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Prediction of Sugar and Carbohydrate in Sapota using Hyperspectral Image Segmentation

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***Abstract*— India offers a diverse range of fruits to its consumers. Each fruit has distinct characteristics, physical and chemical, defining their ripening and consumption stages. Fruits that lack strong physical attribute changes must be chemically analyzed for their ripeness and consumption. One such fruit is sapota, a tropical evergreen fruit-bearing tree. Sapota, a delicious fruit, possesses numerous medicinal and nutritive properties. It has a shorter shelf life, hence, is prone to major post-harvest losses. To overcome this difficulty, we propose a model where we use hyperspectral image segmentation to predict the sugar and carbohydrate values of the fruit. This model determines the sugar and carbohydrate values and in turn, predicts the ripeness of the fruit as there is an increase in the sugar and carbohydrate contents in the fruit with its ripening. The accurate values from the laboratory tests are used to test our model. A near-infrared Hyperspectral Imaging (HSI) system scanned samples with a wavelength range of 874-1734 nm. This model comes as an asset at the industry level and helps determine the ripeness of a large batch of sapota for its timely storage and relegation to retailers and consumers.**

***Index Terms*— Hyperspectral Imaging, Resonon Pika-IR, Near Infrared Spectroscopy, Ridge Regression, Hyperparameter Tuning, Image Segmentation, Machine Learning in Agriculture, Sugar and Carbohydrate Estimation.**

I. INTRODUCTION

Sapota is commonly known as chikoo in India. India is one of the largest producers of sapota in the world. The estimated area under sapota cultivation in India is about 97 thousand hectares and production is about 1176 thousand metric tons. Maharashtra, Gujarat, Andhra Pradesh, Karnataka, Tamil Nadu, West Bengal are the major sapota growing states in India. Sapota offers various and diverse nutrients. It is a rich source of sugar, proteins, ascorbic acid, phenols, carotenoids and minerals, for example phosphorus, calcium, iron, potassium, copper etc.

One can best enjoy the deliciousness of the fruit when it's ripe. However, one of the major postharvest issues is the quick ripening and faster senescence of the edible ripe fruit. Hence, the storage life of the fruit is exceptionally short lived and can only be stored for 7-8 days under ordinary conditions after the harvest. Since it has a shorter shelf life, if the fruit is stagnated in a particular stage for a long time, it will get spoilt and lose its edibility and consequently its value.

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Combined with the difficulty in predicting its ripeness without chemical properties, it's a difficult task to constantly keep a check on the ripeness of this fruit. We have also observed from the previous experiments that as the fruit ripens, its sugar and carbohydrate value increases. Since the shelf life is so short, and the production is huge, we need to find the batches that need immediate circulation in the market so that the batch is not overripened and wasted.

Similarly, the batches that are underripe can be stored for a longer time till the ripened ones are circulated. A lot of fruits can be classified as unripe or ripe based on their physical features, textures, smell, appearance, or other noticeable characteristics. Some of them cannot be easily classified based on physical properties and need chemical analysis or other tests to determine the level of ripeness or maturity. One such fruit is Sapota. Hence, we need a system that can detect the ripeness and classify the batches into the various levels of ripeness so it can be used for further circulation.

II. Literature Study

Paul Martinsen et al. [1] measured the location of soluble solids on the kiwifruit's sliced sides using a NIR imaging spectrometer. A Near-infrared range (NIR) calibration was established by measuring the soluble solids content of plugs cut from thin fruit segments and comparing these readings to spectra taken from the exact places as the plugs. These models were used to depict the spatial distribution of soluble solids concentrations over sliced fruit parts.

Jeroen Lammertyn et al. [2] used non-destructive methods to measure acridness, dissolvable solids, and hardness of Jonagold apples using NIR spectroscopy. The reflectance spectra captured with a bifurcated optical fibre and fruit characteristics including pH, dissolved solids content, stiffness factor, and other textural factors like the elastic modulus of the flesh have been linked in this research. Principal component analysis (PCA), principal component regression, and partial least squares analysis were utilized as multivariate calibration procedures.

Gamal Elmasry et al. [3] utilized Artificial neural network (ANN) technique and HSI to identify chilling injury in Red Delicious apples. To select the best wavelength or wavelengths, classify the apples, and identify firmness changes brought on by chilling injury, feed-forward back-propagation ANN models were established. The potential of the suggested strategies for identifying chilling damage and forecasting apple firmness is highlighted in this research.

Diwan P. Aria et al. [4] chose significant wavebands in HSI to find internal flaw in pickled cucumbers and complete pickles. The k-nearest neighbor classifier and the branch and bound technique were used to determine up to four-waveband subgroups. Online pickle and cucumber quality detection was done using the chosen waveband sets.

Piotr Baranowski et al. [5] employed the PCA and minimal noise fraction analyses of the pictures that were recorded in specific ranges made it feasible to differentiate between areas with tissue defects and sound ones. After pulse heating of the fruit surface, the quick Fourier analysis of the image sequences revealed further details regarding the position and depth of the injured tissue.

Gamal Elmasry et al. [6] established that the HSI system is a crucial non-destructive technology that combines spectroscopy and imaging techniques to not only make a simultaneous direct assessment of various components but also to identify the spatial distribution of such components in the tested products.

Dan Liu et al. [7] emphasized the significance of non-destructive techniques like HSI as an important and effective technique for evaluating the quality of agricultural consumables because it enables assessment of a specimen's chemical build up (spectroscopic component) and external characters (imaging component) in each point of the image with full spectral information.

Jhon Pinto et al. [8] used PCA and other spectral vegetable indices in their non-invasive HSI investigation to examine the ripening status of Hass avocados. In this study, the ripening of a population of 7 Hass avocados over a 10-day period is quantitatively analyzed. Unripe, almost ripe, and ripe avocados were separated into these three categories for the study. The results demonstrated that utilizing a non-invasive acquisition technology, hyperspectral images can be used to identify the level of ripening of avocados.

Leon Amadeus Varga et al. [9] used a hyperspectral camera and the appropriate deep neural network to measure the freshness of fruits. They collected data set on avocados and kiwis for their study and outlined the data gathering procedure in such a way that it is simple to adapt it to different fruits. The authors analyzed the spectral features and empirically validated the trained Convolutional Neural Network (CNN). In addition, a method for visualizing the ripening process is shown. The classification of avocado ripeness using the HS-CNN classifier network achieved high accuracy. As a result, the experiment revealed that exotic fruits can be divided into three classes i.e., ripe, unripe, and overripe.

Peipei Zhang et al. [10] proposed a method, based on hyperspectral photography with a wavelength range of 900–1700 nm, to predict the mechanical properties of apple after impact damage. To extract the necessary region and choose distinctive wavelengths, methods like damaged region identification, PCA, and successive projection algorithms were used. A support vector machine was created using full-band and chosen wavelengths, nondestructive testing of mechanical properties was carried out.

These studies serve as a guide for analyzing the mechanical characteristics of post-harvest fruit and other agricultural goods using HSI. Based on the above studies and an analysis of both physical and chemical properties, we can train a Machine Learning (ML) model to predict the sugar and carbohydrate content in sapota.

II. METHODOLOGY

A. Sample Scanning

Samples of sapota were purchased from a vendor and were stored over a period to let the samples ripe overtime. The samples were collected from only one vendor to reduce the probability of samples from different farms. As different farmers use different chemicals and fertilizers which would help towards producing inaccurate results. These samples were scanned under the Pika-IR hyperspectral camera which functions under the near infrared spectral range.

The samples were scanned in a batch of six from front and back to help in making accurate model. The samples once collected were stored in a natural environment and were allowed to pass three stages of their lifecycles: Raw, Ripped and Overripe. This was done to perform a comparison of the sample across its lifecycle and this provided us with a consistent and accurate results.

B. Hyperspectral Image Camera

The hyperspectral camera used for scanning samples used was a Resonon Pika-IR. It is a high-speed, cost-effective camera that covers the NIR. Our research laboratory consisted of the benchtop system version of this camera.

The highlighting features of the Pika-IR camera are it can capture images high speed images at a maximum frame rate of 521. With a spectral channel of 900-1700nm range and a spectral bandwidth of 4.9mm it also supports spectral resolution of 8.8 nm with a bit depth of 14. Fig. 1 below shows the benchtop system.

First, to prevent the distortion of the HSI, stage speed, exposure duration, and the distance between lens and object are adjusted. These are decided based on the samples size and number of samples to be scanned at a go on the stage.

C. Data Preprocessing and Model Preparation

After the step of data acquisition, we move on to data preprocessing wherein we make our data ready for our ML model. As the images were scanned in the batch of six, there will be some area in the image whose hyperspectral data will not contribute towards analysis.

To remove this unwanted data points, we need to crop our HSI cubes. After cropping these HSI cubes we must read the HSI cubes and transfer this data to a csv file for appropriate analysis. The step of reading the HSI cube and converting into csv was automated.

The samples scanned under the HSI were send for the chemical analysis at a Food Technology Lab just after 30 mins of scanning so that the chemical analysis could be accurate. This helped us in getting the real and consistent values of sugar and carbohydrate content in the batches of sapota scanned.

The dataset generated consisted of the HSI bands data and the sugar and carbohydrate values obtained from chemical analysis.

Table I shown below represents the snapshot of the dataset.

D. Model Analysis

Prediction of sugar and carbohydrate was done by establishing a relationship between the independent variable (168 bands) and the independent variable (sugar and carbohydrate percentage obtained from lab analysis). This relationship was established using the regression model.

We have used ridge regression to predict the values of sugar and carbohydrate. The relationship was backed by our literature review and was also verified after obtaining the results. To build a generalized machine learning model we had to observe a spot between bias and variance which would provide us with accurate and trustworthy results. The model build should neither be underfit nor an overfit model. So, to achieve a balanced fit model we had to observe the graph of bias-variance trade off and find an optimal point.

By considering all the factors we finally arrived at Ridge Regression which helped us improve our and accuracy and along with hyperparameter tuning it gave us near to accurate results. It also helped in obtaining a smooth distribution plot curve which symbolizes that we have been able to achieve a balanced fit model.

TABLE I: THE SPECTRAL MEAN OF SPATIAL DATA AND SUGAR AND CARB CONTENT DATASET

B1	B2	B3	...	B166	B167	B168	Sugar%	Carb%
3105	3138	3153	…	2030	1982	1956	48.03	28.03
3709	3767	3785	…	2398	2345	2283	48.03	28.03
……	……	……	……	……	……	……	……	……
4271	4324	4349	…	2830	2750	2690	45.53	28.03
4411	4458	4496	…	3372	3274	3195	45.53	28.03

III. RESULT AND DISCUSSION

A. Band Selection and Chemical Analysis

During our studies we have found out that in different stages of the life cycle of sapota it has different percentage of sugar and carbohydrate. In the three lifecycles, it has the least sugar and carbohydrate percentage in the unripe stage, and it goes on increasing till the overripe stage. Ethylene is responsible for the process of ripening of fruit. As we have scanned the same batch of sample over the three stages of life cycle of the fruit, these findings can be verified.

Fig. 1 shows the mean spectrum graph of the HSI cube of sapota in three different stages. This mean spectrum graph is plotted by considering all the values of the sample across all 168 bands. All the values corresponding to the sample are plotted and the mean is calculated for the 168 bands. The highlighted region represents the values covered by a particular sample and the bold colored lone represents their mean. The
blue line represents the fruit in unripe stage, the green line represents the fruit in eatable stage and the red line represents the fruit in overripe stage.

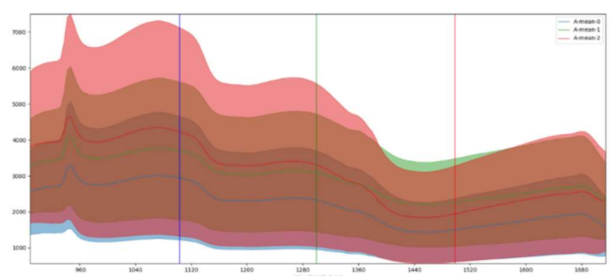

Figure 1: Mean Spectrum Comparison of sapota in different stages

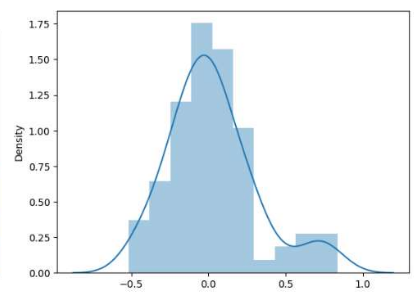

Figure 2: Distribution plot for ridge regression

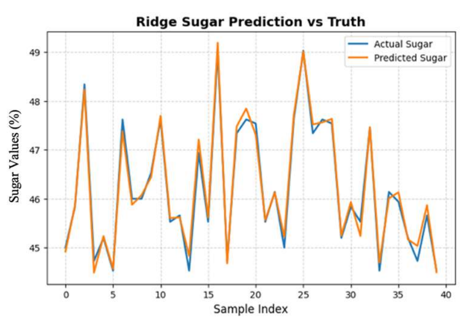

Figure 3: Ridge regression sugar value's comparison

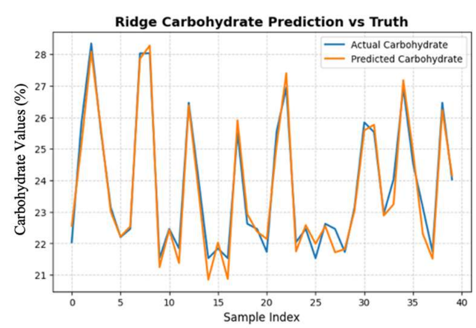

Figure 4: Ridge regression carb value's comparison

During our research we found out that the total reducing sugar value increases as the fruit ripens and in our case the changes can be observed at 970 nm,1190 nm and 1450 nm wherein 1st, 2nd and 3rd overtone of -OH bond is observed due to changing composition of fructose and sucrose. In the figure we can observe that at 1400 nm the effect of 2nd overtone of ethylene dominates as the fruit is in the ripe stage and thus an overlapping of mean spectrum can be observed in the figure.

B. Result of Regression Algorithm

We have predicted the values of sugar and carbohydrate using Ridge Regression which provided us with results near to the actual values. From Table II we can observe that for Linear Regression the R^2 score is -14 which implies that the dataset does not fit the linear model and hence after applying the dataset on the polynomial model with degree 3 the R^2 score improved but a peak was observed at degree 3. So further we applied models performing regularization. The Lasso Regression performing L1 regularization improved the R^2 score drastically but the feature selection was found to be restricting the performance. Using L2 regularization of Ridge Regression we have been able to achieve a R^2 score of 0.9809. After analyzing the graph of predicted and truth values, we found out that the feature selection done using L1 regularization provided us with predicted results far away from truth value. From the Distribution plot shown in Fig. 2 we can observe that in case of Ridge Regression the Distribution plot has the maximum density for the x value as 0 and cover an x-axis range from -0.5 to 1.0 and provides us with smooth curve that signifies, we have obtained a balanced fit model.

We have observed that the predicted values lie in the specified range of 44%-49% for sugar prediction and 21%-28% for carbohydrate prediction. These ranges were also obtained from chemical analysis.

In Fig. 3 and Fig. 4 we have plotted the graph for the predicted values of sugar and carbohydrate for the testing dataset. We can observe that our model is predicting almost accurate values in case of sugar and near to truth values in case of carbohydrate.

C. Statistical Analysis

To validate the correction of our results statistical significance test was performed. We are using Analysis of Variance (ANOVA) significance test [11][12], against the reflectance value of sapota obtained from the hyper spectral imaging camera. The statistical method can be used to analyzed similarity between distinct datasets. Significance testing is used to dissect similarity among sapota samples or to decide the variations between three or more

categorical samples. If hypothesis is rejected, then the data is not having similar pattern. It means there exist a difference between sapota samples.

The Hypothesis is,

H0: $\mu_1 = \mu_2$, Null Hypothesis, there is no differences between the sapota samples

H1: $\mu_1 \neq \mu_2$, Alternative Hypothesis, differences exist.

Table III illustrates the ANOVA outcomes characterizing squares of between mean (BM) of all

categories samples as unripe, ripe and overripe. Table III also describes each dataset's F-statistic value and the group's within-mean (WM) square. In dataset column Set_Day1 to Set_Day5 represent the set of sapota samples scanned on Day1 to Day5.

TABLE II: REGRESSION ALGORITHMS WITH R^2 SCORE

Name of Method	R^2 Score
Linear Regression	-14.0634
Polynomial Regression (3rd Degree)	-9.1163
Lasso Regression	0.7824
Ridge Regression	0.9809

TABLE III: THE SPECTRAL MEAN OF SPATIAL DATA FOR SAPOTA

Dataset	BM	WM	F-statistic	F-critical
Set_Day1	9.52	1.76	5.41	2.13
Set_Day2	9.12	1.84	4.96	2.13
Set_Day3	8.93	1.62	5.52	2.13
Set_Day4	7.45	1.2	6.21	2.13
Set_Day5	8.76	1.73	5.07	2.13
Set_Ripe	1.58	0.83	1.91	2.13
Set_Unripe	2.55	0.98	2.06	2.13
Set_Overripe	2.23	0.86	1.76	2.13

III. CONCLUSION

This paper proposed the analysis of the prediction process of sapota fruit via a non-destructive hyperspectral image system in order to classify them as unripe and ripe. The obtained results show that, applying ML models to the spectral signatures of the sapota, it is possible to predict sugar and carbohydrates as days pass. Moreover, the predicted results were compared with lab tested values, which showed convincing correlations with the lab tested values.

Two main components that contributed the most to obtaining these results are the use of higher wavelength near-infrared bands and the involvement of chemical analysis of samples under image acquisition. The formulated methods use data from the sapota that were collected from the common regional vendors. If the sapota are collected from different farms located in a wide variety of regions the improvement in results will be quite significant. As most portion of the accuracy for our model depends on prediction, it will be greatly helpful to improve the accuracy by increasing the dataset size.

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