Chapter-IV

4 Results and discussions

This chapter provides a detailed discussion on the observations and outputs obtained from implementation of the methodologies mentioned in chapter III. The chapter is divided into 5 subheadings of the 4 objectives.

4.1 Results obtained in classifying tomato as edible or spoilt

In this section results obtained from the customized model in obtaining the highest classification accuracy are elaborated.

4.1.1 Effectiveness of various optimizers during model training

The developed model was trained on the prepared image dataset using three different optimizers in order to identify the optimizer which is best suitable for the considered classification problem. Three different learning rates were set for each optimizer and classification accuracy along with average time taken per step (in 1 epoch) was obtained by training the model. The different cases corresponding to learning rates and optimizers are shown in the Table 4.1. From Table 4.1, it is evident that Adam optimizer provided the highest classification accuracy among the selected three different optimizers.

Table 4.1 Classification accuracy and average time taken in each step of an epoch corresponding to different optimizers and learning rates

Cases	Learning rate	Optimizer	Average time taken per step (in 1 epoch)	Classification accuracy
I	0.01	Adam	698ms	98.32%
II	0.01	RMSprop	743 ms	98.74%
III	0.01	SGD	782 ms	96.64%
IV	**0.001**	**Adam**	**741 ms**	**99.56%**
V	0.001	RMSprop	760 ms	99.10%
VI	0.001	SGD	792 ms	59.24%
VII	0.0001	Adam	769 ms	99.25%
VIII	0.0001	RMSprop	770 ms	99.12%
IX	0.0001	SGD	825 ms	64.71%

4.1.2 Results obtained on binary classification of tomatoes into edible and spoilt

The outcome of the CNN architecture developed to predict the current state of tomato as edible or spoilt as discussed in section 3.1.2.4 of chapter III is elaborated here. In total 810 images were collected during the experiment which works as the dataset for this model. Splitting of the dataset into training and testing classes is done in the ratio 7:3. Out of the 810 images of the dataset 572 images were selected for training randomly and 238 images for testing. The training was carried out iteratively with varying epoch and batch sizes to evaluate the model to give the highest accuracy. The model was trained with 10, 20 and 30 epoch and 8, 16, 24 and 32 batch number. The classification accuracy obtained on the test set on varying epoch and batch size is presented in Fig. 4.1. Overall classification accuracy obtained is above 95% for epoch between 10 and 30 as well as batch size between 8 and 64(Fig. 4.1). The highest classification accuracy of the CNN model was achieved at 20 epoch and 32 batch size. Thus, at the afore-mentioned hyper parameters, the architecture of the CNN model showed an accuracy of 99.70%. The obtained classification accuracy of the model vindicates its applicability in predicting the current condition of tomatoes as edible or spoilt.

Fig. 4.1indicates that the CNN model obtains overall classification accuracy above 95% for epoch between 10 and 30 as well as batch size between 8 and 64. Hence, the classifier was capable of distinguishing the two classes of tomatoes under consideration paving the way for application of deep learning based image processing technique for grading systems. Fig. 4.2 presents the ability of the model to distinguish between an edible and spoilt tomato.

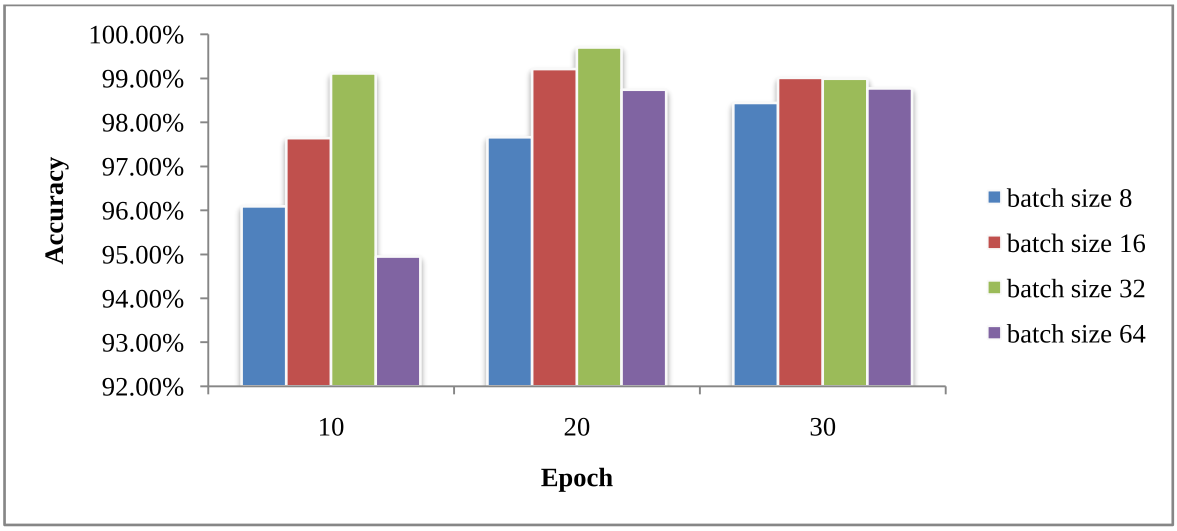


Fig. 4.1 Classification accuracy of customized classification models

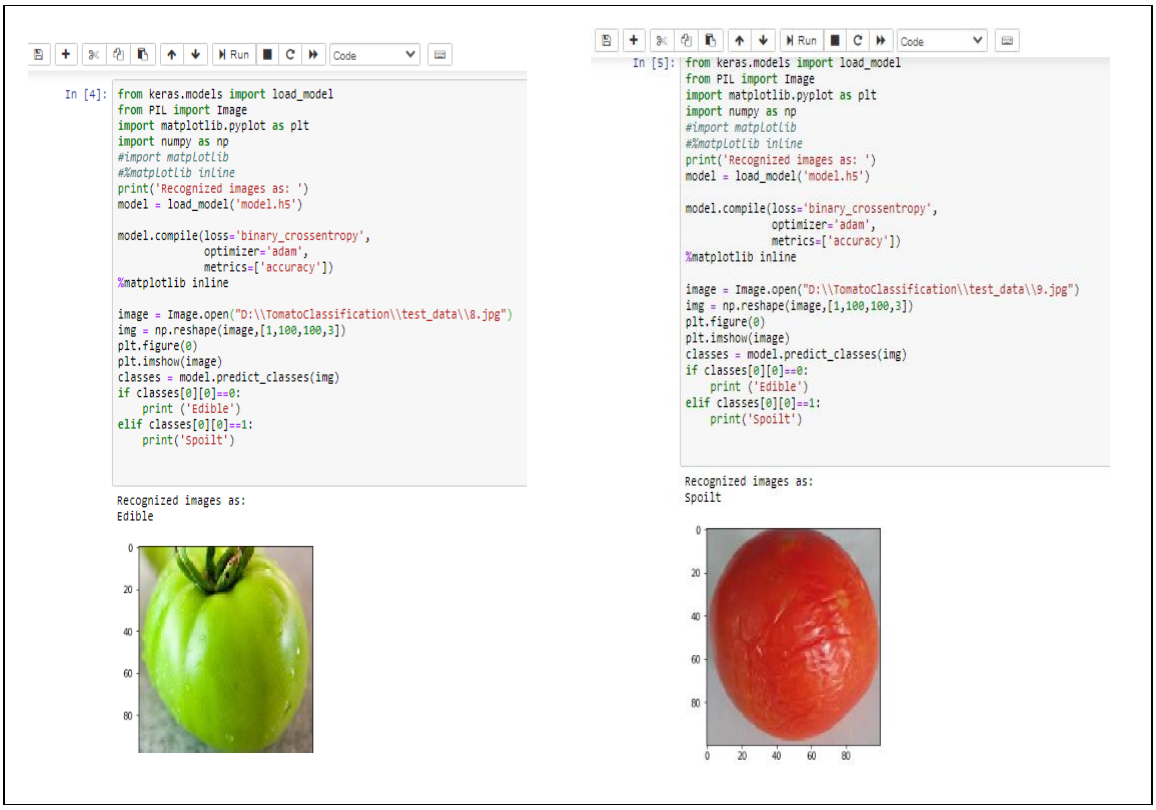


Fig. 4.2 Prediction made by the classification model

4.1.3 Model evaluation

To evaluate the performance of the customized CNN model, a comparison was made between the predicted results, sensory results (actual) and physiological analysis results. From Table 4.2 and Fig. A1, the predictions made by the customized CNN model are at par with the recognition made by the sensory panelist. Also, upon performing texture (firmness) analysis on the similar tomato it was found that firmness values were less than 10 N/mm for spoilt tomatoes. A firmness value of 1.45 N/mm is an indicator to spoilt tomato (Batu, 1995).

Table 4.2 Comparison between model prediction, sensory and physiological evaluation

Sample	Model recognized as	Sensory panelist evaluated as	Firmness value (N)
S1	Spoilt	Spoilt	10.53
S2	Edible	Edible	30.42
S3	Spoilt	Spoilt	10.43
S4	Spoilt	Spoilt	5.74
S5	Edible	Edible	28.22
S6	Spoilt	Edible	9.32
S7	Edible	Edible	44.12

S8	Spoilt	Spoilt	10.28
S9	Spoilt	Spoilt	11.52
S10	Spoilt	Spoilt	19.72
S11	Edible	Edible	56.15
S12	Edible	Edible	37.62
S13	Spoilt	Spoilt	10.53
S14	Spoilt	Spoilt	3.28
S15	Edible	Edible	29.30
S16	Spoilt	Spoilt	2.81
S17	Spoilt	Spoilt	5.53
S18	Edible	Edible	69.24
S19	Spoilt	Spoilt	3.27
S20	Spoilt	Spoilt	4.42

4.1.3.1 Model evaluation using confusion matrix

The performance of the model was validated by establishing a confusion matrix based on the results obtained from Table 4.2. The sensory evaluation was considered “actual values” while model’s evaluation was considered as “predicted values” and further validated using confusion matrix and Pearsons’ correlation. From the confusion matrix, precision, recall and accuracy were calculated (Fig. 4.3).

Confusion matrix		Predicted	
		Edible	Spoilt
Actual	Edible	**7**	**1**
	Spoilt	**0**	**12**

Precision

Precision = TP/ (TP + FP) = 7/(7+0) = 1 **(100%)**

Recall

Recall = TP / (TP + FN) = 7/(7+1) = 0.87 **(87%)**

Accuracy

Accuracy = TP+TN / (TP + TN+ FP + FN)

= 7+12/(7+12+0+1) = 0.95 **(95%)**

Fig. 4.3 Evaluation parameters calculated from confusion matrix

The result of the confusion matrix presumes that the customized CNN model outperforms the task of spoilage detection with precision, recall and accuracy of 100%, 87% and 95% respectively. Precision of 100% means that the model is 100% precise in spoilage detection of tomatoes. From the confusion matrix below it is seen that 12/12 images were predicted spoilt whereas 7/8 images were predicted edible giving a recall of 87%.

4.1.3.2 Model evaluation using Pearsons' correlation

From the results obtained in Table 4.2, correlation is established between them. The developed model showed a Pearson correlation of 0.895, showing that there is strong linear correlation between the predictive model and the sensory evaluation results.

4.2 Results obtained in classifying tomato as mature green, intermediate and advanced

In this objective three different approaches of transfer learning (viz Inception, VGG and ResNet) were employed to evaluate its efficiency in classifying tomatoes into their maturity classes. Based on the methodology discussed in section 3.2.2.4, training of the models on the self-prepared dataset was performed. The conventional architectures of Inception, VGG and ResNet with the learned weights were used with to obtain features. The outputs obtained out of it, were fed to the newly added fully-connected layer to train the self-prepared dataset. These models are such that when number of convolution layers is less, the essential features of the targeted image cannot be learned by the model and when number of layers is more, the model extracts more features leading to over-fitting issues. A comparison is drawn on the architectures in terms of accuracy in classifying tomatoes. Parameters such as number of epochs, batch size and time required to achieve the maximum accuracy were considered for performance evaluation of individual model. In total 950 images were used during the experiment which works as the dataset for every model. Splitting of the dataset into training and testing classes is done in the ratio 7:3. Out of 950 images of the dataset, 665 images were selected for training randomly and 285 images for testing. The training was carried out iteratively with varying number of epoch and batch sizes to evaluate the model. Performance comparison of individual model based on transfer learning approach is discussed in the following subsections. The results obtained are shown in Fig. 4.4.

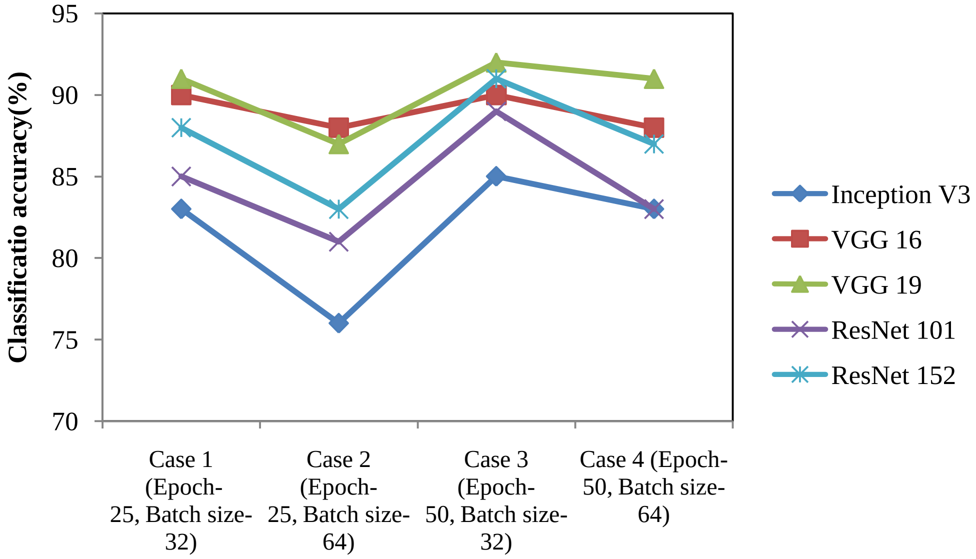


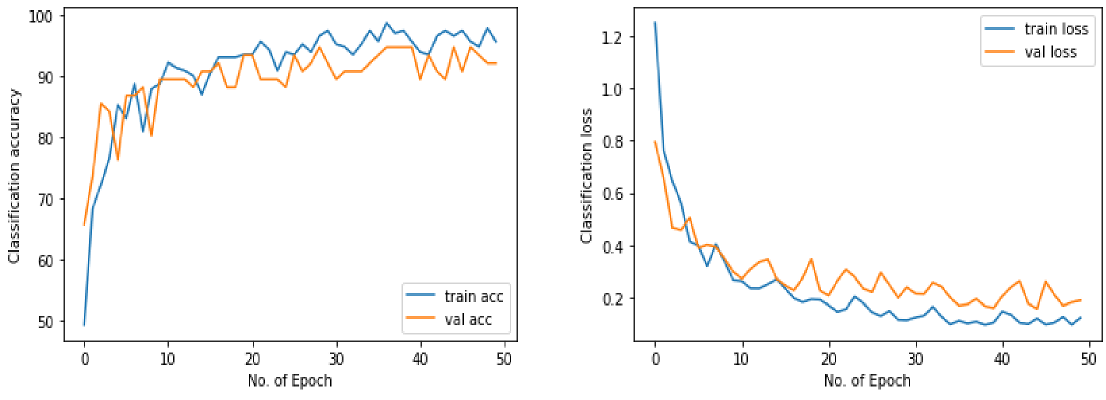
Fig. 4.4 Classification accuracy obtained from different transfer learning models

4.2.1 Performance of VGG 16 based transfer learning model

VGG 16 showed good results achieving accuracy of 94.74% and 95.24% at epoch 25 and 50 at batch size 32. At batch size 64, the highest classification accuracy of 93.42% is achieved which remains same for both epochs 25 and 50. Thus it has been observed that batch size 32 provides higher classification accuracy than batch size 64 at epoch 50. The negative impact of batch size on classification accuracy is due to increase in variance in a batch with large batch size.

4.2.2 Performance of VGG 19 based transfer learning model

VGG 19 gave the highest classification accuracy of 96.05% and 97.37% at epoch 25 and 50 at batch size 32. Secondly it gives accuracy 92.11% and 96.05% at epoch 25 and 50 at batch size 64. Hence in this study VGG 19 has shown highest performance in classification of tomatoes on the basis of maturity. From Fig. 4.5(a), it is evident that the validation accuracy achieved in VGG 19 has higher convergence to the training accuracy. Also in Fig. 4.5(b), the validation loss is a little bit higher than training loss, indicating good performance of the model.



(a) (b)

Fig. 4.5: (a) Classification accuracy using VGG19 on varying epoch sizes (b) Classification loss using VGG19 on varying epoch sizes

4.2.3 Performance of inception V3 based transfer learning model

The inception V3 model gave the lowest classification accuracy of 82.89% and 84.21% at epoch 25 and 50 at batch size 32. And 76.32% and 82.89% at epoch 25 and 50 at batch size 64. Thus, this model has shown the lowest accuracy in the tomato dataset prepared (Fig. A3).

4.2.4 Performance of ResNet101 based transfer learning model

The hybridized ResNet 101 architecture being trained with the tomato dataset gave accuracy 93.42% at epoch 25 and batch size 32. Accuracy increased to 97.37% when number of epochs increases to 50 while batch size being 32 indicating that more number of iterations during training gives more accuracy. Again, the model gave accuracy 89.47% at epoch 25 and batch size 64 and 90.79% at epoch 50 and batch size 64. Hence, we can say that larger batch size has a negative impact on the accuracy.

4.2.5 Performance of ResNet 152 based transfer learning model

The pre-trained architecture of ResNet 152 when restructured and trained with the prepared tomato dataset an accuracy of 93.42% and 96.05% was obtained at epoch 25 and 50 while batch size being 32. And an accuracy of 88.16% and 92.11% was achieved at epoch 25 and 50 while batch size being 64. Thus, we can see that with the increase in number of epochs the accuracy of the architecture increases. It is also seen that the model works better when batch size is fixed to 32. Higher batch size and lower accuracy is due to increase in variance. As the number of images is increased in a batch it leads to slower learning rate and hence, lowers accuracy.

For the consistency of the results, the experiments were repeated three times. Keeping the hyper parameters fixed during the training, the classification accuracy in each step was recorded. The recorded accuracies from the same experiment are averaged to obtain the final classification accuracy. The standard deviation in classification accuracy remained below 2% for all experiments.

4.2.6 Evaluation of models based on performance and training time

Another important evaluation parameter is the training time which is dependent on a number of factors. The training time of a model depends on the size of the dataset, model complexity and the computational speed of the processor. Using a computer with Intel Pentium processor (2.30 GHz clock frequency) on the prepared dataset, the average training time per epoch is shown in Table 4.3. Further, the size of the image (no. of pixels) also affects the computational time. Images with large pixel value led to high training time. However, in this work the image size is augmented to 100 ×100 pixels.

Table 4.3 Training time per epoch of different transfer learning models

Transfer learning model	Computational/training time (per epoch)
VGG 16	21 seconds
VGG 19	29 seconds
Inception v3	15 seconds
ResNet 101	31 seconds
ResNet 152	39 seconds

From above it is found that VGG 19 performed best in three class (mature green, intermediate and advanced) classification with 97.37% accuracy and 29 seconds execution time among the other transfer learning models. Moreover size of dataset does not affect the accuracy of the model.

4.2.7 Model evaluation

Like objective 1.1, a comparison table was established using the model prediction and the sensory prediction results (Table 4.4 and Fig. A2). This table is basically obtained to evaluate the performance of the transfer learning models in maturity class prediction of tomatoes.

Table 4.4 Comparison between model prediction and sensory evaluation

Sample	Model recognized as	Sensory panelist evaluated as
S_1	Advanced	Advanced

S_2	Advanced	Advanced
S_3	Mature green	Intermediate
S_4	Intermediate	Intermediate
S_5	Advanced	Advanced
S_6	Mature green	Mature green
S_7	Intermediate	Intermediate
S_8	Intermediate	Intermediate
S_9	Intermediate	Intermediate
S_{10}	Mature green	Mature green
S_{11}	Mature green	Mature green
S_{12}	Advanced	Intermediate
S_{13}	Intermediate	Intermediate
S_{14}	Mature green	Mature green
S_{15}	Advanced	Advanced
S_{16}	Advanced	Advanced
S_{17}	Intermediate	Intermediate
S_{18}	Mature green	Mature green
S_{19}	Intermediate	Intermediate
S_{20}	Mature green	Mature green

Since color is an important indicator to ripening stage determination. So, color values of the tomato samples were obtained at different stage of ripening. From Table 4.5, it is seen that L*, a* and b* values varied between different classes indicating color has influence on ripening stages. a*/b* is the most widely used reference parameter for color quality in commercial practice. Significant difference in a*/b* values, ΔE, Hue, Chroma between groups indicates difference in classes.

Table 4.5 Physiological analysis of tomatoes

Ripening stage	**L***	**a***	**b***	**a*/b***	**ΔE**	**Hue**	**Chroma**
Mature green	70.19 ±8.47	-2.2 ±7.07	24.53 ±3.83	-0.08 ±0.02	69.42 ±2.82	-55.97 ±0.56	24.62 ±0.87
Intermediate	60.78 ±5.09	12.46 ±5.45	36.24 ±11.08	0.34 ±0.08	60.82 ±3.74	51.10 ±0.41	38.32 ±0.67

Advanced	46.57 ±12.15	25.05 ±2.88	30.90 ±2.47	0.81 ±0.13	49.41 ±1.88	41.64 ±0.38	39.79 ±0.70

4.2.7.1 Model evaluation using confusion matrix

Confusion matrix is an important tool to evaluate the classification performance of different deep learning models. The classification accuracy is usually summarized by performance indicators like precision, recall and accuracy. Hence from the 5 different transfer learning models used, confusion matrixes were obtained. Based on the precision, recall and accuracy of the 5 different transfer learning models, VGG 19 outperformed the task of maturity detection with an accuracy of 95%. From the confusion matrix it can be seen that a total of 7/7 and 7/7 tomato images were correctly classified as mature green and advanced respectively, giving a recall of 100% for both the classes. However, in case of intermediate 5/6 images were correctly classified, indicating 83% recall. This may be due to mixed surface color ranging from green to red in this category. On the other hand, precision was found in the range 88%-100%indicating that the model can predict the ripening stages correctly. The model confused samples belonging to intermediate class with mature green and advanced.

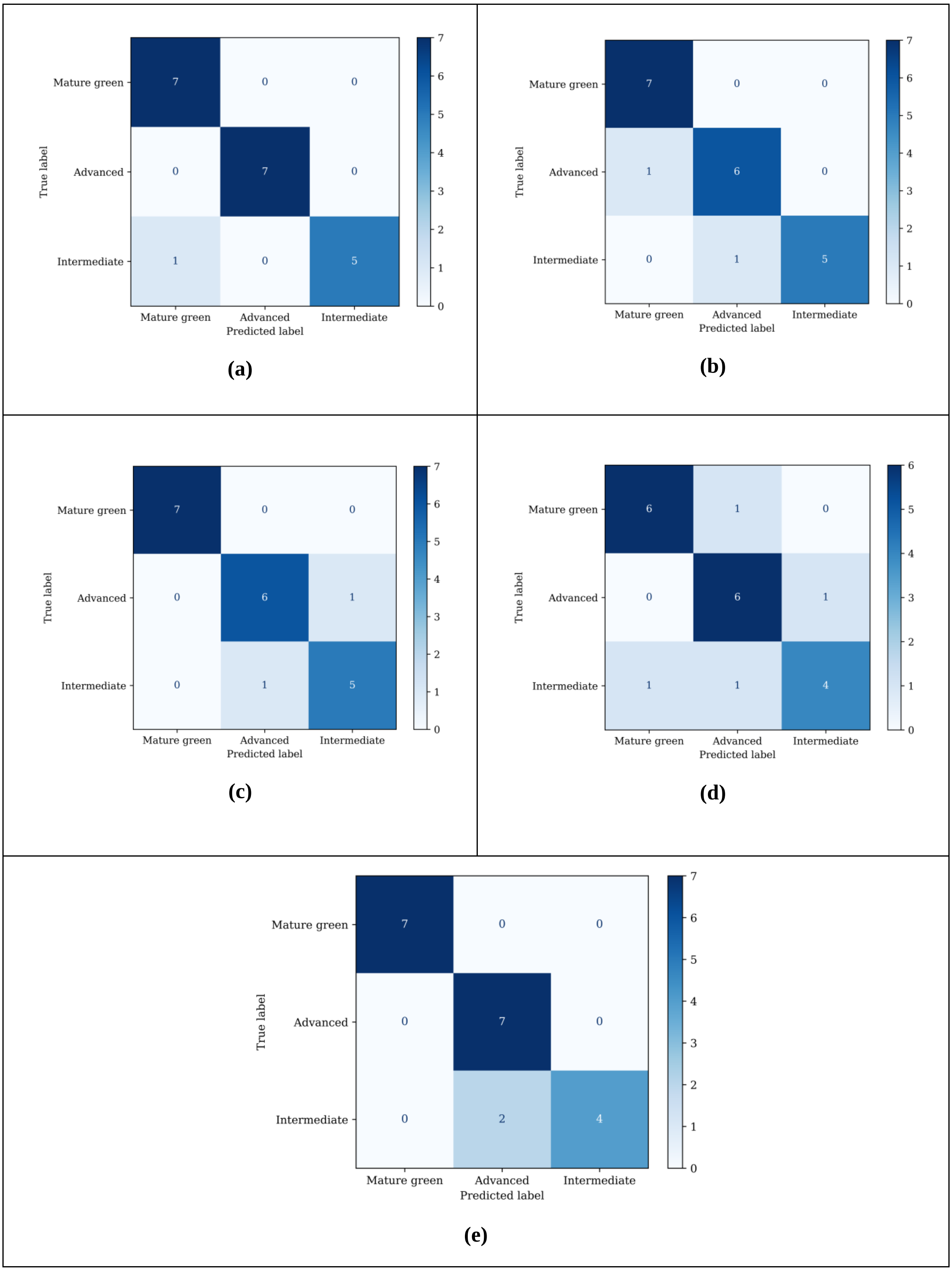


Fig. 4.6 (a) Confusion matrix for VGG 19, (b) Confusion matrix for ResNet101, (c) Confusion matrix for ResNet152, (d) Confusion matrix for Inception v3, and (e) Confusion matrix for VGG 16

Table 4.6 Recall, precision, F1-score, overall accuracy of different transfer learning models

Models	Maturity stage	Recall	Precision	F1-score	Overall accuracy
VGG 19	Mature green	1.00	0.88	0.93	0.95
	Intermediate	0.83	1.00	0.91	
	Advanced	1.00	1.00	1.00	
ResNet 101	Mature green	1.00	0.88	0.93	0.90
	Intermediate	0.83	1.00	0.91	
	Advanced	0.86	0.86	0.86	
ResNet 152	Mature green	1.00	1.00	1.00	0.90
	Intermediate	0.83	0.83	0.83	
	Advanced	0.86	0.86	0.86	
Inception V3	Mature green	0.86	0.86	0.86	0.80
	Intermediate	0.67	0.80	0.73	
	Advanced	0.86	0.75	0.80	
VGG 16	Mature green	1.00	1.00	1.00	0.90
	Intermediate	0.67	1.00	0.80	
	Advanced	1.00	0.78	0.88	

4.2.7.2 Model evaluation using Pearsons' correlation

From the results obtained from Table 4.4, correlation is established between them using Pearsons' correlation. The Pearsons' correlation coefficient obtained is R = 0.919 indicating strong linear correlation between the predictive model and the sensory evaluation results. From the confusion matrix, VGG19 gives the highest classification accuracy of 95 % followed by VGG 16, ResNet and Inception V3. Hence in this study VGG 19 is considered best for classification of tomatoes on the basis of ripening stage.

4.3 Results obtained in predicting physico-chemical properties of tomato from their surface characteristics

After image acquisition, fruit is separated for its physico-chemical analysis as mentioned in section 3.2.2.3 of objective 3. The results obtained from the physico-chemical analysis of tomato and how it is affected upon ripening is discussed below.

4.3.1 Results of physical analysis

Physical analysis included firmness and color analysis. Prior to chemical analysis, physical analysis was performed on the whole tomato. The results are presented in section 4.3.1.1 and 4.3.1.2.

4.3.1.1 Correlation of firmness on ripening

The firmness values decreased upon maturation in tomato as shown in Fig. 4.7. The unripe tomatoes were firm and showed a higher firmness value that ranges from 68-72 N. With increasing maturity, the tomatoes began to soften causing slight change in firmness values at intermediate stage of tomatoes. The tomatoes gets soften as it reaches its advanced stage. The acceptable firmness value considered here is 1.45 Nmm-1 (Batu, 1993). According to Ali Batu, if the firmness values of tomatoes are higher than 1.28 Nmm-1 (slightly soft) it is preferable for salads. And if their firmness is above 1.46 Nmm-1 (very firm) such tomatoes are considered marketable at the supermarket (Batu 1995). Thus, it can be concluded that significant difference is observed in firmness values as tomato passes through its maturity stages from intermediate to advanced. From Fig. 3, it is seen that firmness decreased exponentially upon maturity with days of storage. This difference is due to conversion of polysaccharides to soluble sugar by enzymes which causes softening of tissues. Uluisik (2021) in their work found that firmness in tomatoes significantly declined in the three different varieties reaching softest level in all varieties at its ripe stage stored for 21 days. The results indicate that tomato firmness during storage is directly related to maturity stage, regardless of variety (Uluisik, 2021). The obtained results are then mapped against its respective image.

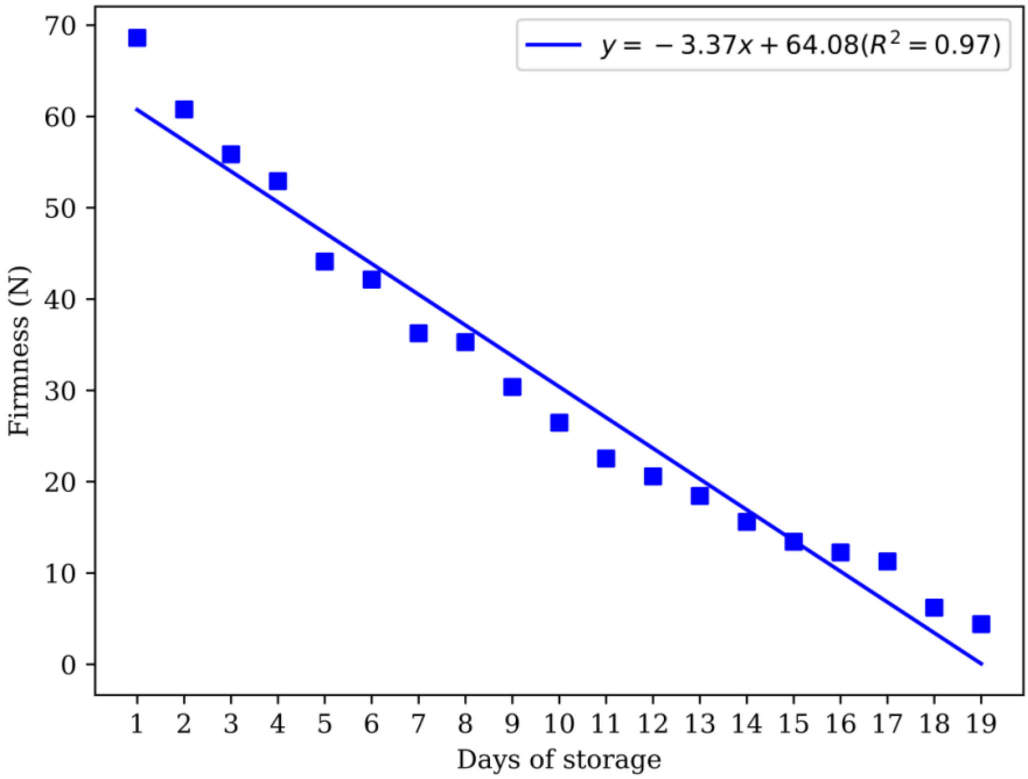


Fig. 4.7 Firmness change in tomatoes with respect to days of storage

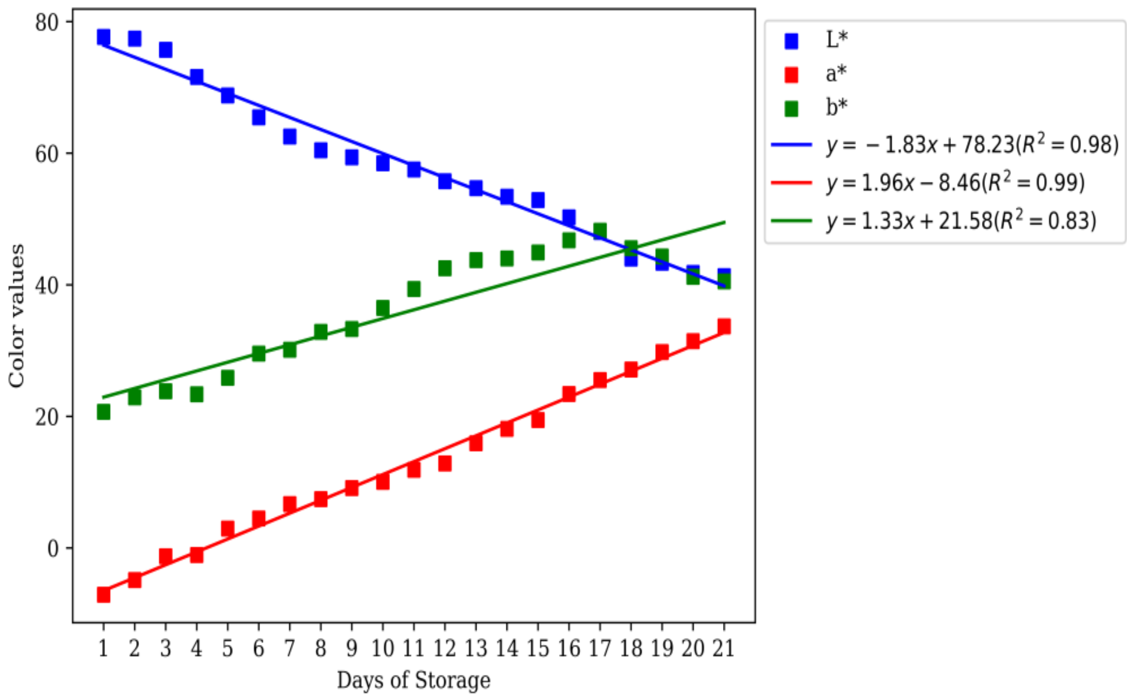


Fig. 4.8 Colour value change in tomatoes with respect to days of storage

4.3.1.2 Correlation of color on ripening

The L*, a* and b* values obtained from Hunter Color Lab were used to correlate color with days of storage corresponding to the maturity stages of tomato. Fig. 4.8 presents the L*, a* and b* color intensities with respect to the storage time (in number of days). For color analysis USDA color classification is considered and compared. a* values give degree of greenness and redness and hence can be considered good indicator to tomato maturity. During the mature green stage, the a* values were negative indicating redness while during advanced stage the a* values were positive indicating redness. b* values give degree of yellowness to blueness which becomes helpful in indicating the intermediate tomatoes. During the intermediate stage the b* values showed a linear trend. Change in b* values is dependent on the days of storage. It increased slightly as tomato ripened from mature green to intermediate stage, indicating that β-carotenes (pale-yellow color) reach their highest concentration during its intermediate stage before reaching full maturity. L* values are reported as degree of brightness to darkness which decreased during the ripening stages and then remained constant, producing a fair correlation (Table 4.7) with the ripening stages. The decrease of L* with maturity reflects the darkening of the tomatoes with carotenoid synthesis and the loss of greenness. Shewfelt et al. (1988) reported the same trend. The obtained L*, a* and b* reading are then correlated against its respective image.

4.3.1.3 Correlation of a*/b* on ripening

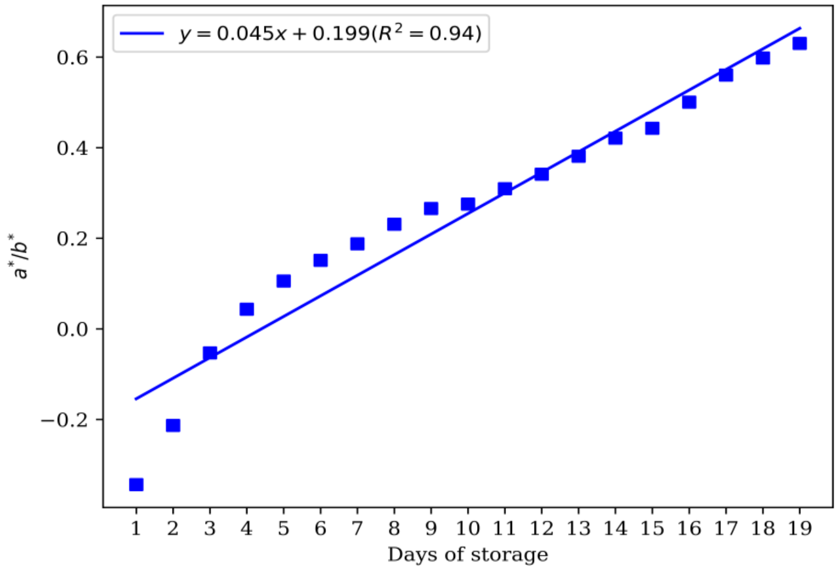


Fig. 4.9 Change in a*/b* values in tomatoes with respect to days of storage

4.3.2 Results of chemical analysis

The tomato after its physical analysis is cut and made ready for chemical analysis. This analysis is mostly destructive and includes the use of chemicals.

4.3.2.1 Correlation of lycopene content on ripening

Lycopene is an important characteristic nutrient substance in tomatoes, and it is also the main coloring material of tomatoes. Thus, it is of practical significance to study the changes of lycopene content during storage period. As shown in Fig. 4.10, the content of Lycopene changes significantly upon tomato ripening. The contents of lycopene increased with the prolongation of maturity in tomatoes. As tomato changes from mature green to red advanced, the Lycopene content was found to increase exponentially. During mature green stages lycopene content was as low as 3.94±0.37 mg/100g. During intermediate stage it increased to 13.06±0.29 mg/100g indicating partial redness. Advanced stage showed a high amount of lycopene augmenting upon maturity of tomatoes as chloroplasts change to chromoplasts and the synthesis of lycopene increases, causing the development of red color (Kirk and Tilney, 1978). Results are in support of the study conducted by Opara et al. (2011). Lycopene results are in correspondence to Clement et al. (2008) 0.92<R2<0.98.

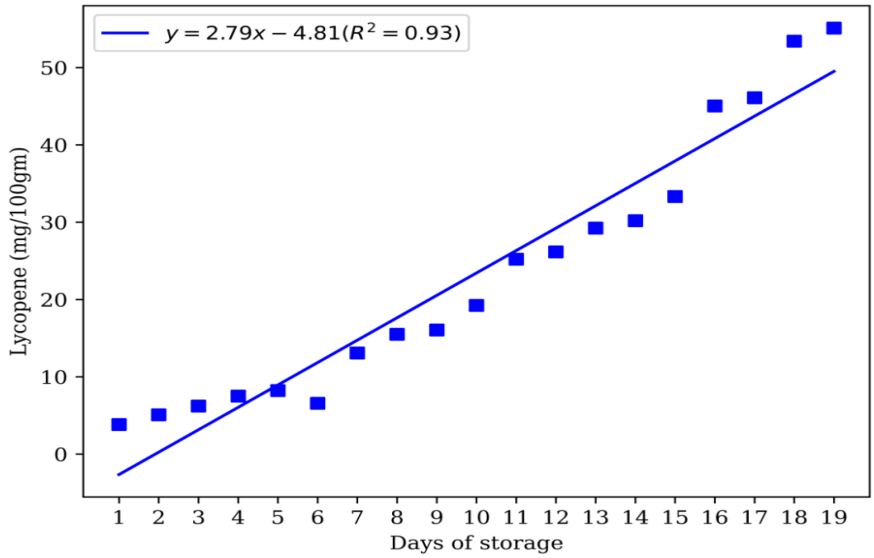


Fig. 4.10 Lycopene change in tomatoes with respect to days of storage

4.3.2.2 Correlation of TA, TSS and pH on ripening

From Table 4.7 below it can be seen that as tomato matured from mature green stage to red advanced stage, its acidity value decreased. According to Tadesse et al. (2015), the higher loss of TA in tomatoes is due to higher respiration and ripening rate where organic acid could be used as a substrate in respiration process. In general, studies suggested that the TA content was decreasing during ripening and storage (Al-Dairi et al., 2021). Similarly at mature green stage, the TSS content of tomato ranged from 4.07° to 3.93° Brix. The values slightly increased with the increase in ripeness of tomato. During the partial and advanced stage, the TSS values ranged between 4.57 to 5.19° Brix and 5.24 and 5.67° Brix. The results followed similar trend in TSS of tomatoes as reported by Luna et al. (2014). Starch is accumulated in green tomatoes that start to fall with the onset of ripening. This decrease in starch is accompanied by rising soluble solids (Eskin, 1989). It has been also reported that total soluble solids increased with color and maturity (Tigist et al., 2011). From the pH values presented in Table 4.7, pH values did not show much significant difference. The pH values varied between 4.38 to 4.55 in its mature green stage, 4.47 to 4.57 in its intermediate stage and 4.51 to 4.77 in its advanced stage. A lower pH is related to a slower respiration rate. The results are in conforming to study of Moneruzzaman et al. (2008) on the pH of tomato fruit. Both, pH and titratable acidity are based on organic acids presents in tomatoes; generally, the organic acids decrease during the storage, because they are used as substrate in the respiration process, which increases with increasing the temperature of storage (Wills et al., 1981).

Table 4.7 Changes in physico-chemical parameters of tomatoes with respect to days of storage

Days[1]	L*	a*	b*	Firm-ness	Lyco-pene	TA	TSS (˚Brix)	pH	Interpreted class as per USDA color classification standard
1	77.67 ±0.87	-7.11 ±0.16	20.68 ±0.21	68.6 ±1.8	3.83 ±1.24	0.93 ±0.12	4.07 ±0.16	4.42 ±0.04	
2	77.41 ±0.45	-4.88 ±0.34	22.9 ±0.12	60.76 ±4.3	5.09 ±2.26	0.88 ±0.08	3.93 ±0.20	4.38 ±0.02	
3	75.71 ±0.76	-1.26 ±0.18	23.82 ±0.18	55.86 ±2.1	6.22 ±3.42	0.84 ±0.07	3.98 ±0.10	4.45 ±0.04	
4	71.59 ±1.12	-1.08 ±0.29	23.35 ±0.13	52.92 ±2.9	7.51 ±2.75	0.75 ±0.07	4.10 ±0.21	4.48 ±0.10	
5	68.77 ±0.65	2.94 ±0.19	25.86 ±0.14	44.1 ±3.2	8.23 ±1.66	0.73 ±0.06	4.11 ±0.09	4.53 ±0.03	
6	65.46 ±0.30	4.47 ±0.3	29.53 ±0.12	42.14 ±1.6	6.58 ±2.81	0.69 ±0.02	4.12 ±0.11	4.55 ±0.02	**(Mature green)**
7	62.54 ±0.69	6.66 ±0.14	30.12 ±0.21	36.26 ±3.5	13.08 ±1.8	0.77 ±0.05	4.57 ±0.13	4.47 ±0.03	
8	60.44 ±1.57	7.43 ±0.22	32.84 ±0.16	35.28 ±2.8	15.5 ±3.5	0.73 ±0.03	4.59 ±0.07	4.43 ±0.04	
9	59.37 ±0.62	9.11 ±0.41	33.28 ±0.25	30.38 ±3.0	16.06 ±2.91	0.68 ±0.05	4.64 ±0.05	4.57 ±0.04	
10	58.47 ±2.08	10.05 ±0.16	36.48 ±0.18	26.46 ±2.3	19.25 ±2.4	0.65 ±0.05	4.73 ±0.09	4.53 ±0.05	
11	57.52 ±1.13	11.87 ±0.21	39.35 ±0.25	22.54 ±4.1	25.22 ±3.08	0.63 ±0.05	5.11 ±0.02	4.43 ±0.06	
12	55.18 ±0.91	12.84 ±0.19	42.52 ±0.14	20.58 ±3.5	26.16 ±4.16	0.57 ±0.05	5.19 ±0.14	4.45 ±0.04	**(Intermediate)**
13	54.31 ±0.51	15.92 ±0.35	43.76 ±0.21	18.44 ±1.9	29.25 ±3.24	0.55 ±0.02	5.24 ±0.12	4.51 ±0.02	
14	53.76 ±0.63	18.11 ±0.18	44.01 ±0.14	15.61 ±2.8	30.2 ±2.18	0.62 ±0.05	4.48 ±0.03	4.57 ±0.08	
15	52.84 ±0.92	19.44 ±0.24	44.9 ±0.3	13.43 ±3.2	33.33 ±1.85	0.59 ±0.05	5.35 ±0.06	4.59 ±0.05	
16	50.59 ±1.19	23.41 ±0.12	46.77 ±0.12	12.25 ±2.3	45.05 ±3.3	0.57 ±0.05	5.54 ±0.04	4.63 ±0.06	
17	48.76 ±0.74	25.53 ±0.15	48.21 ±0.45	11.27 ±4.6	46.11 ±2.45	0.66 ±0.12	5.60 ±0.05	4.69 ±0.09	
18	43.28 ±0.82	27.13 ±0.19	45.56 ±0.21	6.2 ±2.7	53.43 ±1.4	0.46 ±0.13	5.67 ±0.07	4.77 ±0.01	**(Advanced)**

[1] Four samples were randomly selected per day. Experiments were performed in triplicates of each sample. The results were expressed as the means±standard deviation (SD).

4.3.3 Principal Component Analysis

The PCA model was applied to all data to determine the most important variables that explain the determining parameter in ripening. Two principal components explaining 99.2% of the overall variance (96.2% and 3.01% for PC1 and PC2, respectively) divided the ripening stages into four distinct clusters. The factors that most contributed to PC1 (positive side) were: lycopene and firmness followed by color.

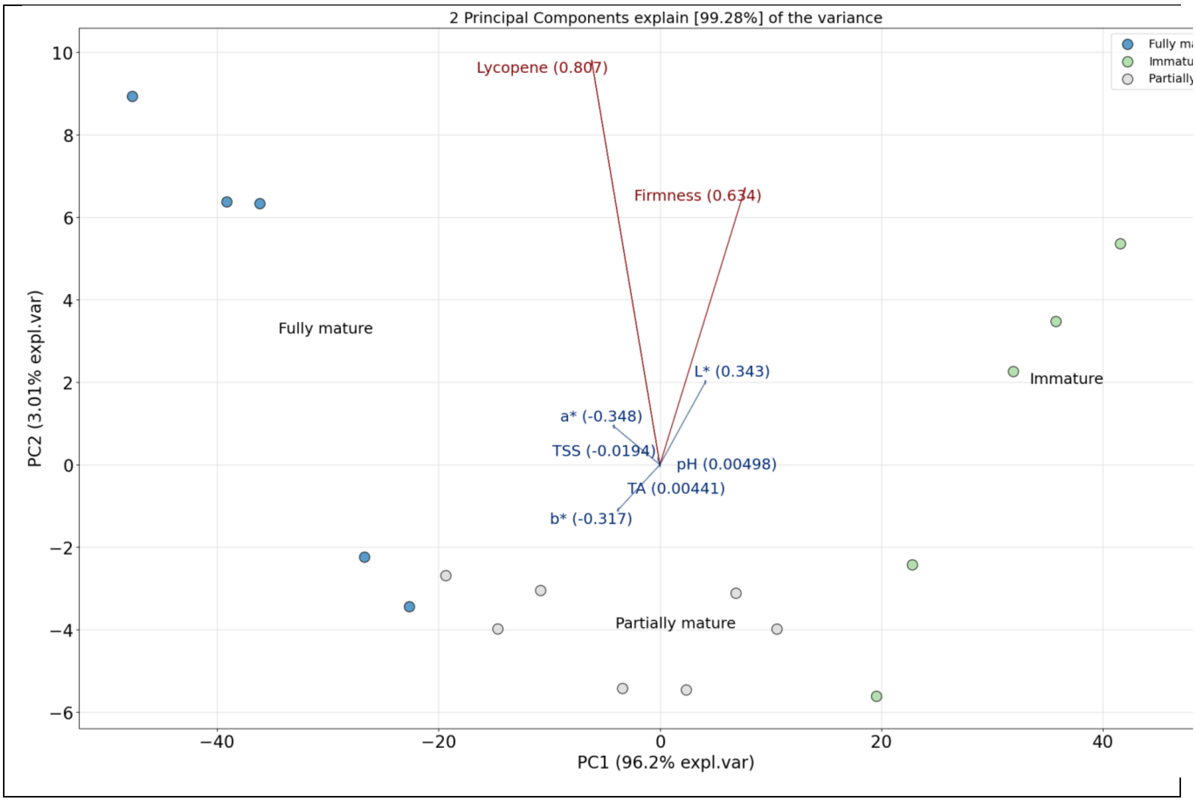


Fig. 4.11 PCA biplot on the obtained result

4.3.4 Statistical Validation

Here, ANOVA was used to calculate the significance of difference between samples means. Table 4.8, Table 4.9, Table 4.10 and Table 4.11 presents the sum of square, degree of freedom (df) and mean square of One-Way ANOVA of TSS, TA, pH, and lycopene respectively. Based on these values, the F's critical value and p value is evaluated, and the highest calculated F value is considered. An F-value compares the variance between groups to the variance within groups. A p-value (< 0.05) indicates that results between the groups are statistically significant. The one-way AVONA results presented in Table 6 depict that there is a statistically significant difference in mean lycopene values between at least two maturity classes {F (2, 15) = [57.64], p<0.001}. Similar observations are also reported for TSS {F (2, 15) = [32.17], p<0.001} followed by TA {F (2, 15) = [20.65], p<0.001} in Table 3 and table 5 respectively. The results presented in Table 3, 4, 5 and 6 indicated that among the four quality parameters lycopene, TA, TSS and pH; lycopene showed the highest discriminating ability for maturity classes with the highest F value. On the other hand, the F value for pH is close to 1 indicating that pH is not a good discriminating factor for maturity class detection. The one-way ANOVA here is successful to compare the effect of maturity on lycopene.

Table 4.8 ANOVA test on TSS values for three maturity stages of tomatoes

ANOVA – TSS

Cases	Sum of Squares	df	Mean Square	F	P	η^2
Maturity	6.476	2	3.238	32.174	<.001	0.811
Residuals	1.510	15	0.101			

Note. Type III Sum of Squares

Table 4.9 ANOVA test on pH values for three maturity stages of tomatoes

ANOVA – pH

Cases	Sum of Squares	df	Mean Square	F	P	η^2
Maturity stage	0.114	2	0.057	1.151	0.343	0.133
Residuals	0.744	15	0.050			

Note. Type III Sum of Squares

Table 4.10 ANOVA test on TA values for three maturity stages of tomatoes

ANOVA – TA

Cases	Sum of Squares	df	Mean Square	F	P	η^2
Maturity stage	0.132	2	0.066	20.650	<.001	0.734
Residuals	0.048	15	0.003			

Note. Type III Sum of Squares

Table 4.11 ANOVA test on lycopene values for three maturity stages of tomatoes

ANOVA - Lycopene						
Cases	**Sum of Squares**	**df**	**Mean Square**	**F**	**P**	**η^2**
Maturity stage	3428.864	2	1714.432	57.641	<.001	0.885
Residuals	446.145	15	29.743			

Note. Type III Sum of Squares

From Fig. 4.12, it can be interpreted that there is no overlapping in lycopene values between classes and hence the obtained results are balanced and reliable for classifying tomatoes into their maturity classes. The mean lycopene value is highest in the case of advanced followed by intermediate and mature green tomatoes. The standard deviation of mature green is lowest followed by intermediate and advanced classes. Therefore, lycopene can be considered a better indicator of maturity class detection.

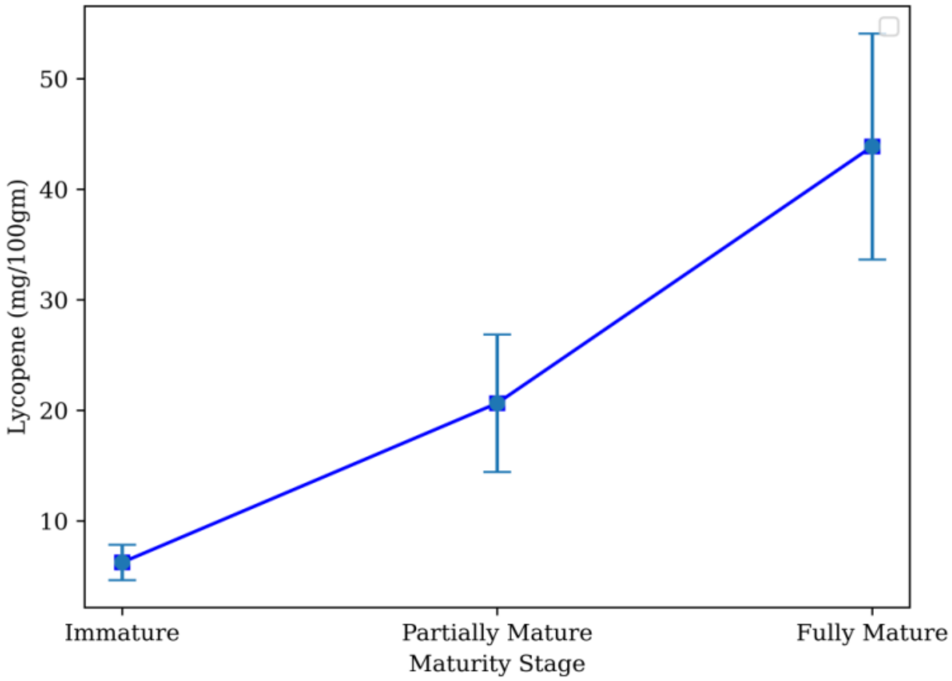


Fig. 4.12 Mean and standard deviation plot of lycopene values for the three maturity stages of tomatoes

Using one way ANOVA, we investigated lycopene as a key indicator tomato maturity class estimation. In Table 4.12 and Table 4.13, lycopene is further correlated with the fruit's physico-chemical parameters using Pearson Correlation.

Table 4.12 Pearsons' correlation between lycopene, TSS and TA values
Pearsons' Correlation

			Pearsons' r	p
Lycopene	-	TSS	0.921	< .001
Lycopene	-	TA	-0.858	< .001
TSS	-	TA	-0.835	<0.001

Again in Table 4.13, c*orrelation* is established between lycopene and the physical parameters firmness and color (a*/b*). From Table 8 it is evident that color and firmness has the highest correlation (0.979), followed by lycopene and firmness (0.910). It can thus be concluded that lycopene content, color and firmness have a very correlation and thus may be used as a determining factor to tomato maturity.

Table 4.13 Pearsons' correlation between Lycopene, firmness and a*/b* values
Pearsons' Correlation

			Pearsons' r	p
Lycopene	-	a*/b*	0.909	< .001
Lycopene	-	Firmness	-0.910	< .001
a*/b*	-	Firmness	-0.979	< .001

4.3.5 Mapping of physico-chemical properties

It is evident that for every different tomato, different values for physico-chemical parameters will be obtained. This study is an attempt to correlate those obtained values with its surface characteristics. Features are extracted from the surface characteristics from the images that are input to the deep learning model. The experimental values corresponding to each maturity stage are averaged to obtain the mean values against that stage. The mean values of a particular maturity stage are then mapped with the image corresponding to it as shown in Table 4.14. It was then analyzed for maturity class detection using deep learning and for estimation of its chemical constituents and physical properties.

From Table 4.14 it found that the mean value of lycopene in its mature green stage is 6.24 ± 1.60. This indicates that lycopene content did not show much variation during its mature green stage indicating slow biosynthesis of lycopene in the initial 1-6 days. The mean value reached 20.64±6.21 in its intermediate stage indicating variations in values upon ripening. The highest mean value of Lycopene was in it advanced stage 41.62±9.62 with a high variation. The highest concentration peaks of lycopene at this stage may be associated to the increasing concentration of geranyl geranyl diphosphate (GGPP) and/or the increasing activation of the enzymes responsible for the conversion (Colombani et al., 2001). In a similar way, TA values are highest in its mature green stage from day 1-6 with values 0.80 ± 0.09. The TA values decreased significantly upon maturation with its value ranging from 0.65±.079 to 0.58±.075. Table 4.14 also shows that TSS increases significantly from 4.05 ± 0.07 to 5.32±0.48 upon ripening from mature green to deep red advanced stage respectively. The pH values of tomatoes in all the three stages are found to be quite similar, ranging from 4.46±0.06, 4.48±0.05 and 4.65±0.08 in mature green, intermediate and advanced stage respectively. Since these values did not change significantly ($p>0.05$) as shown in hence the pH values do not show a good mapping with its respective image.

Table 4.14 Mean firmness, lycopene, TSS, TA, and pH values mapped to images corresponding to each ripening classes

Day	Image	Firm-ness	Lyco-pene	TSS	TA	pH	Class
1-6	   	54.06 ±10.02	6.24 ± 1.60	4.05 ± 0.07	0.80 ±0.09	4.46 ±0.06	Stage I (Mature green)
7-13	   	27.13 ±7.07	20.64 ± 6.21	4.86 ± 0.29	0.65 ±0.08	4.48 ±0.05	Stage II (Intermedia te)

14-18		10.52 ±4.33	41.62 ± 9.62	5.32 ±0.48	0.58 ±0.07	4.65 ±0.08	Stage III (Advanced)

4.3.6 Model Evaluation using confusion matrix

The VGG19 model used for maturity detection was trained and tested using self-prepared tomato dataset containing 900 tomato images of three different maturity classes. Out of 900 images, 75% of the images were used to train the model and the remaining 25% tomato images were retained for validation of the model. The test images were not used to train the deep learning model. On validation, the proposed model achieved validation accuracy of 92% after 50 epochs with batch size of 32. Further, the time taken to classify individual tomato using the proposed model is approximately 650 milliseconds.

The confusion matrix obtained to evaluate the performance of the model is shown in Fig. 7. It can be seen in Fig. 4.13 that a total of 81/81 and 79/79 tomato images were correctly classified as mature green and advanced respectively, giving a recall of 100% for both the classes. However, in the case of intermediate only 48 images were correctly classified out of 65 images, thus, indicating 73.84% recall. This may be due to mixed surface color ranging from green to red. On the other hand, precision was found in the range 86%-100% indicating that the model can predict the maturity classes correctly. F1-score was of the range 85%-98%. It can thus be concluded that the model gives the best results in classifying tomatoes as mature green and advanced. The model confused samples belonging to intermediate class with mature green and advanced. Table 4.15 provides precision, recall, F1-score, cohen's kappa score and overall accuracy of the model on the test set. Precision, recall, F1-score provides a class-wise insight in the correctness of the model.

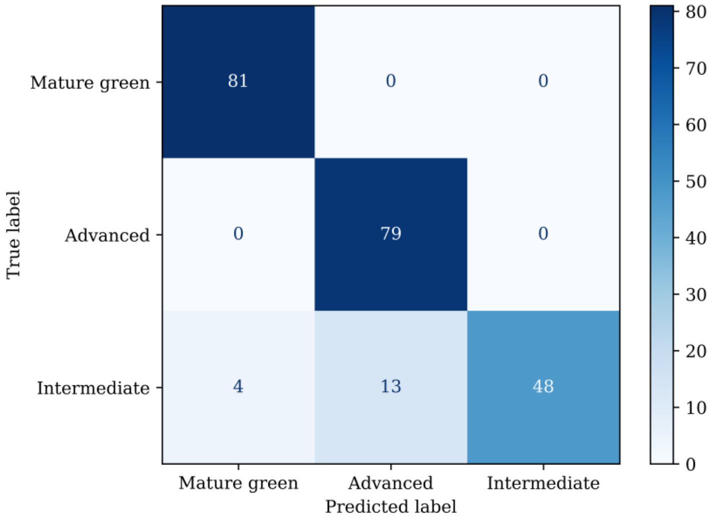
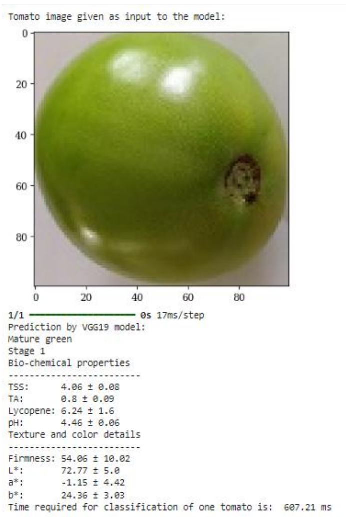


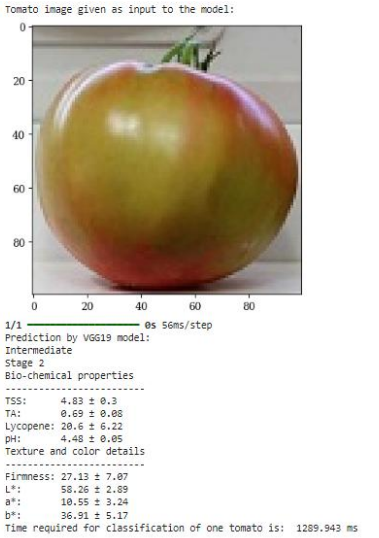
Fig. 4.13 Confusion matrix obtained on the test set

Table 4.15 Classification performance analysis of tomato maturity prediction model

Maturity stage	Recall	Precision	F1-score	Cohen's Kappa	Overall accuracy
Mature	1.00	0.95	0.98		
Intermediate	0.74	1.00	0.85	0.88	0.92
Advanced	1.00	0.86	0.92		

Table 4.16 Comparison of predicted values using deep learning with experimental values by physico-chemical analysis

<table>
<tr><th>PREDICTED VALUES USING DEEP LEARNING</th><th colspan="2">EXPERMENTAL VALUES BY PHYSICO-CHEMICAL ANALYSIS (Physio-chemical analysis of the same tomato image given as input to VGG19 model.)</th></tr>
<tr><td rowspan="11">
</td><td colspan="2">Maturity stage: Mature green
Bio-chemical properties:</td></tr>
<tr><td>TSS (^{o}Brix)</td><td>3.95</td></tr>
<tr><td>TA (% citric acid)</td><td>0.89</td></tr>
<tr><td>Lycopene (mg/100g)</td><td>5.29</td></tr>
<tr><td>pH</td><td>4.41</td></tr>
<tr><td colspan="2">Texture and color details:</td></tr>
<tr><td>Firmness (N)</td><td>60.76</td></tr>
<tr><td>L*</td><td>71.22</td></tr>
<tr><td>a*</td><td>-1.08</td></tr>
<tr><td>b*</td><td>23.61</td></tr>
</table>



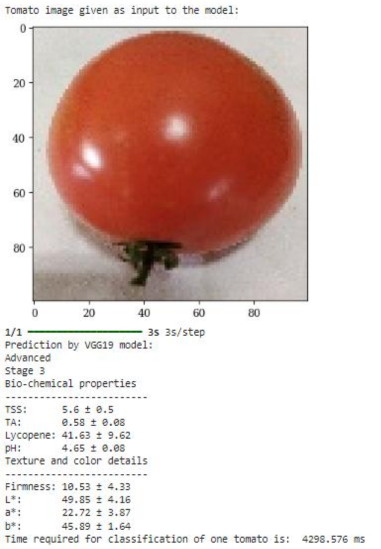
Maturity stage: ***Intermediate***

Bio-chemical properties:

TSS (^{o}Brix)	4.59
TA (% citric acid)	0.74
Lycopene (mg/100g)	15.67
pH	4.48

Texture and color details:

Firmness (N)	30.28
L*	61.85
a*	7.19
b*	31.40



Maturity stage: ***Advanced***

Bio-chemical properties:

TSS (^{o}Brix)	5.37
TA (% citric acid)	0.60
Lycopene (mg/100g)	32.23
pH	4.57

Texture and color details:

Firmness (N)	14.61
L*	53.15
a*	18.53
b*	43.27

4.3.7 Model Evaluation using Pearson correlation

To validate the VGG 19 model in predicting the physico-chemical properties of tomato, on site physico-chemical analysis is performed on the same tomato being used as input to the proposed model. The error of the model is obtained based on the experimental values in Table 4.17. It can be observed that experimental values for lycopene, TSS, TA, firmness, and colour are within the standard deviation of the predicted values of VGG19 model. The VGG19 model thus surmounts the task of predicting the physic-chemical properties of tomatoes non-destructively in real-time from images. However, as discussed in section 4.3.2.2, pH value did not show a good correlation with the other chemical parameters indicating maturity class. The proposed deep learning model may not appropriately predict the maturity class of tomatoes from pH values alone.

Table 4.17 Percentage error obtained between the predicted value and experimental value

Parameters	Ripening stage	Predicted value	Actual value	Percentage Error
TSS	Mature green	4.06	3.95	2.78%
	Intermediate	4.83	4.59	5.23%
	Advanced	5.6	5.37	4.28%
TA	Mature green	0.8	0.89	10.11%
	Intermediate	0.69	0.74	6.76%
	Advanced	0.58	0.6	3.33%
Lycopene	Mature green	6.24	5.29	17.96%
	Intermediate	20.6	15.67	31.46%
	Advanced	41.63	32.23	29.17%
Firmness	Mature green	54.06	60.76	11.03%
	Intermediate	27.13	30.28	10.40%
	Advanced	10.53	14.61	27.93%
pH	Mature green	4.46	4.41	1.13%
	Intermediate	4.48	4.48	0.00%
	Advanced	4.65	4.57	1.75%
L*	Mature green	72.77	71.22	2.18%
	Intermediate	58.26	61.85	5.80%
	Advanced	49.85	53.15	6.21%
a*	Mature green	-1.15	-1.08	6.48%
	Intermediate	10.55	7.19	46.73%
	Advanced	22.72	18.53	22.61%
b*	Mature green	24.36	23.61	3.18%
	Intermediate	36.91	31.4	17.55%
	Advanced	45.89	43.27	6.06%

4.4 Results obtained from prediction of shelf-life of tomatoes based on its surface characteristics

This section presents how quality attributes of tomato degrade upon storage at different temperatures.

4.4.1 Effect of temperature on quality of tomato upon storage

Tomatoes were stored at refrigerated temperatures 5.5±2.2˚C, 18.5±4.9˚C and 29.5±2.1˚C. Temperature is monitored using a digital thermometer. In order to evaluate the change in quality of tomatoes at the above-mentioned temperatures, color and firmness is determined at regular intervals of time. The effect of temperature on quality parameters is discussed below.

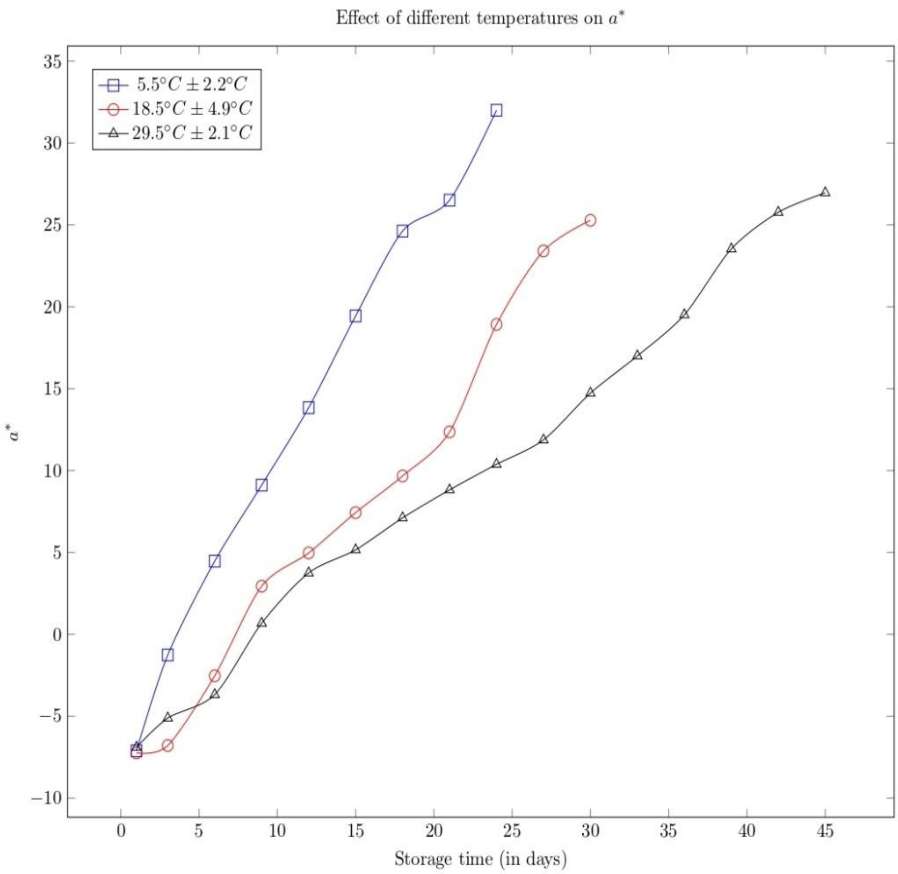


Fig. 4.14 Colour (a*) change in tomato during storage at different temperature

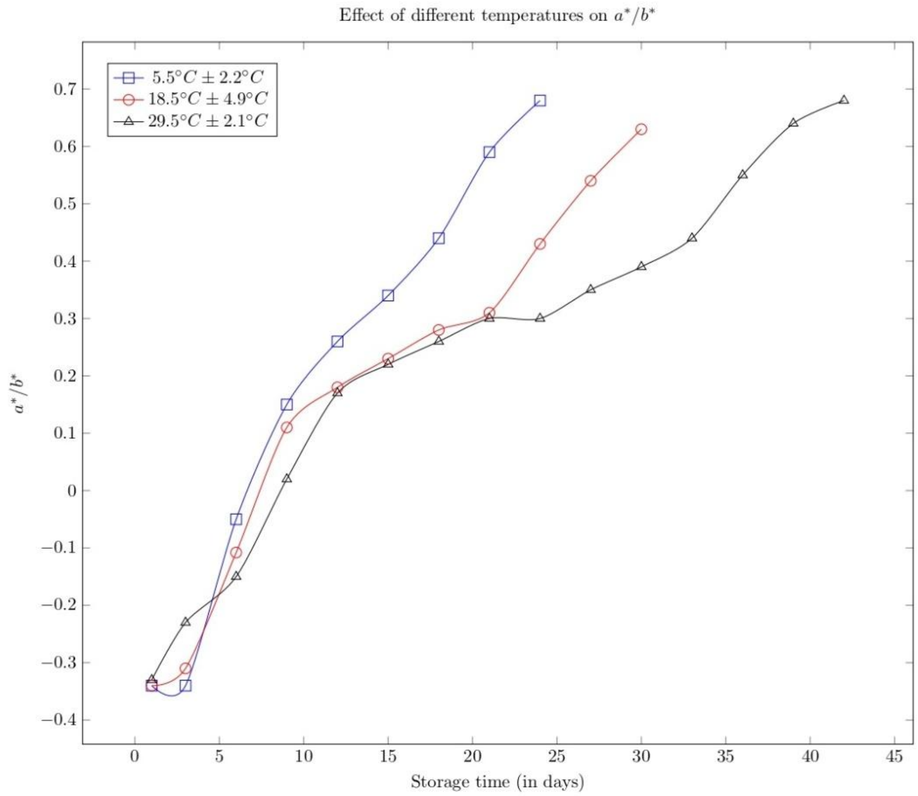


Fig. 4.15 Change in a*/b* values of tomato during storage at different temperature

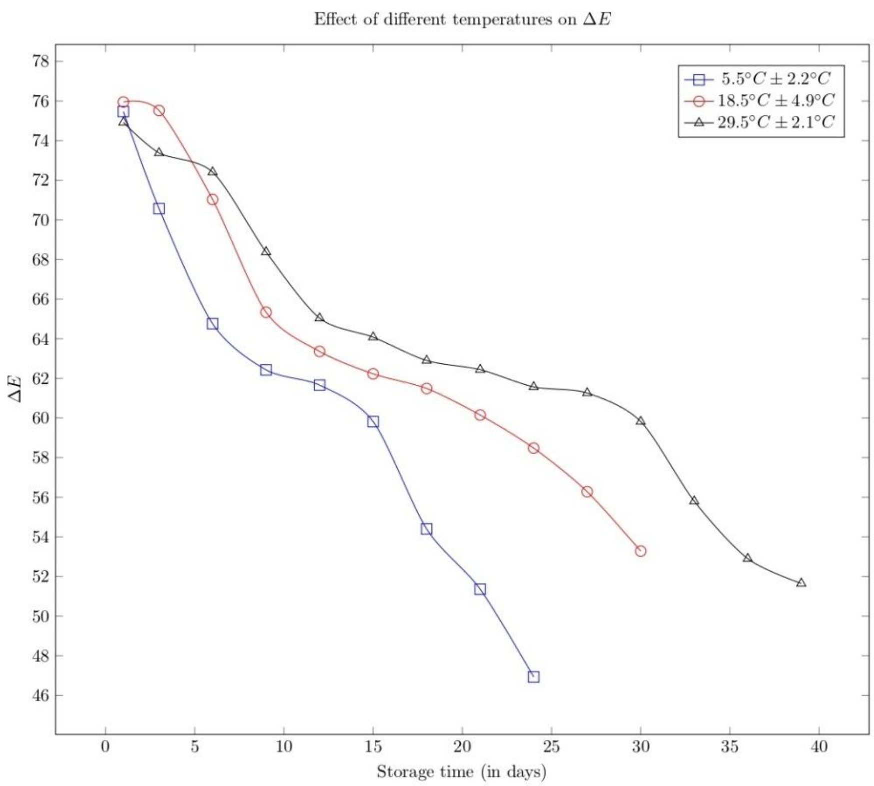


Fig. 4.16 Change in ΔE values of tomato during storage at different temperature

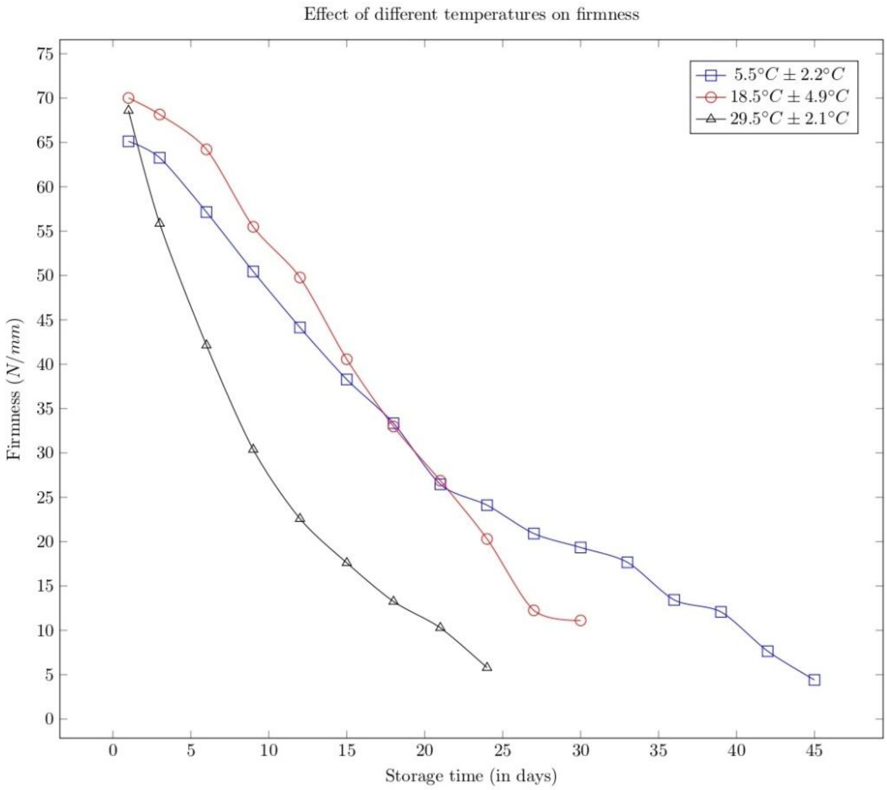


Fig. 4.17 Firmness change in tomato during storage at different temperature

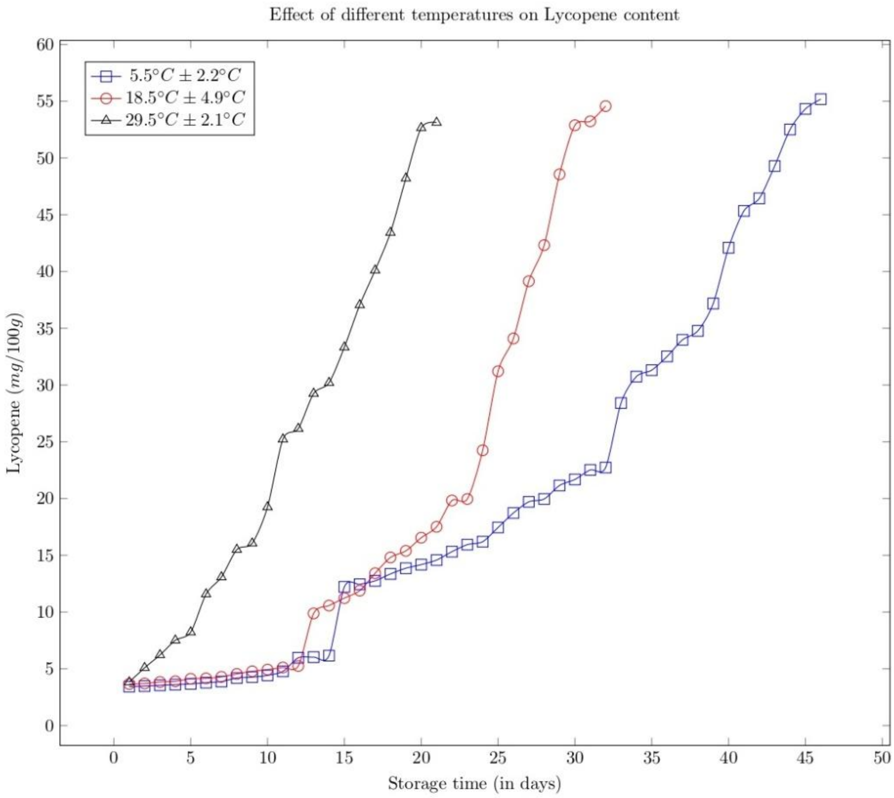


Fig. 4.18 Lycopene change in tomato during storage at different temperature

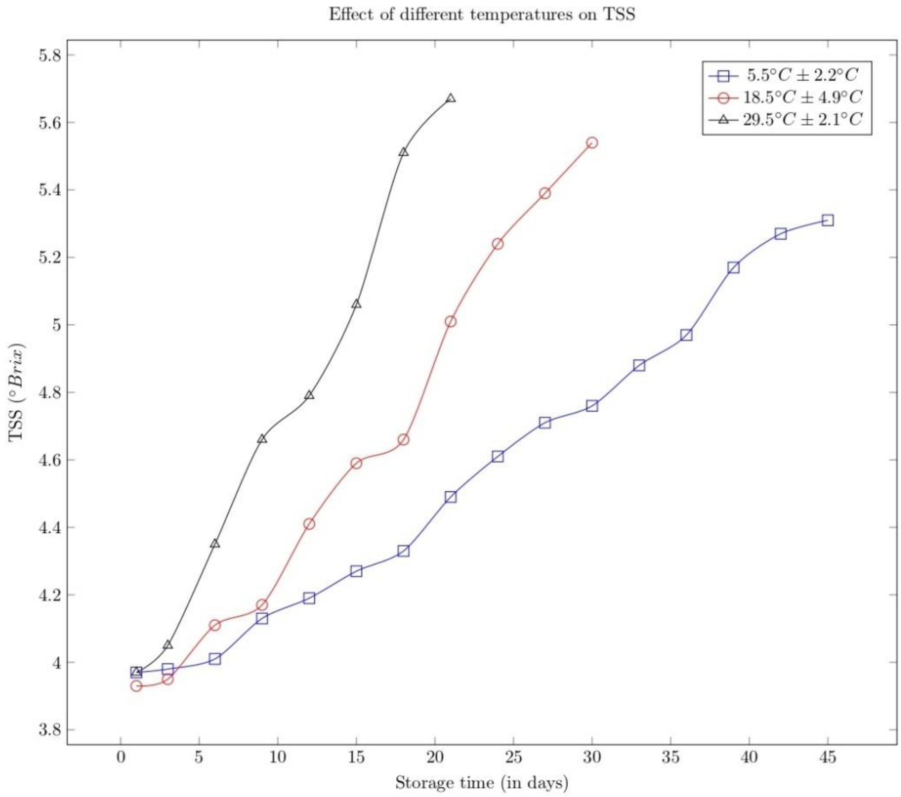


Fig. 4.19 TSS change in tomato during storage at different temperature

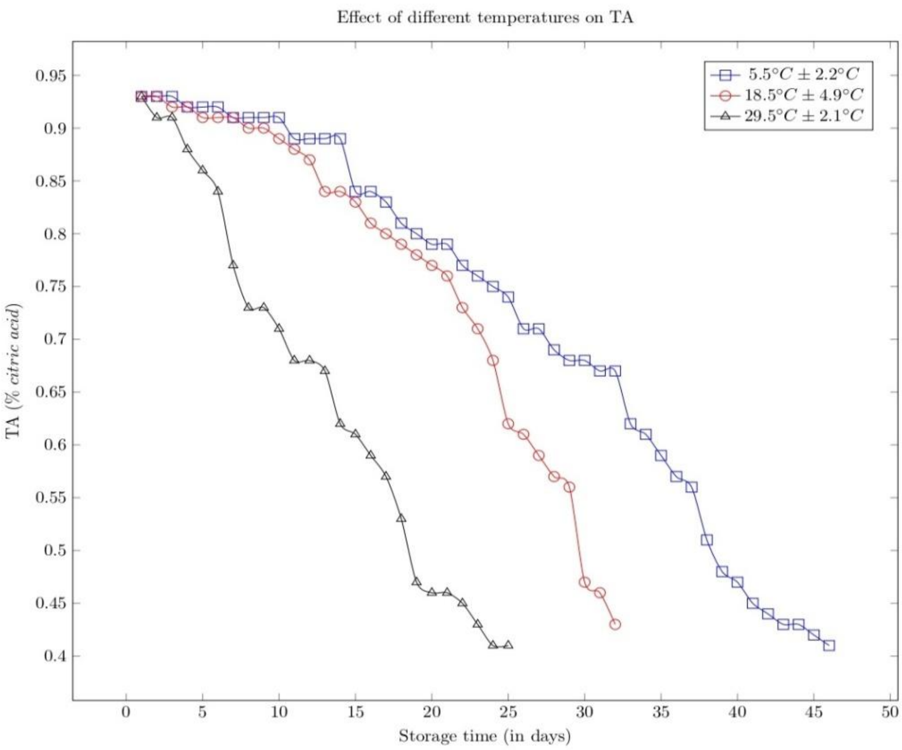


Fig. 4.20 TA change in tomato during storage at different temperature

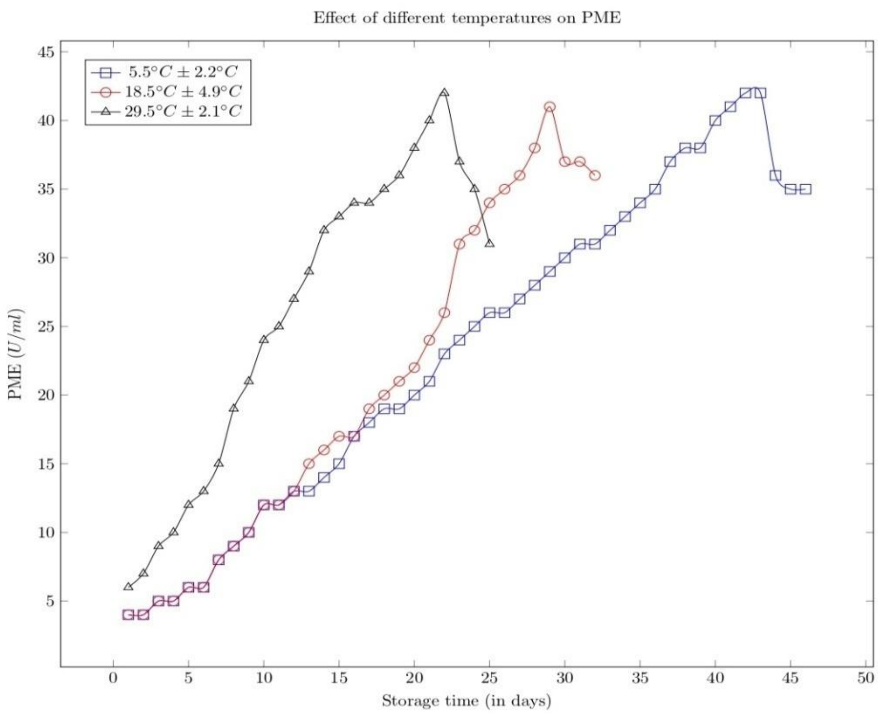


Fig. 4.21 PME change in tomato during storage at different temperature

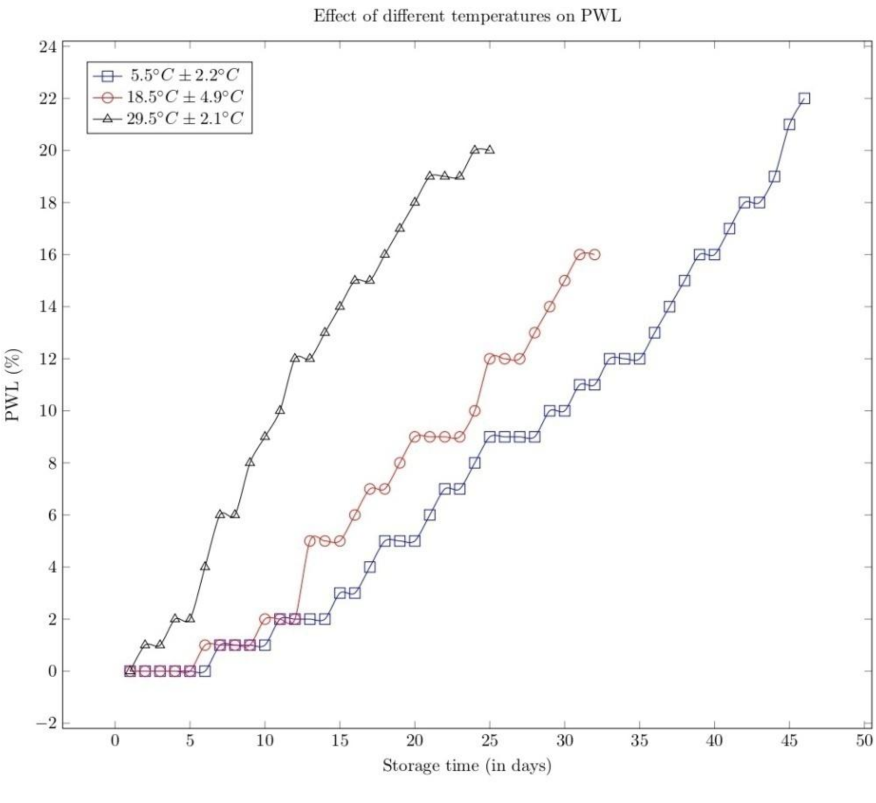


Fig. 4.22 PWL change in tomato during storage at different temperature

The above figures show degradation of physico-chemical attributes of tomato upon storage at three different temperatures. As expected, temperature has a great influence on the quality indices. Color and firmness are the physical parameters considered for the storage study of tomatoes at temperatures 5.5±2.2˚C, 18.5±4.9˚C and 29.5±2.1˚C respectively. From Fig. 4.17, it is seen that firmness follows a declining trend during storage. Firmness decreases abruptly at higher temperatures compared to lower temperatures (Bourne and Comstock, 1986). This decrease in firmness is due to breakdown of cell wall due to activity of enzymes like PG and PME. Activity of PME is discussed below. Secondly, color values increase gradually as tomatoes undergo ripening. From Fig. 4.14, it is seen that higher the temperature, the change in color values from breaker green to dark red is faster. This is due to loss of chlorophyll pigments which are highly accelerated at higher temperatures (Koca et al., 2007). TSS, TA, PWL, lycopene content, PME are considered chemical attributes for shelf-life study of tomatoes. TSS values increase because of hydrolysis of carbohydrate with increase in maturity and thus influenced by storage temperature (Dairi et al., 2021). From Fig. 4.22it is seen that as tomato matures, weight loss increases. Weight loss is mostly related to respiration and transpiration of tomatoes, which is thus less at lower temperature (Javanmardi and Kubota, 2006). TA is aggregation of all acids (volatile and fixed) (Naik et al., 1993). From Fig. 4.20, it is seen that TA values decreases upon storage as maturity proceeds. This decrease is faster at higher temperatures. Lycopene is the main pigment responsible for distinguishing maturity stages of tomatoes (Park et al., 2018). Lycopene content increases with prolongation of maturity. As shown in Fig. 4.18, its content is (3.43 mg/100g) in its breaker stage while (55.18 mg/100g) in its red ripen stage. As discussed above, PME is one of the enzymes responsible for softening of cell wall (Brummell and Harpster, 2001). Contrary to other parameters it is seen that activity of PME is highest at temperature 27.5±2.1˚C while it's lowest at temperature 5.5±2.2˚C. In the case of all the three temperatures the activity of PME shows an increasing trend until it reaches the advanced stage after which there is a remarkable decline in PME value. Highest value (42 U/ml) of PME is found before entering the ripened stage and later declined to (35 U/ml). The results are the same as (Koslanundet al., 2005).Thus, from the above results it is clear that biochemical and physical responses that occur in food are primarily responsible for variations in food quality. Also, temperature has a tremendous effect on the quality indices in maintaining the shelf-life of tomatoes.

4.4.2 Effect of temperature on Decay Rate

From Fig. 4.23 it is observed that decay starts earlier for tomatoes stored at temperature 29.5±2.1˚C followed by 18.5±4.9˚C and 5.5±2.2˚C. This clearly indicates that temperature has an influence on decay rate of stored tomatoes.

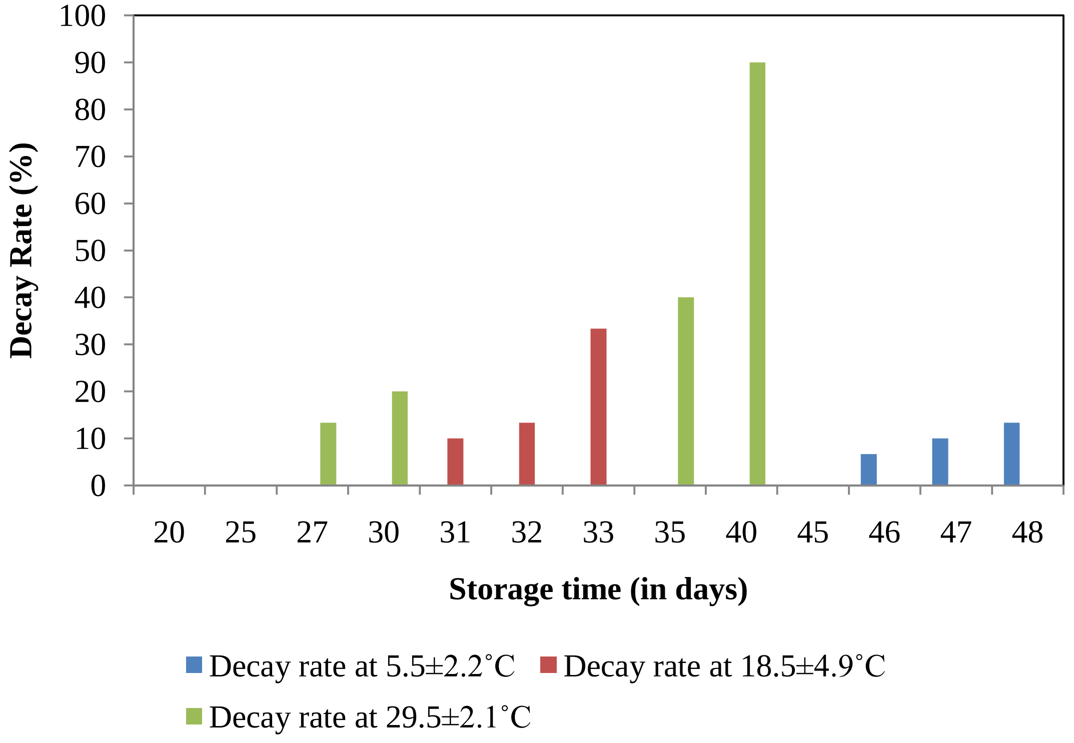


Fig. 4.23 Decay rate in tomato during storage at different temperature

4.4.3 Effect of temperature on Disease Damage Incidence

From Fig. 4.24 it is observed that higher the temperature of storage, higher is the disease damage incidence. From the obtained results it is seen that disease damage starts after decay rate for tomatoes.

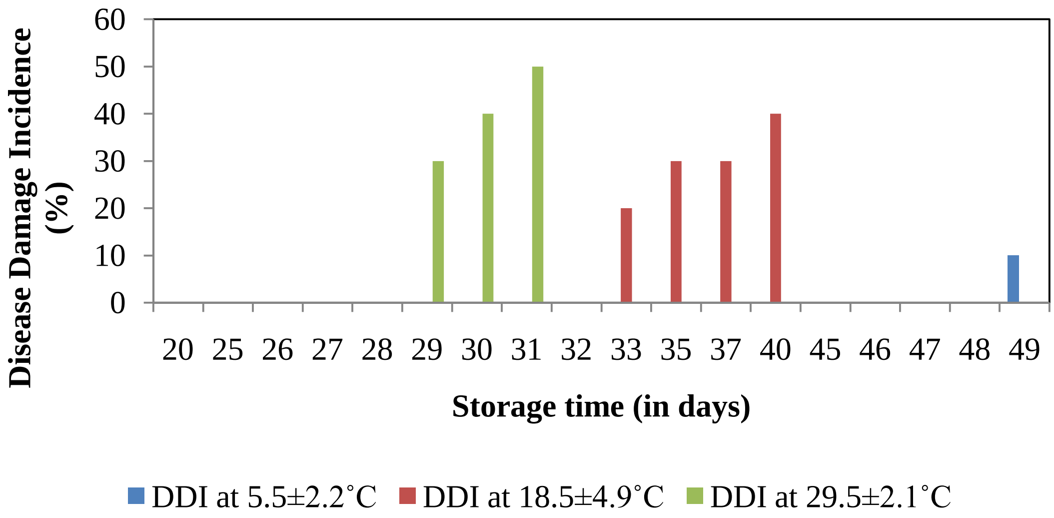


Fig. 4.24 Disease damage incidence change in tomato during storage at different temperature

4.4.4 Effect of temperature on Maturity Index

Maturity index is an indicator to ripening of tomatoes which varies upon storage. Maturity index is achieved earlier at higher temperature 29.5±2.1˚C followed by 18.5±4.9˚C and5.5±2.2˚C.

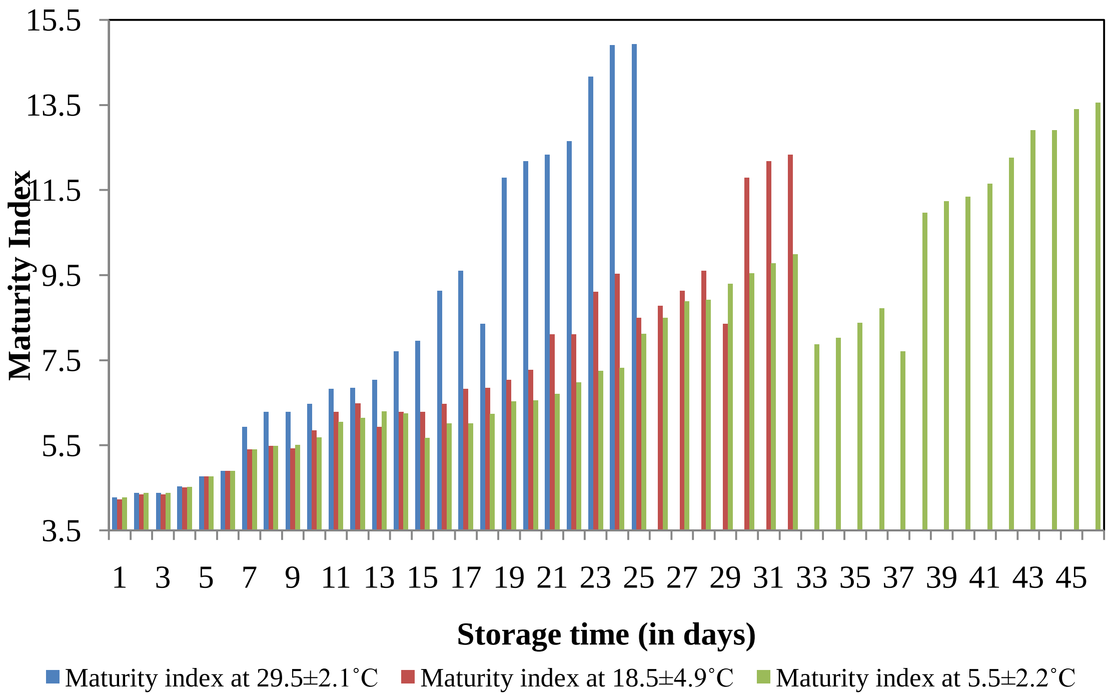


Fig. 4.25Maturity index in tomato during storage at different temperature

4.4.5 Kinetics of changes in quality parameter of tomato during storage

The kinetics of the physico-chemical changes in tomatoes are evaluated using a mathematical kinetic model which is a powerful tool for food quality prediction (Bunkar et al., 2014). Each reaction has its own rate and kinetics. The color, firmness, TSS, TA, PWL, lycopene content, and PME characteristics are fitted in zero-order, first-order and second-order kinetics in tomato during storage at various temperatures. The reaction rates and R^2 values for each reaction order are estimated corresponding to each temperature range. Based on the R^2 values obtained, the reaction order to be considered for shelf-life estimation is determined. Table 4.18 shows the results of a regression study of the zero-order, first-order and second-order kinetics in tomato during storage at various temperatures.

Table 4.18 Rate constant (k) and decision coefficient (R2) of zero-order and first-order kinetic equations

Quality Indices	Temp^r	Zero-order		First-order		Second-order	
	(◦C)	k	R^2	k	R^2	k	R^2
Firmness	5.5±2.2˚C,	-1.318	0.951	-0.053	0.945	0.003	0.617
	18.5±4.9˚C	-2.208	0.978	-0.071	0.935	0.003	0.686
	29.5±2.1˚C	-2.407	0.897	-0.103	0.983	0.006	0.792
a*	5.5±2.2˚C,	0.926	0.980	0.112	0.727	0.006	0.143
	18.5±4.9˚C	1.399	0.983	0.198	0.813	0.019	0.023
	29.5±2.1˚C	1.696	0.928	0.185	0.644	0.043	0.03
TSS	5.5±2.2˚C,	0.032	0.987	0.007	0.994	-0.001	0.992
	18.5±4.9˚C	0.060	0.975	0.012	0.981	-0.002	0.980
	29.5±2.1˚C	0.096	0.959	0.019	0.964	-0.004	0.962
PME	5.5±2.2˚C,	0.874	0.969	0.048	0.886	-0.003	0.664
	18.5±4.9˚C	1.270	0.967	0.076	0.953	-0.006	0.779

	29.5±2.1˚C	1.771	0.982	1.449	0.881	-0.004	0.685
PWL	5.5±2.2˚C,	0.476	0.967	0.078	0.941	-0.009	0.193
	18.5±4.9˚C	0.560	0.971	0.109	0.919	-0.013	0.145
	29.5±2.1˚C	0.913	0.979	0.119	0.804	-0.023	0.383
TA	5.5±2.2˚C,	-0.012	0.959	-0.018	0.915	0.029	0.854
	18.5±4.9˚C	-0.015	0.907	-0.022	0.849	0.032	0.776
	29.5±2.1˚C	-0.023	0.986	-0.036	0.983	0.060	0.958
Lycopene	5.5±2.2˚C,	1.121	0.913	0.067	0.967	-0.006	0.815
	18.5±4.9˚C	1.636	0.838	0.099	0.972	-0.009	0.913
	29.5±2.1˚C	2.584	0.951	0.126	0.934	-0.009	0.758

From Table 4.19 it is found that quality indices of tomato at three different temperatures better fitted with zero-order reaction models. The R^2 values were followed by first-order reaction. The least R^2 values were obtained for second order reaction showing poor performance of the model. The best fitted reaction order model is then considered for calculation of activation energy (Ea), ΔH and ΔS from Arrhenius and Eyring models respectively. The obtained results are plotted in Table 4.19.

Arrhenius equation's linear regression is obtained from the rate constant (k) and temperature (T) values at different storage conditions. Arrhenius equation is thus the plot of 1/T and ln k. The activation energy (Ea) values can describe the influence of temperature on the quality indices. Same follows for determination of ΔH and ΔS values from Eyring equation. The results demonstrate that Ea values ranged from 20.94 to 28.66 kJ/mol. The highest value of Ea was obtained from lycopene, followed by TSS, TA, PWL, PME, firmness and color. ΔH ranged from 18.69 to 25.99 kJ/mol, which is closer with the results obtained for Ea as presented in Table 4.19.

The highest Ea and ΔH value (28.66 kJ/mol and 25.99 kJ) of lycopene implies that higher temperature change was needed to degrade lycopene compared to other quality indices. The a* seemed to have the lowest Ea and ΔH value (20.94 kJ/mol and 18.69 kJ), followed by firmness (20.97 kJ/mol and 18.75 kJ), indicating that the storage temperature has a greater influence on color values (a* value) and firmness of tomatoes. According to Van Boekel (2008), a high Ea value suggests that some chemical reactions in food are very slow at low temperatures but relatively fast at high temperatures. Moreover, the Arrhenius model (with R^2 higher values) showed better performance than Eyring model. Since both Zero-order reaction and Arrhenius model fitted better in all cases, they are found suitable for prediction of shelf-life of tomatoes at different storage temperature.

Table 4.19 Kinetic parameters of zero-order models for quality parameter in tomato

Quality indices	**Arrhenius model**			**Eyring model**		
	Arrhenius Equation	**E_a(kJ/mol)**	**R^2**	**ΔH (kJ)**	**ΔS (J/(mol.K))**	**R^2**
Firmness	ln k=9.331-2523/T	20.97	0.876	18.75	-139	0.876
a*	ln k=8.931-2519/T	20.94	0.969	18.69	-244	0.969
TSS	ln k=12.81-4555/T	24.59	0.999	23.66	-269	0.999
PME	ln k=9.228-2605/T	21.65	1.000	20.31	-245	1.000
PWL	ln k=8.713-2669/T	22.19	0.905	20.79	-250	0.905
TA	ln k=5.074-2675/T	22.23	0.956	18.01	-115.31	0.956
Lycopene	ln k=12.38-3448/T	28.66	0.992	25.99	-243.26	0.992

4.4.6 Predictability of the shelf life of tomatoes at different temperatures

Based on the Arrhenius results, the a* and firmness value changes in tomatoes were recognized as the major form of deterioration. The difference between the initial values of a* and firmness and the predetermined critical values of a* and firmness is used to calculate the shelf life. According to research conducted by Ali Batu firmness and color are the most important factors for determination of tomato quality. If the firmness value is above 1.46 N are very firm and easily acceptable (Castro et al., 2021). Thus, the critical value of firmness is taken as 1.46 N as presented in Table 4.21. And according to Castro et al acceptable a* values of tomato ranged from 17.95-29.68. a* value more than this indicates intense red soft (Rosa et al., 2011). Thus, 35 is taken as the threshold value for end of shelf-life of tomatoes as presented in Table 4.20.

Table 4.20 Values for calculating ASLT from a* value

T (◦C)	k	A_0	A_s
5.5±2.2˚C,	0.461	-8.92	35
18.5±4.9˚C	0.687	-9.26	
29.5±2.1˚C	0.878	-7.94	

Table 4.21 Values for calculating ASLT from firmness

T (◦C)	k	A_0	A_s
5.5±2.2˚C,	1.318	65.12	1.4
18.5±4.9˚C	2.208	70.01	
29.5±2.1˚C	2.407	68.6	

$$t_s = \frac{A_o - 1.4}{11282.41 \times e^{\left(\frac{-2519}{T+273}\right)}} \quad (4.1)$$

$$t_s = \frac{35 - A_o}{7562.82 \times e^{\left(\frac{-2519}{T+273}\right)}} \quad (4.2)$$

Putting the above values in equation (13) and (14), the shelf-life of tomatoes is calculated as 50, 35 and 26 days, at storage temperature of 5.5±2.2˚C, 18.5±4.9˚C and 29.5±2.1˚C, respectively against firmness values from Table 4. Similarly, tomatoes showed shelf life of 46, 34 and 25 days against a* values from Table 3. The experimental and calculated values of shelf-life of tomatoes obtained from the above study are presented in Table 4.22.

Table 4.22 Experimental and calculated value of shelf-life of tomatoes at different temperature

Parameter	Storage temperature (◦C)	Shelf life (Day)	
		Experimental value	Calculated value
Firmness (N)	5.5±2.2˚C,	46	50
	18.5±4.9˚C	32	35
	29.5±2.1˚C	25	26
a*	5.5±2.2˚C,	46	46
	18.5±4.9˚C	32	34
	29.5±2.1˚C	25	25

4.4.7 Relationship between shelf life and storage temperature

Plotting the logarithm of calculated shelf-life of tomatoes (ln t_s) against storage temperature (T), a relationship is established between them. It can be seen in Fig. 4.26that calculated shelf-life of tomatoes has a very good relationship with temperature (R^2=0.997).

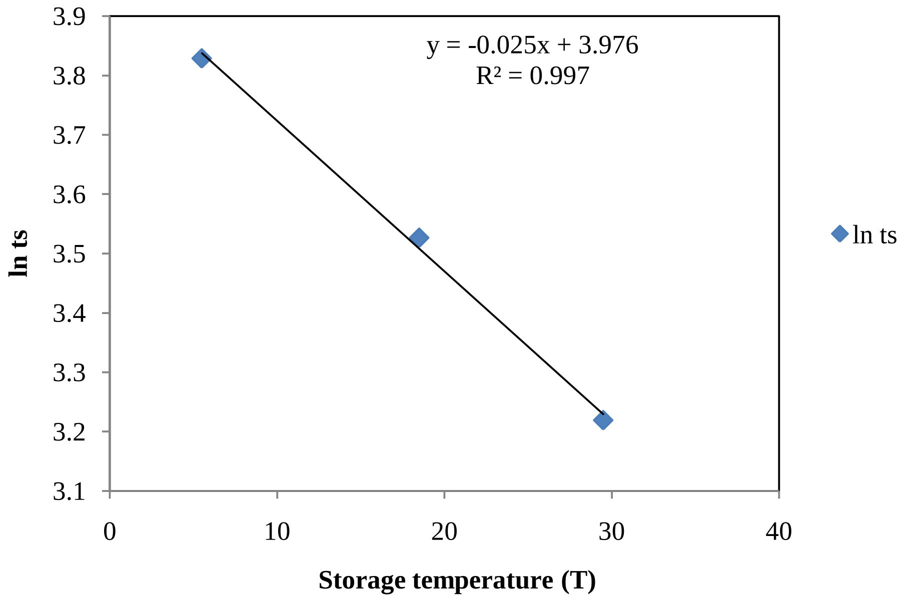
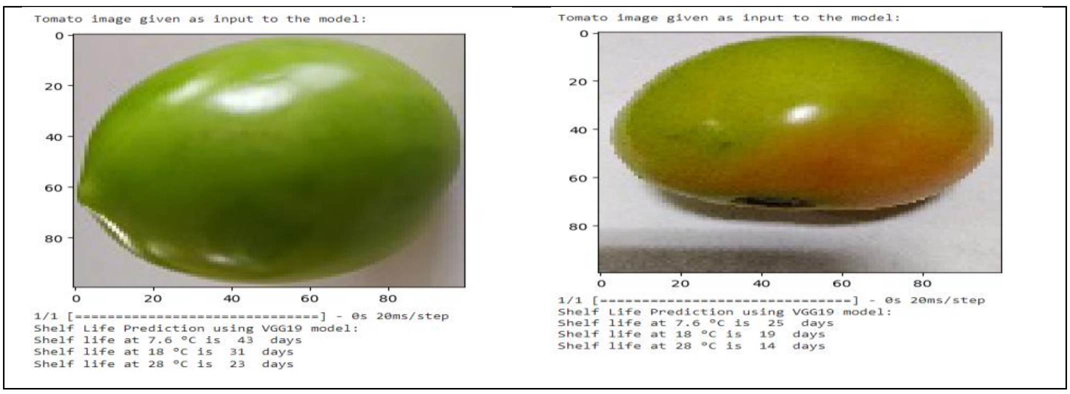


Fig. 4.26 Relationship between shelf life and storage temperature

4.4.8 Application of Deep Learning to estimate the shelf life of tomatoes at different temperature

For making the study more robust and meaningful, the above findings are trained in deep learning architecture with image as input. As discussed in section 2.7, a deep transfer learning model i.e.; VGG 19 is used to classify the tomatoes from its surface characteristics. The Arrhenius equation obtained out of the analysis was incorporated in the model for predicting shelf-life of tomatoes. Based on its surface characteristics, the shelf-life is estimated at three different temperatures. The VGG 19 model in particular was configured for training as: epoch (50), batch size (32), activation function (softmax) and learning rate (0.001). The VGG 19 model is trained with the images acquired throughout the experiment. The model works well with the given data points with a validation accuracy of 94%.



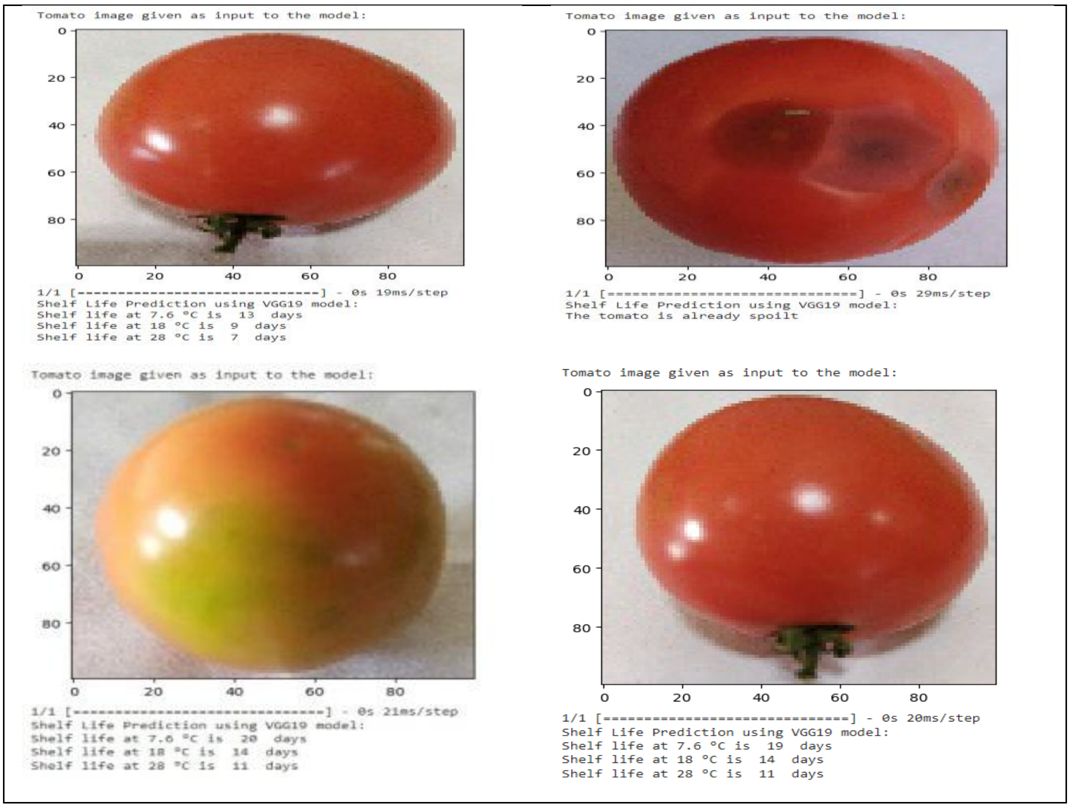


Fig. 4.27 Tomato shelf-life prediction using VGG 19 model

Based on the VGG 19 architecture, the predicted results are presented in Fig. 4.27. The predicted results show better performance in estimating its shelf-life. Given an image to predict its shelf-life, the developed model can thus automatically estimate the shelf-life of that tomato with a recommendation on its time-temperature.

4.5 Results obtained in developing the app for quality inference of tomatoes

This section highlights the performance accuracy of the models selected for developing the app.

4.5.1 Performance comparison of developed models for deployment as mobile app

The models giving the highest classification accuracy have been selected for developing the android based app. The performances of the different models with their classification accuracies are discussed below:

4.5.1.1 Performance of customized CNN model when implemented with TF lite in mobile

The training of the CNN model was carried out iteratively with varying epoch and batch sizes to evaluate its accuracy. The highest classification accuracy of 99.70% was achieved at 20 epoch and 32 batch size.

4.5.1.2 Performance of transfer learning model when implemented with TF lite in mobile

Out of the 5 pre-trained models (VGG 19, VGG 16, inception V3, ResNet 101 and ResNet 152) used, VGG 19 gave highest classification accuracy 97.37% at 50 epoch and 32 batch size.

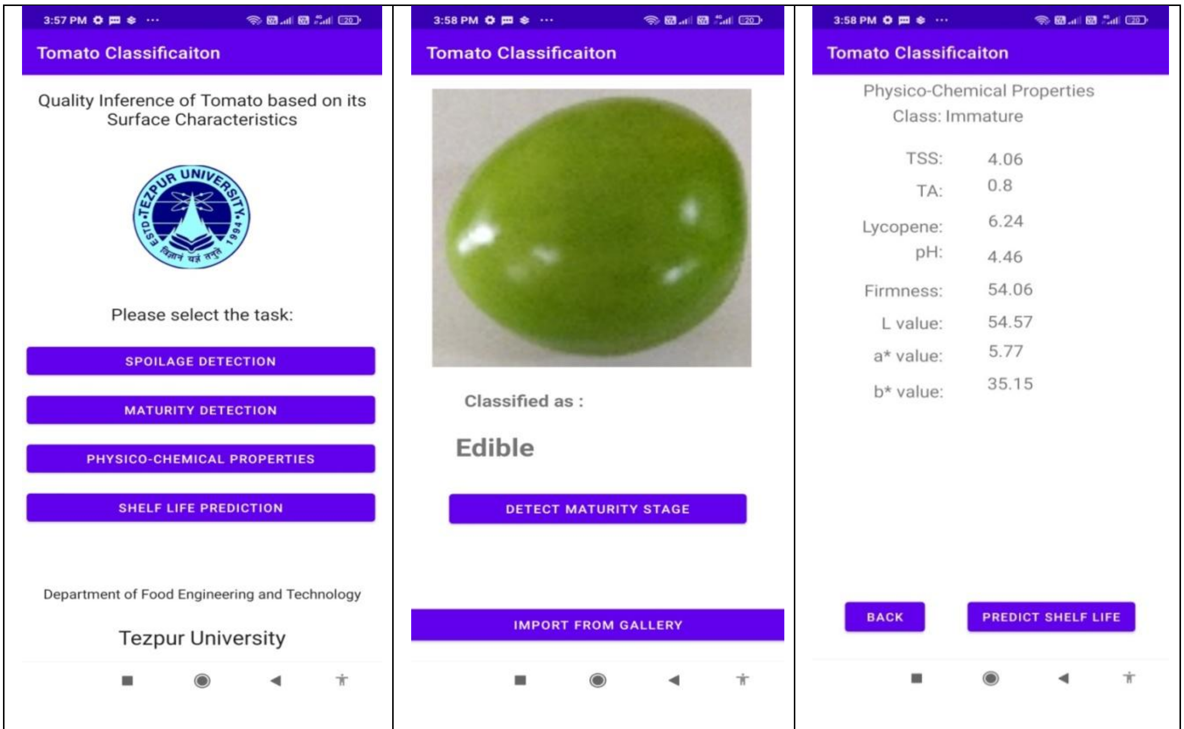
4.5.1.3 Performance of transfer learning model when implemented with TF lite in mobile

VGG 19 outperformed the ripening stage classification of tomatoes based on its surface characteristics with an accuracy of 97.37%. Hence to execute the task of predicting physico-chemical properties of tomato based on it's ripening stages, VGG 19 is used. In predicting physico-chemical properties of tomatoes based on their ripening stages, the proposed model achieved a validation accuracy of 92% after 50 epochs with a batch size of 32.

4.5.1.4 Performance of transfer learning model when implemented with TF lite in mobile

In consideration of the above two cases, VGG 19 was used in predicting shelf-life of tomatoes stored at different temperatures. The proposed VGG 19 model is successful in predicting the shelf-life on tomatoes with an accuracy of 81%.

Accordingly, the developed models were deployed into an app for inference of tomato quality and shelf life with image input. The built application first identifies tomatoes as edible or spoilt. If it is predicted as spoilt, then the application indicates unfit for consumption. And if edible, the app further identifies the maturity stage of tomato as mature green, intermediate and advanced. Secondly the app predicts the physico-chemical properties of the given tomato based on the maturity class. Finally, the app estimates the shelf-life of the given tomato from the image provided. The application is designed in a way that the input image is given to the TFLite model for classification and the output of the model is displayed in the interface of the Application with an option to read the result.



(a) (b) (c)

Fig. 4.28 (a) Initial interface of the application, (b) Spoilage detection interface, and (c) Interface for display of quality parameters

4.5.2 Evaluation of computational capability of the developed app

After development of the android application, an .apk file was generated, which can be installed in android based smart phones (Android Version 4.4 or above). After installation of the application in the smart phone, it was tested for performance analysis. On the home page, an option can be chosen for selecting which quality attributes to be determined as shown in Fig. 4.28 (a). After selecting the required quality criteria an option will flash whether to select an image from the gallery or an image to be captured from the mobile camera as shown in Fig. 4.28 (b). After selecting the image, the application gives the prediction based on the input image. To verify the performance of the application, benchmark tests have been conducted on the sample images extracted from the test set. On the benchmark test, the application provided more than 90 % accuracy for the test cases. The test also indicated that, in addition to the high recognition rate, the application consumed less computation time and was able to make prediction in real-time (<0.67 sec).

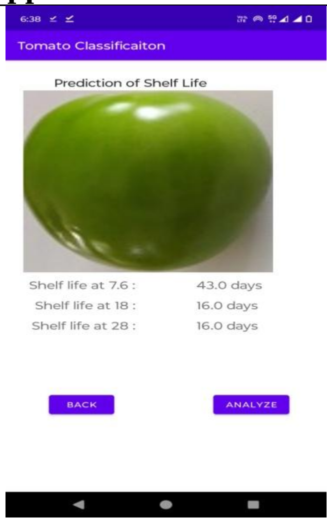
4.5.3 Validation of results predicted by developed app against measurement in real sample

To investigate the app's performance, an experiment was designed to establish the correlation between app's predicted values and the actual values of the quality attributes being considered for laboratory analysis. Some of the test cases on inference made of the app on the tomatoes are shown in Fig. 4.29.

Test image	App inference on spoilage	Test image	App inference on physico-chemical properties
			

Fig. 4.29 App inference spoilage detection of tomato

Considering all the results obtained from the app, sensory and physico-chemical analysis, Pearsons' correlation and percentage error was established respectively. Pearsons' correlation established between apps prediction and sensory evaluation in predicting current state of tomato as edible or spoilt was found to be 0.99. The app's prediction and the sensory panelists' evaluation were highly correlated (0.99) meaning that the app is 99% successful in detecting the current state of tomato as edible or spoilt. In the next case, Pearsons' correlation established between apps prediction and sensory evaluation in predicting current state of tomato as mature green, intermediate and advanced was 0.92. This indicates that the app is 92% successful in detecting the current state of tomato as mature green, intermediate and advanced. Next to this, the physico-chemical analysis results obtained experimentally and from the app was compared by calculating the percentage error in prediction. From the results it is found that the error percentage was <4% for firmness, TSS, TA and pH. For lycopene it was <10%. It was found that lycopene values slightly differ from experimental values which may be due to variety of tomato used. For L*, a* and b* it was <5%, <15% and <10% respectively, the error percentage was highest for a* values followed by b* and L* which may be due to variety of tomato and amount of carotene in trained and test sample. The app's performance was further evaluated for shelf-life (Fig. A4). One of the test cases on the inference of the developed app for shelf-life estimation of tomatoes is plotted below.

<table>
<tr><th>Test images</th><th>App inference on shelf-life</th></tr>
<tr><td></td><td>
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</table>

Fig. 4.30 App inference on shelf life of tomato

Pearsons' correlation was again established between the predicted value and real time values. The results obtained were found to be highly correlated (0.92). From the overall results it can be concluded that quality indices predicted by the app was at par with human inference and experimental results. The app thus outperforms the task of quality inference and can be regarded as a viable solution in food supply chain in a way that during handling storage and prior to processing, it will provide prior information on the tomatoes quality in terms of its current state, physicochemical compositions and shelf-life. Knowing the shelf-life will minimize losses to a great extent.

4.5.4 Challenges faced during deployment of app onto Smartphone

The model was trained using pre-processed images of 100 x 100 pixels. However, input image dimension on an android smart phone tend to be much higher than desired dimension of the input image on the deployed application. To overcome this limitation during deployment, measures were taken to resize the image before feeding it into the model.

4.6 References of Chapter IV

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