce. Wood industries usually perform classification with eyesight of human where this manual method only contributes for about 55 % of accuracy in classification (Ristiawanto, Irawan and Setianingsih, 2019). There are also some traditional methods to classify different wood species, such as wood texture recognition and microscopic detection. These methods are complicated and require a higher cost. Also, they are time-consuming and hence, do not meet the current needs in wood classification technology (Hao, et al., 2019). In order to improve the correction rate of wood classification, some methods and techniques are commonly used by industries such as X-ray computed tomography (CT), Deep Convolutional Neural Network (D-CNN) and through ultrasonic waves.

X-ray computed tomography (CT) is known for being the most feasible method to identify roundwood by internal properties (Breinig, et al., 2015). Hence, CT scanners have been widely used at sawmills in order to identify the interior properties and external log shape of round wood. The logs will be scanned by CT scanner before sawing, followed by the measurements of knot from the simulated value-optimized center yield of 3D log data. After that, a camera-based grading was used for another set of knot measurements for dried timber. Quality assessment of timber will be performed based on the two sets of measurements, from CT data and camera-based scanning data, as well as manual visual grading as a reference. These data obtained will be analyzed by Partial Least Squares (PLS) Regression by creating a prediction model based on the two sets of knot measurements and the quality assessment data from the dry sorting (Olofsson, et al., 2019).

Convolutional Neural Network (CNN) is commonly used for segmentation of image, classification and recognition of object which gives accurate results. Since classification of wood is considered as a texture classification, CNN is suitable for this scenario. To further improve the accuracy of classification, Deep Convolutional Neural Network (D-CNN) is developed from the basis of CNN. This neural network is more suitable for smaller datasets. According to the research done by Ristiawanto, Irawan and Setianingsih (2019), D-CNN was used for wood classification with transfer learning approach and features of bottleneck, which can improve the performance of D-CNN. There were a total of five classes of wood to be graded based on their quality. From their results, 95.69% accuracy of successful wood classification can be achieved.

Besides that, ultrasonic signals can be used to identify distinct species in wood industries. Wood is an anisotropic inhomogeneous material, which is suitable for the passage of ultrasonic waves for classification purposes. This type of method requires complex interactions between the physical vibrations of the ultrasound as well as the wood elastic response. The ultrasound signal was further modified by passing through a transmission medium with elastic anisotropy characteristic. Since diverse types of wood exhibit different elastic responses, the characteristic signals obtained can be examined. These signals will be classified by using neural network system and high accuracy can be achieved, as seen in the studies by Jordan and team (1998).

Hence, wood classification can be performed in various methods such as X-ray computed tomography (CT), Deep Convolutional Neural Network (D-CNN) as well as through ultrasonic waves and most of it are commonly utilized in wood industries nowadays.

2.3 Applications of NIRS in Different Industries

NIR spectroscopy is known as a non-destructive method which is widely used in different sectors and industries to monitor the quality of food, industrial products etc. In the research done by Wang and group (2022), NIR spectral measurement system was used to determine the quality of Kyoho grapes based on their soluble solids content (SSC). As the skin of the grape is thin, the measurement was done in reflectance mode to reflect the internal information in the grapes as well as to obtain accurate spectral data. The spectral data and SSC obtained were both analyzed using MATLAB and The Unscrambler X software. Different methods were used for the analysis, but artificial neural networks (ANN) gave the most accurate results compared to other approaches including partial least squares regression, multiple linear regression and principal component regression. Based on ANN method, the RMSEP (root mean square error of prediction) had a value of 0.62 whereas for the determination of prediction coefficient (Rp^2) was 0.69.

In addition to that, NIR spectroscopy is utilized in milk classification for purity prediction of unknown milk samples. Deshpande, Deshpande and Dhande presented a paper in 2021 to determine the purity of unknown milk samples by utilizing NIRS and machine learning. There were six different values obtained from the NIR sensor based on different spectrum. The spectral data from different milk samples and the equivalent change in values of absorbance were collected. This data will then be used for milk classification between buffalo's milk and cow's milk by utilizing KNN (K-nearest neighbors) algorithm after training of the model. This paper showed that NIR spectroscopy can be used to predict milk purity using linear regression.

Hummel, Sudduth and Hollinger (2001) published a paper that documents the ability of NIR reflectance sensor to estimate the soil moisture and organic matter of surface and subsurface soils. The spectrum data will be obtained from six different types of soil with different moisture levels. These data will then be analyzed using stepwise multiple linear regression. Based on the findings, the standard error for predicting soil moisture was 5.31 % whereas for the organic matter of soil was 0.62 %.

Besides that, NIR sensor can also be used in sea water monitoring as presented in the paper by Wanderlingh, Branca and Vasi (2021). The quality of sea water can be monitored by analyzing the spectrum data collected from NIR sensor which determine the plankton content of the sea water as well as the presence of pollutants.

Trang and team (2019) presented a paper that measured Chlorophyll Content Index (CCI) by using NIR spectrometer. CCI works based on the principle of Soil Plant Analysis Development (SPAD) which determines the relative amount of chlorophyll in the leaf through the absorbance of two wavelengths, which are 653 nm and 931 nm. The higher the value of SPAD, the higher the chlorophyll concentration per leaf unit area. Figure 2.1 illustrates the SPAD system for CCI measurements.

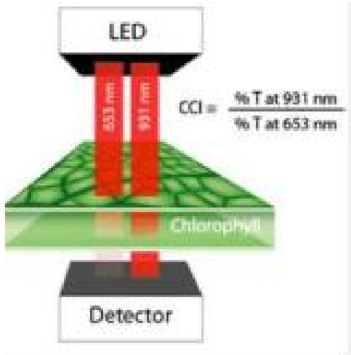


Figure 2.1: SPAD System for CCI Measurements. (Trang, et al., 2019)

The model of NIR sensor used in the project was AS7263 and powered by a Raspberry Pi. Based on the overview of the design, the leaf sample was placed in between the NIR spectrometer and the white LED light source. White LED can provide a wide spectrum of light. When it was turned on, the light will pass through the leaf sample and spectrometer will detect the light through its opening. There are optical components in the sensor where the wavelengths are struck on the photodetectors while the values of light intensity are converted from the photodiode voltages. The NIR spectrometer represents the wavelengths with 6 channels which correspond to 610 nm, 680 nm, 730 nm, 760 nm, 810 nm, and 860 nm. The absorption or transmission level of the leaf samples to specific wavelengths will determine the amplitude in each channel. The Raspberry Pi was used to receive this data and save it as an Excel file before being processed by computer. The data processed in computer will present six spectrum levels in the NIR region that signifies which spectrum levels were partially absorbed or partially passed through by the samples. Since the chlorophyll will absorb red light, the intensity of "red" in spectrometer and five other channels in NIR sensor will be take note. All the results obtained will then be analyzed using CCI.

In a nutshell, it can be concluded that the applications of NIR spectroscopy not only limited to agriculture sector, but it is also applicable to other industries as well.

2.4 Spectra Data Collection

Based on the research published by Schimleck and team (2018), the mechanical characteristics of clear wood samples (pine species) were estimated using NIR spectroscopy on radial and transverse surfaces of the wood, by identifying their density, modulus of elasticity (MOE) as well as modulus of rupture (MOR). A fiber-optic probe was used together with the NIR beam to capture the reflected NIR spectra from the wood surfaces. This was done by implementing a contact probe-equipped ASD AgriSpec backpack portable NIR spectrometer as well as a scanning spectrometer of Foss NIRSystems Model 5000.

Another research has been done by Yu and group (2019) to determine the MOE and MOR values of Mongolian oak wood by using an optical-fibre probe with one-chip spectrometer from INSION Co. Figure 2.2 shows the construction of spectrometer for spectrum data collection.

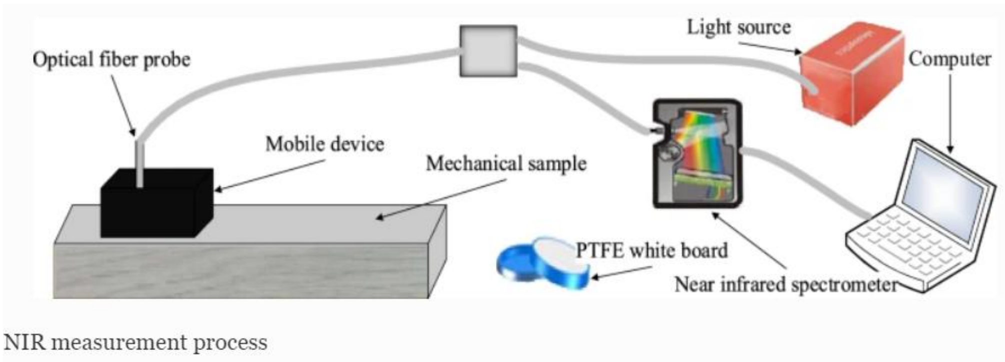


Figure 2.2: Spectrometer Construction for Spectrum Data Collection. (Yu, et al., 2019)

Besides MOE and MOR, moisture content (MC) is also widely used in the analysis of wood classification as found in the studies by Santos and team (2020). Forty Eucalyptus wood species were used for classification which the moisture content of each wood specimen was examined. The samples were first drenched with water to collect spectra data. At the same time, monitor the mass loss of each wood sample. The moisture content of those specimens is found to be 12 % at equilibrium level. After that, NIR spectra of the wood specimens were collected on three surfaces, namely radial, tangential, and transverse surfaces. Two methods were used respectively in spectra acquisition, which were integrating sphere and optical fiber. The network diagram for estimating moisture content with two acquisition approaches on different surfaces of wood is shown in Figure 2.3.

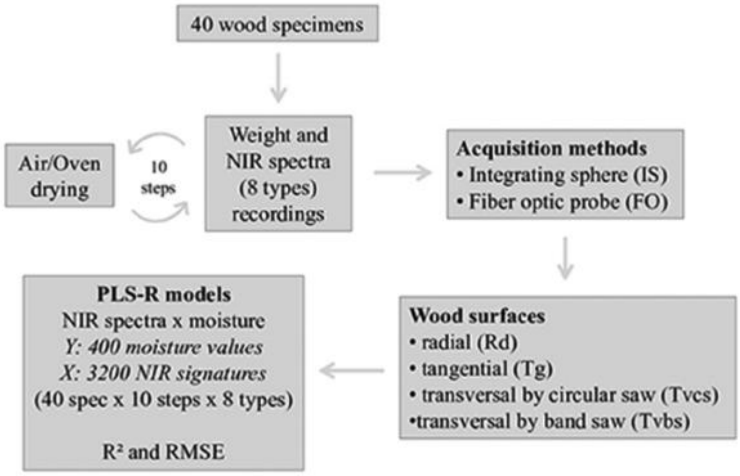


Figure 2.3: Network Diagram for Moisture Content Estimation. (Santos, et al., 2020)

Furthermore, in the research published by Kurata (2018), NIR spectroscopy was used to estimate the moisture content of two types of softwood (Chamaecyparis obtusa and Pseudotsuga menziesii) and the prediction accuracy was obtained. A monochromatic light source was used to irradiate the wood samples and the reflectance of the light was obtained. The wood samples that were stored in humidity chamber were first measured with NIR spectroscopy followed by drying the wood samples to calculate their water contents. This was to examine the correlation between the collected spectral data and the moisture content of various wood samples.

Moreover, Haartveit and Flæte (2008) had conducted two different cases of wood classification, including classification of Scots pine into heartwood and sapwood and separation of various spruce species.In the case of classifying heartwood and sapwood, 32 scans of spectra were collected and averaged in reflectance mode by using a NIR Systems 6500 spectrophotometer with an optic-fibre probe. Whereas for the spruce species, PerkinElmer Spectrum One NTS system and Near Infrared Reflectance Accessory (NIRA) were used to collect scanning of spectra of the wood samples.

The studies done by Braga and team (2011) showed that NIR spectroscopy can be utilized to classify solid wood samples of Swietenia Macrophylla by using a Tensor 37 FT-IR spectrometer and a fiber-optic probe to collect spectra data of each wood sample.

Peng and team (2021) presented a paper to estimate the walnut kernel's moisture content using NIRS. The spectrometer used was FOSS NIRS DS2500. The tungsten halogen lamp and the spectrometer were both utilized to collect the NIR spectrum with wavelength range from 780 nm to 2500 nm from the walnut.

In addition to that, Watanabe, Mansfield and Avramidis (2011) conducted a study to classify green hem-fir timber by means of NIR system with the predicted value of moisture content and compare it with the values obtained using commercial capacitance type of moisture meter. The accuracy of the NIR system was then evaluated. In their study, LF-1900 spectrometer was used in the mode of reflectance and the spectra data were collected at 4nm intervals between 1200 nm and 2116 nm. The fiber optic probe was positioned on the wood samples at 90 °. As a reference, a piece of commercial microporous Tefl was used. DC lamps were illuminated on the surface of the samples at 30 ° and then it was placed perpendicular to the samples in longitudinal direction. Ten scans were performed on each sample and the results will be averaged to obtain a single spectrum. Both spectra from upper and bottom surface of each wood sample were obtained. the collected data were divided into a calibration set and a validation set, which a total of 108 out of 180 spectra data were calibration set whereas the remaining will be the validation set. These data will then be used in multivariate analysis for green hem-fir timber prediction.

Moreover, Yang and team (2015) conducted a study to identify three types of wood, namely Pometia sp., Instia sp. and Couratari sp. For each of the species, 105 samples were collected so a total of 315 samples were to be used in the analysis. The spectra of wood will be collected at 1nm intervals within the range of wavelength from 350 nm to 2500 nm. The NIR system consisted of an ASD Field Spec spectrometer, a white background of Teflon and a 8 mm light spot that mounted on the fiber-optic probe. Each wood sample will be illuminated at three sections, including cross, radial, and tangential sections to collect the spectra data for further analysis.

Collection of spectrum data by using NIRS can be performed in many ways, using spectrometer, normally equipped with an optic-fiber probe to identify the mechanical characteristics of wood samples for classification purposes.

2.5 Interpreting and Analyzing Spectra Data

Schimleck and team presented a paper in 2018 which used partial least squares (PLS) regression, standard error of calibration (SEC), standard error of cross validation (SECV) and coefficient of determination (R^2) to perform analysis to estimate the calibration performance of NIR spectroscopy on different pine wood species.

In the studies of Yu and group (2019), correlation linear embedding model (CLE-PLS) was used to estimate the modulus of elasticity (MOE) as well as modulus of rupture (MOR) of Mangolian oak wood to investigate the relationship of those values with NIR spetra collected from the experiment. Figure 2.4 shows the development of CLE-PLS model.

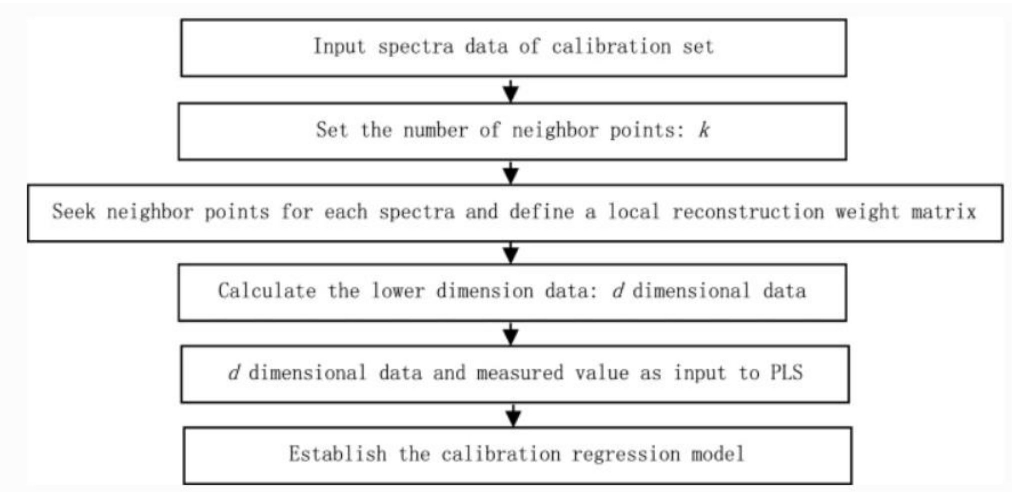


Figure 2.4: Development of CLE-PLS Model. (Yu, et al., 2019)

Partial Least Squares (PLS) regression and Principal Component Analysis (PCA) were calculated to analyse the correlation of the wood moisture content in the research of Santos and team (2020). PLS is a linear modeling technique used to compress the spectra and project the data onto PLS components. Partial least square (PLS) regression is used for dependent variables prediction and its analysis based on a set of independent variables. The prediction can be done by extracting the orthogonal factors (latent variables) from the independent variables. When an exceptionally large set of independent variables are available, PLS regression is useful in this case to predict dependent variables. Whereas PCA is a popular technique of multivariate data analysis. It is suitable for large datasets by reducing high dimensions data to lower dimensions while retaining information as much as possible. PCA can also improve interpretability of the datasets (Jolliffe and Cadima, 2016). The ratio of performance to deviation (RPD), which is calculated as the ratio between the standard deviation of the reference values and the root mean square error is used to evaluate the performance of wood classification. The coefficient of determination (R^2) will be used to further assess the LS-R model's precision in estimating the wood samples' moisture content based on the estimated and reference values obtained. As a result, the spectra data obtained from the wood samples' transverse surfaces by integrating sphere method gave the best performance with R^2p equaled 0.96 and RMSEP equaled 8.56 % whereas for the method of fiber-optic probe, R^2p equaled 0.83 and RMSEP equaled 20.09 %. Hence, it is the ideal model to estimate the Eucalyptus wood species' moisture content (Santos, et al., 2020).

According to Kurata's findings in 2018, two softwoods were predicted in their moisture content using NIR spectroscopy and principal component regression (PCR). PCR is a technique that decreases a great number of explanatory variables to a smaller number of principal components in a regression model. The datasets are usually first performed using PCA, after that, the treated data will go through PCR for dimension reduction (Artigue and Smith, 2019). The values of R^2 varied between 0.93 to 0.96 while RMSECV varied between 0.82 to 1.01 for the calibration results. Whereas the prediction results ranged from 0.86 to 0.93 for R^2 and 0.75 to 0.97 for RMSEP. The calibration performance of the models was good as there was no difference in the PCR results obtained (Kurata, 2018). Table 2.1 below calibrated the PCR results for moisture content prediction by using pretreated NIR spectrum.

Table 2.1: PCR Results for Moisture Content Prediction. (Kurata, 2018)

Species	Section	Factors	R^2	RMSECV	R_p^2	RMSEP
C. obtusa	Cross section	3	0.93	0.99	0.88	0.85
	Radial section	3	0.95	0.83	0.89	0.75
	Tangential section	3	0.95	0.82	0.90	0.82
P. menziesii	Cross section	3	0.94	0.98	0.86	0.75
	Radial section	3	0.96	0.87	0.93	0.87
	Tangential section	3	0.95	1.01	0.90	0.97

According to Haartveit and Flæte (2008), Partial Least Squares (PLS) Regression models obtained an accuracy value of 96.3 % in the classification between sapwood and heartwood, whereas for the separation of spruce species was 94 %, which both results showed that the classification performance were good.

In the studies of Braga and team in 2011, since the NIR spectra data of different wood samples (Swietenia Macrophylla) collected were similar, as shown in Figure 2.5, a visual inspection of NIR spectra was not helpful for wood classification in this case.

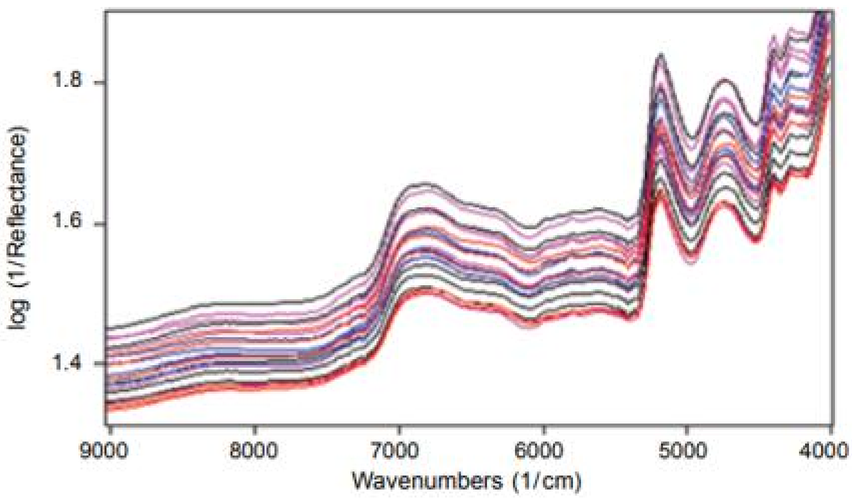


Figure 2.5: NIR Spectra Data. (Braga, et al., 2011)

Hence, PLS-DA models were used to analyze the spectra data of wood specimens instead. However, studies showed that this analytic method would only be suitable for routine classification of large volume of wood samples as it can perform better distributions and predict probabilities (Braga, et al., 2011).

In the study conducted by Watanabe, Mansfield and Avramidis (2011) to classify green hem-fir timber, the spectra data collected from wood samples were separated into calibration and validation set respectively, wherein 72 of the 180 spectra data were the validation set and 108 of the 180 spectra data were classed as the calibration set. Figure 2.6 shows the PLS model of predicted moisture content by using NIR system versus the actual value of moisture content obtained using oven-dry approach (calibration set). The solid line indicated whether the predicted values matched the measured values (R^2 =1). This PLS regression model exhibited high accuracy in predicting the moisture content, which ranged from 35 % to 105 %.

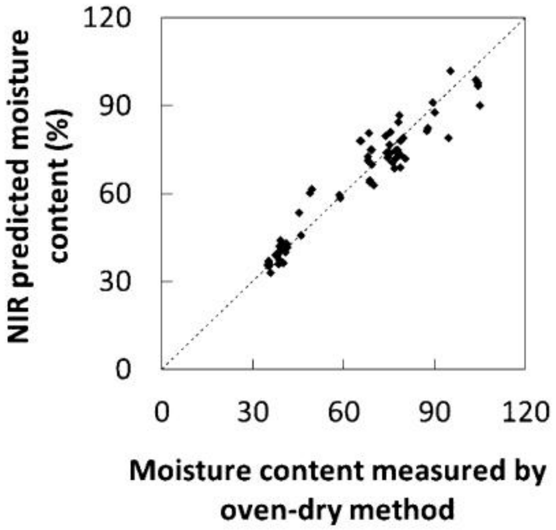


Figure 2.6: PLS Model of Predicted Moisture Content versus Actual Moisture Content. (Watanabe, Mansfield and Avramidis, 2011)

This showed that PLS regression model was suitable to use for moisture content prediction within the basic density range which was between 298 kg/m^3 to 508 kg/m^3. Also, without the requirement for an adjustment for wood density, the NIR system was useful for moisture content prediction.

The three most common chemometric approaches used in these studies were PLS regression, PCA and PCR where they were suitable for larger datasets or samples for better distributions and predict probabilities.

2.6 NIR Sensor AS7263

Wang and group presented a paper in 2022 that utilize a NIR spectral system with NIR sensor modeled AS7263 to determine the quality of Kyoho grapes based on their soluble solids content (SSC). The data collected from this sensor will be averaged to obtain a mean value for further analysis. Figure 2.7 shows the NIR sensor prototype.

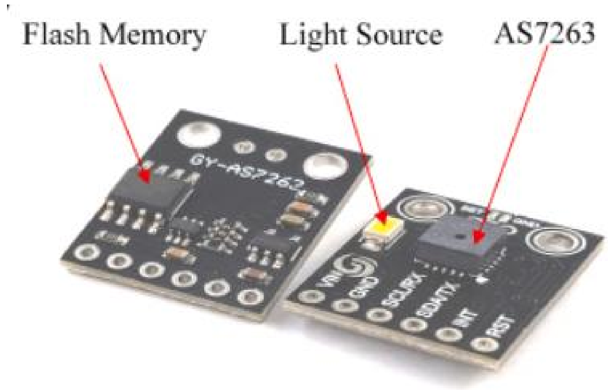


Figure 2.7: NIR Sensor Prototype. (Wang, et al., 2022)

Trang and team (2019) published a research paper that measured the Chlorophyll Content Index (CCI) by using NIR sensor modeled AS7263 and powered by a Raspberry Pi. Figure 2.8 shows the overview of the system and the prototype used.

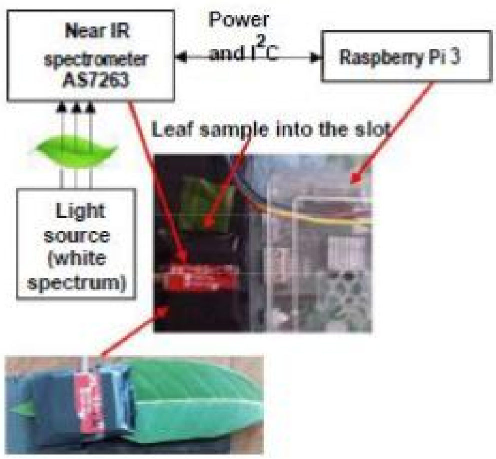


Figure 2.8: Overview of NIR System in CCI Measurement. (Trang, et al., 2019)

In the study of Sulistyo and team (2021), a NIR spectrometer was built using AS7263 sensor and Arduino. The sensor will capture the NIR reflectance signals of siamese oranges. In their design, an LED was used to emit the orange samples' surface, while the reflected light from the samples' surface will then be captured by the AS7263 sensor and the data will be sent through the Arduino for interpretation. Figure 2.9 shows the design of NIR spectrometer in this paper.

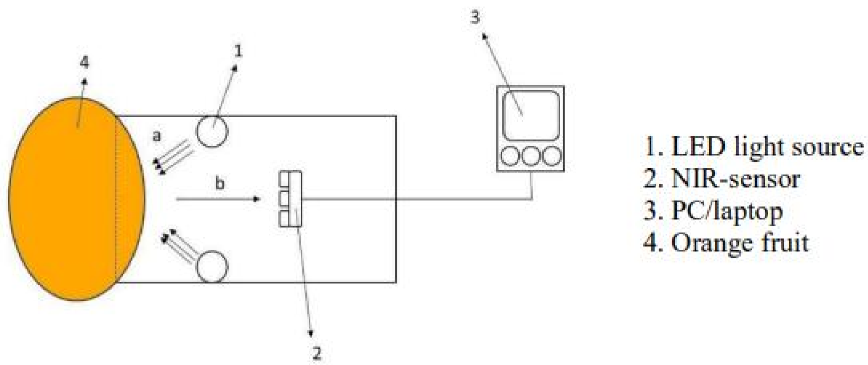


Figure 2.9: Design of NIR Spectrometer. (Sulistyo, et al., 2021)

The accuracy of classification will be estimated using mean absolute percentage error (MAPE) with three different methods, by means of simple regression, multiple regression and backpropagation neural network (BPNN). The result showed that BPNN was the most accurate method with lowest value of MAPE.

Besides that, Yumang and group presented a paper in 2021 that implemented NIR sensor modeled AS7263 and spectroscopy to estimate the concentration of uric acid. The sensor measured the amount of light that was reflected from the person’s wrist. Raspberry Pi 3 B+ was utilized to change the data collected into concentration of uric acid. The prototype built obtained an average percentage difference of 6.61 % against a uric acid meter. Hence, it can be concluded that NIR sensor was helpful in estimating the uric acid concentration. In short, NIR sensor AS7263 is commonly used in various applications and in the construction of spectrometers which can achieve high accuracy. Hence, it is suitable to be used in wood classification system which can identify different types of wood by just collecting the spectra data from the sensor.

The application of NIR sensor modeled AS7263 in different systems signified its usefulness in classification, estimation of mechanical and chemical properties as well as in determining quality of various samples.

2.7 Data Acquisition Mode

There are total of three measuring modes in NIR spectroscopy, which are transmission mode, transflection mode and diffuse reflection mode. In transmission mode, a directed or parallel light source is illuminated on the sample. As shown in Figure 2.10, some of the light will be absorbed, but the remainder will be transferred to the detector. This kind of measuring mode is appropriate for direct transmission of transparent liquids, as well as slightly scattering samples such as grain and pasty in diffuse transmission (Bruker, 2022).

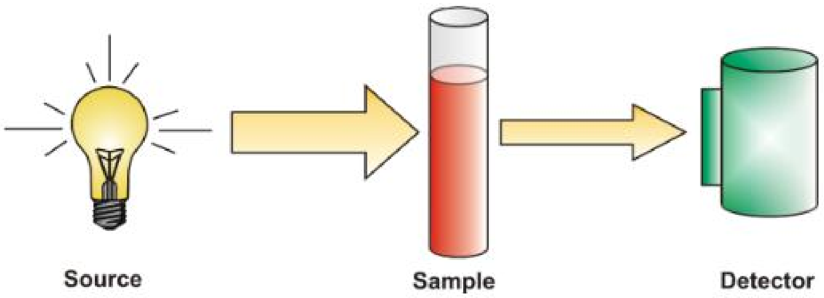


Figure 2.10: Transmission Mode. (Bruker, 2022)

Whereas in transflection mode, which is an extension of the transmission technique, composed of both transmission and reflection modes. The light that is directed through the sample will be reflected by the mirror that is placed behind the sample and back to the probe of diffuse reflectance or integrating sphere through the sample. This type of measurement mode will be suitable for emulsions, gels, and turbid liquids (Bruker, 2022)..

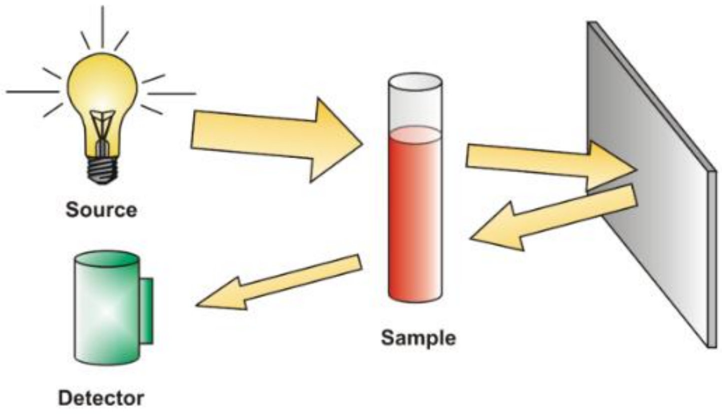


Figure 2.11: Transflection Mode. (Bruker, 2022)

Diffuse reflectance mode happens when light is reflected from the solid surfaces. When a light beam transmits onto the surface of the samples, the samples will reflect the light back to the detector. In an integrating sphere, a parallel beam will be directed onto the sample and numerous diffuse reflections at the gold-plated inside surface of the sphere will distribute the reflected light reflected light to “homogenize” the light. Because of this, integrating spheres is suitable for inhomogeneous samples (Bruker, 2022).

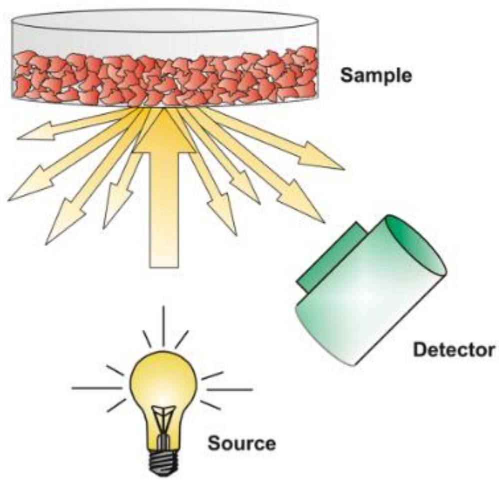


Figure 2.12: Diffuse Reflectance Mode. (Bruker, 2022)

It can be concluded that in NIRS applications, the three most common data acquisition modes are the transmission mode, transflection mode and diffuse reflection mode, whereby three modes have different ways of collecting data in various kinds of substances.

2.8 Data Acquisition at Reflectance Mode

In a publication, Peng and team (2021) described how to use NIR spectra data to determine the moisture content in walnut kernels. The spectra data of walnut kernel in diffuse reflectance mode were collected as shown in Figure 2.13. From Figure 2.13, the spectral energy absorption of all the spectral curves happened at different wavelengths (1210 nm, 1450 nm, 1725 nm, 2328 nm). The differences of the absorption peaks can be explained with the internal component contents of walnut kernel samples. It showed that the dominant absorption peaks happened at 1450 nm and 1940 nm respectively, as the internal component of the samples contained the first overtone and combination overtone of the O-H stretching vibration. When IR light was directed on a sample, part of the light will be absorbed by the sample for molecular vibrations. C-H, N-H, O-H and S-H chemical bonds have different modes of vibration such as stretching, rocking and bending at different vibration frequencies, including fundamental, overtones and combination. At specific vibrational frequencies, these bonds will absorb light where frequencies match with their vibrational frequencies. The signal of absorbance is affected by the concentration of absorbing chemical bonds in the light path. When the absorbing chemical bonds concentration is high, it will give more pronounced absorption signals in the spectrum.

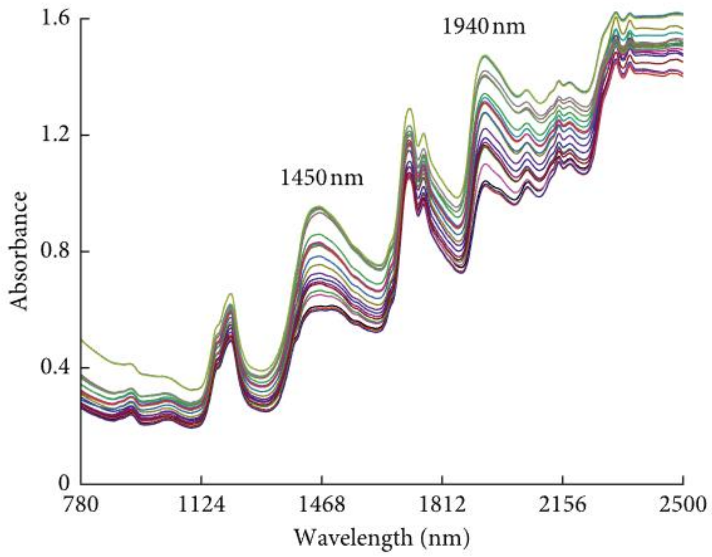


Figure 2.13: NIR Diffuse Reflectance Spectra of Walnut Kernel Samples. (Peng, et al., 2021)

Kandala, Naganathan and Subbiah (2008) conducted the prediction of moisture content in food products by using NIR spectroscopy in reflectance mode. In this case, whole peanut kernels with 8 % moisture content were used and placed in the Petri dish. When the Petri dish with the peanut samples was set in motion on the turntable, the halogen lamp above them was activated, and the resulting reflectance spectra were recorded. The spectra data were collected within the range of 1000 nm to 1800nm. The calibration set consisted of nine different moisture levels, which included 8 %, 10.11 %, 12.26 %, 16.3 %, 17.88 %, 19.41 %, 21.77 %, 22.04 % and 25.84 %. A total of 30 NIR reflectance spectra were obtained for each of the moisture level and the PLSR model was developed using the averaged spectra. Figure 2.14 shows the mean spectral data for four unique moisture levels in peanuts. The spectra of different moisture levels displayed a comparable shape, but the amplitude varied across all levels, as demonstrated in Figure 2.14.

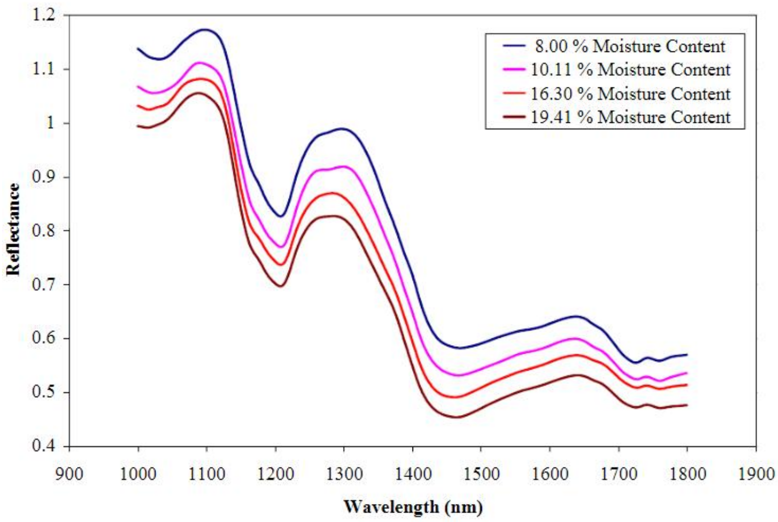


Figure 2.14: Average Spectra of Four Distinct Moisture Levels. (Kandala, Naganathan and Subbiah, 2008)

Park and team (2017) predicted five different Korean softwood species, which were Korean pine, red pine, larch, cypress, and cedar using NIR spectroscopy. Their chemical properties such as extractives and lignin contents were to be used for wood distinction. There was a total of 40 mesh wood samples to be scanned. 12 scans of each sample were averaged and recorded in the range of 680 nm to 2500 nm at intervals of 1 mm. Figure 2.15

shows the spectra data of 19 samples. Lignin bands were observed at the spectral region between 1000 nm to 1200 nm whereas the cellulose component can be observed in the range of 1200 nm to 1600 nm.

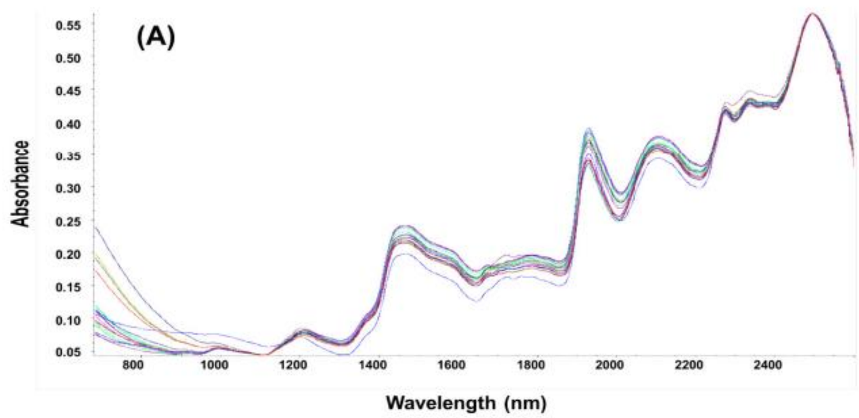


Figure 2.15: Spectra Data of 19 Softwood Species. (Park, et al., 2017)

Yang and team (2015) presented a wood classification system by using NIR spectroscopy in diffuse reflectance mode. NIR spectra were collected for each of the sample, namely Pometia sp., Instia sp. and Couratari sp. Figure 2.16 shows the NIR spectra data for three different types of wood in their respective cross, radial, and tangential sections. Based on the figure, there were peaks observed from the spectra curve, which include 1473 nm, 1925 nm, 2092 nm and 2267 nm. The maximum point observed at 1473 nm resulted from the vibrational stretching of higher harmonics in the O-H bond of cellulose. While the peak at 1925 nm was influenced by the asymmetric stretching and distortion of the O-H atoms caused by water. The peak at 2092 nm resulted from the deformation of O-H and C-H bonds, in addition to the O-H stretching vibration of both cellulose and xylan. Lastly, stretching of O-H and C-O bonds from the lignin produced an overtone that caused the peak at 2267 nm.

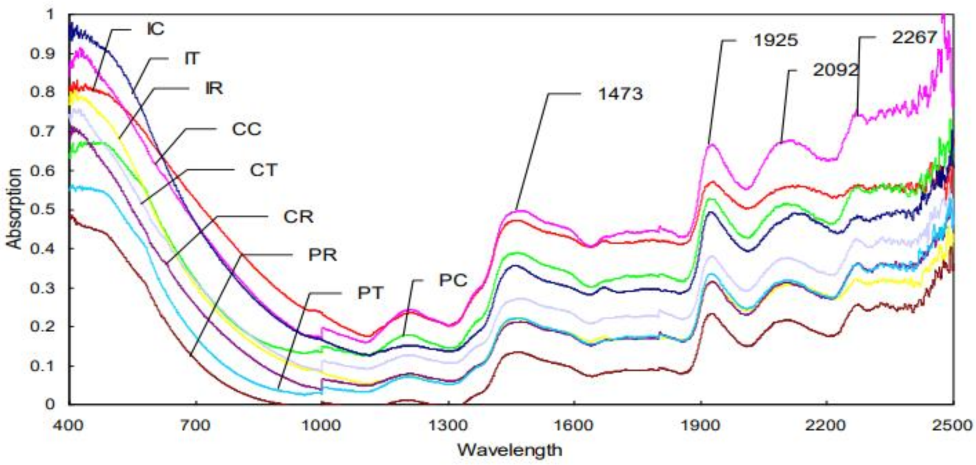


Figure 2.16: NIR spectra data for three different types of wood in three sections. (Yang, et al., 2015)

Note: Intsia, Couratari, and Pometia were the wood species represented by the first letter, while the cross, radial and tangential sections of the wood were denoted by the second letter.

In wood classification, most of the NIR spectroscopy is used in the reflectance mode instead of transmission and transflection modes. This is due to the reflectance mode can easily reflect the internal information of a sample while at the same time, retain the spectral data in the sample (Wang, et al., 2022).

2.9 Summary

This chapter provides an overview of research and studies carried out by various researchers, starting with an introduction to Near Infrared Spectroscopy (NIRS) and its applications across different industries. The chapter also discusses about traditional alternatives in wood classification. Furthermore, it covers the collection of spectra data and methods to interpret and analyze such data. Additionally, the chapter also focuses on the NIR sensor AS7263 and its different acquisition modes. The research related to utilizing the reflection mode for data acquisition is also discussed in detail.

Overall, this chapter provides a comprehensive review of the different aspects related to the use of NIRS for wood analysis and classification. It covers the basic principles of NIRS, traditional alternatives in wood classification, data collection and analysis methods, and the latest developments in the field using the AS7263 NIR sensor.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Wood Samples Preparation

Three wood species, Hevea, Jelutong (Dyera costulata) and Chengal (Neobalanocarpus heimii) were collected and used in this study. Hevea, also known as Rubberwood, has a density of 560 to 640 kg/m^3. Jelutong is a light hardwood with density of 420 to 500 kg/m^3 whereas Chengal is a heavy heartwood with density of 915 to 980 kg/m^3. Each Hevea, Jelutong and Chengal block sample was prepared for research purposes. Figures 3.1, 3.2 and 3.3 show the block samples from Hevea, Jelutong and Chengal, respectively.

Figure 3.1: Hevea Sample Block.

Figure 3.2: Jelutong Sample Block.

Figure 3.3: Chengal Sample Block.

The dimensions of Hevea, Jelutong and Chengal block samples are 25 cm x 2 cm x 5.3 cm, 9.7 cm x 2 cm x 4 cm and 8.7 cm x 2 cm x 6 cm respectively. These wood samples will be treated at room temperature with humidity at 50 % to 60 %.

3.2 Design of NIR Spectrometer

NIR spectra of three wood specimens will be collected in diffuse reflectance mode by using a NIR spectrometer modeled AS7263 from SparkFun. AS7263 has a multi-spectral sensor that is capable of measuring six channels (R, S, T, U, V and W) of different wavelengths, which are 610, 680, 730, 760, 810 and 860 nm respectively. Each channel has a Gaussian filter characteristic and a 20 nm full width half maximum bandwidth. AS7263 is equipped with an analog-to-digital converter (ADC) that facilitates the current integration of the photodiode in every channels. There is also an on-board LED on the AS7263 that can be used to illuminate the wood samples for measurements. The LED Driver Circuit presents in the sensor will oversee the programmable LEDs which act as the light source. Besides, the temperature sensor, Universal Asynchronous Receiver or Transmitter (UART), Internal Resistance-Capacitance Oscillator (16 MHz), Spectral ID Engine, and Inter-Integrated Circuit (I2C) are all included in the sensor (Wang, et al., 2022). Figure 3.4 shows the construction of NIRS prototype. Assuming the reflective surface as the surface of the block sample, when the on-board LED emits light onto the wood surface, the light will reflect to the 6-channel NIR sensor and send to microcontroller for interpretation and data reading. In this study, the NIR sensor AS7263 utilized is depicted in Figure 3.5.

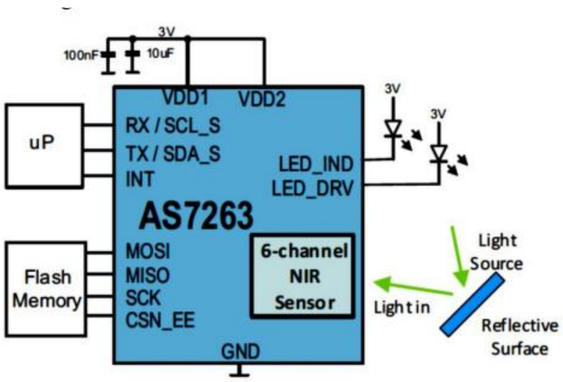


Figure 3.4: Construction of NIRS Prototype. (Sulistyo, et al., 2021)

Figure 3.5: Prototype of AS7263 Sensor. (SparkFun, n.d.)

The NIR sensor will interface with a microcontroller to read and process the spectra data collected from the sensor itself. Arduino UNO is used in this study to construct the prototype. The Arduino board will be programmed using the Arduino Software (IDE) to output the data readings. A jumper adapter cable is also used to connect the AS7263 to the Arduino's pins.

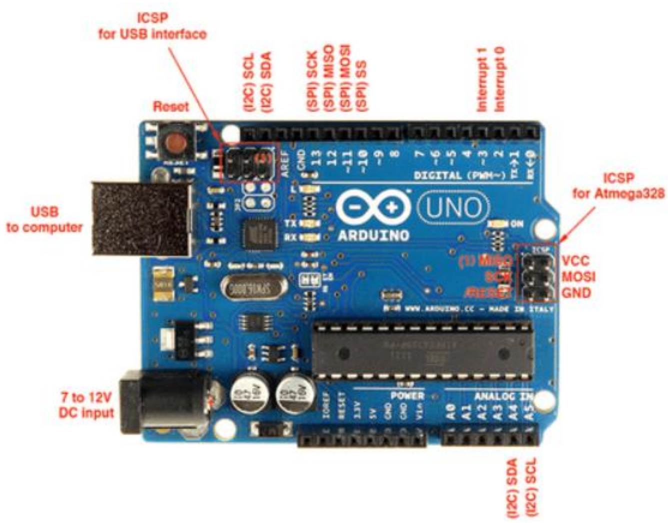


Figure 3.6: Arduino UNO. (Ober, 2012)

Moreover, an I2C LCD display is connected to Arduino in order to print or output the result on the screen display.

3.3 Circuit Design and Construction

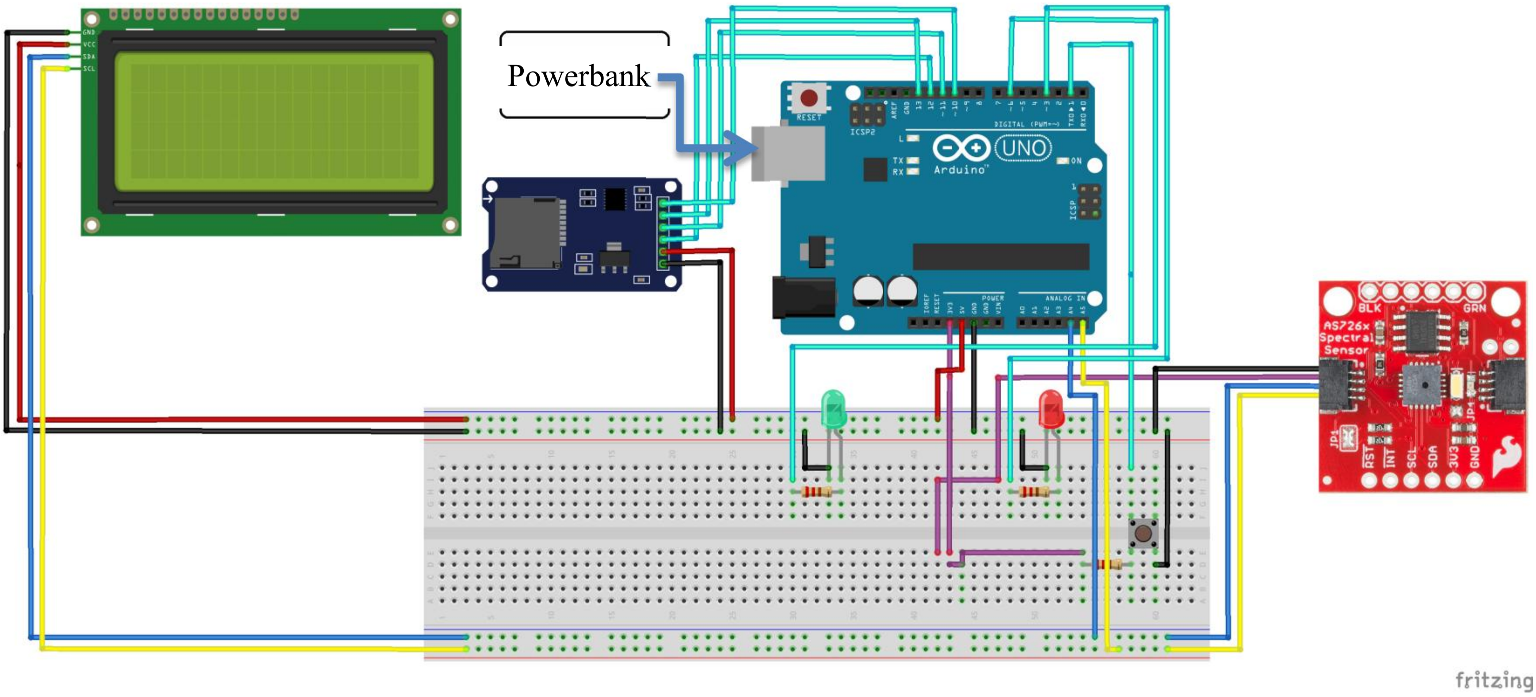


Figure 3.7: Circuit Construction of NIR System.

Figure 3.7 depicts the electronic components' layout and connections that interface with the Arduino UNO. The system comprises an Arduino UNO, a push button, two LEDs, an LCD, an NIR sensor modeled as AS7263 and a microSD card adapter. The NIR system is powered by an external power source in the form of a power bank. The respective roles of the components utilized in the circuit are outlined in Table 3.1.

Table 3.1: Electronic Components Employed and their Respective Functions.

Component	Functions
NIR sesnor (AS7263)	To measure intensity of reflected light for Hevea, Jelutong and Chengal at channels R, S, T, U, V and W.
Arduino UNO	Used for spectra data processing and analysis.
LCD 20x4	To display the median readings of six channels for each wood piece being measured and the respective

	classifying result.
MicroSD card adapter	To transfer data to and from a standard SD card. Used with Arduino UNO to access the spectra data for further processing.
Red LED	To indicate the end of each measurement attempt.
Green LED	To indicate the start of each measurement attempt.
Push button	Start button to initiate the system.

3.4 Near Infrared Spectra Acquisition

The NIR system is designed to obtain measurements of the light intensity of various wood species across six different wavelength channels (610, 680, 730, 760, 810, and 860 nm) through three attempts. Initially, the system will prompt the user to place the wooden sample on the platform, following which an on-board LED of AS7263 will emit light onto the sample. To ensure the preservation of accurate spectral data, the sensor will operate in diffuse reflectance mode. The wood surface will absorb a portion of the light while the NIR sensor will collect the remaining wavelengths that are reflected off the surface. The readings from these three attempts will be averaged, and the resulting median set of data will be displayed on LCD screen and stored on a SD card through a microSD card adapter that interfaces with Arduino for further analysis and data processing of classification. A set of 15 measurements will be conducted on various wood species, each under different ambient conditions such as daytime, nighttime, and dark settings to analyze the variations in their spectra data. Additionally, the system will undergo testing using different objects and by altering the measurement surface of each wood sample to assess the feasibility of the system and observe changes in spectra data. The data obtained from these experiments will be tabulated, along with their corresponding channel readings.

3.5 Analysis and Interpretation of Spectra Data

Firstly, the calibrated readings of six channels are obtained and tabulated for three different types of wood: Hevea, Jelutong, and Chengal. These readings serve as a reference for detecting each wood species by comparing the calibrated data with actual measurements. Next, the system analyzes the spectral data to classify the wood as either "Hevea", "Jelutong", "Chengal" or "Others." The classification results, along with the median readings of the six channels for each particular wood, are stored on an SD card through a MicroSD card adapter interfacing with Arduino. The information stored on the SD card is accessed using 'Spyder' to plot various graphs that display the spectral data for all types of wood. These graphs provide a visual representation of the data, which can be further analyzed and interpreted. Python is used to plot the graphs with relationships between the intensity of reflected light from the wood surface and the wavelengths at the R, S, T, U, V, W channels, using the 'matplotlib' library.

3.6 Evaluation on System Accuracy and Feasibility

The feasibility of the NIR system as an alternative in wood classification is evaluated based on its classification accuracy. This evaluation includes analyzing its success rate in accurately classifying wood samples, examining how changes in ambient conditions affect classification results, and measuring the data variation resulting from using different measurement surfaces for wood samples. The success rate of classification is determined by the number of successful attempts out of 15 trials. Furthermore, by employing 'Spyder' software and utilizing the stored spectra data in an SD card, the reflected light intensity across various wavelengths for different types of wood is plotted. It is possible to examine the shape of the graph that displays the spectral data to confirm that wood species of the same type exhibit a consistent spectral pattern. Hence, by taking into account all relevant factors and analyzing the spectral data for each type of wood, a determination can be reached regarding the feasibility and practicality of employing the NIR system, culminating in the conclusion of this study.

3.7 Overview of the Wood Classification System using NIRS

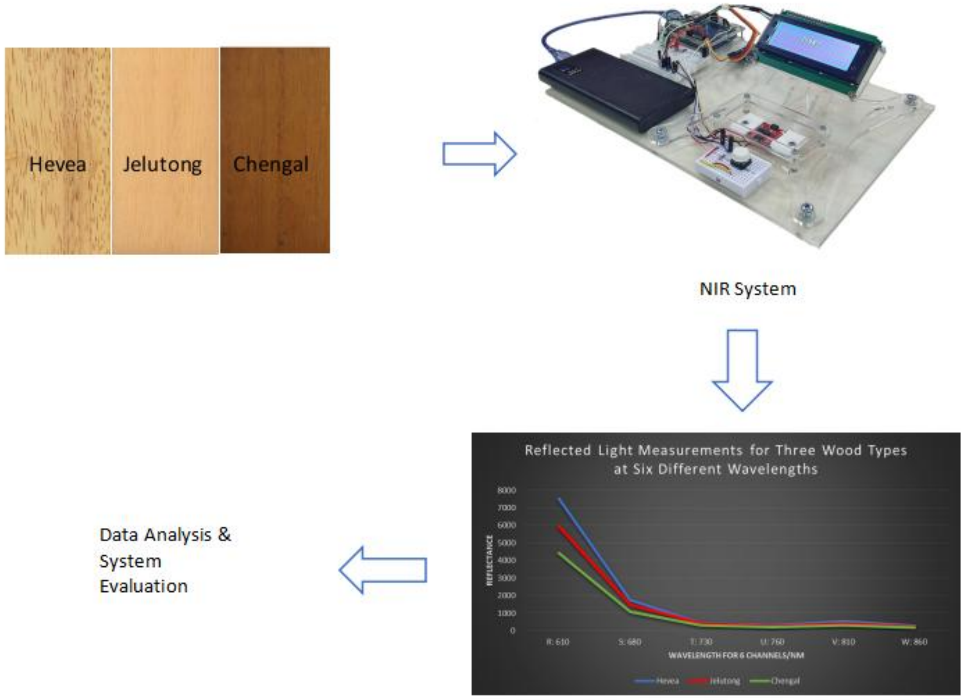
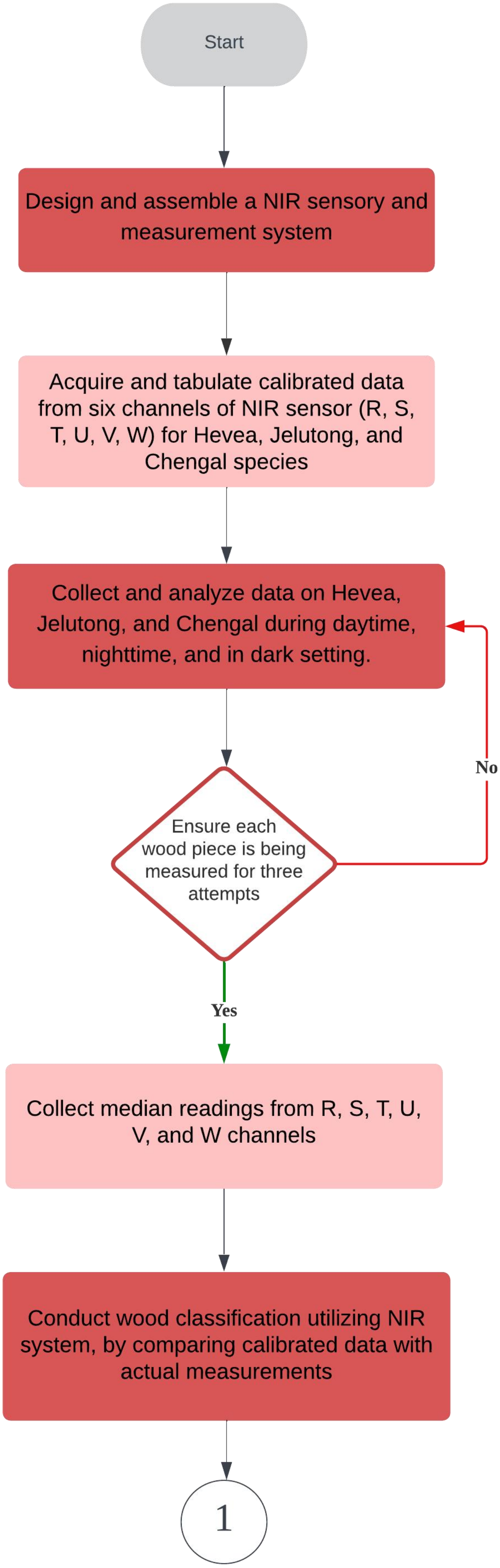


Figure 3.8: Schematic overview of the process in wood classification using NIR spectroscopy.


Start
Design and assemble a NIR sensory and measurement system
Acquire and tabulate calibrated data from six channels of NIR sensor (R, S, T, U, V, W) for Hevea, Jelutong, and Chengal species
Collect and analyze data on Hevea, Jelutong, and Chengal during daytime, nighttime, and in dark setting.
Ensure each wood piece is being measured for three attempts
No
Yes
Collect median readings from R, S, T, U, V, and W channels
Conduct wood classification utilizing NIR system, by comparing calibrated data with actual measurements
1

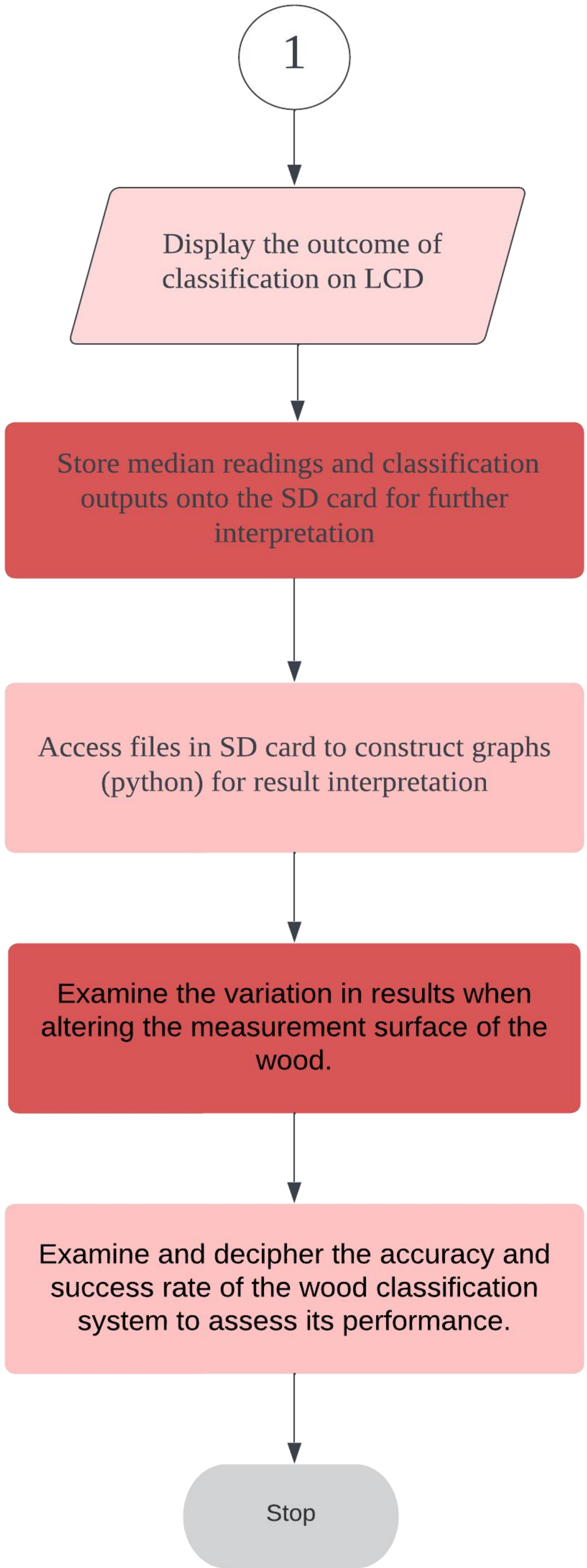


Figure 3.9: Flowchart of Wood Classification Process Using NIRS.

3.8 Gantt Chart and Work Plan

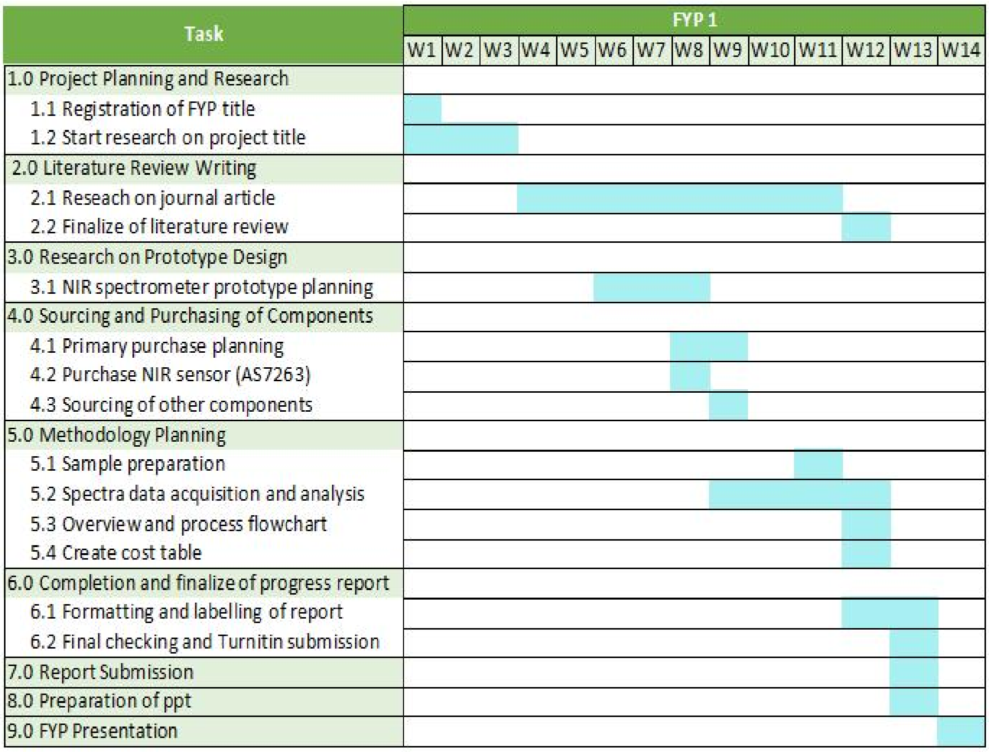


Figure 3.10: Gantt Chart of FYP1.

Figure 3.11: Gantt Chart of FYP2.

Table 3.2: Total Cost of Prototype.

No	Item	Quantity	Cost per unit (RM/unit)	Total cost (RM)
1	NIR sensor (AS7263)	1	142.12	149.12
2	Sensor jumper adapter cable	1	7.23	7.23
3	LCD display 20x4	1	19.90	19.90
4	3D printing for sensor holder	2	19.90	19.90
5	Female to Male (FM) 40pcs	1	3.70	3.70
6	170 holes mini breadboard	1	6.40	1.50
7	Arduino UNO R3 casing box	1	5.90	5.90
8	6mm M3 screw	80	0.16	12.90
9	Micro SD card adapter	1	10.30	10.30
10	Acrylic board 210mm x 297mm	1	38.90	38.90
11	Laser cutting and 3D printing of prototype	1	100	100
	Total cost			367.25

The total cost of constructing the wood classification prototype in this project is around RM367.25.

3.9 Summary

The initial focus in this chapter is on the preparation of wood samples, followed by the design of the near-infrared system that involves circuit construction and prototype fabrication. Subsequently, the chapter covers the steps involved in acquiring spectral data, analyzing and interpreting it. The accuracy of the system is also evaluated in this chapter. Lastly, to provide a comprehensive understanding of the wood classification system, the chapter also includes a flowchart, work plan as well as the total cost of the prototype.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Design and Fabrication of Final Prototype

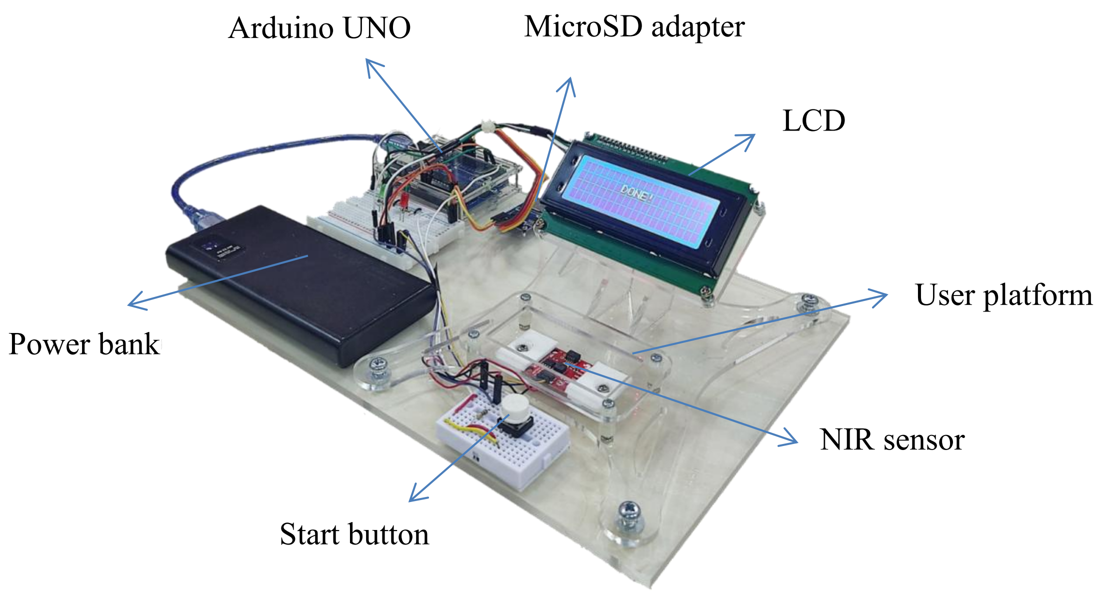


Figure 4.1: Overview of the Wood Classification System.

Figure 4.1 shows the complete prototype of the wood classification system using a near-infrared sensor. The prototype can be categorized into three construction parts, comprising the user platform, circuit design, and base fabrication. Acrylic is the primary material utilized in the production of the prototype. To fabricate the user platform, the first step involves designing a 3D model as shown in Figure 4.2, which is then manufactured through laser cutting and 3D printing techniques.

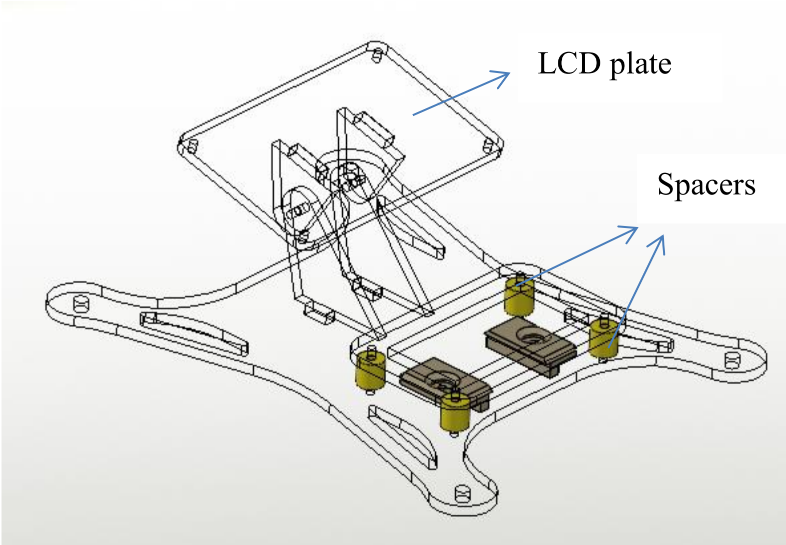


Figure 4.2: 3D Drawing of User Platform.

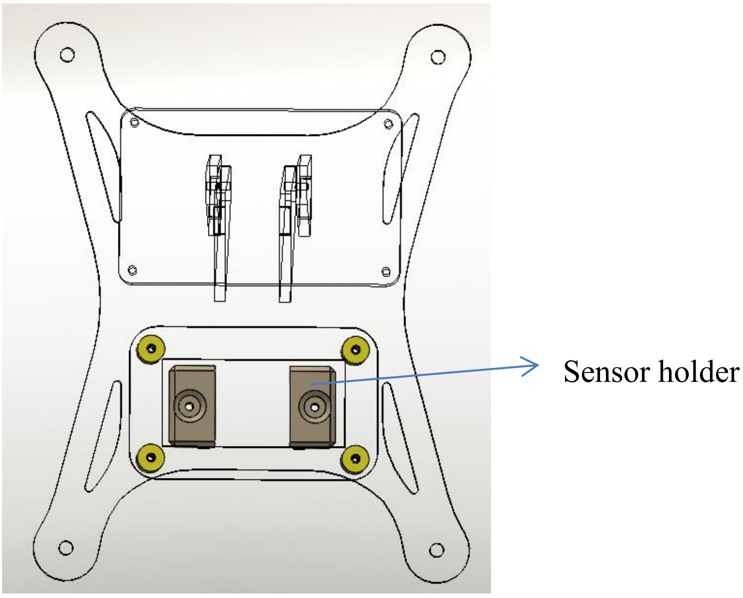


Figure 4.3: Top View of User Platform.

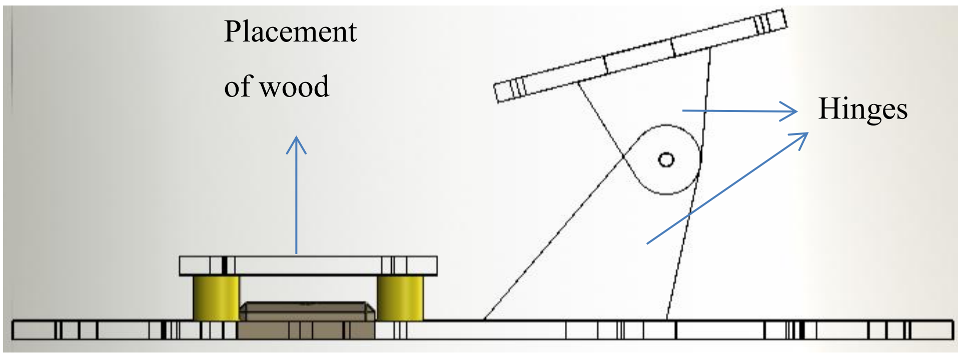


Figure 4.4: Side View of User Platform.

The 3D model of the user platform made up of acrylic features an LCD plate, which holds the LCD display in position through M3 screws. It is connected to the base plate by hinges that offer adjustable angles for the user to modify the LCD's screen position. Two sensor holders are also attached to the base plate, which firmly locks the sensor in place to ensure measurement accuracy. Also, in order to maintain a constant measurement distance between the wood sample and the sensor while taking readings, four spacers are placed between the sensor and the platform for placement of wood.

Whereas for the electronic circuit construction, the NIR sensor, push button, LEDs, LCD, microSD card adapter as well as the power source (power bank) will be interfacing with Arduino.

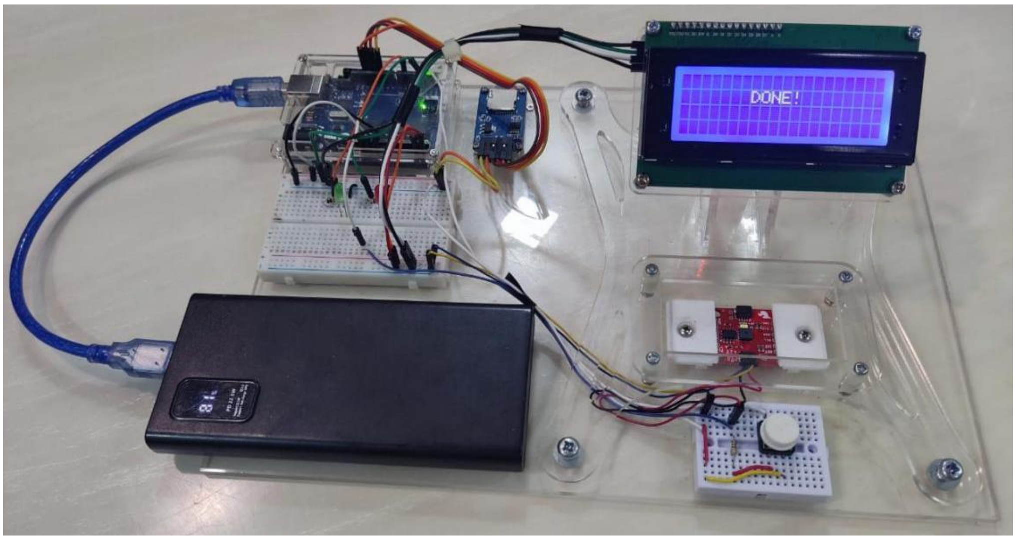


Figure 4.5: Prototype of Wood Classification System.

As can be seen from Figure 4.5, the red and green LED, the LCD, MicroSD card adapter are connected to Arduino at different pin on the same breadboard. Meanwhile, a different breadboard will be used for the push button and NIR sensor, specifically for user interface purposes.

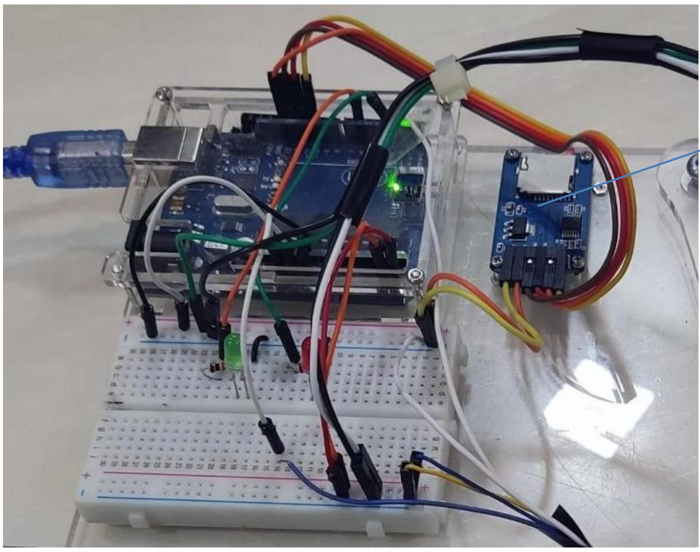


Figure 4.6: Circuit Construction of NIR System.

Lastly, the base board is also constructed from acrylic and underwent laser cutting to create holes for the components, with measurements taken for their required sizes. This was done in preparation for screwing the components onto the board.

4.2 Results Acquisition

The near infrared sensor is equipped with six different channels that capture and discern varying wavelengths of light within the near-infrared spectrum to measure the intensity of reflected light, specifically designated as R, S, T, U, V, and W channels. Each of the channels provides various information regarding the composition and characteristics of the objects being measured. The wavelength of the light in the R channel is approximately 610 nm, which is within the visible red range and it is responsible to account for color intensity of wood as wood colour can provide information such as age or treatment of the wood being measured. Whereas channel S is having wavelength at around 680 nm, it is accountable for moisture level and water content measurements in an object. T channel indicates wavelength at 730 nm and normally used for moisture content measurements and wood chemical analysis such as cellulose. Furthermore, the wavelength of light present in the U channel is approximately 760 nm and has similar usage as channel T. V channel and W channels are located at 810 nm and 860 nm respectively in the light spectrum. These six channels can effectively help to reflect data or determine the composition of an object to ease the classification procedures.

The values obtained from each channel will indicate the quantity of photons at each wavelength that the sensor has observed. And these values will be calibrated to a standard of reference in order to obtain reliable measurements of the characteristics of the materials being studied. In this project, the calibrated readings of the six channels for three types of wood, namely Hevea, Jelutong and Chengal are first obtained and tabulated in Table 4.1. Tolerances will be applied to all readings.

Table 4.1: Calibration Data for Intensity of Light in the Channels R, S, T, U, V and W for 3 Different Wood Species.

Wood species	**Calibrated Readings for Six Channel / $\mu W/cm^2$**					
	R	**S**	**T**	**U**	**V**	**W**
Hevea	7000 ± 10%	1715 ± 4%	420 ± 5%	277 ± 4%	505 ± 6%	278 ± 6%
Jelutong	6100 ± 8%	1520 ± 6%	415 ± 10%	260 ± 9%	425 ± 9%	235 ± 8%
Chengal	4650 ± 8%	1150 ± 11%	320 ± 9%	200 ± 11%	335 ± 10%	187 ± 11%

A total of 15 trials of data collection were carried out using three distinct wood types, aimed at evaluating the accuracy and success rate of the NIR system in effectively classifying various materials. For each trial, every wooden sample is placed on the NIR sensor for three consecutive attempts and these readings from the six channels, R, S, T, U, V, W will be sorted in ascending order to get the median values out of the three sets of data. Then, the median readings are recorded and used for subsequent data analysis. This is due to the median being less affected by outliers and can minimize error during data collection which helps in improving the accuracy of the system. The criterion for a successful classification is met when four or more channels (≥4) from the median readings of a particular wood sample fall within the calibrated data range, as presented in Table 4.1. In other words, if four or more channels' readings for a specific wood sample are within the calibration data range, it will be considered as successfully classified. In addition to collecting data for Hevea, Jelutong, and Chengal wood samples, data has also been gathered for several random objects. The classification results for these objects will be categorized as "Others" indicating that the measured object does not belong to the three types of wood that are being classified. This is done to highlight that these objects are not part of the wood types being analyzed.

In trials 1 to 3, the wood pieces are measured during daytime, whereas for trials 4 to 6, they are measured at night, and for trials 7 to 9, they are measured under a dark environment. From trial 1 to 9, measurements only took on one particular surface of each wood sample. Hence, during trials 10 to 12, a different surface on the wooden block is chosen as the measurement surface to assess whether the obtained channel readings are consistent with the previous measurements. The classification results are also recorded to determine the feasibility of the NIR system in accurately classifying samples with different surfaces. If the obtained readings are found to be dissimilar to the previous data in trials 1 to 9, potential reasons for this discrepancy will be discussed in later sections. Additionally, trial measurements were conducted on a few random objects that were not wood samples, spanning from trial 13 to 15. All trials are conducted at room temperature. The results obtained will determine the extent to which the classification results are influenced by different ambient conditions using the NIR system. Table 4.2 shows the results obtained for a total of 15 trials, including the median readings for the six channels, the wood or object detected by the system and the actual wood or object it actually belongs to, followed by the accuracy of classification.

Table 4.2: Data Collection for 15 Trials Conducted under Varying Ambient Conditions.

Trial	**Actual Wood**	**Median Readings for 6 Channels / µ W/cm²**						**Wood Detected by NIR System**	**Successful Classification (Yes/No)**
		R	**S**	**T**	**U**	**V**	**W**		
1	**Hevea (Daytime)**	7517.77	1742.13	442.08	293.88	532.18	285.82	Hevea	Yes
2	**Jelutong (Daytime)**	5940.05	1485.14	403.75	259.41	415.91	225.40	Jelutong	Yes
3	**Chengal (Daytime)**	4428.80	1068.62	297.71	185.03	315.73	175.44	Chengal	Yes
4	**Hevea (Night)**	7471.13	1690.73	431.48	282.99	516.98	274.20	Hevea	Yes

5	**Jelutong (Night)**	5854.93	1477.65	393.96	253.06	407.86	221.92	Jelutong	Yes
6	**Chengal (Night)**	4593.22	1081.47	300.97	185.94	317.52	174.28	Chengal	Yes
7	**Hevea (Dark)**	7591.23	1713.22	433.93	284.80	527.71	280.01	Hevea	Yes
8	**Jelutong (Dark)**	5805.95	1447.67	389.88	249.43	402.49	218.43	Jelutong	Yes
9	**Chengal (Dark)**	4459.12	1057.91	290.37	179.59	311.26	170.80	Chengal	Yes
10	**Hevea (Other surface)**	9192.27	1961.63	521.20	316.55	614.47	323.00	Others	No
11	**Jelutong (Other surface)**	7721.83	1827.79	507.33	322.90	535.76	283.50	Others	No
12	**Chengal (Other surface)**	3260.38	982.96	249.59	161.45	248.65	146.40	Others	No
13	**Random object 1**	8626.72	1656.47	402.12	275.73	605.53	319.52	Others	Yes
14	**Random object 2**	3658.02	811.64	209.62	136.96	256.70	137.10	Others	Yes
15	**Random object 3**	11895.26	1799.95	416.80	307.48	813.03	383.42	Others	Yes

According to Table 4.2, by taking trial 1 as an example, the median readings for channels R, S, V and W fall within the calibrated range of Hevea as shown in Table 4.1. Based on the criteria, a successful classification is met when four or more channels from the median readings of a particular wood sample fall within the calibrated data range. Hence, this wood sample is recognized as Hevea by the system and this attempt is successful.

In a series of 15 trials, the system achieved a success rate of 12 successful classifications. Notably, the system demonstrated the ability to accurately detect three distinct types of wood in varying environmental conditions, including daytime, nighttime, and under dark conditions. Besides, the system also exhibited proficiency in successfully classifying three random objects as "other objects" when measured using the NIR system. Failure in classification is only observed when the wood surface being detected has changed to a different surface for all three types of wood. This observation shows that the NIR system is very sensitive as it is capable of detecting subtle variations in different regions of the same wooden block, leading to varying readings. However, this statement does not hold true when a different surface is employed, as it may impact the accuracy of the classification results. Whereas the overall accuracy achieved through the completion of 15 trials is only 80 %.

4.3 Data Analysis and Discussion

From Figure 4.7 to Figure 4.9, the graphs of the reflected light intensity across six different wavelengths at channels R, S, T, U, V and W for Hevea, Jelutong and Chengal are plotted respectively by employing 'Spyder'. Although the spectra data for three types of wood exhibit the same characteristics in terms of shape and spectral pattern, it is evident that various wood species display different levels of light reflectance at different wavelengths. Figure 4.10 displays the overall reflected light intensity for three types of wood in a single graph.

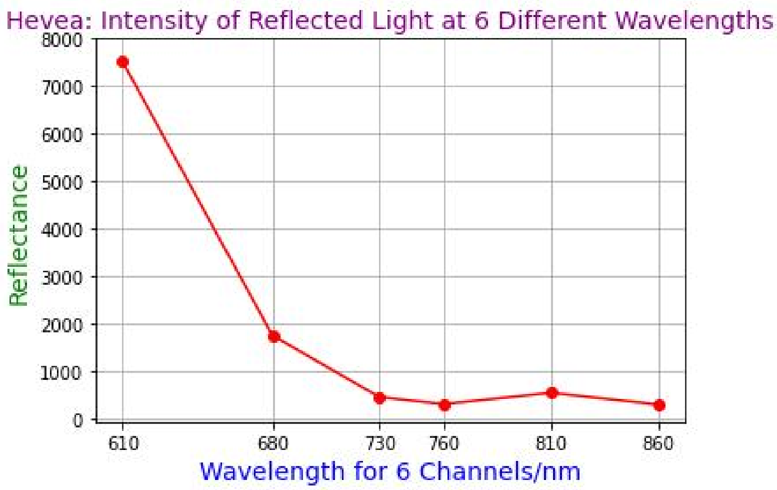


Figure 4.7: Graph of Reflectance Spectra across Various Wavelengths for Hevea.

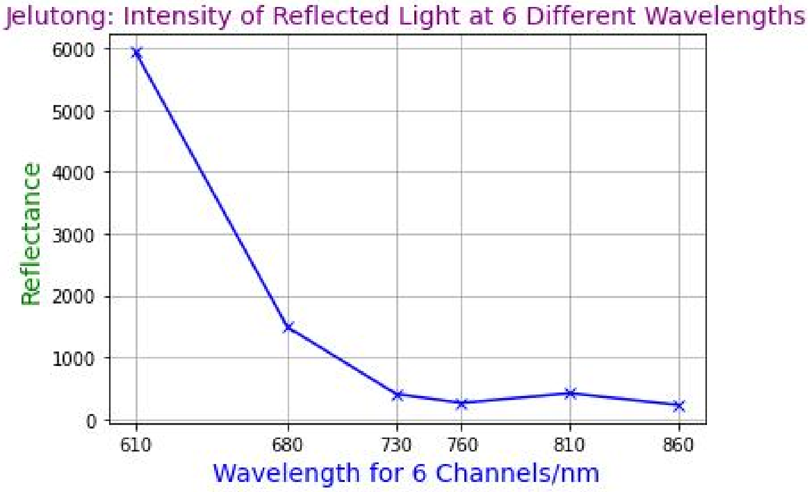


Figure 4.8: Graph of Reflectance Spectra across Various Wavelengths for Jelutong.

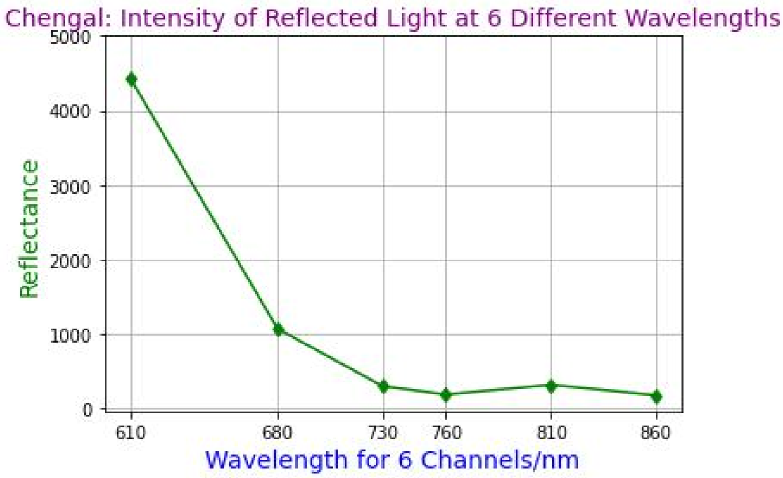


Figure 4.9: Graph of Reflectance Spectra across Various Wavelengths for Chengal.

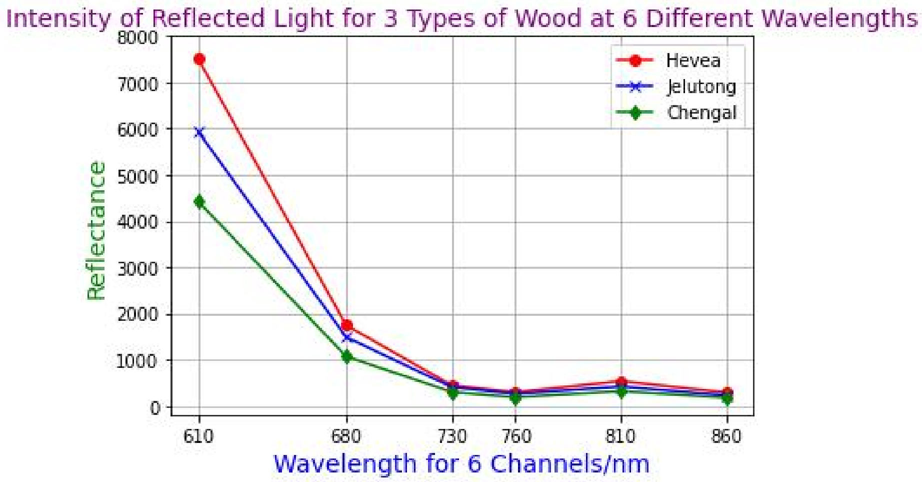


Figure 4.10: Graph of Reflected Light Intensity across Various Wavelengths for All Three Types of Wood.

In Figure 4.11, a comparison of spectral data between different types of wood and a randomly measured object can be observed.

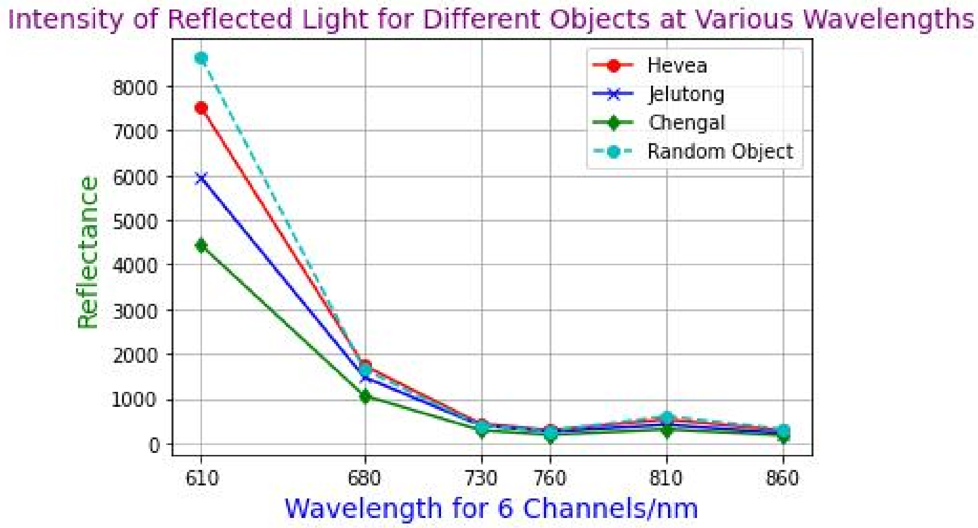


Figure 4.11: Graph of Reflected Light Intensity at Different Wavelengths for All Three Types of Wood and a Random Object.

As discussed above, three wood samples are detected by the NIR system at varying environmental conditions. Although the classification results can be influenced by the intensity of the light source being used to measure wood samples, the on-board LED of the NIR sensor is designed to provide an appropriate intensity level, thereby increasing the stability of the light source to ensure consistent output measurements. Due to its stability, the output of the system only possesses minimal fluctuations to prevent variations in the spectra data. Besides, it demonstrates a high reproductivity which gives consistent results regardless of the environmental conditions. This can be proved in Figure 4.12 to Figure 4.14, when the wooden blocks are being measured during daytime, nighttime or even under dark conditions, the classification results are successful even though there would be a little fluctuation in the channels readings. The data collected during nighttime, daytime and under the dark have slight fluctuations of around 1 % to 4 %, which fall well within the tolerance limits set for all channels. Hence, the system possesses high accuracy in classifying wood samples despite changes in ambient conditions.

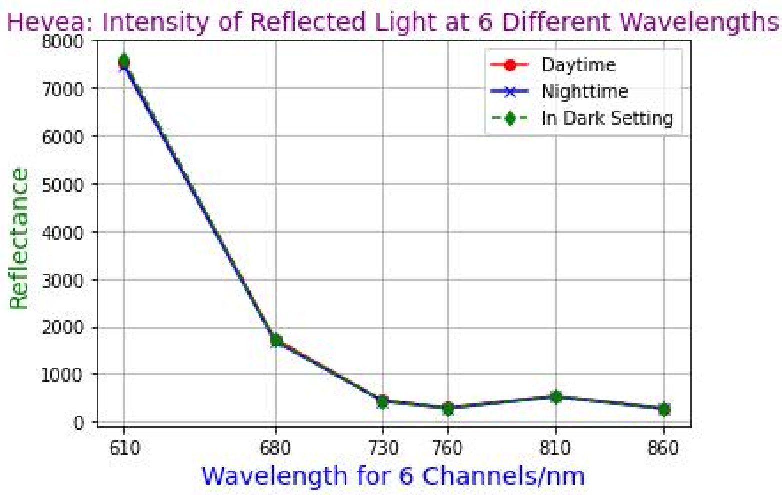


Figure 4.12: Graph of Reflected Light Intensity under Various Ambient Conditions for Hevea.

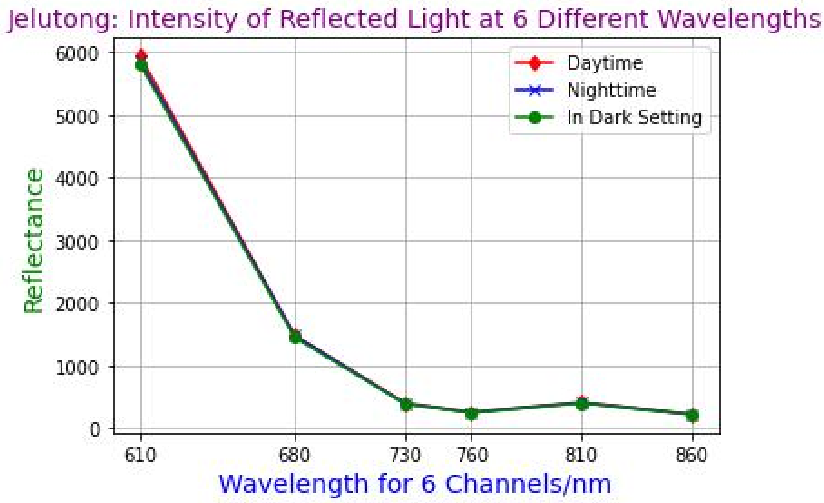


Figure 4.13: Graph of Reflected Light Intensity under Various Ambient Conditions for Jelutong.

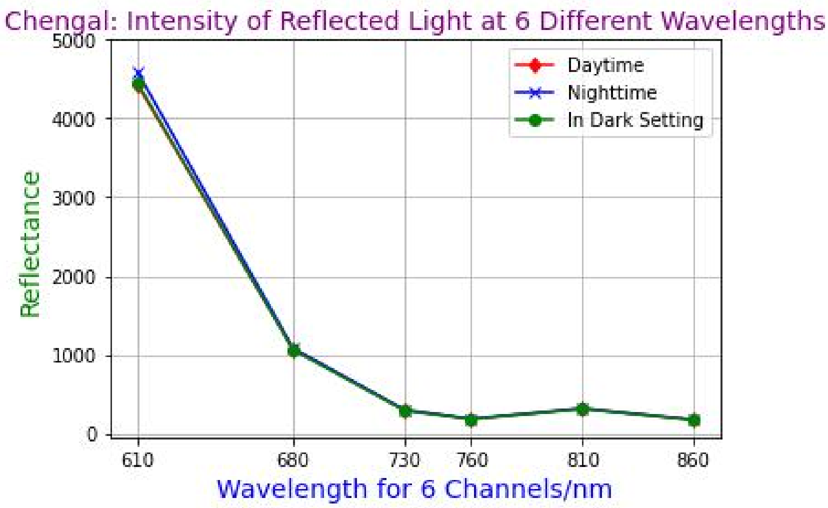


Figure 4.14: Graph of Reflected Light Intensity under Various Ambient Conditions for Chengal.

According to observations, when the surface of measurement of each wood sample has changed, the results will exhibit disparate variances. This is possibly due to the differences in properties of each surface on the wood specimen. Different surfaces of a wood sample will exhibit different properties and characteristics in terms of surface roughness, grain orientation, moisture content, colour intensity as well as aging and weathering. Taking Hevea as an example, from Table 4.2, trials 1, 4 and 7 are conducted using the surface shown in Figure 4.15. Whereas for trial 10, the measurement surface has changed to Figure 4.16. It is apparent from the two figures that Figure 4.15 possesses a smoother surface in comparison to Figure 4.16, which appears considerably rougher.

Figure 4.15: Smooth Surface on Hevea.

Figure 4.16: Rough Surface on Hevea.

As the measurements of the NIR system is conducted in diffuse reflectance mode, rough surfaces can significantly affect the reflection of light. When light strikes on a rough surface, the incident light is scattered in various directions due to the presence of microstructures on the wood surface. The higher the surface roughness, the higher the scattering of incident light. As a result, the reflectivity of the wood surface will be reduced and the spectra data collected are inaccurate compared to a smoother surface. In contrast, a smoother surface possesses better reflectivity or produces better reflection when stroked by an incident light (Collier, et al., 2016). This is proved in Table 4.2, when the overall channels' readings on a rough surface of Hevea are much higher than the readings on its smoother surface. This statement holds true for both Jelutong and Chengal while using two different surfaces for measurement.

In fact, the colour intensity of a wood piece has a huge effect on the spectra data being collected on different wood surfaces. This can be explained in three different aspects, namely absorption, reflection and the scattering of light. A darker or highly-pigmented wood piece absorbs more near-infrared light as compared to lighter-coloured wood (Stuart-Fox, et al., 2017). This is due to darker wood having high concentrations of pigments, for example, lignin which absorbs part of the near-infrared light and this in turns affect the accuracy of NIR measurement. Next, as some of the near-infrared light has been absorbed by the dark pigments, less light will be reflected back to the sensor by the wood having a darker surface. Scattering may also occur when the dark pigments interact with the incident light which results in change in spectra data. The change in wood colour is accountable by channel R in the NIR sensor. In short, it can be proved that lighter-coloured woods give better accuracy and interpretation of near-infrared readings.

Other than surface roughness and colour intensity, grain orientation is also a factor that impacts the spectra data obtained on different wood surfaces. As mentioned earlier, wood is anisotropic and its properties may vary depending on the measuring directions. Grain orientation differs along the longitudinal, radial and tangential directions on the surface being measured. They can exhibit different strength and stiffness properties on each surface. Same goes to the moisture content, the degree of exposure to moisture or surface treatment can lead to the differences in water level on every wood surface. The variation in moisture content among the wood samples can impact the reflectivity of the wood surfaces, as moisture has the ability to absorb near-infrared light and cause light scattering. Last but not least, the property which contributes to different spectra data being captured on different surfaces is aging and weathering (Jain and Singh, 2003). Each surface may experience varying levels of exposure to environmental conditions such as sunlight, temperature fluctuations and other weathering effects which can contribute to aging and weathering effects.

Figure 4.17 to Figure 4.19 display the spectral data at two different surfaces (reference surface and other surface) for Hevea, Jelutong and Chengal respectively. The reflectance levels of the two surfaces of various types of wood species exhibit significant differences in intensity of reflected light. This variation can be attributed to the distinct characteristics and properties of each surface as discussed above.

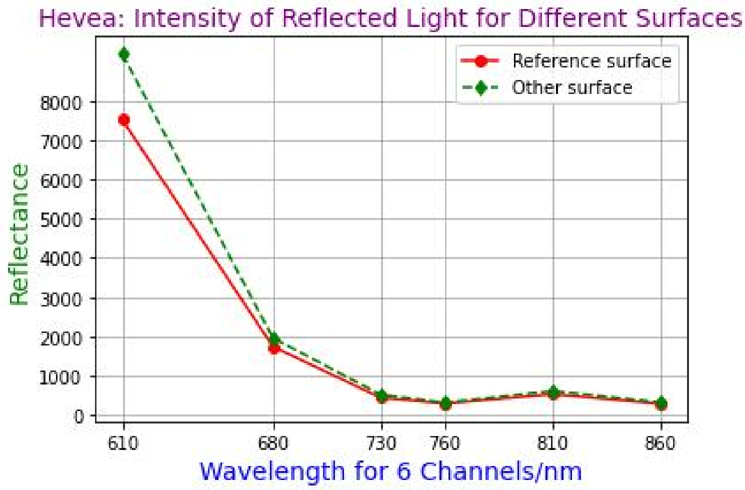


Figure 4.17: Graph of Reflectance at Various Surfaces for Hevea.

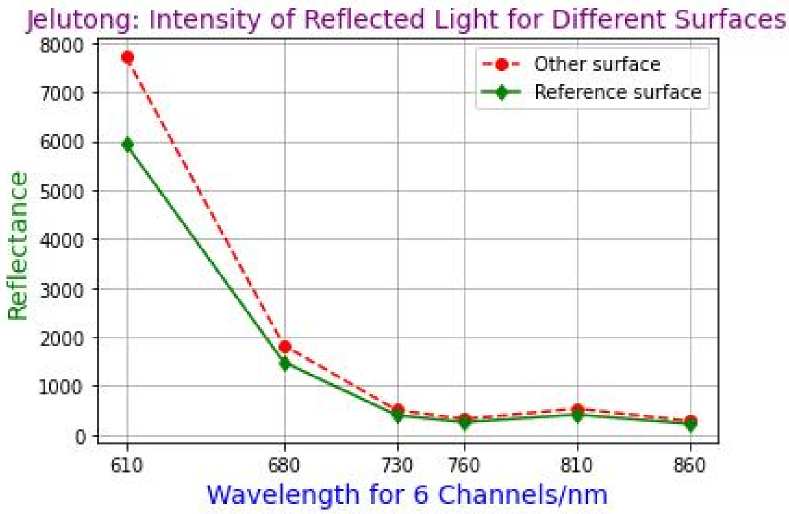


Figure 4.18: Graph of Reflectance at Various Surfaces for Jelutong.

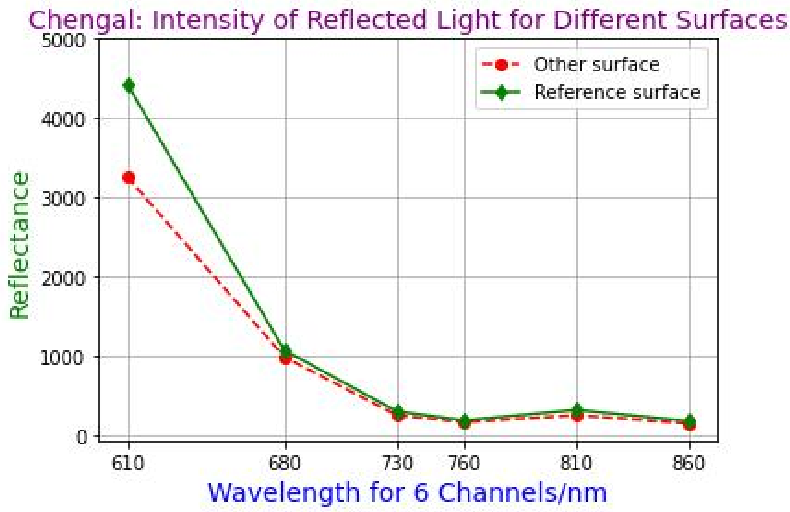


Figure 4.19: Graph of Reflectance at Various Wood Surfaces for Chengal.

As seen from the readings obtained in Table 4.2, the overall channel's readings of Hevea is the highest, followed by Jelutong and Chengal. This can be explained by the characteristics and properties of the measurement surfaces of each particular wood samples. By looking at channel R, which is accountable for the color intensity of wood, Hevea is having the highest value at around 7500 µW/cm2 ,while comparing to Jelutong (~5900 µW/cm2) and Chengal (~4400 µW/cm2). As explained earlier, when the color of the wood appears to be darker, it will absorb more near-infrared light due to the high concentration of pigments presented on the surface of the wood. Thus reducing the light at near-infrared range being reflected back to the sensor, leading to the reduction in light counts at wavelength 610 nm. Scattering may also occur when the dark pigments interact with the incident light which results in a change in spectra data. Compared to the other two surfaces, Hevea has lighter-colored surfaces with lower color intensity. This means that less light will be absorbed by the surface and more light will be reflected back to the NIR sensor at 610 nm. Due to a higher capture of light in the range of near-infrared by the R channel, the light counts or intensity at 610 nm would be significantly higher. In contrast, Chengal has the darkest measurement surface, which results in the highest light intensity. However, the dark pigments present on Chengal will absorb some of the light being illuminated to its surface, leading to lower reflectivity and less light being reflected back to the NIR sensor. As a result, the light intensity captured by the R channel in Chengal will be low. The color intensity of Jelutong falls between Hevea and Chengal, which means that its R channel's reading also falls in between the channel's readings of the other two surfaces.

Channels S, V, and W are primarily dedicated to measuring the moisture level and water content in the wood by analyzing the reflectance of light to the sensor. Due to the tendency of water to absorb NIR light, a higher moisture content in wood results in increased absorption of light by the wood itself. Additionally, moisture in wood can cause light scattering and reduce the reflectivity of the wood. Wood tends to appear darker when it has higher moisture content, and as mentioned, darker surface will result in lesser light being captured by certain channels. As a result, the amount of light reflected at wavelengths at 680 nm, 810 nm and 860 nm are notably reduced. Hevea exhibits higher readings in channels S, V, and W, indicating lower moisture level and water content in the wood. This suggests that only a small amount of incident light is absorbed by Hevea, with the majority being reflected back to the sensor. The readings in Table 4.2 highlight that Hevea captures more light at wavelengths of 680 nm, 810 nm, and 860 nm compared to other samples. On the other hand, Chengal is inferred to have the highest moisture level and water content among the samples analyzed. Moisture in Chengal tends to absorb part of the incident light, leaving only some of the light being reflected to the sensor, resulting in the lowest readings in these channels for Chengal. Similarly, the light collected at 680 nm, 810 nm, and 860 nm for Jelutong falls in a balanced spectrum between Hevea and Chengal, suggesting a moderate level of moisture and water content in Jelutong.

Typically, in wood classification, channels T and U are sensitive to the absorption bands of cellulose and are able to determine the cellulose content in wood samples. The reason behind this is that cellulose exhibits absorption bands with distinct characteristics in the near-infrared region, when the intensity of the reflected light at wavelengths 730 nm and 760 nm are gathered, these cellulose content is helpful in differentiating various types of wood sample. Cellulose tends to absorb near-infrared spectrum, the intensity of reflected light at channels T and U will be affected by the amount of cellulose in the wood samples. Based on the observations. Chengal has the highest cellulose content as most of the near-infrared light is absorbed by cellulose and only a remaining amount of light has been reflected back to the sensor, giving a lowest level of light intensity at the respective channels. Whereas Hevea exhibits lowest cellulose content, resulting in low absorption of near-infrared light by cellulose. Consequently, a maximal amount of light is reflected back to the sensor.

The spectra data of Hevea and Jelutong are very close to each other, except for the readings at channels R, S and V. This implies that there are notable differences in the colour intensity and moisture content of both wood samples. Whereby the spectra data of Chengal have substantial disparity with both Hevea and Jelutong. Chengal exhibits dissimilar properties in terms of moisture content, colour intensity as well as cellulose content when compared with other samples. This can be seen from Table 4.2, where all levels of light intensity at various wavelengths are having comparatively low values among three types of wood.

4.4 Evaluation of Wood Classification System

The feasibility and functionality of near-infrared spectroscopy on wood classification can be assessed through the limitations and capability of the sensor to accurately discriminate diverse wood species. According to the outcome of this study, the NIR sensor is capable of classifying various wood species, Hevea, Jelutong and Chengal based on spectra data collected from each sample on the same measurement surface. The system demonstrates its ability to detect different wood or object and discern precisely the actual wood or object it actually belongs to by reading and interpreting data from the six channels of wavelengths (R, S, T, U, V, W) regardless of change in ambient conditions, for instance, daytime, nighttime and in dark setting. Also, it showcases remarkable reproductibity by consistently yielding reliable results. However, it is imperative to acknowledge that potential alterations in the wood surface may impact the reliability of the results, which is recognized as one of the limitations of the NIR system.

One of the system's notable features that aids in preserving result consistency is the consistent intensity of the NIR sensor's on-board LED light source, which minimizes the ratio of signal-to-noise level in measurements. The grade of the collected spectra data is reliant on the level of intensity of the light source used to illuminate the wood samples. Low intensity of the light source may yield weak signals, resulting in reduced signal-to-noise ratio and spectral quality. Conversely, excessively high intensity of the light source may also impact measurement accuracy.

Change in measurement surface of wood samples for detection will exhibit disparate variances in the level of light reflection intensity at various wavelengths, impacting the accuracy of the classification results. In fact, the shape of the spectrum at different surfaces will vary accordingly, resulting in dissimilar data when compared to the calibrated data. As such, the system is unable to identify the origin of the wood when there are alternations in the measurement surface. This mainly due to the surface roughness, colour intensity, moisture content or cellulose content of the wood that contribute to the variations of the surface reflectivity.

Another limitation of the NIR system in wood classification is due to the effect of external light sources. When the system is exposed to another light source with high intensity or brightness other than the on-board LED of the NIR sensor, it may distort the measurements of the sensor and develop fluctuations in the spectra data as well as the classifying results. As the light source will interfere with near-infrared rays from the NIR sensor and contaminate the spectral readings by introducing unwanted spectral features. Hence, during the detection of wood samples, it is necessary to ensure that there are no external high-intensity light sources in close proximity to the NIR sensor in order to preserve the consistency of the results throughout the data collection.

In addition to that, the measuring distance between the wood sample and the NIR sensor can yield varying spectra data. In order to ensure the consistency of results and reproductivity of the system, a fixed measuring distance or separation has to be maintained. Owing to this, an user platform for the placement of wood piece and NIR sensor has been devised for the precise positioning of wood samples and NIR sensors, maintaining a consistent and fixed distance between them, in order to uphold data accuracy and measurement consistency.

In summary, the NIR system exhibits both strengths and limitations. It has the capability to generate consistent and accurate spectra data for classification purposes when measuring wood samples from a calibrated surface under a stable and appropriate intensity of light source, free from interference from external light, and maintaining a fixed distance with the NIR sensor.

4.5 Summary

In this chapter, the design and fabrication process of the ultimate prototype is outlined, including the user platform fabricated using 3D printing and laser cutting, the base board, and circuit construction. Furthermore, the calibrated data and actual readings for each wood type are acquired and tabulated for different trials. The spectra data are analyzed, and the respective graphs based on the spectra data are plotted and interpreted. Evaluation on the system's feasibility and accuracy is also performed based on the success rate of wood classification being conducted in this study. A high success rate indicates that the classification model is accurate and can be used for practical applications. On the other hand, a low success rate indicates that the model needs further improvement to achieve better accuracy.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In a nutshell, the aim of this project is to access the capability of a low-cost and portable NIR sensor in classifying several types of wood, which are Hevea, Jelutong and Chengal by using spectroscopic methods. To achieve this objective, a properly calibrated sensory system with an NIR sensor was designed and set up to collect data from wood samples. The collected spectra data were analyzed to identify the type of wood each specimen belongs to, and the results were tabulated.

According to the results and graphs obtained, the system successfully classified three types of wood into their respective species regardless of change in different ambient conditions such as daytime, nighttime and in dark settings. This indicates that the NIR system is not affected by the environment and can be effectively utilized regardless of changes in conditions. Each wood species exhibited different spectral readings in terms of the intensity of reflected light at six different channels, R, S, T, U, V and W. However, the precision and feasibility of the system are susceptible to potential fluctuations in the measurement surface, which could lead to distinctive characteristics of spectral data in relation to the levels of light reflectance across various wavelengths during measurements taken by the NIR system. The variations are typically attributed to a range of factors including surface roughness, grain orientation, moisture content, color intensity, aging, and weathering, as discovered by the study.

To summarize, the study has effectively accomplished its aim of evaluating the feasibility of utilizing spectroscopic techniques with a low-cost and portable NIR sensor to classify various types of wood. The NIR system has been shown to be capable of accurately classifying the three types of wood examined, and it has been demonstrated to be reliable in various environmental conditions. Nevertheless, as discovered by the research, the accuracy and applicability of the system are susceptible to changes in the measurement surface.

5.2 Recommendations for Future Work

There is still room for improvements in the wood classification system constructed in this study. Several recommendations for future development can be introduced such as the implementation of weight sensor in the system, specifically on the user platform of the prototype. This is to ensure that the spectra readings obtained for each attempt of each wood species is accurate in which the system only starts acquiring data when the weight sensor detects some weight or force applied to the user platform, indicating the presence of the wood is ready to be measured. This addition would minimize errors that may occur when spectral readings are obtained without the presence of wood, which could affect the median readings. The accuracy of the system in interpreting the data could be significantly improved with this feature.

Other than that, another potential improvement to the system would be to utilize a shield cover. This would involve enclosing the wood classification system completely using a shield cover, which would prevent external light sources from interfering with the classification process. This is due to when the system is exposed to another light source with high intensity or brightness other than the on-board LED of the NIR sensor, it may distort the measurements of the sensor and develop fluctuations in the spectra data as well as the classifying results. As the light source will interfere with near-infrared rays from the NIR sensor and contaminate the spectral readings by introducing unwanted spectral features. Hence, during the detection of wood samples, it is necessary to ensure that there are no external high-intensity light sources in close proximity to the NIR sensor in order to preserve the consistency of the results throughout the data collection.

In addition, a recommendation for future improvement of the wood classification system is to incorporate an interrupt feature in the NIR system. This feature would enable users to interrupt the classification process by pressing a push button, allowing for the restarting of a measurement attempt due to various reasons, thereby reducing the likelihood of human error. By pressing the interrupt button, the system would loop back to the previous operation and initiate the same attempts of measurement again. This would save time as users would not have to wait for the completion of the first classification in order to make corrections for other attempts.

Last but not least, it is worth noting that the system can undergo further modifications by integrating machine learning techniques. Specifically, a large dataset of spectra data for Hevea, Jelutong, and Chengal wood samples can be collected from every surface and utilized as a training set for a machine learning algorithm or deep learning model to develop an accurate wood classification system. The objective of this system would be to predict specific outcomes, such as classification results, based on test data consisting of light intensity at various wavelengths. The performance of the algorithm can be assessed by measuring the success rate and efficiency of the classification system. Once the model attains remarkable accuracy, it can be combined with the wood classification system to improve its accuracy by utilizing spectral data obtained from all surfaces of the wood specimens.

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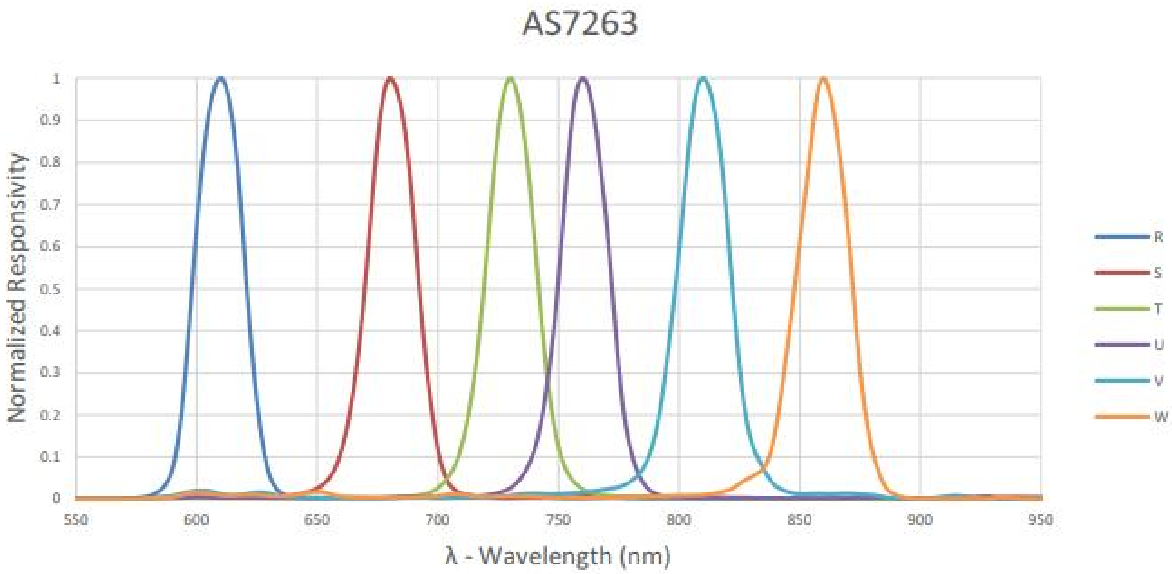
APPENDICES

Appendix A: Graphs



Graph A-1: Spectral Responsivity of 6 Channels in AS7263 Sensor

Appendix B: Tables

Table B-1: Optical Characteristics of AS7263 (Pass Band)

Symbol	Parameter	Test Conditions	Channel (nm)	Min	Typ	Max	Unit
R	Channel R	Incandescent (2), (4)	610		35 (3),(4)		counts/ (μW/cm^2)
S	Channel S	Incandescent (2), (4)	680		35 (3),(4)		counts/ (μW/cm^2)
T	Channel T	Incandescent (2), (4)	730		35 (3),(4)		counts/ (μW/cm^2)
U	Channel U	Incandescent (2), (4)	760		35 (3),(4)		counts/ (μW/cm^2)
V	Channel V	Incandescent (2), (4)	810		35 (3),(4)		counts/ (μW/cm^2)
W	Channel W	Incandescent (2), (4)	860		35 (3),(4)		counts/ (μW/cm^2)
FWHM	Full Width Half Max		20		20		nm
Wacc	Wavelength Accuracy				±5		nm
dark	Dark Channel Counts	GAIN=64, T_{AMB}=25°C				5	counts
f	Angle of Incidence	On the sensors			±20.0		deg

Appendix C: Figures

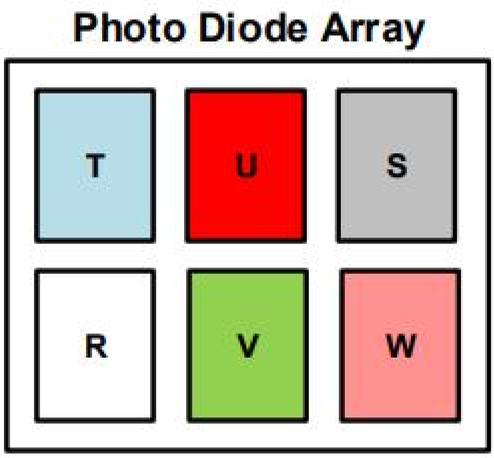


Figure C-1: Photodiode Array of AS7263 Sensor