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Identification of mango variety using near infrared spectroscopy

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ABSTRACT

The structure of the proposed framework is separated into three stages: i) foundation deduction, ii) component extraction, and iii) preparing and characterization. At first, K-implies grouping methods were carried out for foundation deduction. The second step applies color, texture, and shape-based feature extraction methods. Finally, a "merging" fusion feature is analyzed with a C4.5, support vector machine (SVM), and K-nearest neighbors (KNN). Overall, the recognition system produces an adequate performance accuracy with 97.89, 94.60, and 90.25 percent values by utilizing C4.5, SVM, and KNN, respectively. The experimentation points out that the proposed fusion scheme can significantly support accurately recognizing various fruits and vegetables.

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1. INTRODUCTION

The national fruit of India is the mango (Manifera indica L.), and it is said to be the "king of fruit" [1], [2]. Mangoes usually grow in tropical regions, and it is a popular fruit in Asian countries [3], [4]. The economic value of mangoes is higher as they are embedded with "adaptability, high nutritive value, richness in variety, delicious taste, and excellent flavor". In India, more than thousands of varieties of mangoes are available, and based on the time of ripening, they are classified as early, mid-season, and late. Pre-harvest cultural practices like pest control, fertilizers, climatic conditions, and growth regulators are managed in mango harvesting. Post-harvest management adds value to the products and freshness, expansion of storage life, and attractive appearance to deliver quality products to buyers [5], [6]. In today's technological era, it is essential to maintain the health of human beings by providing them with good-quality fruits. This becomes possible only when the fruits are graded according to their internal and external features. The external features like size, color, and shape tell about the ripening of the fruits and the external damage from insects. This can be visually seen; hence, grading based on external features is easy [7]-[9]. Further, a mango could not be considered good with only the external elements. The internal components like the total suspended solid (TSS), acidity, pH, and moisture content are also essential. Indian mangoes have a great demand in local and foreign markets due to their taste and aroma [10]-[12].

The assessment and inspection of these mangoes are done manually, which consumes more time and high labor costs. As a solution to this, come into the field of the “non-destructive and automated fruit grading system” with the image processing technique [13]-[15]. This helps increase the accuracy of quality control and, at the same time, helps decrease production losses. In the non-destructive technique, image processing is explored for mango assessment as it has advanced automatic grading techniques that reduce the errors and time consumed for grading.

Momin *et al*. [16] developed a novel approach for automatically classifying and grading mangoes without human intervention. Initially, the mangoes were split into the category of ripened and unripe. Then, they were graded based on their size and color. The CIELab color space’s performance was analyzed using the image database to explore the diverse colors of mangoes. Further, the dominant density range with the CIELab color model was utilized for color feature extraction. In addition, the properties of the ellipse were utilized for calculating the size feature, and based on the color and size features, they were graded. Further, the dominant density range with the CIELab color model was utilized for color feature extraction. In addition, the properties of the ellipse were utilized for calculating the size feature, and based on the color and size features, they were graded. Tripathi and Maktedar [17] have proposed a new approach for grading the mangoes in which the projected area, perimeter, and roundness features were extracted in the image acquisition and processing system. The XGA format color camera of 8-bit gray levels using fluorescent lighting was utilized for image acquisition.

Nandi *et al*. [18] presented an efficient denetic adaptive neuro fuzzy inference system (GANFIS) for classifying and grading mangoes. The color, shape, and texture features were extracted from the mangoes by reading the 2D images using the GANFIS approach. The components were selected using the genetic algorithm, and then the adaptive neuron fuzzy inference technique was deployed for classification and grading. Nandi *et al*. [19] have designed and developed a non-destructive infrared spectroscopy instrument for automatically grading mangoes. This approach was generated using the near infrared (NIR) spectroscopy technology, and the data was collected for six days to know how the quality of the fruit had increased as it ripened. Zhen *et al*. [20] introduced a novel grading approach for grading mangoes based on their external features and weight. Mangoes were graded into three grades in terms of length, width, defect, and weight features using the four machine learning models random forest (RF), linear discriminant analysis (LDA), support vector machine (SVM), and K-nearest neighbors (KNN) [21]. The application of machine vision for fruit grading is depicted in Table 1.

Table 1. Application of machine vision for fruit grading

Application	Pre-processing	Feature extraction	Data analysis	Accuracy in %	Reference
Sorting	Ostu threshold	Colour and size	Fuzzy rule	94.97	[16]
Grading	Binary threshold	Shape and size	Back propagation neural network (BPNN)	80	[17]
Grading	Binary threshold	Mass	Static analysis	97	[18]
Sorting	Gamma curve fitting	Colour	Coefficient	98	[19]
Sorting	Convolution filter	Colour, mass	Artificial neural network (ANN)	80	[20]
Grading	Threshold-techniques	Size	Caliber model	89.5	[21]
Grading	Hyperspectral image (HSI)	Texture	Neural network (NN)	93.33	[22]
Grading	Adaptive threshold	Colour, shape	Principal component analysis (PCA)	92	[23]

2. METHOD

In the experiment, 300 sets of mangos were purposed from the local market of a different city. The mango shopkeeper said that all mango are similar in size and shape and, most importantly, are disease-free. One hundred dashari mangos (50 from Varanasi and 50 from Pune), 100 Langra mango (50 from Varanasi and 50 from Pune), and 100 Chausa mango (50 from Varanasi and 50 from Pune) from two main local markets. Before measurements, all the collected samples were put together in airtight polyethylene bags and refrigerated for two days at ($24 \pm 1\ ^{\circ}C$). Then, these mangoes were cleaned with clear water, dried, and stored for about 3 hours at room temperature ($24 \pm 2\ ^{\circ}C$). The mango images are collected in real time for this research. The large set of mangoes for each of the grades was collected for six days, and the sample images contained for Dashari, Langra, and Chausa are shown in Figure 1. In this research, 100 Dashari mangos (30 from Varanasi and 30 from Pune), 100 Langra mango (30 from Varanasi and 30 from Pune), and 100 Chausa mango (30 from Varanasi and 30 from Pune) are considered for the prediction set, remaining 180 mangoes used for the calibration set. The calibration set in this used for building machine-learning models, whereas the prediction set is used to evaluate the performance of the machine-learning models.

2.1. Spectra acquisition

NIR spectroscopy has been proven effective in determining internal quality attributes. NIR has been widely used to determine agricultural and food product varieties and chemical properties. In the form of diffuse reflectance mode, the arrangement of the measurement system is made, and here, the spectra range is from "400 to 1,000 nm," and as a result, there are 1,888 data points for each spectrum. The spectrum is collected and transformed using the software Ocean View (Ocean Optics, USA). The evaluation of mango is done at room temperature ($24 \pm 2\ ^{\circ}C$). The system is turned into action mode 1 hour prior to the time of implementing the measurements, which was done to warm up the system. The optical fiber probe of NIR should be contacted with the measured sample surface of mangoes as closely as possible to neglect the air interference and the surface reflectance. Further, the spectra were obtained for each of the mango samples at 15 different randomly selected locations along the mango's equator. All the locations were scanned ten times, a total of 150 scans were done, and the resultant was acquired as the average value of the 150 scans.

2.2. Soluble solids content and total acid content

The internal attributes of soluble solids content (SSC) and total acid content (TAC) could determine the quality of mango. These attributes are greatly affected by the variety and cultivation region of mango. Using the domestic juicer, the flesh is extracted from each mango at room temperature ($24 \pm 2\ ^{\circ}C$). The TAC values were extracted by taking 1.0 mL filtered juice with a pH meter of pH5S (Sanxin, China). In addition, a handheld digital refract meter Pal-1 (Atago, Japan) is used to extract the SSC values. The extracted values were measured thrice, and their mean was used for data analysis.

2.3. Principal component analysis

The critical issue when utilizing NIR spectrometry on data analysis is a massive volume of information since machine learning techniques may go down with exceptionally dimensional frameworks inside the information [6]. Since the extra information in spectra may reduce the accuracy of machine learning models. A typical arrangement is to utilize specific complex learning calculations to diminish the dimensionality so that the presentation of models could be exceptionally advanced. In this regard, PCA is a good data mining algorithm and has been extensively used in NIR data. The PCA is to reduce data dimension and orthogonalize the original multidimensional data to obtain a set of values of linearly uncorrelated variables to minimize the chance of over-fitting and enhance the speed of the training model. This arrangement of the group is called principal components [22].

2.4. Support vector machine

In general, SVM is said to be a "non-probabilistic binary linear classifier" and a two-class classifier, where the input data is split into two segments to form a hyperplane [23]. To discover the isolating "hyperplane in the SVM algorithm", it's important to consider the "saddle" purpose of "Lagrange work", which can be decreased to the issue of "quadratic programming".

$$\begin{aligned} -L(\lambda) = -\sum_{d=1}^{Q} \chi_d + \\ 1/2.\sum_{d=1}^{Q}\sum_{k=1}^{Q} \chi_d{\cdot}\chi_k{\cdot}y_d{\cdot}y_k{\cdot}\lambda(z_d, z_k) \rightarrow \min_{\chi}, \\ \sum_{d=1}^{Q} \chi_d{\cdot}y_d = 0, 0 \leq \chi \leq Cr, d = \bar{1}, \bar{Q} \end{aligned} \tag{1}$$

2.5. K-nearest neighbors classifier

The KNN algorithm is an instance-based learning method that is simple to execute regulated machine learning calculations [24]. In the training phase, all the input features of F (i, h) are solely memorized; hence, it can tackle the characterization and relapse issues. Then, the characteristics to be classified are compared over the defined distance measure. Similar features are said to be nearest neighbors and KNN can be included. Presently the test information is anticipated on the model constructed. There are specific separation measures and approaches like Euclidean separation, Manhattan distance, and Makowski distance measures can be used for the consistent variables.

$$\text{Euclidean distance} = \sqrt{\sum_{l=1}^{K}(X_l - Y_l)} \tag{2}$$

Here, X_l and Y_l are two points on the feature set $F(i, h)$. The classified result from KNN is indicated as Out_{CNN}.

2.6. Artificial neural network model

ANN encapsulates three layers: input, output, and hidden layers [25]. The hidden, input, and output neurons are denoted as hid, ip, op, respectively.The bias weight of the hidden neurons hid is depicted as $wg^N_{b.hid}$. The bias weight of the output neuron is indicated as $wg^N_{b.op}$. In addition, $wg^N_{ip,hid}$ represents the weight from ip^{th} input neuron to hid^{th} hidden neuron and $wg^L_{hid,op}$ is the weight from hid^{th} hidden to op^{th} output neuron. Further, (3) exhibits the predicted output of the network, which is referred to R_{pre}. The (4) represents the error function $F(er)$ between actual outputs R_{act} and predicted the output R_{pre}. $F(i, h)$ refers to the extracted features. The activation function in (3) and (4) is represented as AF. The mathematical formula for the hidden layer is depicted in (3).

$$\text{Hidden} = AF\left(wg^N_{b,hid} + \sum_{ip=1}^{N_p} wg^N_{ip,hid} F(i, h)\right) \tag{3}$$

$$R_{pre} = AF\left(wg^L_{b,op} + \sum_{hid=1}^{N_z} wg^L_{hid,op} \text{Hidden}\right) \tag{4}$$

$$F(er) = \underset{|wg^N_{b,hid}, wg^N_{ip,hid}, wg^L_{b,op}, wg^L_{hid,op}|}{\text{argmax}} \sum_{op=1}^{N_0} |R_{act} - R_{pre}| \tag{5}$$

3. RESULTS AND DISCUSSION

PCA will be used to extract the valuable data from given spectra. In this experiment, the performance and robustness of the established models were evaluated by comparing the predicted values with the measured values. The statistic root mean square error of calibration (RMSEC) and root mean square error of prediction (RMSEP). Next, three techniques were implemented to build the machine learning model to identify the mango variety. The three methods were ANN, SVM, and KNN. Figure 1 shows the flow chart of the process.

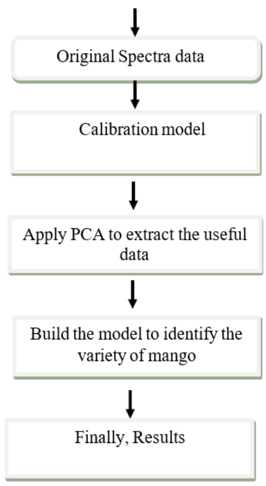

Figure 1. Flow chart for data processing of NIR

3.1. Data analysis average NIR spectrum of each variety

Table 2 listed the SSC distribution of mango used in this experiment; Table 3 listed the TAC distribution. The proposed model's SSC range is from 7.91 to 9.225 Brix, the max value varies between 14.127 to 15.965, and the mean value is between 11.68 to 13.97. While the TAC range of the min is 2.20 to 4.85, the max range is between 4.14 to 5.37 and from 3.14 to 4.01 for a mean of TAC.

Table 2. Summary statistics of SSC of mango samples

Sample set	Min	Max	Mean
Dashari mango from Varanasi	8.695	14.425	11.68
Dashari mango from Pune	9.225	14.127	11.97
Langra mango from Varanasi	7.91	15.347	12.58
Langra mango from Pune	8.56	15.965	13.01
Chausa mango from Varanasi	8.90	15.58	13.45
Chausa mango from Pune	8.82	15.85	13.97

Table 3. Summary statistics of TAC of mango samples

Sample set	Min	Max	Mean
Dashari mango from Varanasi	3.54	4.26	3.58
Dashari mango from Pune	3.87	4.98	3.21
Langra mango from Varanasi	4.85	4.34	3.12
Langra mango from Pune	2.20	5.37	4.01
Chausa mango from Varanasi	2.92	4.56	3.45
Chausa mango from Pune	2.37	4.14	3.97

3.2. PCA process

Many factors in the information vector may include insignificant data and degrade the performance accuracy of the machine learning framework. PCA technique must be applied to pre-process spectra data for dimension reduction. Table 4 shows the contribution and accumulative contribution rates of PC 1 to PC 8. Table 4 states that for the first PC 1, the contribution rate is 78.32, and for the second PC contribution rate is 14.98%.

Table 4. The contribution and accumulative contribution rates

PCs	Contribution rate (%)	Accumulative contribution rate (%)
PC 1	8.32	78.32
PC 2	14.98	91.53
PC 3	5.85	94.34
PC 4	1.20	97.37
PC 5	0.92	98.56
PC 6	0.37	99.14
PC 7	0.19	99.16
PC 8	0.16	99.75

3.3. Experiment results

The optimal number of neurons is 16 in the hidden layer selected for the ANN model shown in Table 5. The accuracy rate for the identification of mango based on NIR by ANN, SVM, and KNN model is shown in Table 6. The results show that performance could be more satisfactory. The average accuracy of the PCA-ANN model on the calibration set is 53.16%, and on the prediction set, the average accuracy rate of the PCA-ANN model is 35.40%. This table depicts the mango variety's identification accuracy by support vector machine techniques. It has been shown with the results that the PCA-SVM model on the calibration set produces 98.14% performance accuracy, and on the prediction set, the performance rate is 86.0%.

Table 5. The best number of neurons in the hidden layers of ANN models

Dimension reduction methods	The number of neurons
PCA	16

Table 6. The accuracy of proposed ANN, SVM, and KNN model

Set	Calibration set PCA (%)	Prediction set PCA (%)
Dashari mango from Varanasi	76, 100, 100	42, 95, 95
Dashari mango from Pune	22, 97.52, 97.52	15.32, 96, 96
Langra mango from Varanasi	46.87, 100, 100	61.07, 98,98
Langra mango from Pune	89.87, 96.17, 100	39.14, 80, 80
Chausa mango from Varanasi	15.24, 100	5.98, 85
Chausa mango from Pune	68.71, 100, 98.24	48.87, 97, 97
Total	53.16, 98.14, 99.29	35.40, 86.0, 91.84

In combination with chemometric analyses, NIR spectroscopy showed potential in identifying specific mango varieties under study [26]-[28]. The Alphonso and Banganapalli cv at a five percent significance level were predicted with an accuracy of 99.07% and 99.58%, respectively. In contrast, the Dasheri and Malda variety can be identified at an accuracy level of 98.37% and 94%, respectively. The proposed methodology gives the PCA-KNN model an average accuracy rate on calibration and prediction rate set of more than 90.0%. The table states that with the PCA-KNN model on the calibration set, the accuracy rate is mainly 99.29%; on the prediction set, the average identification accuracy is 91.84%. While comparing with the identification accuracy of all the machine learning model, it could be observed that the PCA-KNN model produce better results. With the results, we can conclude that supervised learning-based algorithms could give better prediction performance. PCA-SVM model could identify Dashari mango, Langra mango, and Chausa mango from Varanasi with 100% accuracy. Whereas PCA-KNN has identified the Dashari mango, Langra mango, Chausa mango from Varanasi, and Langra mango from Pune with 100% accuracy, with is better than existing techniques. The comparison shows that it significantly improves the identification of mango variety using NIR spectroscopy.

4. CONCLUSION

In this paper, the experiment results show that it is possible to design a framework based on NIR spectroscopy algorithms to detect a variety of mango fruits. PCA techniques are used for data dimension reduction. The three machine learning techniques, such as ANN, SVM, and KNN, were utilized to build a model for detecting a variety of mango. Through experimental results, it is very identical that it is possible to develop the framework for identifying the mango image based on NIR spectroscopy between 400 to 1,022 nm. The KNN model, with a value of 99.29%, produces the highest accuracy compared to the other two models, SVM and ANN model. In PCA-KNN has 99.29% accuracy for the calibration model and 91.84% accuracy for the prediction model. At the same time, the PCA-SVM model has 98.14% accuracy for the calibration model and 86.0% accuracy for the prediction model. The lowest accuracy rate has been achieved with PCA–ANN model with a value of 53.16% accuracy for the calibration model and 35.40% accuracy for the prediction model.

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