Deep Learning based Non-Destructive Evaluation of Physiochemical Parameters for Post Harvested Pomegranate Fruits

Surekha V Yakatpure[1*]

Department of ECE
Visveswaraya Technical University, Belagavi, Karnataka
*Email: surekha.sakhare@gmail.com

Dr. Krupa R Rasane[2]

Professor & Head,
Department of Electronics and Communication,
Jain College of Engineering Belgavi, Karnataka-590014, India.
Email: kru_ran@yahoo.com

Dr. K. Dinesh Babu[3]

Principal Scientist,
National Research Centre on Pomegranate (NRCP),
Solapur, Maharashtra- 413255, India.
Email: ckdhinesh@gmail.com

Abstract: In recent years, there has been an increasing consumer demand for fresh fruits of improved quality. Nowadays, pomegranate fruits attained increased popularity because of their high nutritional values and pharmacological characteristics. In order to assess the fruit's quality, the prediction of physiochemical parameters is necessary. Thus, the proposed work utilized a deep learning model for prediction analysis. The proposed work has studied a non-destructive determination of physiochemical parameters for pomegranate fruits. The internal images of the pomegranate fruit are obtained using magnetic resonance imaging (MRT). Then, the fruit quality is determined by predicting the physiochemical parameters like TSS, pH, acidity and firmness by combining the features of physiochemical and the GLCM (Gray Level Co-occurrence Matrix). The proposed study used the LSTM (Long-Short Term Memory) model and Stacked Dense Deep LSTM (SDD-LSTM) for prediction purposes. The performance of both the LSTM and SDD-LSTM based prediction models is measured by evaluating the metrics like a square of the correlation coefficient (r^2), root mean square error of calibration (RMSEC), and root mean square error of prediction (RMSEP). Also, the obtained results of the proposed prediction models, along with the combined features, are compared with other machine learning techniques. The result analysis shows that the proposed SDD-LSTM and GLCM have a higher potential for non-destructive assessment of physicochemical values of pomegranate fruit, which may be helpful in fruit post-harvest management.

Keywords: **Magnetic Resonance Imaging; Physiochemical features; GLCM; LSTM; SDD-LSTM; Deep learning network; Fruits quality.**

1. Introduction

Nowadays, consumer requirements for increased quality vegetables and fruits have been rising. In the advanced food industry, food health and quality are essential factors. Hence, enhancing the reliability and accuracy of the post-harvest process with quality assessment must be performed for fruits. The traditional food computation techniques are inefficient and highly destructive. Thus, it is necessary to establish a non-destructive evaluation technique for predicting fruit quality. The pomegranate fruit is the most significant fruit in subtropical and tropical regions like India, Afghanistan, Mediterranean countries, Iran and the Middle East [1]. The pomegranate fruit has an increasing demand because of its high nutrition and multi-functionality.

Moreover, this fruit attains an optimal price in the overall market. The seeds of the pomegranate are consumed directly and also consumed as fresh juice. This fruit is also utilized in coloring agents and flavoring. The pomegranate contains the appropriate quantity of vitamins, sugar, polyphenols, acids, polysaccharides and essential minerals. Iran is considered the most famous for pomegranate fruits, where 650,000 tons of pomegranates are produced in a year, and nearly one-quarter of pomegranate fruits are exported to other countries yearly.

Pomegranate cultivation in India has been increasing steadily in recent times and has become a major exporter with the availability of cold storage even in rural areas. However, the fruit's uses are varied, and the pomegranate fruit's quality is crucial for consumers, processors and producers. The fruit quality after harvest can be well described by the physiochemical attributes such as TSS, firmness and pH value [2]. The farmer can maintain the marketable life of the fruit by grading them for export, processing units or the local market over a longer period of the year when the internal quality of the fruit is well known. The traditional techniques for obtaining such quality markers are all destructive in nature as well as time consuming.

Various researchers have developed different techniques for quality determination and grading pomegranate fruit. The non-destructive techniques which are recently been utilized for evaluating the quality of pomegranates are Computer Topography (CT), Machine vision, Ultrasonic etc. [3, 4].

Nevertheless, CT and X-rays are more harmful due to electromagnetic radiation emission. Because of the random thickness of the pulp and skin, the non-destructive evaluation techniques had penetration limits and were inappropriate for internal quality detection [5]. Multispectral imaging is also utilized for quality detection of the fruits to find out the maturity time of fruits to maintain their storage period and post-harvest life [6]. This method has several limitations, and it fails to predict the quality of the fruit with reduced error [7].

Magnetic resonance imaging (MRI) is an important technique utilized in the medical field to detect specific diseases. This imaging technique can be employed to acquire proper scans of several human body tissues. This MRI is highly appropriate for non-destructive imaging of material that involves water and is also utilized in food science and industry. In the 1980s, MRI scanning was employed for identifying physiochemical values of non-destructive evaluation of varied fruits and vegetables. In recent years, advanced technology in MRI has been utilized for grading the fruit's quality [8]. The existing studies used Nuclear Magnetic Resonance for the non-destructive evaluation of pomegranate fruits which provides 0.54 for predicting acidity, 0.63 for soluble solids and 0.6 for pH [9]. The work of the MRI involves communication between hydrogen molecules and radio waves in the water present in the fruit with a high magnetic field. Compared with CT and X-ray scans, the MRI has reduced ill effects and can sense the living cell's hydrogen level. This learns the fruit's internal structure and soft text texture. In addition, the image contrast is represented by MRI and is more accurate than X-ray imaging. This MRI scanning technology is also used to analyze fruits' internal quality and grading. Some of the previous studies carried out to analyze the internal quality of fruits are illustrated in Table 1.

Table 1 Internal qualities of fruits and food determined by MRI in previous studies

SI.No	Internal attribute	Fruit/Food	Author	Reference
1.	Mealiness Internal breakdown	Apple and Peach	P. Barriero	[10]
2.	Water-core	Apples	Wang S.Y, Herremans,	[11], [12]
3.	Internal damage	Tomato	Milczarek	[13]
4.	Internal Quality	Orange	Wasiu A. Balogun,	[14]
5.	TSS	Pomegranate	Khusroo	[8, 4]
6.	Physiochemical values	Loin	Daniel Caballero	[16]

The internal quality assessment of apple fruit was presented [10], where the unhealthiest fruit is analyzed using histogram skewness. Here, the increased value of histogram skewness is considered an affected fruit. The increase in water content in the apple is also a disturbance, which shows up as an intensity change in the associated region in the MRI scan [11]. On the other hand, a water core was established over large apple varieties, and a model based on the histograms of MRI images distinguished healthy fruit from unhealthy fruit [12]. Similarly, internal damage in tomatoes is analyzed in [13]. Also, further work was done using orange fruits, using a neural network to categorize the healthy and unhealthy fruits, which determine pixel intensity. The performance analysis was performed by measuring the parameters like MSE and R^2 [14]. MRI technology was utilized for internal chemical values prediction of pomegranate, which are markers of internal health which assist in identifying the fruit's maturity index [8].

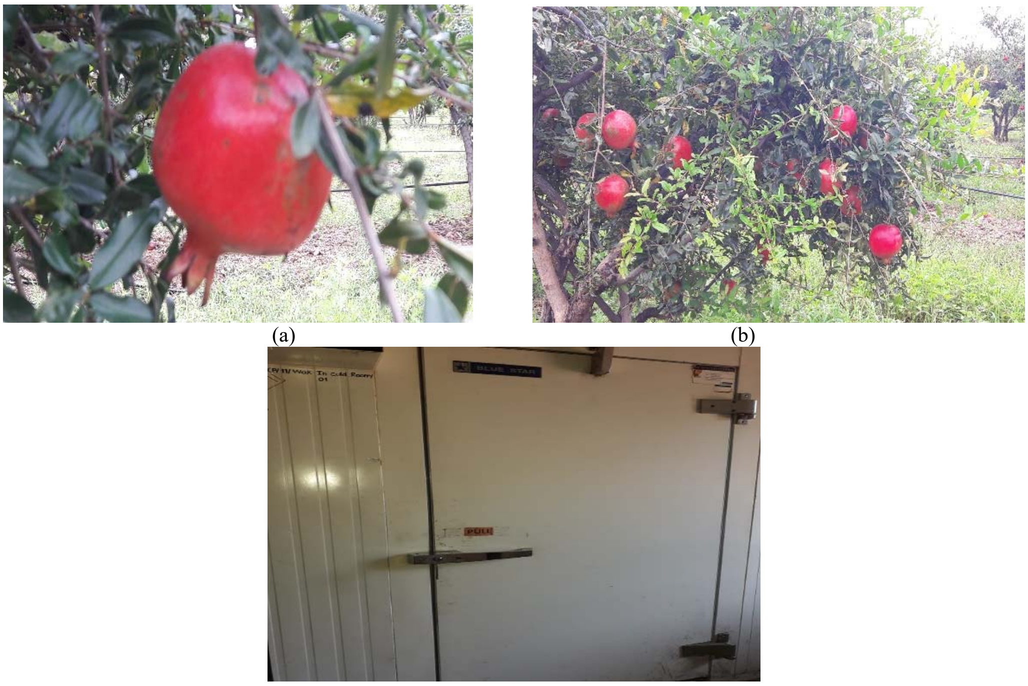
Gray Level covariance features and five run-length textures were attained for MRI of the pomegranate fruit. Also, further work was carried out to predict TSS using MLP NN and could predict the maturity with R = 0.93 and R=0.90 for training and test data [15]. In recent decades, researchers have introduced the model for predicting several physiochemical values of loins [16]. Thus, the proposed work chooses the MRI scanning technique for non-destructive evaluation of pomegranate fruit using physiochemical and texture features, markers of the fruit's quality without fruit loss. It can evaluate post-harvest fruit storage management so that the fruit is available on the market all year round. In this, the physiochemical features and GLCM based texture features obtained from the MRI are combined with a deep learning model to predict the pomegranate fruit properly.

2. Materials and Methods

2.1 Samples of Pomegranate Fruits

At a fruit age of 155 days, around 199 fruits were harvested directly from the farm. Fruits were collected from Shej Babulgaon, Mohol, Tal and Dist Solapur. The fruits are of the Bhagwa variety, mainly grown in Maharashtra, India, as it is in high demand. Farm spread is on 5 acres and the farming layout involved 2 plants with 10 feet spacing and 2 rows with 15 feet spacing. The harvesting of the pomegranate was done on August 3 2021. Here, the fruits were chosen randomly to store for 3 months in cold temperatures [17] at National Research Center on Pomegranate (NRCP), Solapur in Maharashtra, India. The fruits were randomly divided into 4 parts. For analyzing fresh fruits, 75 fruits were collected on August 3 and transmitted to MRI scanning to obtain the MRI images of the fruits. For storage analysis, 134 fruits were kept in cold temperature storage. After the completion of the scanning process, the fruits were brought to NRCP laboratories for chemical tests. All physiochemical values were recorded in the register, and after one month of storage on September 3, 47 fruits were used for study MRI scanning and then it was tested in the lab.

Then, after the second month of cold storage, 31 pomegranate fruits were taken for analysis on October 3. The remaining 46 fruits were collected on November 3, 2021, and then made available for laboratory testing. Figure 1 depicts the fruit, farm and cold storage. The proposed work utilizes the MRI technique for scanning the fruit. These scanned images are fed to the feature extraction process. The features extraction stage extracts both physiochemical and texture features. The physiochemical features are TSS (Total Soluble Solid), pH, acidity and firmness. The texture features are extracted using the GLCM approach, which extracts contrast, homogeneity, dissimilarity, energy and correlation. Finally, the pomegranate fruit’s quality is detected using the LSTM method.



(a) (b) (c)

Figure 1: (a) 155 DAFB fruit (b) Farm for harvest (c) Cold storage at NRCP

2.2 Scanning of Pomegranate Fruit using MRI

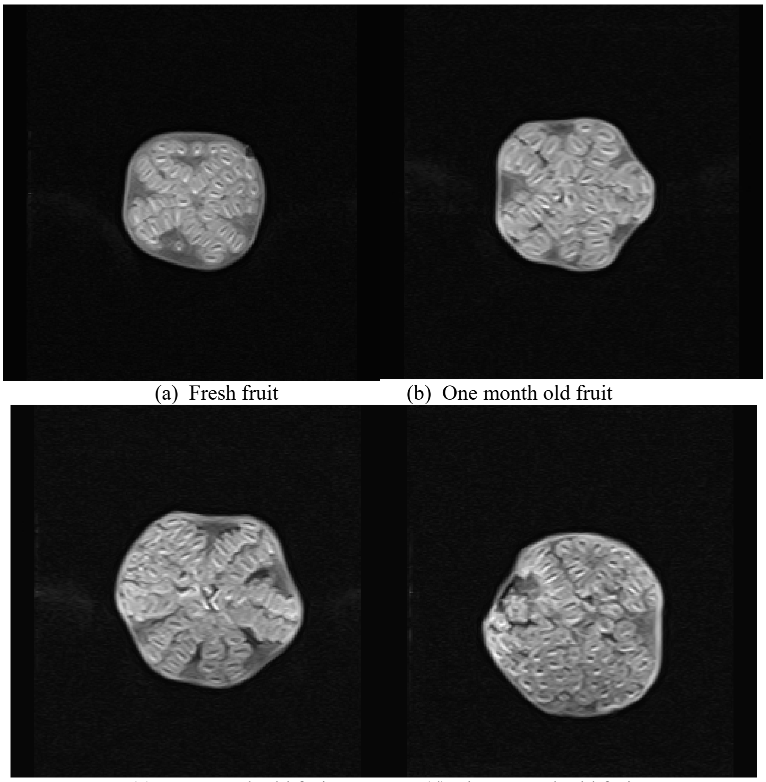
The pomegranate fruit attained from farm and at Shri Markandaya Solapur, Sahakari Rugnalaya and Research Center, Solapur are scanned through 1.5 T MRI scanner with two-dimensional (2D) spin echo sequence. The samples were located in a pre-decided position in the coil. The equatorial slice images of the pomegranate fruit were attained by performing the scanning process. Each MR image was obtained using varied sequences and an extra image was created from the diffusion weighted images. The signal intensity of spin-echo images is represented as,

$$S_I = H_0\left(1 - 2e^{-(R_t - E_t)/t_1} + e^{-R_t/t_1}\right)e^{-E_t/t_2} \qquad (1)$$

Where, S_I represents the signal intensity, H_0 mentions the net magnetization, which is directly proportional to the proton density, t_1 specifies the spin-lattice relaxation time and the spin-spin relaxation time is mentioned as t_2. The interval among pulses is manipulated by the sequence parameters like Echo time E_t and Repetition time R_t. The spin echo images are attained by adjusting the E_t and R_t of spin echo sequence with varied weighting. The signal intensity of fast spin echo images is described as,

$$S_I = H_0 e^{-E_t^{eff}/t_2} \tag{2}$$

The middle region in k-space predominantly finds out the contrast of the image. The effective echo time E_t^{eff} is defined when the middle k-space data is attained, so the S_I in the fast spin echo image is initially a function of E_t^{eff}. The proposed work scans the pomegranate fruit of fresh, one month old, two month old and three months old. Figure 2 represents the scanned fruit images through MRI.



(a) Fresh fruit (b) One month old fruit

(c) Two month old fruit (d) Three month old fruit

Figure 2: Scanned images using MRI

The scan parameters used in the proposed study and the previous study are listed in Table 2.

Table 2: Scanning parameters as performed on MRI machine of 1.5T

Author	MRI Scanner	TR	TE	FOV	Slice Thickness	Inter slice gap	Total slices	Matrix
Alireza Khoshroo	1.5T scanner	800 ms	18 ms	29.6 cm	3 mm	1.56 cm	12	336 by 512
Present Work	1.5T scanner	800 ms	18 ms	29.6 cm	3 mm	1.56 cm	18	256 by 256

In the above Table 2, the parameters which are performed for the scanning process in the present and previous work are clearly shown. Here, the proposed work makes the fruit into 18 slices, and the previous work used the fruit with 12 slices. After the scanning process, the fruits were taken to the National Research Center of Pomegranate (NRCP) in Solapur for test analysis. The test analysis is done by extracting the physiochemical and texture features from the scanned images.

2.3 Feature Extraction

The feature extraction is performed to analyze the status of the fruits where essential features are highly needed. For this purpose, the proposed study extracts physiochemical and texture features. The feature extraction enhances the prediction performance of the proposed deep learning method.

2.3.1 Physiochemical Feature Extraction

The following physiochemical features extracted in the proposed study are TSS, pH, acidity and firmness.

TSS: TSS is one of the significant parameters for determining fruit quality. It states the quantity of soluble solids available in liquid. The value of TSS influences the fruit's taste because it can represent its sweetness level. Also, this TSS involves organic acids, fats, carbohydrates, minerals and proteins of the specific fruit. In addition, the TSS was measured using a Refractometer on the Atago model Pal-α in % Brix [18]. The same instrument was used for all stages during our experiments in the NRCP laboratories.

PH: The term pH computes the concentration of acidity, hydrogen ions or alkalinity of a given sample. The pH scale is mainly between 0 and 14. The value of pH less than seven is considered acidic, and higher than seven is assumed as alkaline or basic solutions. It provides the given fruit's chemical condition and limits the presence of biological functions, nutrients, chemical behaviours and microbial activity. Measurement of pH was done using pH700 of EUTECH Instrument model. For this purpose, the juice was mechanically extracted from fruit samples and placed in beakers with the numbering done on it.

Acidity: The fruit's acidity is represented by the availability of organic acids, citric and malic acids. These are the major acids presented in ripe fruits, and the factors affecting the concentration of such acids in fruits are highly necessary for enhancing fruit quality. Acidity is also the main determinant of the quality and taste of several fruits.

Firmness: The crispness of fruit is termed firmness, and it is essential to establish a price and quality grade of fruit. Firmness was measured with the digital fruit penetrometer /hardness tester of Parisa Technology with 0.01 Kg or 0.1 N resolution. Inserting an 8 mm probe into fruits, where this puncturing test was conducted on the equatorial part, the opposite sides of each fruit and the average value were noted. The maximum force needed for puncturing the fruit is declared as the firmness of the fruit.

After the extraction of physiochemical features, the texture features are extracted using 2D-GLCM.

2.3.2 Texture Feature Extraction using 2D-GLCM

In extracting texture information from the images, the proposed work used the gray level co-occurrence matrix function explained by Haralic et al. [19]. These GLCM features are much known tools in second order statistical texture extraction functions. Various relationships make the GLCM generate several textures describing useful information. They all are working on M_x, X, M_y image with pixels of the gray level scale $(0,1.......G_r-1)$. The matrix is a 2D square matrix and $P(1,m)$ is the normalized intensity, wherein every element in the matrix gives the probability for the correlation of intensity values at l and m, at a particular distance metrics of d as 1 and angle of θ as 0, 45, 90, 135. The proposed work extracts the texture features followed by contrast, homogeneity, dissimilarity, energy and correlation.

Contrast: Contrast is a statistical metric where an image's spatial frequency is determined and a different moment of GLCM. It gives the difference between the highest and the lowest values in the adjacent pixels. This texture provides the amount of the corresponding variations at a particular position in the fruit image. An image with poor contrast is shown as the GLCM concentration term around the principal diagonal, indicating the presence of lower spatial frequency content. The evaluation of contrast is given as,

$$Contrast = \sum_{l=0}^{N-1} \sum_{m=0}^{N-1} P(l,m)\left|l-m\right|^2 \tag{3}$$

Homogeneity: The term homogeneity is defined as the reciprocal of difference at the moment. It measures the homogeneity in the image where it counts higher values for lesser differences in grey intensity in the paired elements. Homogeneity is highly sensitive to the existence of the closest elements placed diagonally in the GLCM matrix. When the elements in the image contain similarities, then homogeneity carries a higher value. In GLCM, we see that the contrast and the homogeneity have a strong correlation, but in inverse relation, i.e. homogeneity increases when contrast reduces with energy constant.

$$Homogeneity = \sum_{l=0}^{N-1}\sum_{m=0}^{N-1}\frac{P(l,m)}{1+|l-m|} \quad (4)$$

Dissimilarity: The dissimilarity texture measures the local changes in intensity in the provided image.

$$Dissimilarity = \sum_{l=0}^{N-1}\sum_{n=0}^{N-1}P(l,m).|l-m| \quad (5)$$

Energy: The angular second moment measures the textural repetitions occurring in the pixels. This finds the disorders occurring in the texture of the image. Energy is calculated as the square root of an angular second moment. When this second angular moment takes its maximum value as one, the energy also takes one. This maximum energy value occurs whenever the gray level pattern takes a constant and periodicity form.

$$Energy = \sum_{l=0}^{N-1}\sum_{m=0}^{N-1}P(l,m)^2 \quad (6)$$

Correlation: This is a metric where the linear relation amongst the gray level of the pixels in the image exists.

$$Correlation = \sum_{l=0}^{N-1}\sum_{m=0}^{N-1}\frac{(l-\mu_l)(m-\mu_m)}{\sigma l^2 \sigma m^2} \quad (7)$$

The provided equations calculate the mentioned features above from 3 to 7 [20]. These extracted features are fed to the deep learning model to predict fruit quality with non-destructive evaluation.

2.4 Quality Prediction of Fruits using the LSTM Approach

The proposed work prefers the LSTM method for pomegranate quality prediction because of its efficacy. Using LSTM minimizes the complexity and affords a high range of parameters like input bias, output bias and learning rate [21]. This LSTM model involves a memory cell that can manage the gathered information in memory for a long duration. Also, this deep learning model diminishes the vanishing gradient issue. The LSTM is an advanced version of RNN that can learn long term dependencies. German researchers Hochreiter and Schmidhuber initially proposed the LSTM model. This proposed model is intended to solve the problems of error backflow. There are three gates presented in the LSTM method as input gate, output gate and forget gate. The neurons available in the LSTM model hold these three gates and memory cells. The model is updated by retaining the information and is performed by the forget gates and cell states. The architecture of LSTM is shown in Figure 3.

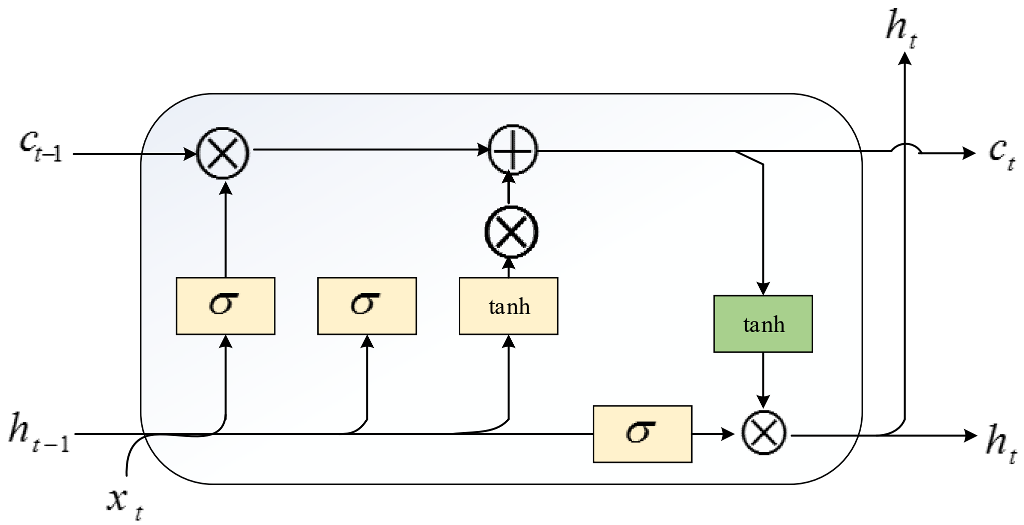


Figure 3: LSTM architecture

The following equation (8) evaluates the cell state and gates sequentially.

$$A_t = \sigma\left(\omega_z^A z_t + \omega_v^A v_{t-1} + b^A\right) \quad (8)$$

The output of forget gate is represented in the above equation where, σ mentions the sigmoid activation function, ω_z^A mentions the input z weight factor of the forget gate, trainer input at time t is represented as z_t, the output of preceding hidden layer is mentioned as v_{t-1} and the forget gate's bias factor is indicated as b^A.

$$O_t = \sigma\left(\omega_Z^O z_t + \omega_v^O v_{t-1} + b^O\right) \quad (9)$$

The above equation (9) specifies the output of the input gates, where, ω_z^I mentions the input gate's weight factor for input z , the weight factor among the input and hidden units is indicated as ω_v^I , the preceding output of the hidden unit is specified as v_{t-1} and the input gate's bias factor is mentioned as b^I .

$$h_t = relu\left(\omega_z^h z_t + \omega_v^h v_{t-1} + b^h\right) \tag{10}$$

The initial hidden layer's output is attained via equation (11), and such an output can be afforded as input to the upcoming hidden layer. Here, the activation function is indicated as $relu$, the input gate's weight factor for input z is represented as ω_z^I , z_t represents the input value at the time t , the weight factor between both input and hidden units is specified as ω_v^I , the preceding hidden unit's output is indicated as v_{t-1} and the bias factor of the input gate is denoted as b^I .

$$S_t = A_t \circ S_{t-1} + I_t \circ h_t \tag{11}$$

Equation (11) indicates the cell state evaluation. Here, the forget gate's output is represented as A_t , $\circ$ denotes the Hadamard product, S_{t-1} mentions the preceding cell state, and the input gate's output at a time t is considered as I_t and h_t is specified as the output of the hidden layer at the time t .

$$O_t = \sigma\left(\omega_z^O z_t + \omega_v^O v_{t-1} + b^O\right) \tag{12}$$

Where, σ mentions the sigmoid activation function, the output gate's weight factor for the input z is represented as ω_z^O , the weight factor between the output and hidden units is denoted as ω_v^O , the preceding hidden layer output is indicated as v_{t-1} and the output gate's bias factor is specified as b^o .

$$v_t = O_t \circ relu\left(S_t\right) \tag{13}$$

The evaluation of the hidden state is stated in equation (13), which O_t mentions the output gate at the time t and the cell state at the time t is represented in S_t . The traditional LSTM is employed to process time series data. Also, the last output is used to evaluate the result using a linear regression layer and is represented as,

$$\overline{y_i} = \omega^l q_i^T \tag{14}$$

Where, $\omega^l \in L^{k \times x}$ mentions the size of the attained output. The proposed work observed that the learning power of the neural network is not improved appropriately using the LSTM approach. Although the LSTM cell can resolve the vanishing gradient problems, the prediction accuracy is still influenced by the simple network structure. Thus, in order to improve the learning power and prediction accuracy, the proposed work adopts Stacked Dense Deep LSTM (SDD-LSTM) model [22]. Using this SDD-LSTM approach, predictive analysis is further performed.

2.5 Proposed SDD-LSTM for Fruits Quality Prediction

The deep architectures in the neural network provide an effective capability for self-learning of features. Hence, stacking various LSTM layers for a deep LSTM model is more powerful, enhancing learning power and accuracy. It helps the network to effectively predict the physicochemical parameters. The proposed SDD-LSTM comprises several LSTM layers and dense layers, providing output sequences for each input. Various LSTM cells are connected to the LSTM layers. The input of the first layer of LSTM is the raw data, and the remaining LSTM layers is the hidden state of the previous LSTM layers. The architecture of the proposed SDD-LSTM is depicted in Figure 4.

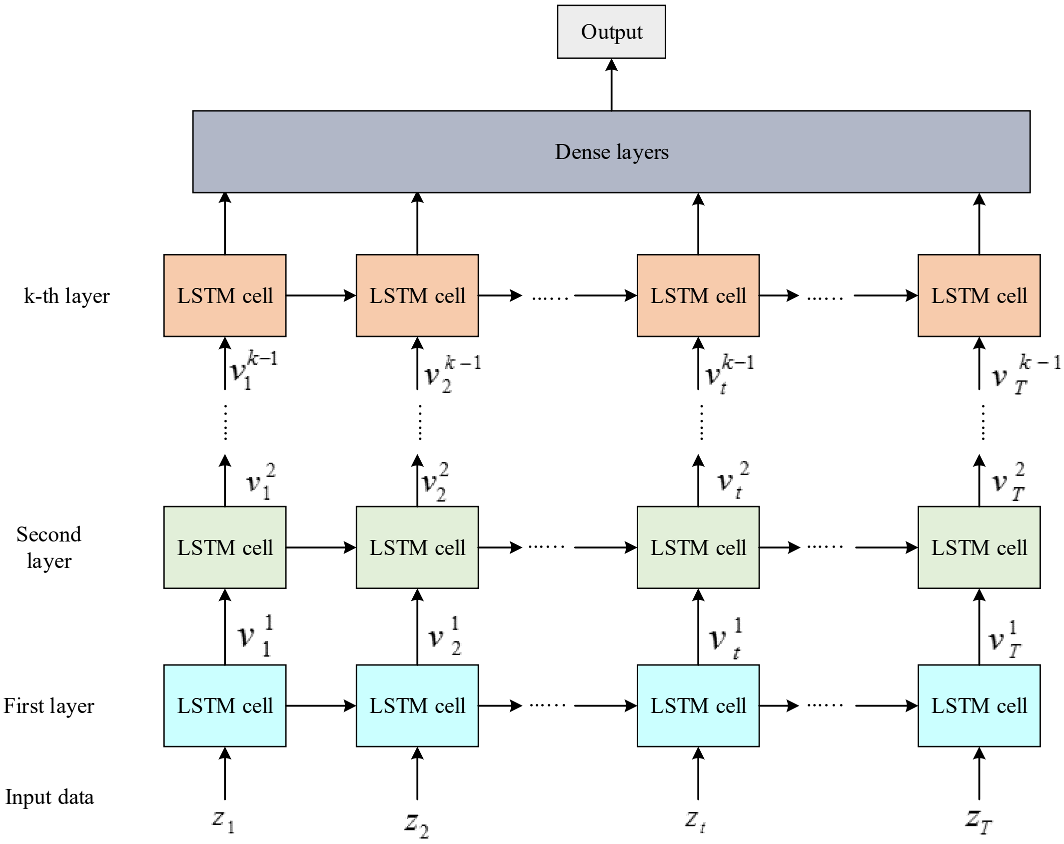


Figure 4: Proposed SDD-LSTM structure

The output of the hidden layers is propagated forward over time. It is also used as the input of the upcoming hidden layer of the LSTM network. Hence, the k^{th} layer can be updated as,

$$A_t^k = \sigma\left(\omega_k^A z_t^{k-1} + \omega_v^A v_{t-1}^k + b_k^A\right) \quad (15)$$

$$O_t^k = \sigma\left(\omega_k^O z_t^{k-1} + \omega_v^O v_{t-1}^k + b_k^O\right) \quad (16)$$

$$h_t^k = relu\left(\omega_k^h z_t^{k-1} + \omega_v^h v_{t-1}^k + b_k^h\right) \quad (17)$$

$$S_t^k = A_t^k \circ S_{t-1}^k + I_t \circ h_t^k \quad (18)$$

$$v_t^k = O_t^k \circ relu\left(S_t^k\right) \quad (19)$$

The first layer's input is raw temporal information, while the first layer's output is extracting raw information from fruit and is considered a useful feature for prediction. The remaining LSTM layers use the previous layer as input, and the output of the last LSTM layer is transferred to a fully connected or dense layer for prediction purposes. The cross entropy loss is represented as,

$$L_{f'}(f) = -\sum_i \left(f_i'\log(f_i) + (1 - f_i')\log(1 - f_i)\right) \quad (20)$$

Where, f_i mention the predicted probability of the sample i and the positive probability are mentioned as f_i'. The neural network obtains an error during training and generates a loss function. Thus, optimization of the weight parameter is important to reduce the loss. Hence, the SDD-LSTM model used the Adam optimizer to manage the training error during prediction. The proposed SDD-LSTM performs the network model to learn the aspects of the raw temporal information from varied characteristics at each step. In addition, the neural network system becomes highly deeper with the proposed SDD-LSTM structure.

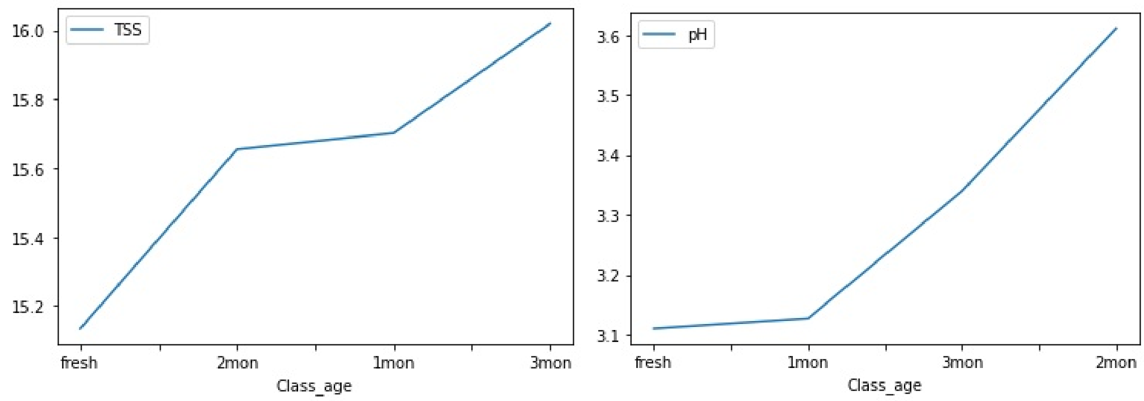
3. Results and Discussions

This section provides the result analysis of the proposed LSTM based non-destructive evaluation. The prediction of fruit quality using physiochemical and texture features through the LSTM model is established in this study. All measurements were done using the standard measuring instruments in the NRCP laboratory. Our samples of age 155 have been studied for various stages of storage, the proposed work studied fresh fruit, one month of cold storage, two months of cold storage and three months of cold storage. The fruits were scanned for every stage and brought to the laboratories for testing. The values of various physiochemical values for all stages of our observation are illustrated in Table 3.

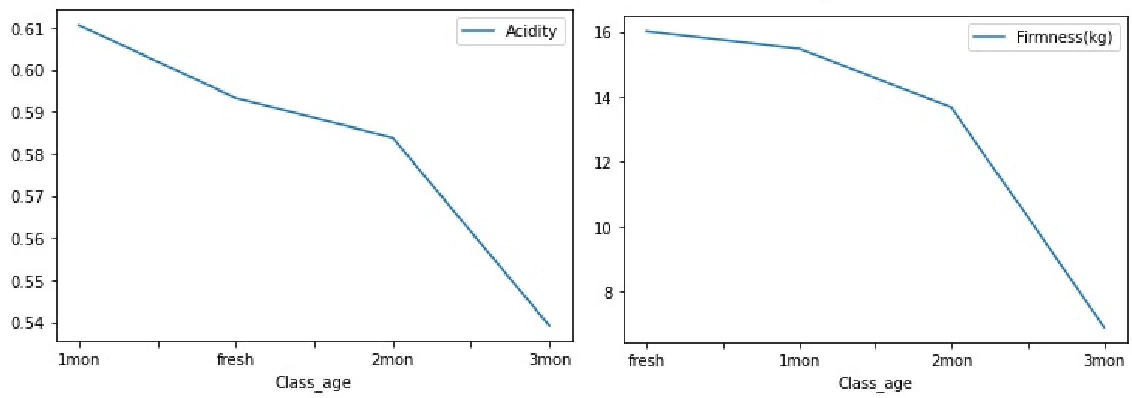
Table 3: Measurement of several physiochemical values of Bhagwa fruit of 155 days DAFB under fresh, one month storage, two month storage and three month storage conditions

Physiochemical Attributes	S1 Fresh			S2 One Month			S3 Two Month			S4 Three Month		
	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg
TSS	16.4	13.3	15.13	16.8	14.1	15.7	16.2	14.5	15.66	16.6	15.2	16.02
pH	3.27	2.94	3.11	3.336	3.02	3.13	3.94	3.45	3.61	3.5	3.24	3.34
Acidity	0.7	0.5	0.59	0.7	0.5	0.61	0.7	0.5	0.58	0.6	0.3	0.54
firmness	21.8	0	15.58	20.04	5.025	15.48	20.86	0	13.68	75.5	0	6.11

As can be observed from Figure 5, the TSS and pH values improved with increasing storage time. After the 3rd month, the fruit decreased, and the firmness reduced. Some fruits got damaged and could not be scanned. Firmness and acidity reduced with an increase in storage period. The aim of the work here is the non-destructive prediction of the physiochemical and textural values of pomegranate fruits using the LSTM network. The proposed work analysis the results of the LSTM based prediction, and the attained results are compared with the existing machine learning approaches.



(a) TSS (b) pH



(c) Acidity (d) Firmness

Figure 5: Physiochemical measurements for each storage age of the fruit

The measurement of physiochemical features for all the storage ages of the pomegranate fruit is depicted in Figure 5.

3.1 Performance Metrics

The performance metrics utilized to predict the efficiency of the proposed LSTM model are square of correlation coefficient (r^2), root mean square error of calibration (RMSEC), and root mean square error of prediction or validation (RMSEP).

- ***Correlation coefficient:*** It provides the statistical relationships among two samples, and the computation of r^2 is given as,

$$r = \sum_{i=1}^{m}\left(\hat{x}_i - x_i\right)^2 \Big/ \sum_{i=1}^{m}\left(\hat{x}_i - x_n\right)^2 \tag{21}$$

- ***RMSEC:*** It measures the variations among samples predicted by a proposed LSTM model, and the values are noticed in calibration. RMSEC is formulated as,

$$RMSEC = \sqrt{\frac{1}{m_c}\sum_{i=1}^{m_c}\left(\hat{x}_i - x_i\right)^2} \tag{22}$$

- ***RMSEP:*** During the prediction process, it computes the differences among samples predicted by an LSTM method.

$$RMSEP = \sqrt{\frac{1}{m_p}\sum_{i=1}^{m_p}\left(\hat{x}_i - x_i\right)^2} \tag{23}$$

Where, $\hat{x}_i$ mentions the predicted value of observation i, the measured value of observation i is represented as x_i, x_n indicates the mean value of the prediction or calibration set and the amount of observation is denoted as m, m_c and m_p. Basically, the best model must have an increased correlation coefficient and reduced RMSEP and RMSEC values.

3.2 Prediction Analysis of Physiochemical Values of pomegranate Fruit Through LSTM model using Physiochemical Features

Using proposed LSTM model, the predictions of all the physiochemical values such as total soluble solids, pH values, acidity and firmness of the fruit are enabled. These are the predicted values measured destructively in the laboratories of NRCP

3.2.1 Prediction of TSS Through LSTM

The prediction model for TSS using the LSTM approach is illustrated in Figure 6. In this, calibration and a validation analysis are performed to predict the TSS level of the fruit. This TSS prediction is important to determine the fruit's quality effectively. The calibration model of TSS obtained the r^2 score of 0.9608, and RMSEC is 0.018. On the other hand, the TSS prediction in validation samples of fruits attains the r^2 score is 0.9607 and RMSEP is 0.0181.

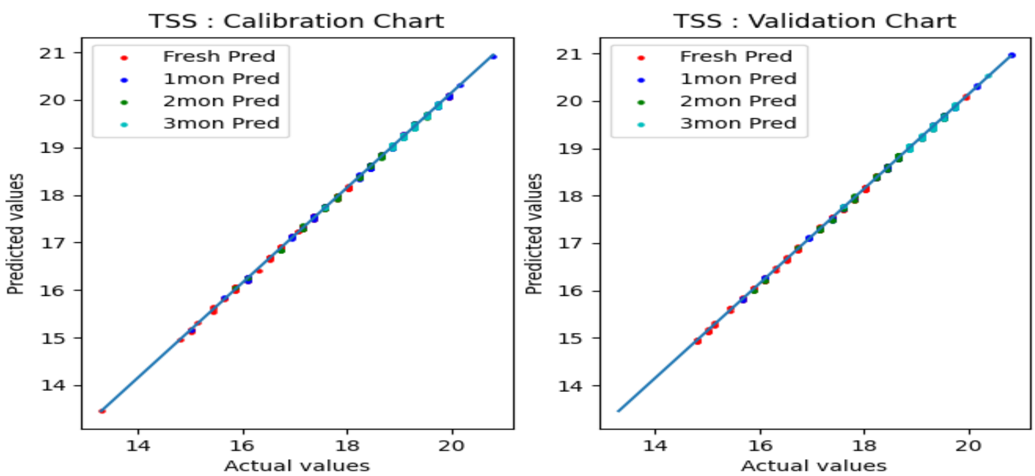


Figure 6: Correlation observed between TSS from lab measurement and predicted TSS of calibration and validation for pomegranate fruit of Bhagwa cultivar

3.2.2 Prediction of pH Through LSTM

Using LSTM, the pH prediction of pomegranate is performed and is depicted in Figure 7. The pH value determines the presented hydrogen level in the provided samples. The prediction of pH value is significant in determining fruits' maturity. In the calibration model, the pH value obtains the r^2 score of 0.9566 and the RMSEC of 0.0162. Similarly, the model predicted TSS for validation samples of fruits with an r^2 score of 0.9558 and RMSEP of 0.0153.

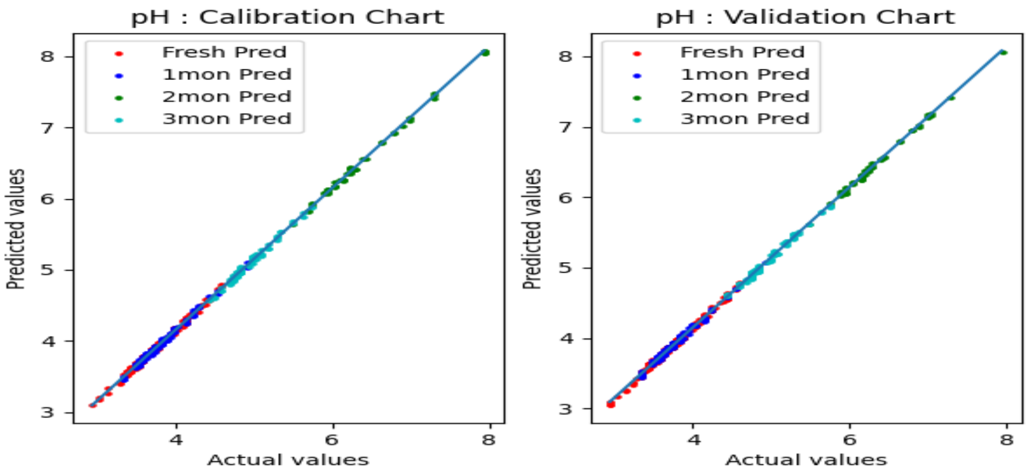


Figure 7: Correlation observed between pH from lab measurement and predicted pH of calibration and validation for pomegranate fruit of Bhagwa cultivar

3.2.3 Prediction of Acidity Through LSTM

The acidity level of given pomegranate fruits is predicted using the LSTM approach. Figure 8 mentions the calibration and validation analysis of the acidity prediction. The r^2 score obtained from the calibration model of acidity is 0.9727, and RMSEC is 0.0177. Also, the prediction of acidity for validation samples of fruits attains the r^2 score of 0.9668 and RMSEP of 0.0182.

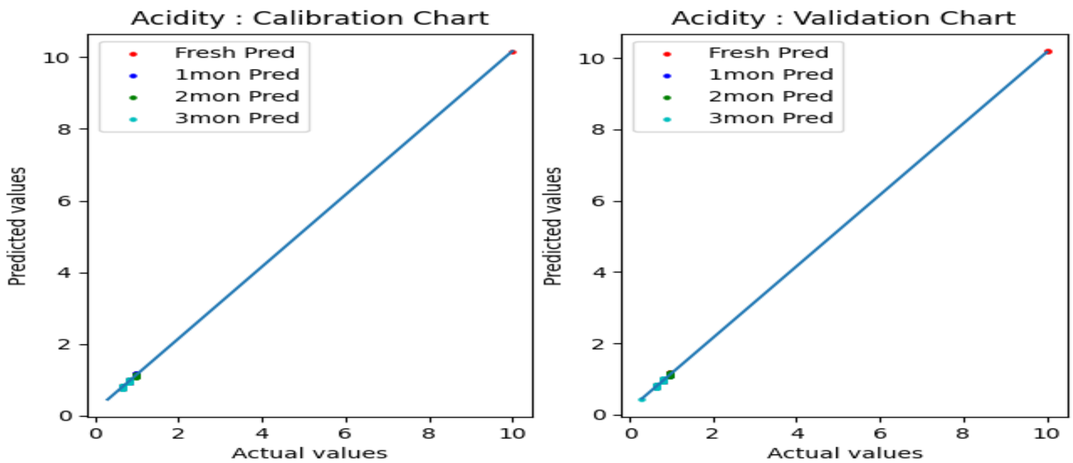


Figure 8: Correlation observed between acidity from lab measurement and predicted acidity of calibration and validation for pomegranate fruit of Bhagwa cultivar

3.2.4 Prediction of Firmness Through LSTM

The level of firmness in the fruit is predicted through the LSTM method. The prediction is performed for both calibration and validation. In calibration, the firmness prediction obtains the r^2 score of 0.9996 and RMSEC of 0.0179_kg. In validation, the firmness prediction in pomegranate fruit attains the r^2 score of 0.9996 and RMSEP of 0.0186_kg. Figure 9 represents the prediction result analysis of firmness using the LSTM model.

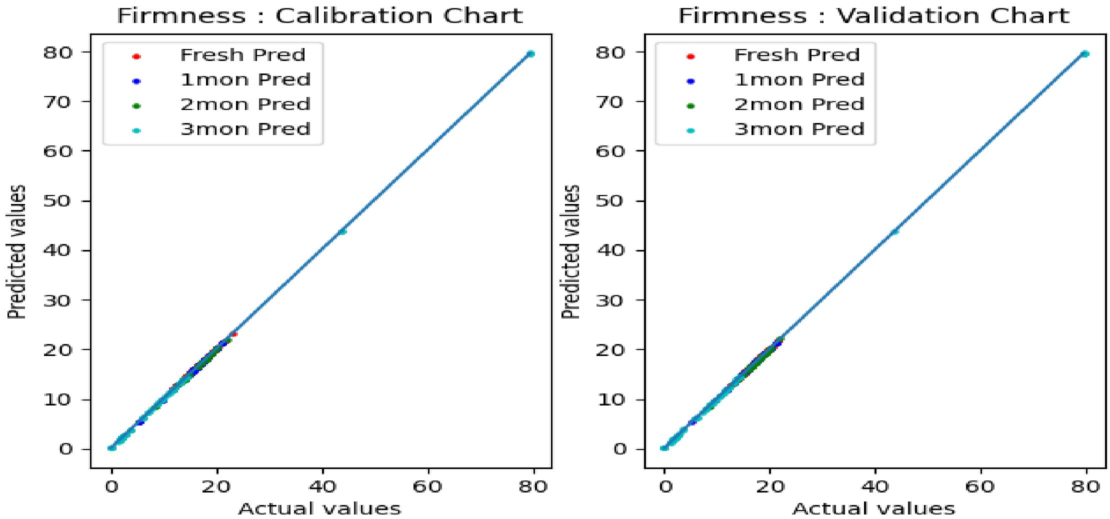


Figure 9: Correlation observed between firmness from lab measurement and predicted firmness of calibration and validation for pomegranate fruit of Bhagwa cultivar

3.3 Prediction Analysis of physiochemical Values using GLCM Features and Physiochemical Features Through LSTM Model

The proposed study combines the GLCM features with physiochemical features to predict pomegranate fruit's maturity through the LSTM approach. The GLCM features like energy, contrast, homogeneity, dissimilarity and correlation are predicted to know the fruit's quality.

3.3.1 Prediction of TSS using both Physiochemical and GLCM Through LSTM

The TSS of fruits is predicted by the proposed LSTM model with GLCM and physiochemical features. Using these features, the TSS of fruit is analyzed accurately. The simulation results from TSS prediction through physiochemical and LSTM are 0.9818 of r^2 score value and 0.0153 of RMSEC in the calibration model. In validation, the obtained r^2 score is 0.9828, and RMSEP is 0.0156. Figure 10 represents TSS's calibration and validation results in the prediction analysis using combined features.

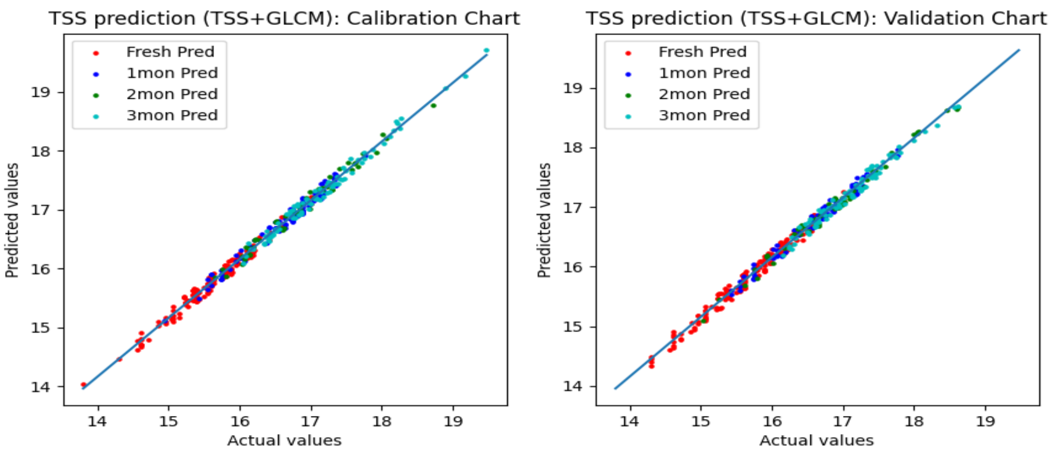


Figure 10: Measured TSS Values of Fruits using the Combination of Physiochemical and GLCM Features

3.3.2 Prediction of pH using both physiochemical and GLCM through LSTM

The proposed study predicts the pH value by combining both features. The pH value of the fruit is analyzed for calibration and validation. The prediction is performed by varying the freshness of fruits for up to three months. The prediction of pH using combined features attains the r^2 score of 0.976 and the RMSEC of 0.0124 in calibration, and for validation, the attained r^2 score is 0.9767 and RMSEP is 0.0125. Figure 11 illustrates the calibration and validation of pH prediction analysis using GLCM and physiochemical features.

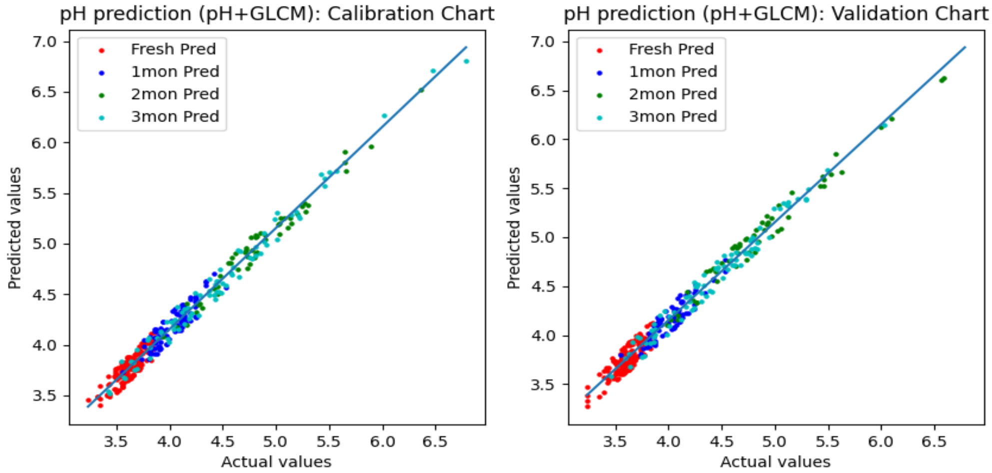


Figure 11: Measured pH values of fruits using the combination of physiochemical and GLCM features

3.3.3 Prediction of Acidity using Physiochemical and GLCM Through LSTM

The acidity of fruits is predicted by integrating both physiochemical and GLCM features. The results are evaluated for both calibration and validation models. In calibration, the proposed LSTM with combined features obtained the r^2 score of 0.9732 and the RMSEC is 0.0126. In validation, the prediction of pH obtains the r^2 score of 0.967 and RMSEP of 0.0125. Figure 12 represents the calibration and validation of acidity prediction using combined features.

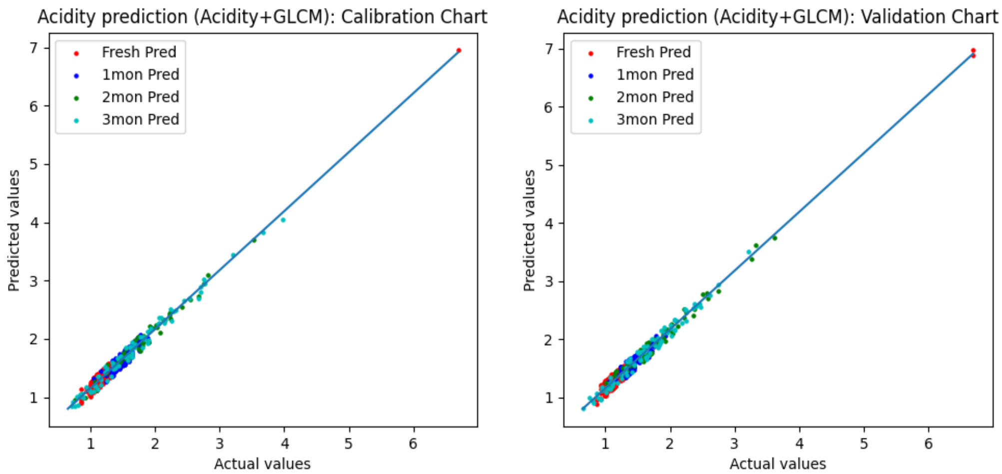


Figure 12: Measured acidity values of fruits using the combination of physiochemical and GLCM at varied angles

3.3.4 Prediction of Firmness using Physiochemical and GLCM Through LSTM

The firmness of pomegranates fruits is predicted through the proposed LSTM approach using combined physiochemical and GLCM features. The simulation results of the firmness prediction in the proposed LSTM with combined features are given a 0.997 r^2 score and 0.0118 RMSEC in the calibration model. On the other hand, the attained r^2 score is 0.9997, and the RMSEP is 0.0123 in validation. The calibration and validation analysis of firmness prediction using physiochemical and GLCM features is shown in Figure 13.

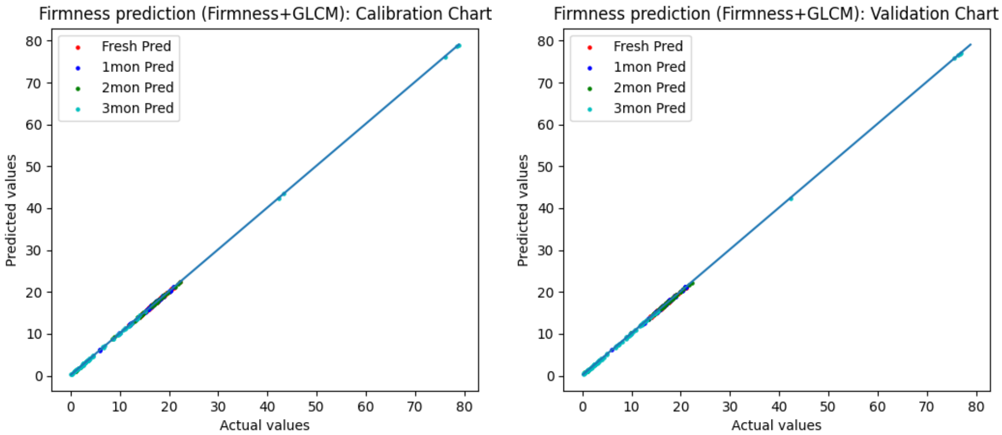


Figure 13: Measured firmness values of fruits using the combination of physiochemical and GLCM at varied angles

3.4 Prediction Analysis of physiochemical Values of Pomegranate Fruit Through SDD-LSTM Model using Physiochemical Features

With the aid of the proposed SDD-LSTM, the physiochemical values like TSS, pH, acidity and firmness are predicted, and the quality of the pomegranate fruit is evaluated. In the NRCP lab, the predicted values are destructively measured.

3.4.1 Prediction of TSS using Through SDD-LSTM

Figure 14 mentions the prediction analysis of TSS value using the SDD-LSTM approach. The fruit TSS level is predicted by performing the analysis of both calibration and validation. Using SD-LSTM, the TSS prediction obtained the r^2 score of 0.9802, and RMSEC is 0.0172 for calibration. Similarly, the TSS prediction in validation attained the r^2 score of 0.98 and RMSEP of 0.0174.

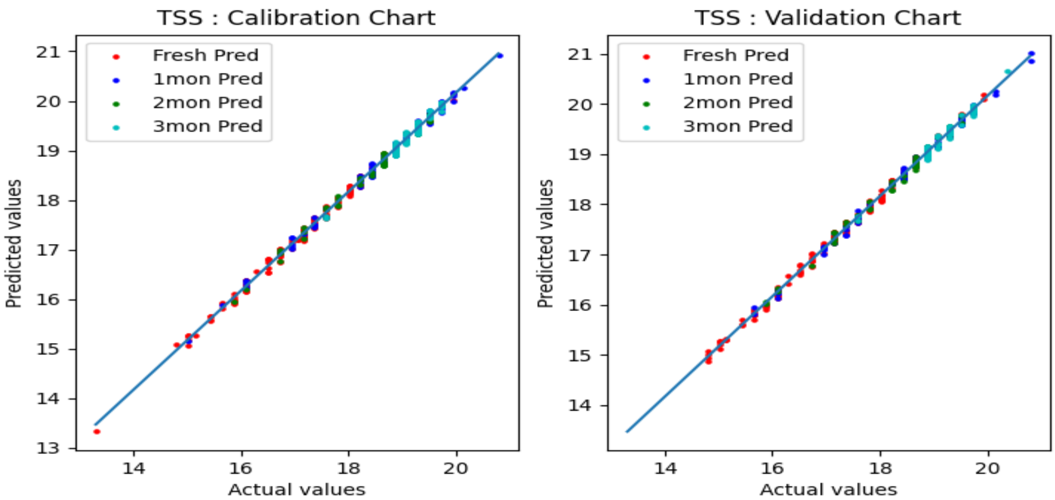


Figure 14: SDD-LSTM based TSS prediction using physiochemical features

3.4.2 Prediction of pH through SDD-LSTM

The pH value of fruits is predicted using physiochemical parameters with the SDD-LSTM approach. Figure 15 illustrates the prediction analysis using the proposed SDD-LSTM. In the prediction results, the pH value attains the r^2 score of 0.9575 and RMSEC of 0.0153 for the calibration model. The validation results show that the pH value obtains 0.9637 for the r^2 score and 0.0151 for RMSEP.

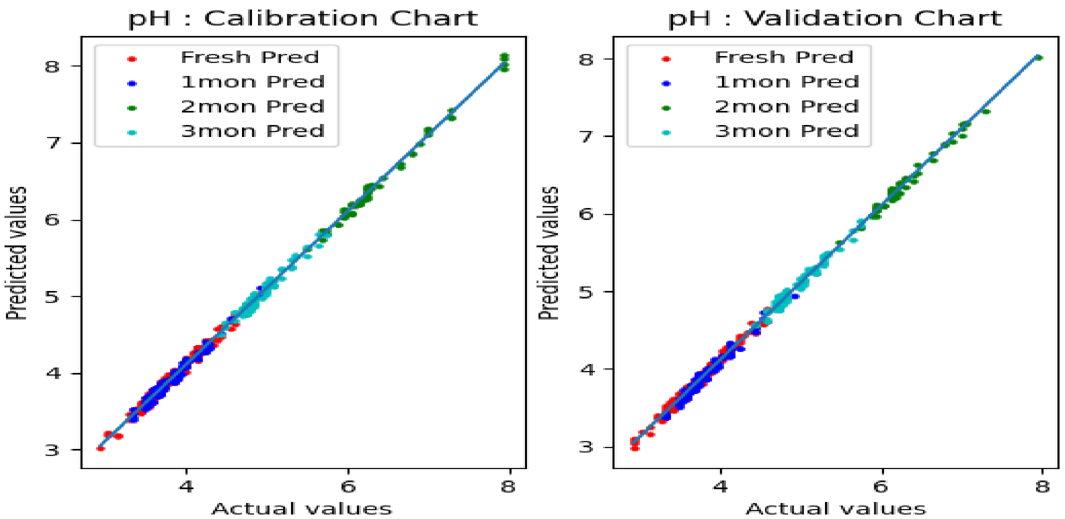


Figure 15: SDD-LSTM based pH prediction using physiochemical features

3.4.3 Prediction of Acidity Through SDD-LSTM

The proposed SDD-LSTM model predicts the acidity level of pomegranate fruits using the physiochemical features. Figure 16 represents the calibration and validation analysis for predicting the acidity level of fruits. The calibration model's attained r^2 score is 0.975, and RMSEC is 0.0154. On the other hand, validation results exhibit the r^2 score, and RMSEP of acidity prediction is 0.9651 and 0.0152.

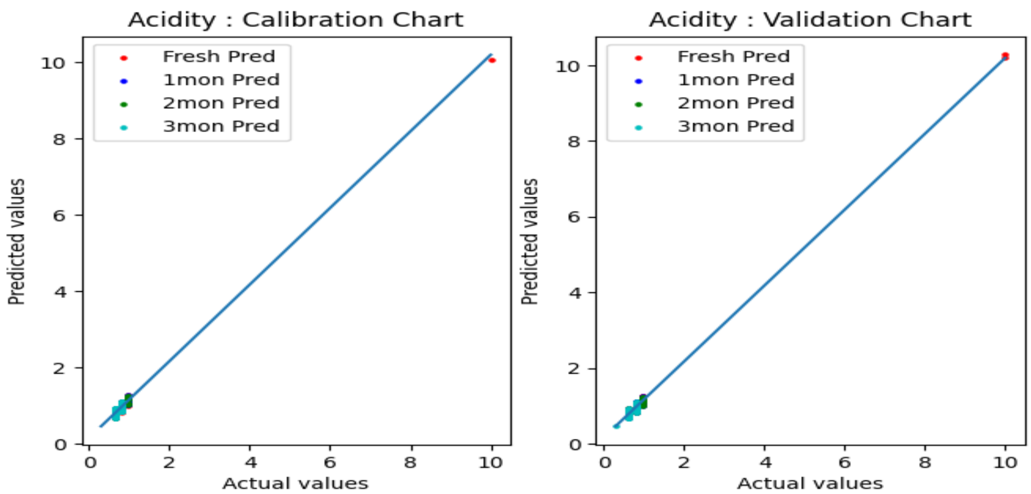


Figure 16: SDD-LSTM based acidity prediction using physiochemical features

3.4.4 Prediction of Firmness Through SDD-LSTM

The firmness level of fruits is initially predicted using the physiochemical features through the proposed SDD-LSTM approach. The prediction result analysis of both calibration and validation is depicted in Figure 17. The firmness prediction provides the r^2 score of 0.9998 and RMSEC of 0.0155_kg in calibration. In validation, the firmness prediction attains the r^2 score of 0.9998 and RMSEP of 0.0154.

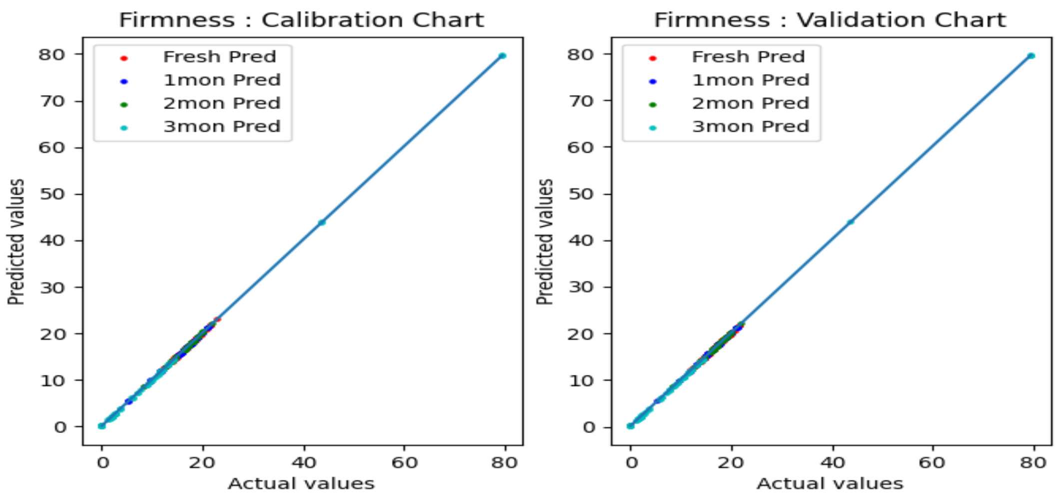


Figure 17: SDD-LSTM based firmness prediction using physiochemical features

3.5 Prediction analysis of physiochemical values using GLCM features and physiochemical features through SDD-LSTM model

Using SDD-LSTM, the proposed work predicts the physiochemical parameters by integrating GLCM and physiochemical features. The features of GLCM are energy, homogeneity, correlation, contrast and dissimilarity. The mentioned features are combined with the physiochemical features like TSS, pH, acidity and firmness to predict the physiochemical values of fruits.

3.5.1 Prediction of TSS using both physiochemical and GLCM through SDD-LSTM

The proposed SDD-LSTM method predicts the TSS of fruits through GLCM and physiochemical features. Using SDD-LSTM with combined features, the r^2 score and RMSEC attained for the TSS prediction in calibration are 0.9853 and 0.0119. In the validation model, an achieved r^2 score in the TSS prediction is 0.9855, and RMSEP is 0.0116. The calibration and validation results of TSS prediction using integrated features through SDD-LSTM are shown in Figure 18.

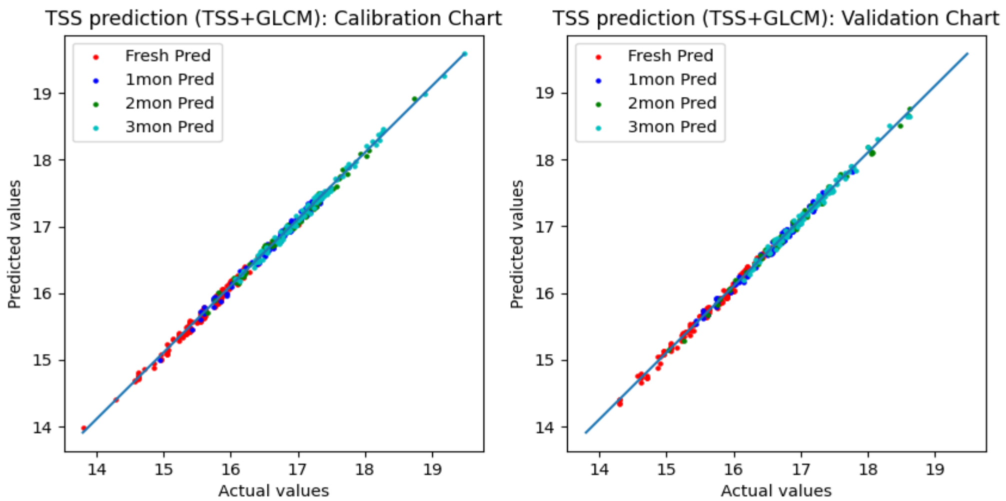


Figure 18: Predicted TSS values of fruits using the combination of physiochemical and GLCM features through SDD-LSTM

3.5.2 Prediction of pH using both physiochemical and GLCM through SDD-LSTM

The pH prediction of pomegranate fruits is analyzed by combining both physiochemical and GLCM features. The prediction is made by varying the fruit's quality from fresh fruit to three month old fruits. In the calibration model, the pH prediction exhibits the r^2 score of 0.978 and RMSEC of 0.0121. The obtained r^2 score and RMSEP for predicting pH in the validation are 0.9773 and 0.0122. The calibration and validation results of pH prediction using the proposed SDD-LSTM approach are depicted in Figure 19.

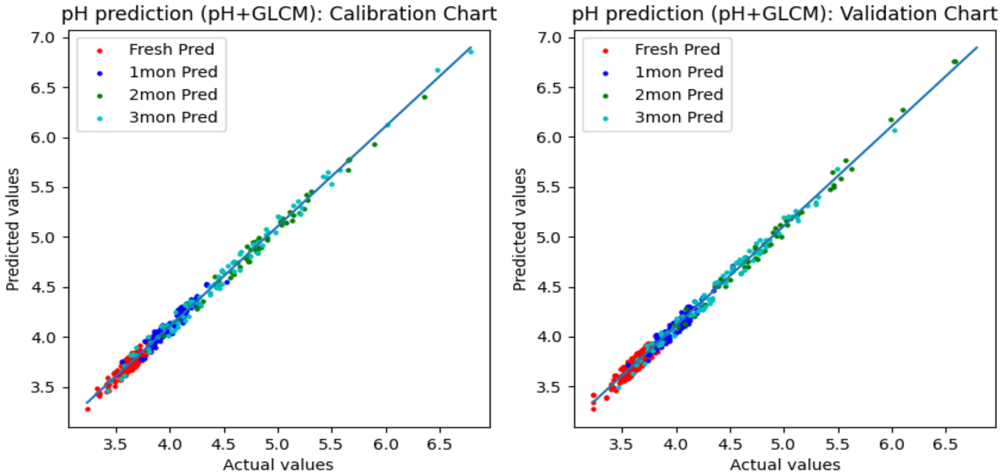


Figure 19: Predicted pH values of fruits using the combination of physiochemical and GLCM features through SDD-LSTM

3.5.3 Prediction of acidity using physiochemical and GLCM through SDD-LSTM

Fruit acidity is predicted by integrating both physiochemical and GLCM features. The results are evaluated for both calibration and validation. In the calibration model, the acidity prediction attains the r^2 score of 0.9754 and RMSEC of 0.0116. The validation results in acidity prediction provide the r^2 score of 0.9723 and RMSEP of 0.0121. Figure 20 represents the calibration and validation of acidity prediction using combined features.

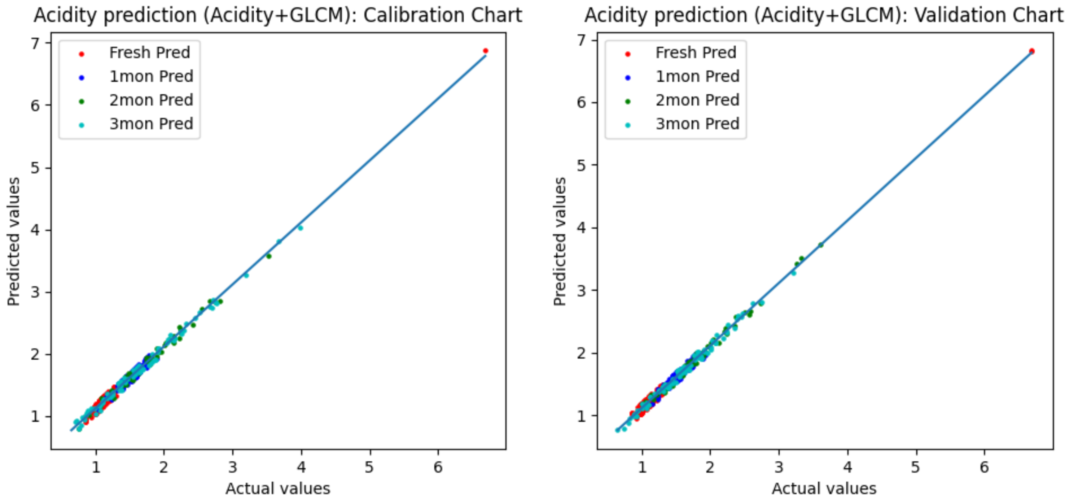


Figure 20: Predicted acidity values of fruits using the combination of physiochemical and GLCM features through SDD-LSTM

3.5.4 Prediction of firmness using physiochemical and GLCM through SDD-LSTM

With the aid of the proposed SDD-LSTM, the firmness value of the provided fruits is predicted using GLCM and physiochemical features. For firmness prediction, the attained r^2 score and RMSEC in calibration are 0.9998 and 0.0116. The validation results of the proposed firmness prediction provide the r^2 score is 0.9998 and RMSEP is 0.0122. Figure 21 represents the calibration and validation results of firmness prediction of fruits using combined features.

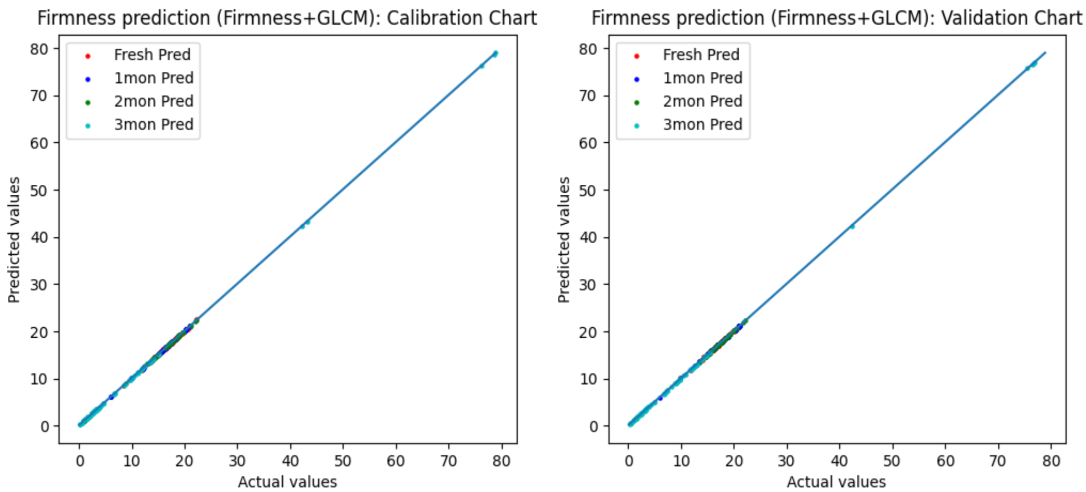


Figure 21: Predicted firmness values of fruits using the combination of physiochemical and GLCM features through SDD-LSTM

The proposed study compares the attained results from the LSTM and SDD-LSTM model with machine learning algorithms like Decision Tree Regression (DTR) and Linear regression (LR). Table 4 shows the comparative analysis of the proposed deep learning model with the machine learning algorithm.

Table 4: Performance comparison for proposed deep learning models and other machine learning techniques

		Calibration		Validation	
	Attribute	**r^2**	**RMSEC**	**r^2**	**RMSEP**
DTR	**TSS**	0.89	0.15	0.93	0.1
	pH	0.83	0.03	0.836	0.3
	Acidity	1	0	1.0	0
	Firmness	0.96	0.425	0.97	0.43
LR	**Attribute**	**Calibration**		**Validation**	
		r^2	**RMSEC**	**r^2**	**RMSEP**
	TSS	0.93	0.136	0.95	0.105
	pH	0.9	0.02	0.95	0.02
	Acidity	0.97	0.036	0.98	0.01
	Firmness	0.94	0.177	1	0.178
LSTM (Only physiochemical parameters)	**Attribute**	**Calibration**		**Validation**	
		r^2	**RMSEC**	**r^2**	**RMSEP**
	TSS	0.9608	0.018	0.9607	0.0181
	pH	0.9566	0.0162	0.9558	0.0153
	Acidity	0.9727	0.0177	0.9668	0.0182
	Firmness	0.9996	0.0179	0.9996	0.0186
SDD-LSTM (Only physiochemical parameters)	**Attribute**	**Calibration**		**Validation**	
		r^2	**RMSEC**	**r^2**	**RMSEP**
	TSS	0.9802	0.0172	0.98	0.0174
	pH	0.9575	0.0153	0.9637	0.0151
	Acidity	0.975	0.0154	0.9671	0.0152

	Firmness	0.9998	0.0155	0.9998	0.0154
LSTM (Physiochemical +GLCM)	**Attribute**	**Calibration**		**Validation**	
		r^2	**RMSEC**	**r^2**	**RMSEP**
	TSS	0.9818	0.0153	0.9828	0.0156
	pH	0.976	0.0124	0.9767	0.0125
	Acidity	0.9732	0.0126	0.967	0.0125
	Firmness	0.9997	0.0118	0.9997	0.0123
SDD-LSTM (Physiochemical +GLCM)		**Calibration**		**Validation**	
		r^2	**RMSEC**	**r^2**	**RMSEP**
	TSS	0.9853	0.0119	0.9855	0.0116
	pH	0.978	0.0121	0.9773	0.0122
	Acidity	0.9754	0.0116	0.9723	0.0121
	Firmness	0.9998	0.0116	0.9998	0.0122

The performance comparison analysis of the proposed LSTM and the SDD-LSTM using only physiochemical and combined features are shown in Figure 22 and Figure 23.

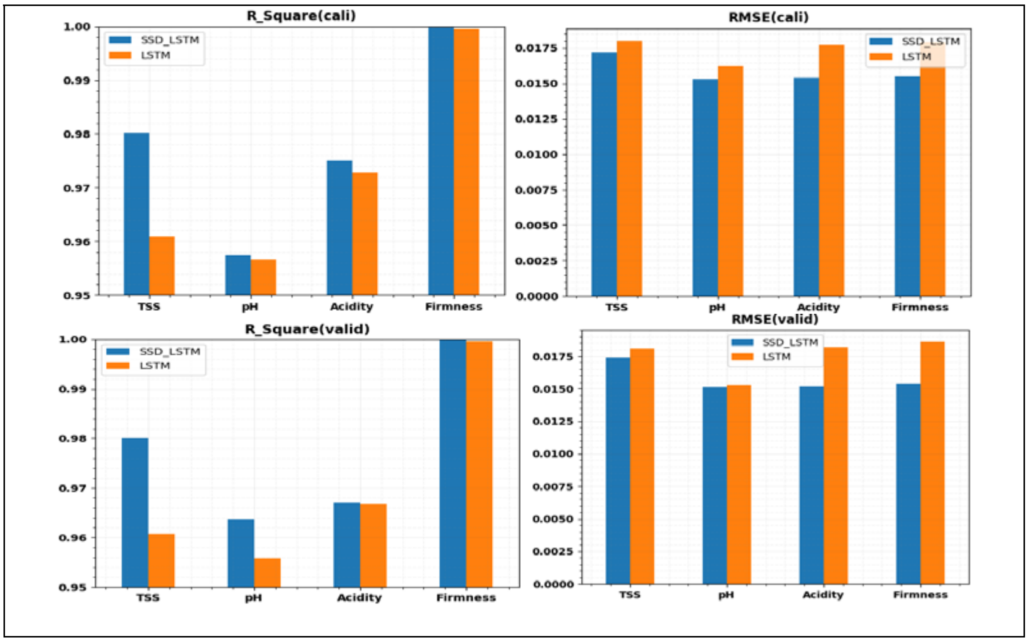


Figure 22: Comparison analysis of LSTM and SDD-LSTM using only physiochemical features

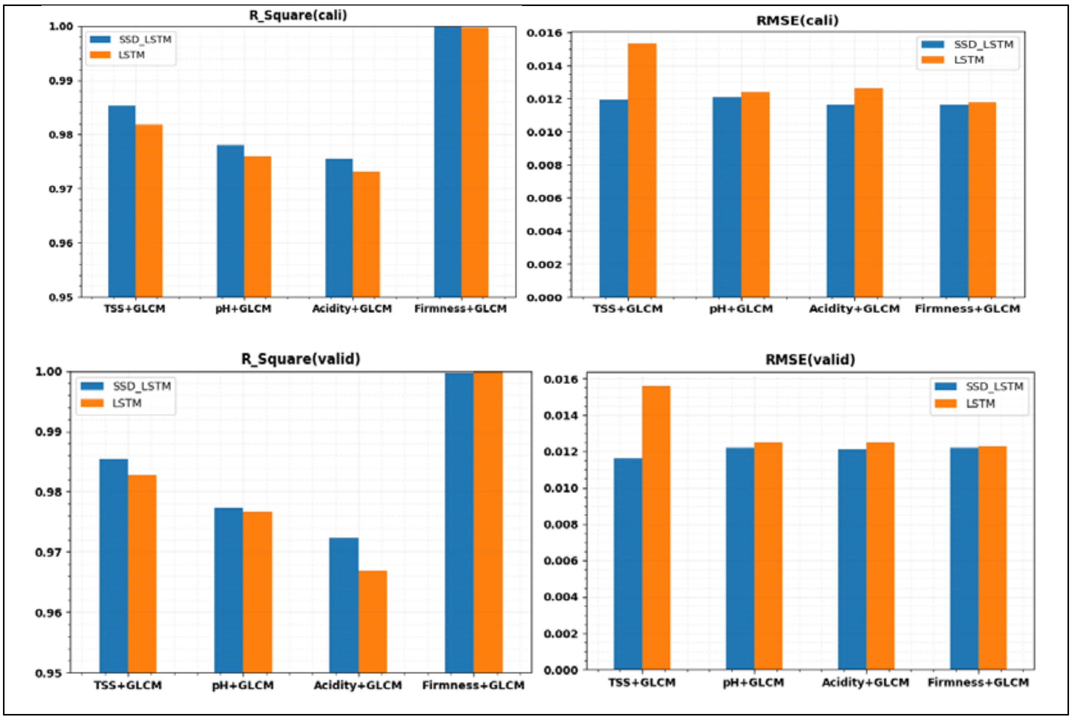


Figure 23: Comparison analysis of LSTM and SDD-LSTM using physiochemical and GLCM features

The comparison analysis shows that the proposed SDD-LSTM is better than the LSTM and other machine learning approaches in terms of r^2, RMSEC and RMSEP. The existing machine learning algorithms obtain reduced results because of overfitting issues and large time requirements. Overfitting occurs when the machine learning algorithms learn all the information of the given input data during prediction and the noise available in the training data to the extent that it can affect the overall performance. Moreover, the machine learning techniques suffer from the maximum loss function, increasing the error rate.

The proposed deep learning based SDD-LSTM model provides a higher range of parameters like input bias, output bias and learning rates. Thus, there has no necessity for fine adjustments. Because of the backpropagation, the SDD-LSTM model reduces the computational complexity. Also, the SDD-LSTM solves the overfitting issues by minimizing the number of units. The attained loss function in the prediction process of SDD-LSTM is reduced by optimizing the weight parameters using the Adam optimizer. This Adam optimizer maintains the weights to reduce the error rate and decreases the loss function.

Thus, the result analysis in the proposed work states that the proposed deep learning model is highly effective for non-destructive evaluation.

4. Conclusion

In this work, the LSTM and SDD-LSTM models have been proposed for the non-destructive evaluation of pomegranate fruits. Here, the prediction process is performed by combining both physiochemical and GLCM features. The GLCM features are obtained from the Magnetic resonance imaging system, and the physiochemical values are measured from the laboratory for the fruits of 155 days. The performance evaluation of the SDD-LSTM approach along with physiochemical and GLCM features obtained the results in calibration are $\mathbf{r^2}$ = 0.9853, RMSEC= 0.0119_Brix for TSS, $\mathbf{r^2}$ = 0.978, RMSEC = 0.0121 for pH, $\mathbf{r^2}$ = 0.9754, RMSEC = 0.0116 for acidity and $\mathbf{r^2}$ = 0.9998, RMSEC= 0.0116 for firmness. Similarly, the obtained results in validation are $\mathbf{r^2}$ = 0.9855, RMSEP = 0.0116 _Brix for TSS, $\mathbf{r^2}$ =0.9773, RMSEP = 0.0122 for pH, $\mathbf{r^2}$ = 0.9723, RMSEP = 0.0121 for acidity and $\mathbf{r^2}$ = 0.9998, RMSEP = 0.0122 for firmness. The results showed that the proposed SDD-LSTM is much better than the LSTM model. Other machine learning algorithms also provide enhanced predictions for TSS, pH, acidity and firmness. Combining both physiochemical and GLCM features, the chemical parameters are predicted through SDD-LSTM and attain improved results rather than only physiochemical features. The efficacy of the proposed work is analyzed by comparing the proposed deep learning models with other machine learning techniques. The comparative analysis resembles that the proposed SDD-LSTM obtains enhanced results than the other techniques. This knowledge of the study for storage of fruits can be utilized for managing fruit in the market throughout the year and also can be used in the pomegranate fruit processing industries for various uses such as providing fresh arils, fresh juice, and oil extraction. Thus, the proposed study helps to understand the freshness of the fruit and its shelf life. In future, the optimization algorithm will be integrated with the classification stage to attain more performance. Moreover, different features will be extracted to the extent of the efficacy of the proposed model.

Conflict of Interest Statement:

The author(s) declare(s) that there is no conflict of interest.

References

[1] Abdelbasset, W.K., Nambi, G.; Elkholi, S.M.; Eid, M.M.; Alrawaili, S.M.; and Mahmoud, M.Z. (2022): Application of neural networks in predicting the qualitative characteristics of fruits, Food Science and Technology, **42**.

[2] Fawole, O.A.; Opara, U.L. (2013b): Effects of maturity status on biochemical concentration, polyphenol composition and antioxidant capacity of pomegranate fruit arils (cv. 'Bhagwa'), J. S. Afr. Bot, **85**, pp. 23–31.

[3] Blasco, J.; Cubero, S.; Gomez-Sanchis, J.; Mira, P.; Molto, E. (2009): Development of a machine for the automatic sorting of pomegranate (Punica granatum) arils based on computer vision, J. Food Eng, **90**, pp. 27–34.

[4] Payel, G.; and Sunil, C.K. (2014): Quality Analysis of Pomegranate by Non-Destructive Soft X-Ray Method, J Food Process Technol, **5**, pp. 6, DOI: 10.4172/2157-7110.1000341

[5] Kim, S.M.; Chen, P.; McCarthy, M.J.; and Zion, B. (1999): Fruit internal quality evaluation using online nuclear magnetic resonance sensors, Journal of Agricultural Engineering Research, **74**, pp. 293–301.

[6] Rasool, K.; Emadi, B. et el. (2017). Determining quality and maturity of pomegranates using multispectral imaging, Journal of the Saudi Society of Agricultural Sciences, **16**, pp.322–331

[7] Baohua, Z.; and Zhou, J. (2018); Hyperspectral Imaging and Their Applications in the Non-destructive Quality Assessment of Fruits and Vegetables, Intechopen, **72250**.

[8] Alireza, K.; Keyhani, A.; Zoroofi, R.A.; Yaghoobi, G. (2011): Non-destructive Inspection of Pomegranate Maturity using Magnetic Resonance Imaging and Neural Networks, CIGR Section VI International Symposium on Towards a Sustainable Food Chain Food Process, Bio processing and Food Quality Management.

[9] Lu, Z.; McCarthy, M.; (2013): Assessment of pomegranate post-harvest quality using nuclear magnetic resonance, Postharvest Biology and Technology, **77**, pp. 59–66.

[10] Barreiro P.; Ruiz-Cabello, J.; Fernandez-Valle, M.E.; Ortiz, C.; and Ruiz, M. (2000): Mealiness assessment in apples and peaches using MRI techniques Article in Magnetic Resonance Imaging, **18**(9), pp.1175-81 , 2000

[11] Wang, S.Y.; Wang, P.C.; Faust, M. (1988): Non-destructive detection of water-core in apple with nuclear magnetic resonance imaging, Scientia Horticulture, **35,** pp. 224-234.

[12] Herremans, E.; Melado-Herreros, A.; Defraeye, T.; Verlinden, B.; Hertog, M. Verboven, P.; Nicolai, B.M. (2014): Comparison of X-ray CT and MRI of water core disorder of different apple cultivars, Postharvest Biol. Tech, **87,** pp. 42-50.

[13] Milczarek, R. (2009): Multivariate image analysis: An optimization tool for characterizing damage-related attributes in magnetic resonance images of processing tomatoes . PhD dissertation, University of California, Davis, CA., USA.

[14] Balogun, W.A.; Salami, M.J.E.; McCarthy, M.J.; Mustafah, Y.M.; Aibinu, A.M. (July-2013): Intelligent Technique for Grading Tropical Fruit using Magnetic Resonance Imaging, International Journal of Scientific & Engineering Research, **4**(7), pp. 216 ISSN 2229-5518,

[15] Khoshroo, A.; Keyhani, A.; Zoroofi, R.A.; Rafiee, S.; Zamani, Z.; Alsharif, M.R. (March 2009): Classification of Pomegranate Fruit using Texture Analysis of MR Images, Agricultural Engineering International: the CIGR Ejournal, Manuscript **1182**(11).

[16] Daniel C.; Durán, T.A.M.; Caro, A. (2017): Applying 3D texture algorithms on MRI to evaluate quality traits of loin, Article in Journal of Food Engineering, **222**, pp. 258-266, 2017

[17] Adel, A.K. (1984 July- August): Responses of pomegranates to ethylene treatment and storage temperature, CALIFORNIA AGRICULTURE.

[18] McGlone, V.A.; Kawano, S.; (1998): Firmness, dry-matter and soluble solids assessment of post-harvest kiwifruit by NIR spectroscopy, Postharvest Biol, Technol, **13**, pp.131–141.

[19] Haralick, R.M.; Shanmugam, K.; Dinstein, I.H.; (1973): Textural features for image classification, IEEE Transactions on Systems, Man, and Cybernetics SMC, **3**(6), pp.610–621 DOI 10.1109/TSMC.1973.4309314.

[20] GLCM Equations. (2011): Gray Level Co-occurence Matrix equations. Available at https://scikitimage.org/docs/0.7.0/api/skimage.feature.texture.html, (accessed January 8 2022).

[21] Yu, Y.; Si, X.; Hu, C.; and Zhang, J. (2019): A review of recurrent neural networks: LSTM cells and network architectures, Neural computation, **31(**7), pp.1235-1270.

[22] Ma, M.; Liu, C.; Wei, R.; Liang, B.; and Dai, J. (2008): Predicting machine's performance record using the stacked long short-term memory (LSTM) neural networks, Journal of Applied Clinical Medical Physics, **23(**3), pp. e13558.

Authors Profile

Surekha V. Yakatpure obtained B.E. degree in the department of electronics and telecommunications at JNEC, Marathwada University, Aurangabad. Also, she obtained M.E. degree in the department of electronics and telecommunication at KIT, Solapur University, Kolhapur. Currently, she is pursuing PhD from VTU in Belagavi, Karnataka. Her areas of specialization are image processing, pattern recognition, machine learning, and signal processing. She has 23 years of teaching experience. Presently, she is working as an assistant professor in the department of electronics and telecommunications at A G Patil Institute of Technology, Solapur, India. Honours and Awarded with Fellowship to IEI Calcutta. Life member to ISTE. BOS member at Solapur University.

Dr. Krupa R Rasane is currently working as a Professor & Head of the department of Electronics and Communications at Jain College of Engineering Belgavi, India. Honours and awards include Outstanding Small Branch Counsellor Award IEEE Bangalore Section 2020. Best IEEE Researcher Award in IEEE Bangalore Section Membership to bodies are IEEE USA, Senior IEEE Member Computer Society of India. Her research interest includes Automation and Control Systems Areas and subject expertise include embedded system, Image compression using VLSI, IOT and Network Cybersecurity.

Dr. K. Dhinesh Babu obtained B.Sc (Agri.) degree from Faculty of Agriculture, Annamalai University in 1995, M.Sc.(Horticulture) from Horticulture College & Research Institute, Tamil Nadu Agricultural University, Coimbatore in 1998 and Ph.D (Horticulture) from College of Horticulture, Kerala Agricultural University, Thrissur, Kerala in 2005.