Chapter-III

3 Materials and methods

This chapter of the thesis includes all the materials (raw materials, instruments, software and hardware) used while conducting the experiments. The methodology employed to achieve the objectives of this study are also discussed in detail. This chapter is arranged into 5 sections in the following manner: section 3.1 and section 3.2 includes materials and methodology for objective 1, section 3.3 includes materials and methodology for objective 2, section 3.4 includes materials and methodology for objective 3 and section 3.5 includes materials and methodology for objective 4.

3.1 Materials and methodology for deep learning-based classification of tomato as edible or spoilt

This section is split into 2 sub sections: 3.1.1 which consists of all the materials and 3.1.2 where the procedures adopted for completion of this objective are detailed.

3.1.1 Materials

The section will elaborate on the raw materials, equipments, software tools as well the hardware set up used in fulfilling this objective.

3.1.1.1 Raw materials

As this work involves classification of tomatoes into edible and spoilt class, the first step involved collection of raw tomatoes. Tomatoes of hybrid variety namely ‘PUSA 120’ were collected from a local farm in Meghalaya, India. Fresh and firm tomatoes were collected, washed and kept in laboratory condition for image acquisition. 160 tomatoes plucked on the same day were selected after visual inspection for any damage due to transportation or pests. A total of 150 tomatoes having uniform shape, size and color were selected manually. The selected tomatoes were labeled properly for further analysis.

3.1.1.2 Image acquisition setup

After collection of raw materials, the second step involved capturing images of the tomatoes and then preparing a dataset. Images of the collected tomatoes were captured both in- (a) a self designed wooden box and (b) open condition. The self designed wooden box is of dimension 71.6 × 61 × 61 cm. The inner walls of this self designed image processing chamber were pasted with white chart paper sheets. On the upper surface, a slit has been made in order capture images using camera. In order to illuminate the target object, two light sources (Phillips tube light with 18 Watt) were used inside the chamber. For placing the sample inside, a small bench covered with white chart paper has been prepared which is of dimension 30.3 cm x 20.5 cm x 18.5 cm. A mobile camera of 8 MP resolution was used for capturing the image.

3.1.1.3 Instruments

For the measurement of texture (firmness), a texture analyzer (TA.XT Plus, Stable Micro System) was used. Flat plate compression test was performed to evaluate firmness of tomato whole fruit as described by Constantino et al., (2021). Fruit was compressed at the equatorial region by means of the flat plate until it deforms 5 mm of the surface. Flat plate used was of diameter 150 mm and fastened to a load cell with a capacity of 50 kgf. For this analysis, test-speed was set 5mm/s. Newton (N) was used to record the firmness measurements.

3.1.1.4 Hardware

The image processing and machine learning task was performed using a Lenovo E49 series laptop with the following hardware configurations; Intel Pentium processor CPU M330 @ 2.30GHz, 3.05 GB RAM, and 240 GB SSD.

3.1.1.5 Software tools

Various software platforms are available that have capability to performing deep learning on images datasets. To perform python deep learning tasks Anaconda3 was installed. For deep learning functionality, conda package installer was used to install Keras library in Anaconda3. Keras is a high-level software for developing deep neural networks and delegates computation at the lower-level. So, for low-level computations Keras relies on “backend engines”. There are various backend engines which are supported by Keras and change in backends result in change in performance of the neural network. Theano and Tensorflow are the two most popularly used backends in Keras. In this work, Tensorflow was installed in Anaconda3 to be used as Keras backend. The prime objective of Keras is to build the CNN model and train it on the self prepared dataset. To maintain quality and consistency in deep learning image datasets, the primary method is image pre-processing which involves techniques like resizing, cropping, normalization and augmentation. Pre-processing is done to standardize image dimensions removing noise and enhance relevant features; ensuring model receives consistent data for training and evaluation. Here, OpenCV python library was used for preprocessing works such as image cropping and resizing. Along with these libraries, other python libraries such Numpy, Scipy, etc., were also used in various computational works. Lastly, to manage all the libraries and the development environment, the Anaconda package manager was used.

3.1.2 Methodology

This section puts forward the proposed methodology for classification of tomato into edible and spoilt based on surface characteristics.

3.1.2.1 Acquisition of images

After visual inspection, images of tomatoes were acquired with the help of the specified mobile camera during the whole process. Images were captured using the self-designed wooden box and in open condition. While capturing the images, it was ensured that the distance between the sample and the camera position (held perpendicularly with respect to the tomato) was almost invariant. However, the lighting condition was varied by clicking some images in the wooden box, some under sunlight and rest under room light. This was done in order to train the model in different lighting condition so that, different lighting condition do not impact the results.

3.1.2.2 Preparation of dataset

For capturing images, a batch of 10 tomatoes out of 150 tomatoes was randomly selected. The dataset of edible and spoilt tomatoes was prepared from the acquired images (Fig. 3.1). Tomato images were taken during the whole process under different condition as mentioned in sectioned 3.1.2.1. Images of tomatoes were captured both using the image acquisition setup and under ambient conditions. Around 6 images per tomato were taken every day, starting from the second day of harvest until it was completely spoilt or rotten. The images were then transferred to the E49 series Lenovo laptop with Intel Pentium processor (2.30GHz) and 3.05GB RAM for further processing. After transferring images were renamed, cropped and resized to 100x100 pixel and stored in two separate directories based two conditions: edible and spoilt. Each image of tomato contains pixel values comprising of red, green and blue colour channel, these pixel values carry information about the external features of the tomatoes. During the experiment, the images were further randomly split into training and test sets in the ratio of 7:3 i.e. training set contains 70% images and test dataset contains 30% images.

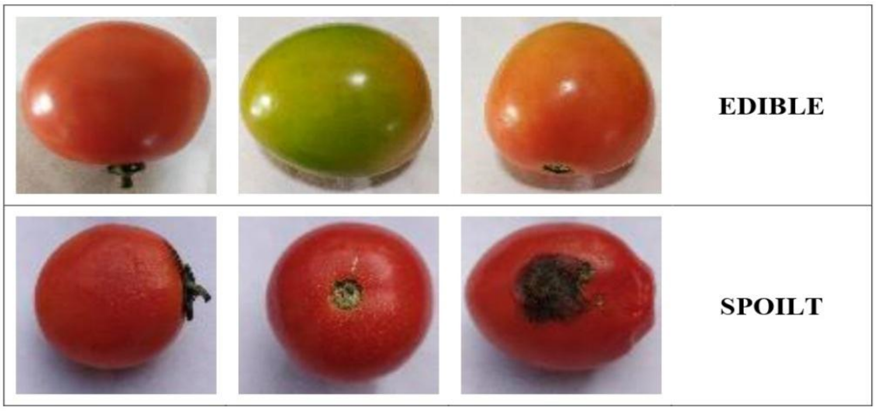

Fig. 3.1 Categorization of images for dataset preparation

3.1.2.3 Building the CNN model

The deep learning architectures are a sequence of convolutional layers with activation functions, fully connected, pooling layers and lastly softmax layer. Convolutional layers are accountable to feature extraction, while fully connected layers are accountable to classification. These architectures are highly configurable by fine-tuning their hyper-parameters (O'Donoghue and Roantree, 2015). To perform the targeted task of classifying tomatoes into edible and spoilt, some of the layers were configured into a customized model. Three 2-D convolutional layers with a 3×3 kernel size make up the created model, which is used to extract spatial features. Additionally, rectified linear activation function (ReLU) was applied in each convolution layer. Following all of the convolutional layers, there was a maxpool layer that computes the maximum, or largest, feature point in the region enclosed by the filter by sliding a 2x2 filter across the feature map's channels. In essence, it shrinks the feature maps produced by the convolutional layer. After the last maxpooling layer, a dropout layer with 25% dropout rate was applied. Subsequently, a 1D feature vector was obtained by flattening the output of the dropout layer. Fig. 3.2 displays the several layers of the CNN model that was utilized for this study. The 1D feature vector obtained was given as input to a dense layer having 256 neurons. The dense layer is a fully connected layer which learns the patterns in the feature vector. The dense layer uses ReLU activation function. A dropout layer with 40% dropout was also used to prevent the model from over fitting. Another dense layer having

256 neurons and ReLU activation function was again applied. Then again a dropout layer with 30% dropout was applied on the output of the dense layer. Then the output of the dropout layer was given as input to the last layer i.e., the output layer. In the output layer, a single neuron with sigmoid activation function was used to classifying the tomatoes images into two classes: edible and spoilt.

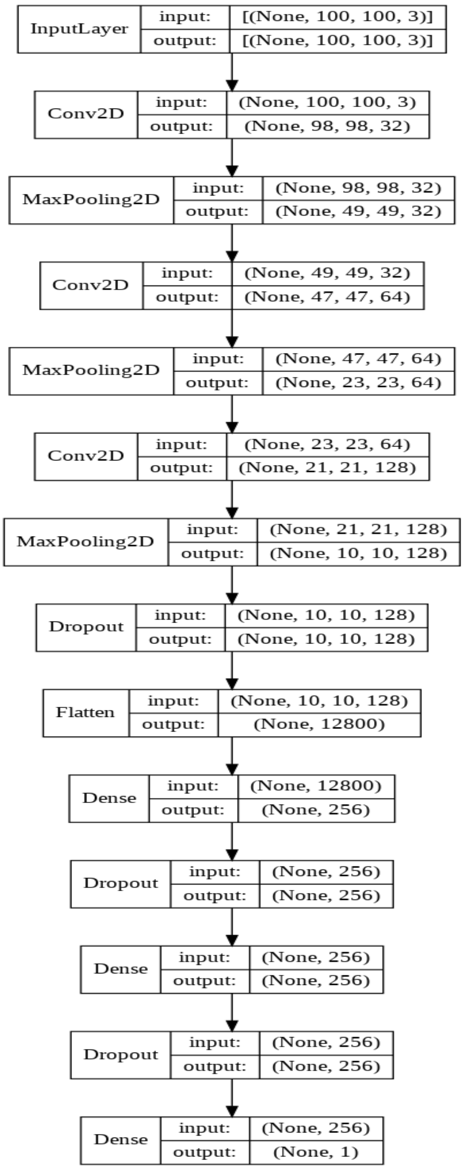

Fig. 3.2 Customized CNN model

3.1.2.4 Training the CNN model

The next important step after building the model was to train it on the self prepared tomato dataset. The CNN model was trained using 70% of the tomato images and with equal number of images of each class. During the training phase, the Adam optimizer with a learning rate of 0.001 and a binary cross entropy loss function was employed.

Various researchers claim that epoch and batch size are two hyper-parameters that mostly affects the accuracy of a model. In this study the model was trained iteratively with different number of epoch and batch size to test the accuracy of the model in classifying tomatoes as edible or spoilt. Number of epoch is a hyper-parameter that indicates the number of iterations of the learning algorithm over the entire training dataset. Here, the model was trained iteratively setting epoch sizes 10, 20, and 30 to observe whether the model had any over fitting or under fitting issues. Batch size is that parameter which adjusts the error rate of the working model after training the specified number of samples. Batch size of 8, 16, 32, and 64 were set during the experimentation and accuracy of the model during training and validation was recorded.

3.1.2.5 Physiological analysis

Most tomato samples that are spoiled are caused by fungi rather than bacteria (Khalid et al., 2024). The fruits may therefore alter in terms of flavor, aroma, appearance, or texture (Ghosh, 2009). Thus, the physiological parameter considered as an indicator to spoilage detection is firmness.

3.1.2.6 Sensory analysis

Sensory analysis was carried out at the end of model development to evaluate the performance of the model. This analysis was conducted by a group of 15 semi-trained panelists. They were trained for USDA defect detection standards of tomatoes. This evaluation made by the panelists was considered to be true predictions. The training included familiarity with terminology, identification and categorization of tomatoes. In addition Finger-Test was performed by the same group of panelist to evaluate the textural property of the given sample as an indicator to its quality as published by (Ranatunga et al., 2008). The analysis was conducted in individual booths at even lighting condition. Isolated booths were provided with a view to eliminate external influence (Fig. 3.3). Even lighting condition was provided to eliminate interference of light. Panelists were provided with samples labelled from 1 to 20. Every booth was provided with computer set up to go through the USDA defect classification standards. The panelists were asked to evaluate the tomatoes for its current state as edible or spoilt and score accordingly. The final sensory scores were then compared with the output of the predictive model. This evaluation was for assisting validation of the established model. To ensure reliability of the customized deep learning model, a confusion matrix was developed and a correlation test was performed between both.

Panelist 1 **Panelist 2** **Panelist 3**

Fig. 3.3 Sensory analysis performed by semi-trained panelist

3.1.2.7 Performance Evaluation

Performance of the customized CNN model was evaluated developing a confusion matrix and Pearsons' Correlation (Fig. 3.4). From the confusion matrix, precision, recall and accuracy of the model was established. Precision measures the proportions of the predicted positives that were actually positive. Recall measures the proportion actual positive cases that the model correctly identifies as positive. Accuracy represents the proportion of all classification that was correct regardless of whether they were positive or negative. Performance matrices like precision and recall provide a way to measure accuracy of a model in terms of positive and negative predictions. Pearsons' correlation coefficient is one of the most common ways of measuring a linear correlation. It is ranges between -1 and 1 measuring strength and direction of relation between two variables. -1 indicating perfect negative correlation and vice-versa while 0 indicating no correlation. Pearson Linear correlation was conducted to establish significant correlation between the predicted results and sensory results. Based on the correlation established, the developed model's performance can be evaluated.

		Predicted label	
		Positive	**Negative**
True label	**Positive**	TP (True Positive)	FN(False Negative)
	Negative	FP (False Positive)	TN (True Negative)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Fig. 3.4 Confusion matrix and evaluation parameters

3.2 Materials and methodology for classifying tomato as mature green, intermediate and advanced.

This section is split into 2 sub sections: 3.2.1 which consists of all the materials and 3.2.2 where the procedures adopted for completion of this objective are detailed.

3.2.1 Materials

This section enlists all the raw materials, equipments, hardware and software tools as well as the pre- existing transfer learning models used to achieve the target of this objective.

3.2.1.1 Raw materials

This work focused on the classification of tomatoes, so the basic raw material used was tomato. Tomatoes were collected from a local vendor near Tezpur University. Tomatoes purchased were of variety ‘PUSA 120’, which included mature green, intermediate and advanced tomatoes. A total of 105 tomatoes were selected, washed, rinsed and made ready for image acquisition.

3.2.1.2 Image acquisition setup

The images were acquired in the similar way as mentioned in section 3.1.1.2.

3.2.1.3 Instruments

For the measurement of firmness, a texture analyzer (TA.XT Plus, Stable Micro System) was used. Firmness values were recorded in Newton (N). Color values (L^*, a^*, b^*, ΔE and Hue) were determined using Hunter Color Lab (Reston, Virginia, USA model).

3.2.1.4 Hardware

The image processing and machine learning task was performed using a Lenovo computer as mentioned in section 3.1.1.4

3.2.1.5 Software tools

Software tools used were same as described in section 3.1.1.5.

3.2.1.6 Deep transfer learning approach

Transfer learning is a deep learning approach where the weights of the layers are pre-trained on standard image datasets. The pre-trained layers are then used for fine-tuning in the target dataset. Fine-tuning is a concept of transfer learning which needs a bit of learning (Vrban and Podgorelec, 2020). It is proved that the fine-tuned architecture is much faster and more accurate than custom built models (Poojary et al., 2021). Pre-trained weights often carry useful information. Upon application pre-trained model relaxes the tedious task of training architecture from starting point. The pre-trained layers already consist of learned weights which ease the features extraction as well. Thus, in the case of transfer learning, an established model already exists for solving our targeted tasks. Hence, the model used for solving our targeted task needs not to train from scratch, which is less tedious and time-saving. This is the main motive behind using transfer learning for solving the targeted classification task in this objective. The pre-trained models used for this study were VGG, Inception, and ResNet.

(Simonyan and Zisserman, 2014) proposed the VGG architecture, which is trained on an ImageNet dataset consisting of over 14 million images with 1000 classes. VGG architectures are the most widely used architectures showing good results both for image classification and localization problems. Developing architectures is to evaluate CNN's depth over its accuracy when working with an extensive image dataset. VGG 16 and VGG 19 are the two categories of VGG, which are named after the number of layers it contains. VGG16 model is a combination of convolutions layers and fully connected layers. In total there are 16 layers with five blocks and a max-pooling layer in each block as shown in Fig. 3.5(a). In contrast to VGG16, VGG19 has 19 layers with additional convolution layers in the bottom-most three blocks as shown in Fig. 3.5(b). Both VGG16 and VGG19 have shown great performance in the image recognition and classification, and thus are used in this study.

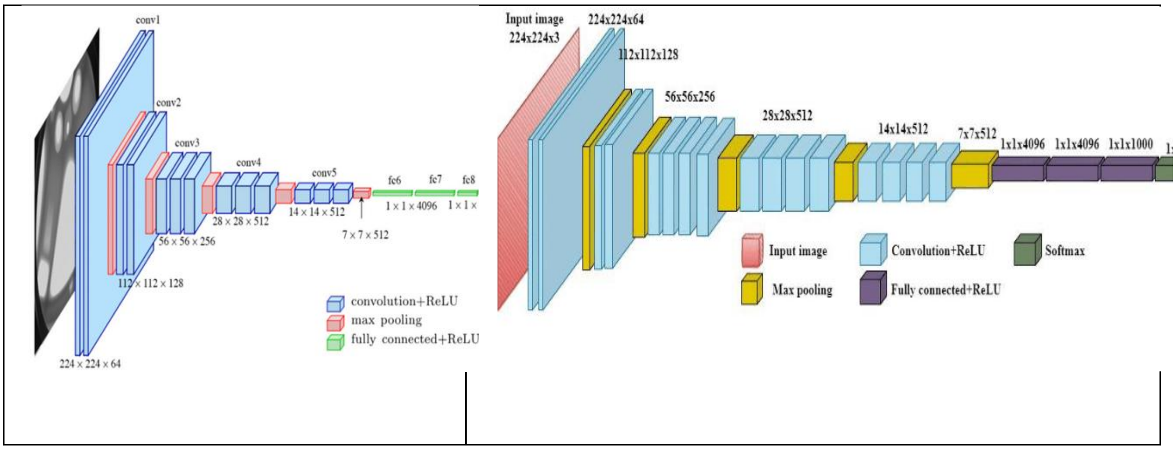

Fig. 3.5 Architecture of (a) VGG 16 (Bangar, 2022) (b) VGG 19 (Nguyen et al., 2022)

Inception V3 is one of the four inception modules which were first developed by (Szegedy et al., 2016). Compared to Inception V1 and V2, factorization was introduced in Inception V3, reducing the dimensionality in its layers as shown in Fig. 3.6. This, in turn, reduces the over fitting problem.

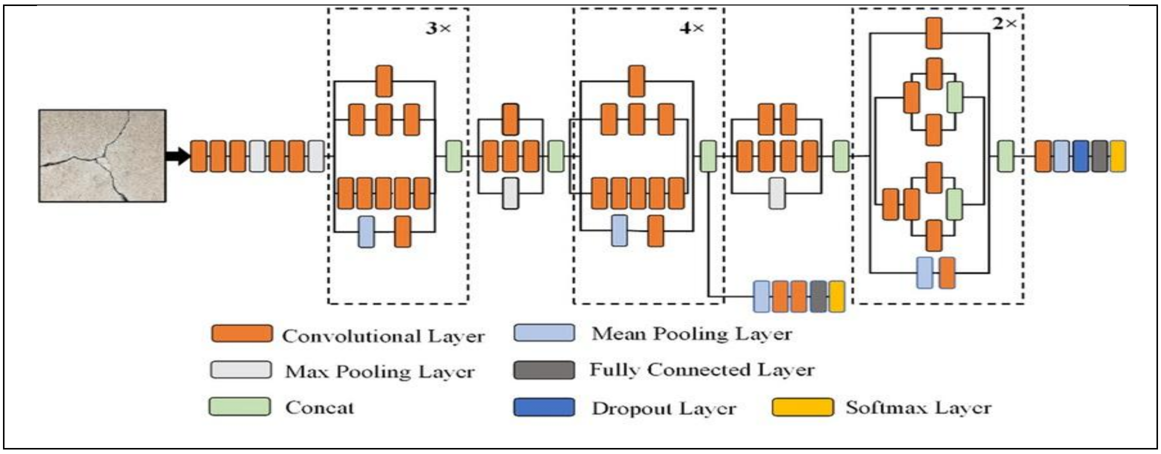

Fig. 3.6 Inception v3 architecture (Ali et al., 2020)

(He et al., 2016) developed the ResNet architecture bringing out a revolution in the field of image recognition by introducing the concept of residual learning. ResNet152, ResNet101, ResNet50, ResNet34and ResNet18 are the popular variations of ResNet according to their layers. The ResNet152, ResNet101, ResNet50, ResNet34 and ResNet18 network have 152, 101, 50, 34 and 18 layers respectively and can classify images into 1000 object categories. In this work, ResNet101 and ResNet152 are used as shown in Fig. 3.7 and Fig. 3.8 respectively.

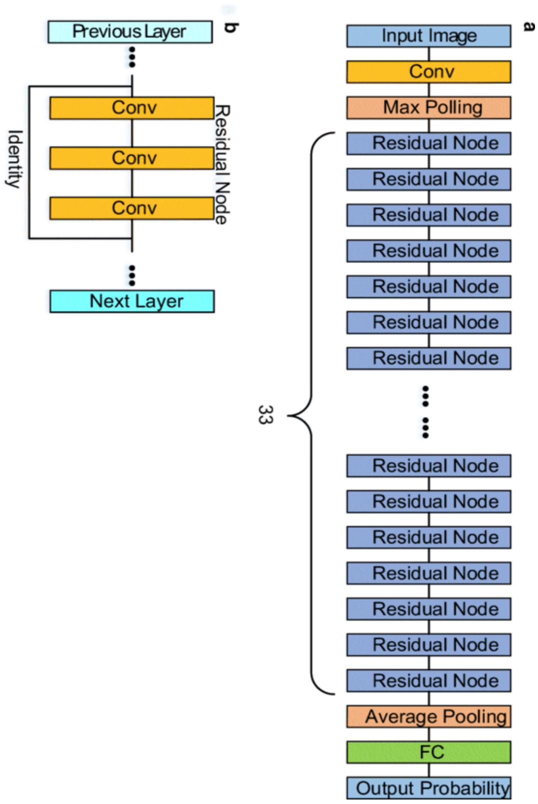

Fig. 3.7 ResNet101 architecture (Li et al., 2020)

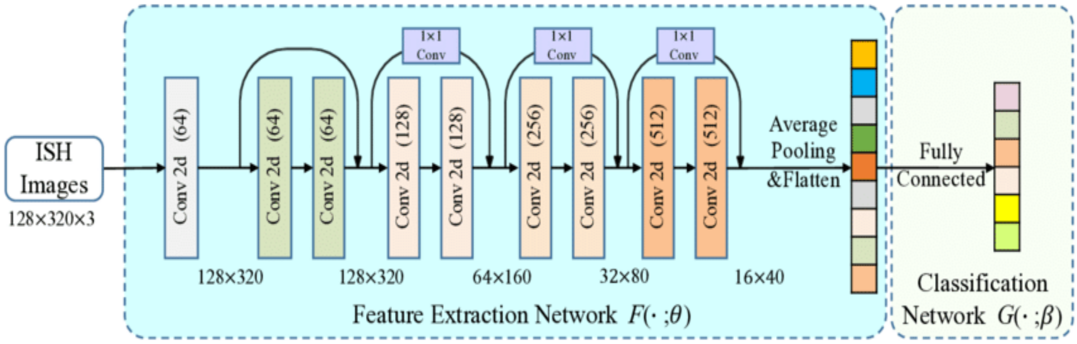

Fig. 3.8 ResNet152 architecture (Cai et al., 2014)

3.2.2 Methodology

This section puts forward the proposed methodology for classification of tomato into mature green, intermediate and advanced based on surface characteristics.

3.2.2.1 Acquisition of images

The tomatoes being collected for analysis were washed, sorted and made ready for image acquisition. Tomato images were acquired using a Smartphone camera with resolution of

48MP. The images were acquired in laboratory conditions under non-uniform lighting conditions. Non-uniform lighting condition refers to both under sunlight and using image processing box. The image processing box is a setup that is made ready for acquiring images from a fixed height, placing the camera in a fixed position. Lights are used inside the box for the purpose of illumination. Images were taken right from the next day of harvest. Around 6 images were captured per day for preparation of dataset. Thus the dataset is prepared from these acquired images comprising of mature green, intermediate and advanced tomatoes. Clear and distinct images were considered for further pre-processing in this study.

3.2.2.2 Data augmentation

The images captured using a Smartphone camera was then loaded in the laptop where all the necessary processing was done. Processing here includes all the pre processing operations as well as model implementation. At first the selected images were taken for preliminary processing where the images were cropped using OpenCV python library. Secondly the images were renamed and then resized into lower pixels value of 100×100. Each image of tomato contains pixel values comprising of the red, green, and blue colour channels. These pixel values carry information about the external features of the tomatoes.

3.2.2.3 Preparation of dataset

After visual investigation the pre-processed images were categorized into the three classes- mature green, intermediate and advanced as shown in Fig. 3.9. This categorization is done based on USDA classification on ripening stage. Further each image in the respective classes was labelled accordingly. During the experiment, the images were randomly split into two, training, and testing sets in the ratio of 7:3, i.e., the training set contains 70% images, and the test dataset contains 30% images.

Mature green

Intermediate

Advanced

Fig. 3.9 Categorization of dataset into mature green, intermediate and advanced

3.2.2.4 Application of transfer learning approach

Deep learning models are comprised of layered architecture where different layers are arranged in sequence. These layers have the capability to extract features out of the input images, learn and finally predict the output. While in transfer learning, pre-trained models are used as a feature extractor. The extracted feature out of this model is then used by the classifier for classification. The layers used in the classifier are trained with new dataset to achieve the desired output in less training time. In this work, three transfer learning models based on CNN are employed. These models include, VGG, Inception, and ResNet. These models were applied for the classification of tomatoes as mature green, intermediate, and advanced.

3.2.2.5 Fine tuning of hyper-parameters

In the working model a set of parameters called the hyper-parameters govern the learning process. Fixing of hyper-parameter depends on both the working model as well as the working dataset. Finding the best combination of hyper-parameters is the target of every model. So in order to achieve the best classification accuracy in a model, hyper-parameters such as the number of epochs, batch size, and the learning rate is varied over the training set during the experiment. From previous researches, it is seen that fine-tuning the hyper-parameters improve the accuracy of the model. The performance of a model is determined by the value of the hyper-parameters for which highest classification accuracy is obtained. Hence in this objective, the transfer learning models were trained setting epoch values of 25 and 50 and batch size of 32 and 64, and its effect on the model's accuracy was evaluated. Normally, the deep learning models are trained in batches and the size of a batch remains fixed during the training process. Selection of appropriate batch size depends on the number of images in the dataset. For continuous purpose, the batch size should be varied to obtain the optimum classification accuracy. The best combination of hyper-parameters achieved enables us to the performance of the architectures. Moreover to reduce over fitting and under fitting issues the models input images were trained with image data generator. The image data generator in the mentioned models rescales, shear, zoom and flips the input images provided. The motive was to maximize diversity of training inputs and also augment the images while the training undergoes diminishing the noises. Again the models were trained with loss function namely ‘categorical cross entropy’ and optimizer namely ‘adam’. The learning rate is set to 0.001, which is default in Keras library. It is important to note that these hyper-parameters were set during training only to maximize the accuracy of the model. The set of parameters used during training the model is summarized in Table 3.1.

Table 3.1 Parameter used during experiments

Parameters	Values
Epoch	25, 50
Batch size	32, 64
Learning rate	0.001
Optimizer	Adam
Loss function	Categorical cross entropy

3.2.2.6 Physiological analysis

Color values (L*, a*, b*, ΔE and Hue) and Texture (firmness) were the two parameters mostly considered as an indicator to ripening. Color and firmness values of the tomato samples were measured after image acquisition.

3.2.2.7 Sensory analysis

Sensory analysis was conducted by a group of 15 semi-trained panelists. The panelists followed (a). USDA standards on ripening classification and (b). Finger test (Batu ., 1998) to categorize the tomatoes as mature green, intermediate and advanced.

3.2.2.8 Performance evaluation of the transfer learning models

Confusion matrix was established for the different models and its performance was evaluated in terms of precision, recall and accuracy as mentioned in section 3.1.2.7. This was done on a random set of samples on the basis of sensory evaluation made by semi-trained panelists. Pearsons’ correlation was also established between the model’s prediction and the sensory panelist evaluation. The model with highest classification accuracy is considered to establish Pearsons’ correlation.

3.3 Materials and methodology for estimation of physico-chemical properties of tomato based on their surface characteristics

This section is split into 2 sub sections: section 3.3.1 which consists of all the materials and section 3.3.2 where the procedures adopted for completion of this objective are detailed.

3.3.1 Materials

The section highlights the raw materials, chemical, instruments, software, hardware and statistical tools used for accomplishment this objective.

3.3.1.1 Raw Materials

The raw material of interest thoroughly used in this work was tomato. PUSA 120, a high yielding hybrid variety of tomato was chosen to conduct the experiment. 120 tomatoes of uniform shape and size harvested on the same day were collected from a local farmer of Tezpur, Assam, India. It was then sorted, washed and kept in laboratory condition for image acquisition and physico-chemical analysis.

3.3.1.2 Image Acquisition Setup

After collection of raw materials, the second step involved capturing images of the tomatoes and then preparing a dataset. Images of the collected tomatoes were captured both in- (a) a self designed wooden box and (b) open condition as described in section 3.1.1.2.

3.3.1.3 Chemicals

Reagents and chemicals of analytical grade (A.R.) from Hi Media and Merck, Germany were utilized for chemical analysis. Every glassware that was utilized was borosilicate and sterilizable.

3.3.1.4 Instruments

For the measurement of texture, a texture analyzer (TA.XT Plus, Stable Micro System) was used. Color was determined using Hunter Color Lab to obtain the L*, a* and b* color readings.

3.3.1.5 Hardware and Software Tools

For performing deep learning computations, softwares used were as described in 3.1.1.5.

The hardware used was a HP computer with the following hardware configurations; Intel Core i3 CPU M330 @ 2.13GHz, 3GB 15 RAM, and 240 GB SSD.

3.1.1.1 Statistical Tools

Experimental data obtained out of the physico-chemical analysis were subjected to determine the coefficient of determination (R^2) in MS Excel. Physico-chemical data were also subjected to one way analysis of variance ($p<0.05$) using JASP. JASP is an open-source as well as free tool for statistical analysis provided by the University of Amsterdam. In this work JASP was used to establish correlation between the quality parameters performing ANOVA and Pearsons' correlation.

3.3.2 Methodology

The methodology adopted in fulfilling this objective is detailed in the below sub-sections.

3.3.2.1 Collection of Tomatoes

Tomatoes of equal maturity, shape and size harvested on the same day were collected from a local farmer of Tezpur, Assam. It was then washed, sorted, and made ready for physical as well as chemical analysis.

3.3.2.2 Image Acquisition

Image acquisition started with proper labeling the sorted tomatoes. Images were acquired with a mobile phone camera at both even and uneven lightning conditions. Even condition refers to the self-designed image processing box. And uneven condition refers to capturing to images in open condition under sunlight. The images captured using a digital camera was then loaded in the laptop where all the necessary processing is done. Processing here includes all the preprocessing operations as well as model implementation. The selected images were taken for preliminary processing where the images were cropped using OpenCV python library. The images were renamed and then resized into lower pixels value of 100 ×100. Each image of tomato contains pixel values comprising of the red, green, and blue color channels. These pixel values carry information about the external features of the tomatoes.

3.3.2.3 Fruit separation and physico-chemical analysis

After image acquisition the tomatoes were made ready for physical analysis followed by chemical analysis. Physical analysis includes texture (firmness) and color analysis. Chemical analysis includes determination of lycopene content, TA, TSS and pH. Firmness was measured using TAHD-Plus, Stable Micro Systems, UK model performing the flat compression test. During this test a flat end probe of 150 mm diameter made of stainless steel was attached to the load cell50kgf. The test was performed for each tomato at a pre-test speed of 5 mm/s, compressing the fruit at the equatorial region (Huang et al., 2018). This force/displacement curve yields three property parameters: the slope measured between the point of first contact and the point corresponding to the maximum force (CS) in N/mm; the maximum force (or CF) in N; and the force/displacement area (CA) in Nmm. Here, firmness (Nmm-1) is defined as the force/deformation curve's average slope (Adegoroye et al., 1989). For colour estimation, Hunter Lab, Reston, Virginia, USA model was used. On the tomatoes' surface, measurements of color were made in the equatorial zone. Depending on the size of the tomato, the color was measured a minimum of five times and a maximum of ten times, averaging seven times for each tomato. A white tile was used to calibrate the colorimeter. Data are presented using the L*, a*, and b* systems.

3.3.2.4 Chemical analysis

Lycopene estimation was done using spectrophotometrically at 503 nm (Davis et al., 2003). , A portable digital refractometer (Atago®, with a corrected value for 25˚C) was used to test the TSS (expressed in ˚Brix) of tomatoes. Titration was performed with 0.01N sodium hydroxide (NaOH) to quantify titratable acidity (Saad et al., 2014). TA was expressed in percent citric acid. Using an electronic pH meter, pH was measured in accordance with AOAC standard protocol. A buffer solution was used to standardize the pH meter.

3.3.2.5 Mapping of physic-chemical properties

The results obtained out of the physico-chemical analysis were then tabulated. Simultaneously the acquired images were pre-processed. After that a relationship was established between the image and the physico-chemical values against each maturity class.

3.3.2.6 Statistical Validation

All experiments were carried out in triplicate. The results obtained out of the experiments were analyzed using statistical tools available in Microsoft Excel and JASP. All results were expressed as the average ± standard deviation of triplicate (Microsoft Excel 2007 Analysis Toolpak). Regression analysis in Microsoft Excel desktop applications is done using the Regression tool in the Analysis ToolPak. Microsoft Excel was primarily used to tabulate the results and perform linear regression between the determined physico-chemical parameters against days of storage. MS Excel provides the trend line and coefficient of determination, R2 value, providing an insight into the effect of physico-chemical parameters upon maturity. Further, principal component analysis (PCA) was performed to obtain the principal components on the data, in order to determine the most influencing parameter on ripening. Secondly JASP was used to perform Pearsons' Correlation and one way ANOVA. Pearsons' Correlation test was used to analyze correlation between the physico-chemical parameters. The maturity detection parameter, which had the strongest correlation, was determined. Additionally, one-way analysis of variance (ANOVA), and the Duncan's multiple range test is used to determine the significance of the difference in sample means from the data. There is a substantial difference when $P < 0.05$.

3.3.2.7 Model Training

A deep learning model was used for training the self-prepared dataset. The deep learning model was trained with the images acquired against each maturity class. Transfer learning is a widely used technique in deep learning where pre-trained deep neural networks are used in classification problem with lesser or smaller dataset. From the previous objective, it was found that VGG 19 outperforms other transfer learning techniques in three class classification problems and hence finds application in this study (Begum and Hazarika, 2022). In this work, the convolutional layers and dropout layers of the VGG19 model were used for feature extraction. However, these layers were not trained on the current dataset. The output from the last layer of the VGG19 model was flattened to one-dimensional array and given as input to a dense layer having 64 neurons and ReLU activation function. This layer was thus used for maturity classification based on the features extracted by the VGG19 model from the tomato images. Finally, output of the dense layer is given as input to another dense layer of 3 neurons which predicts the maturity class using a softmax activation function. The physico-chemical analysis results obtained against each class was then mapped to their respective images and the model was trained accordingly. The output of the developed model thus predicts the physico-chemical properties of tomatoes from image input.

3.3.2.8 Model Performance evaluation

The performance of the proposed VGG19 model was further evaluated by obtaining a confusion matrix. Performance metrics such as accuracy, precision, recall, F1 score, Cohen's Kappa score were calculated from the confusion matrix using Table 3.2.

Table 3.2 Metrics used for performance evaluation

Performance metrics	Formulation	Physical significance
Accuracy (Acc)	$Acc = \frac{TP + TN}{TP + FP + FN + TN}$	It is the overall prediction correctness of the model
Precision (Pr)	$Acc = \frac{TP}{TP + FP}$	It is the ratio of real positive in all predicted positive by the model
Recall (Rc)	$Acc = \frac{TP}{TP + FN}$	It is the prediction correctness of the model on positive samples
F1-score (F1)	$F1 = \frac{2 * Pr * Rc}{Pr + Rc}$	It is the harmonic mean between precision and recall
Cohen's kappa score (**κ**)	$\boldsymbol{\kappa} = \frac{P_o - P_e}{1 - P_e}$	It is used to measure the inter-rater reliability of quantitative items

3.4 Materials and methodology for estimation of shelf-life of tomato based on their surface characteristics.

This section is split into 2 sub sections: section 3.4.1 which consists of all the materials and section 3.4.2 where the procedures adopted for completion of this objective are detailed.

3.4.1 Materials

This section includes raw materials, chemicals, hardware, software and statistical tools used to conduct the storage study.

3.4.1.1 Raw materials

The raw material of interest thoroughly used in this objective was tomato. PUSA 120, a high yielding hybrid variety of tomato was chosen to conduct the experiment. Hybrid tomatoes of uniform shape and size harvested on the same day were collected from a local farmer of Tezpur, Assam, India. It was then sorted, washed and kept in laboratory condition for image acquisition and physico-chemical analysis.

3.4.1.2 Image Acquisition Setup

As described in section 3.1.1.2

3.4.1.3 Chemicals

For chemical analysis, reagents and chemicals of analytical grade (A.R.) were used and all were from Hi media and Merck, Germany make. All glasswares used were sterilizable and borosilicate.

3.4.1.4 Instruments

For the measurement of texture, a texture analyzer (TA.XT Plus, Stable Micro System) was used. Color was determined using Hunter Color Lab to obtain the L*, a* and b* color readings. A digital thermometer was used for recording the storage temperature.

3.4.1.5 Hardware and Software Tools

As described in section 3.3.1.5

3.4.1.6 Statistical Tools

As described in section 3.1.1.1.

3.4.2 Methodology

This section elaborates the methodology adopted to estimate the shelf-life of tomatoes under different storage temperatures.

3.4.2.1 Collection of tomatoes

Tomatoes of equal size and maturity having even surface were collected from a local farmer of Tezpur, Assam. Hybrid variety of tomato PUSA 120 was considered. It was then washed, sorted and made ready for image acquisition followed by measurement of quality indices.

3.4.2.2 Temperature selection

Three different temperatures (5.5±2.2˚C, 18.5±4.9˚C and 27.5±2.1˚C) were chosen for estimating the shelf-life of tomatoes. Each storage condition consisted of around 150 tomatoes. Three temperatures are chosen such that one is refrigerated temperature and other two mimic summer and winter temperature of Assam.

3.4.2.3 Image acquisition

Image acquisition starts with proper labeling the sorted tomatoes. Images of stored tomatoes were captured everyday using a mobile phone camera at both even and uneven lighting conditions.

3.4.2.4 Measurement of quality indices

Color and texture (firmness) are the physical parameters that are mostly considered for storage quality estimation (Raiola et al., 2014). Again chemical attributes such as TSS, TA, pH, lycopene content, PWL, PME are mostly affected during storage. Hence, these parameters were considered good indicator to shelf-life estimation study for this objective.

3.4.2.5 Color measurement

For colour estimation, Hunter Lab, Reston, Virginia, USA model is used. The values are reported as L* (degree of brightness to darkness), a* (degree of redness (+) to greenness (−) and b* (degree of yellowness (+) to blueness (−). Color values were determined as followed by (Shehata et al., 2021).

3.4.2.6 Firmness analysis

Textural parameter i.e.; firmness was measured using TAHD-Plus, Stable Micro Systems, UK model. Firmness was tested as described by (Batu & Thompson, 1993).

3.4.2.7 Percent Weight Loss

In order to determine the percent weight loss, weight of tomatoes were taken from day 0 (initial weight) until it reaches its advanced stage (final weight) as described by (Jois et al., 2016). The percent weight loss (PWL) is expressed as in equation (*(3.1*).

$$PWL(\%) = \frac{Initial\ weight - weight\ on\ the\ day\ of\ observation}{Initial\ weight} \times 100 \quad (3.1)$$

3.4.2.8 Total soluble solids

For determining the Total Soluble Solid (TSS), the tomato fruit was cut into slices. Juice was extracted and TSS as measured with a digital refractometer (PR-101a, Atago, Co., Tokyo, Japan) as described by (Magwaza and Opara, 2015).

3.4.2.9 Titratable acidity

10 g of the remaining samples was weighed; homogenized and extracted using distilled water for measuring the Titratable Acidity (TA) of tomato. TA was measured by the acid-base titration using a titration unit as described by Ranganna 1986 and expressed in percentage of citric acid (Ranganna, 1986).

3.4.2.10 Lycopene content (LC)

Lycopene was measured according to the method described by Ranganna 1995 (Ranganna, 1995). The color was measured in a spectrophotometer at 503 nm. Lycopene content of sample was calculated by using the relationship that optical density (OD) of 1.0 = 3.1206 μg of lycopene per ml. The formula for lycopene estimation is given in equation ((3.2).

$$LC\ (mg/\ 100gm) = \frac{3.1206\ \times OD\ of\ the\ sample\ \times volume\ made\ up\ to\ \times 100}{1 \times weight\ of\ the\ sample\ \times 1000} \quad (3.2)$$

3.4.2.11 Pectin Methyl Esterase

The PME activity was determined titrimetrically at pH 7.0 and 25°C by means of a titration unit as described by (Guzmán et al., 2010). The reaction mixture consisted of 20 ml of a 1% citrus pectin solution, containing 0.1 M NaCl and 1 ml of PME extract. The pH of the reaction mixture was determined twice, at the beginning of the reaction and again after 1 min. The activity of PME is expressed as the difference in pH between both determinations and is expressed as in equation (3.3).

$$PME\ (U/ml) = \frac{(ml\ of\ NaOH)(N\ of\ NaOH)}{(ml\ of\ extract)(time\ \ in\ min)} \quad (3.3)$$

3.4.2.12 Kinetics of the Quality Parameter of tomato during storage

In this work empirical models based on zero, first and second order reaction was used and kinetic parameter such as reaction rate and activation energy was obtained. Equation ((*3.4*) gives the rate law used for determining quality change in tomato upon storage is-

$$\frac{dY}{dt} = -kY^n \tag{3.4}$$

Where, Y denotes quality index at a given time, t is the time of storage (d), k is the reaction rate (d^{-1}) and n is the reaction order which is determined by putting n = 0, 1 and 2, respectively. The following equation ((*3.5*), ((*3.6*), and ((*3.7*) are thus obtained:

$$\text{Zero order:} \qquad Y = Y_o - \mathrm{kt} \tag{3.5}$$

$$\text{First order:} \qquad Y = Y_o e^{-kt} \tag{3.6}$$

$$\text{Second order:} \qquad \frac{1}{Y} - \frac{1}{Y_o} = kt \tag{3.7}$$

The temperature dependence of reaction rate 'k' is described using the Arrhenius model and the Eyring model. The Arrhenius model is shown in equation ((*3.8*).

$$k = A \,.\, e^{-\frac{E_a}{RT}} \tag{3.8}$$

Where, A is Arrhenius constant, E_a is activation energy in kJ/mol; R is gas constant in J/(mol·K); T is storage temperature in K;

The Eyring model based on transition state theory is shown in equation ((*3.9*).

$$\ln\frac{k}{T} = -\frac{\Delta H}{R}\frac{1}{T} + ln\frac{k_B}{h} + \frac{\Delta S}{R} \tag{3.9}$$

Where, $\triangle H$ and $\triangle S$ are enthalpy and entropy of activation respectively; R is the ideal gas constant, 8.314 J/(mol·K); h is the Planck constant, 6.626×10^{-34} J s; T is the absolute storage temperature (K); k_B is the Boltzmann constant, 1.381×10^{-23} J/K.

3.4.2.13 Shelf-life estimation of tomatoes stored at different temperatures

After knowing the key parameters, the shelf life of tomatoes at different temperatures were predicted using Equations ((*3.10*), ((*3.11*) and ((*3.12*) for the zero, first and second-order reactions, respectively:

$$\text{Zero order reaction: } t_s = \frac{A_0 - A_s}{k_T} \tag{3.10}$$

$$\text{First order reaction: } t_s = \frac{\ln(\frac{A_o}{As})}{k_T} \tag{3.11}$$

$$\text{Second order reaction: } t_s = \frac{\left(\frac{1}{A_o}\right) - \left(\frac{1}{As}\right)}{k_T} \tag{3.12}$$

where k is the reaction rate at temperature T, t_s is the shelf life, A_0 is the value at the start of the shelf life, and A_s is the value at the end of the shelf life.

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

With 19 connection layers (16 convolution layers and 3 fully connected levels), the VGG-19 is a deep learning neural network architecture. The fully connected layers categorize the tomato images based on the attributes that the convolution layers have extracted from the input images. In addition, the max-pooling layers will reduce the features and avoid over fitting, as described in Fig. 3.10. The obtained results are fitted into the VGG 19 model that can automatically estimate the shelf life of tomatoes at three different temperatures. VGG 19, a viable solution to maturity classification with a classification accuracy of 97.37% at epoch 50 and batch size 32 (Begum and Hazarika, 2022). Thus VGG 19 is considered for this study for estimating shelf-life in tomatoes from its surface characteristics.

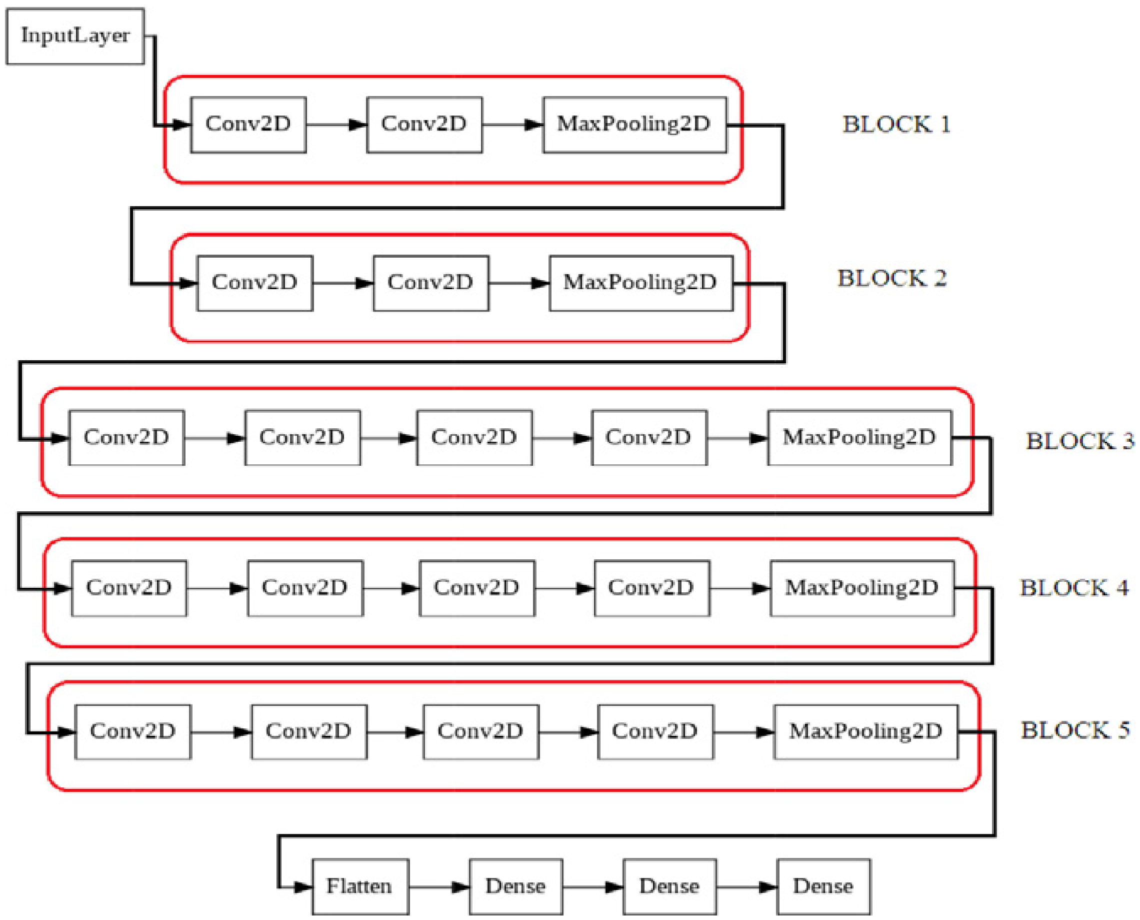

Fig. 3.10 Different layers in VGG 19 architecture

3.5 Materials and methodology for app development

This section is split into 2 sub sections: section 3.5.1 which consists of all the materials and section 3.5.2 where the procedures adopted for completion of this objective are detailed.

3.5.1 Materials

This section the materials used while developing an app for quality inference of tomato.

3.5.1.1 Android phone

In this work, the primary objective was to develop an android application where the trained deep learning models can be deployed. The basic material in this objective is thus an android phone. Android phone used for implementation of this objective has the following specifications: version: 10 (Android Q), brand name: Xiaomi, and model name: Note 7S. The smartphone has Qualcomm Snapdragon 660 (14 nm octa-core processor with clock speed upto 2.2GHz) and 4 GB RAM. It also has cameras with 48

MP +5MP AI dual in the rear end and 13 MP in the front end. Upon testing the application, the device did not lag or hang during its operation. The developed application can be install in any smart phone with Android version 7 (Nougat) or higher.

3.5.1.2 Hardware and software

The development of the android application involved different hardware and software components. The hardware was basically a HP laptop built with Intel Core i3 processor (x64-based processor with clock speed of 2.13GHz) and 3 GB installed RAM. Windows 10 was used as the operating system in the laptop and for android application developed, Android Studio Electric Eel. 2022.1.1 was installed. Java programming language was used to implement the algorithm associated with the flow of the application. In the application, not only it is possible to take images of tomato by the Smartphone camera but also images stored in the Smartphone memory can be used.

3.5.2 Methodology

In this objective an application was built for on-site assessment of quality and shelf-life of tomato. The app is built from four different CNN based models that is focused on assessment of quality attributes of tomato. However, it is very challenging to directly deploying Tensorflow based CNN models are then to a lesser computationally intensive model using TFLite for smooth functionality. The built app can function by taking images on site or by uploading images stored in the Smartphone. After taking/calling the image, the images are resized to 100 × 100 as the models are trained on image size 100 × 100. Then, the color components R, G, and B of each of the image pixels is normalized between 0 and 1. The normalized image is then given as input to the respective deep learning models for classification. The detected parameters of the image are then used to generate the final output. The application consists of six activity windows which includes the main screen, menu, spoilage detection, maturity detection, physico-chemical properties detection and storage-time indication. The application also includes six Java classes corresponding to each activity window. After the development of the application, its performance in predicting spoilage, maturity class, physico-chemical properties and shelf-life of tomatoes was evaluated. This evaluation was done on a random lot of tomato samples and experimentally determining its quality attributes to compare with the app's inference.

3.5.2.1 Model selection

The CNN models developed from the previous three objectives for quality inference were considered for building the app. Models were selected based on the performance of classification.

3.5.2.2 Model deployment

The models showing promising results with high accuracy in classification were selected. The selected models were then deployed in an android application for quality inferences of tomatoes from its surface characteristics with image input. The selected TensorFlow based CNN models are converted to TFLite for smooth execution of the app. TensorFlow Lite (TFLite) is a collection of tools to convert and optimize TensorFlow models to run on mobile and edge devices.

3.5.2.3 Android Application development

The android application is developed in order to explore to applicability of the deep learning models in hand-held devices with camera facility such as smart phones, etc. Smart phones are portable and can fulfill the needs of real-time monitoring (Pongnumkul et al., 2015). Further, smart phones are becoming into mini-computers that can help with difficult tasks like sample detection and data processing, with the emergence of user-friendly operating systems, apps, high-quality cameras, cloud computing, and many other features (Ma et al., 2022). Developments in android phone digital cameras have assisted in capturing images to provide real-time input to the models. The build application can capture image from the onboard camera or load image from the directory. The image was then preprocessed automatically to meet the input requirements of the model and then used for inference. The inference mechanism employed in this application is depicted using the flow diagram shown in Fig. 3.11.

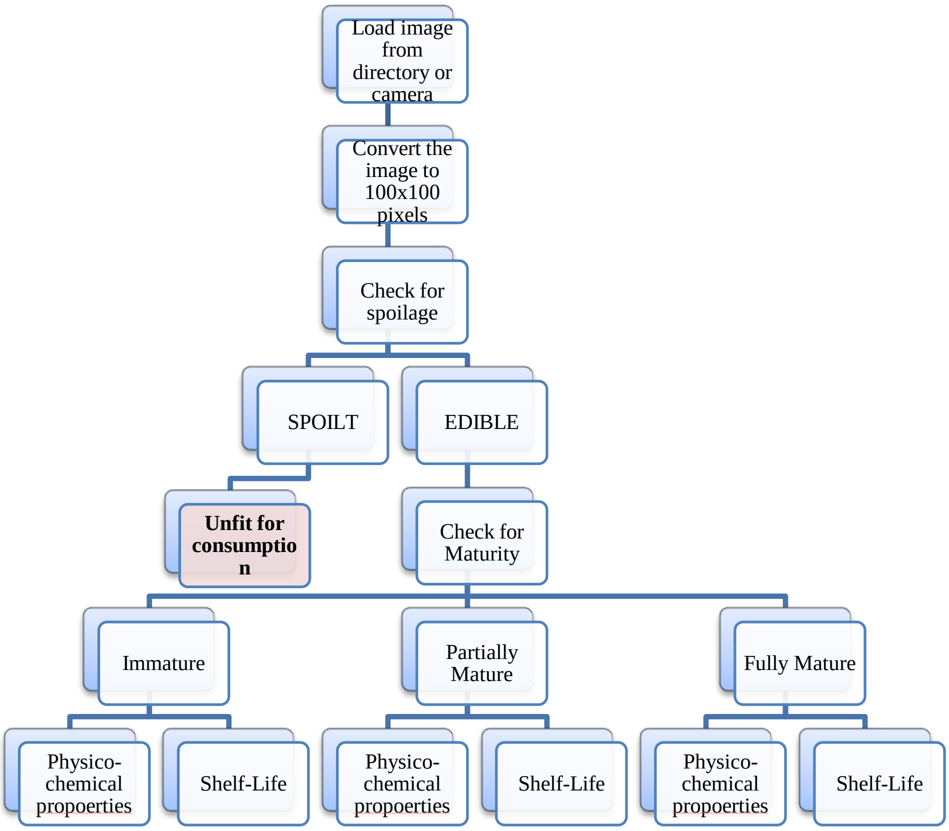

Fig. 3.11 Flow diagram of the android application

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 made in such a way that the TFLite model receives an input image for classification, and the model's output is shown in the application's interface along with option to read the result.

3.5.2.4 Performance evaluation of the developed app

The app's performance for real time assessment of tomato quality was evaluated using Pearsons' correlation and calculating error percentage. Pearsons' correlation was established using the predicted results of the app and the on-spot sensory analysis result. Also error percentage was calculated between the predicted values and experimental values in case of physico-chemical properties. Performance evaluation of the app was conducted on a random sample of tomatoes. 40 tomatoes were randomly purchased from a local vendor irrespective of variety and maturity stage. The samples were then made ready for the experiment in laboratory condition. The experiment was divided into three segments- (a) At first 20 samples were analyzed for spoilage detection and maturity classification by a group of 20 semi-trained panelists. (b) Secondly physico-chemical analysis was performed on the same lot of tomatoes to access for color (L*, a* and b*), firmness, TSS, TA, pH and lycopene content. (c) Thirdly remaining 20 samples were kept at 5ºC, 185ºC and 275ºC for shelf-life analysis. For part (a) the results obtained were then compared to the inference made by the app using Pearsons' correlation. For part (b) the results obtained were then compared to the inference made by the app by calculation percentage error in prediction. For part (c) the results obtained were then compared to the inference made by the app using Pearsons' correlation.

3.6 References of Chapter-III

Adegoroye, A. S., Jolliffe, P. A., & Tung, M. A. (1989). Textural characteristics of tomato fruits (Lycopersicon esculentum) affected by suns. *Journal of the Science of Food and Agriculture*, 49, 95–102. https://doi.org/10.1002/jsfa.2740490110

Ali, L., Alnajjar, F., Jassmi, H. A., Gocho, M., Khan, W., & Serhani, M. A. (2021). Performance Evaluation of Deep CNN-Based Crack Detection and Localization Techniques for Concrete Structures. *Sensors, 21*(5), 1688. https://doi.org/10.3390/s21051688

Bangar, S. (2022, June 29). VGG-Net Architecture Explained - Siddhesh Bangar - Medium. *Medium*. https://medium.com/@siddheshb008/vgg-net-architecture-explained-71179310050f

Batu, A. (1998). Some factors affecting on determination and measurement of tomato firmness. *Turkish Journal of Agriculture and Forestry*, *22*(4), 411–418.

Batu, A., & Thompson, A. K. (1993). Effects of cross-head speed and probe diameter on instrumental measurement of tomatoes firmness. In *Proceedings of the International Conference for Agricultural Machinery and Process Engineering*, pp. 1340–1345.

Begum, N, & Hazarika, M. K. (2022). Maturity detection of tomatoes using transfer learning. *Measurement: Food,* 7, Article 100038.

https://doi.org/10.1016/j.meafoo.2022.100038

Cai, L., Wang, Z., Kulathinai, R., Kumar, S., & Ji, S. (2014). Deep Low-Shot Learning for Biological Image Classification and Visualization from Limited Training Samples. *arXiv preprint arXiv:2010.10050*. https://doi.org /10.48550/ arXiv.2010.10050

Constantino, L. V., Rossetto, L. M., Benassi, M. T., Oliveira, C., Zeffa, D. M., Koltun, A., Resende, J.T.V., & Gonçalves, L. S. A. (2021). Physico-biochemical characterization of mini-tomatoes and internal preference mapping based on consumer acceptance. Scientia Horticulturae, 282, 110034.

Davis, A. R., Fish, W. W., & Perkins-Veazie, P. (2003). A rapid spectrophotometric method for analyzing lycopene content in tomato and tomato products. *Postharvest Biology and Technology 28*,425–430. https://doi.org/10.1016/S0925-5214(02)00203-X

Vrbančič, G., & Podgorelec, V. (2020). Transfer learning with adaptive fine-tuning. *IEEE Access, 8*, 196197-196211. http://dx.doi.org/10.1109/ACCESS.2020.3034343

Ghosh, A. (2009). Identification of microorganisms responsible for spoilage of tomato (Lycopersicon esculentum) fruit. *Journal of Phytology, 1*(6), 414–416.

Guzmán, M., Sánchez, A., Salas, M. C., Del Moral, F., & Valenzuela, J. L. (2010). Relationship between pectin-methyl esterase activity and softening in 'Raf' tomato fruit. *Acta Horticulturae, 934*, 1291-1296. https://doi.org/10.17660/ActaHortic.2012.934.175

Huang, Y., Lu, R., Chen, K. (2018). Prediction of firmness parameters of tomatoes by portable visible and near-infrared spectroscopy. *Journal of Food Engineering, 222*, 185–198. https://doi.org/10.1016/j.jfoodeng.2017.11.030

O'Donoghue, J., & Roantree, M. (2015). A framework for selecting deep learning hyper-parameters. In *British International Conference on Databases*, pp. 120–132. http://dx.doi.org/10.1007/978-3-319-20424-6_12

Jois, S. N., Roohie, K., D'Souza, L., Suma, F., Devaki, C. S., Urooj, A., Krell, R., & Prasad, K. N. (2016). Physico-chemical qualities of tomato fruits as influenced by pranic treatment-an ancient technique for enhanced crop development. *Indian Journal of Science and Technology, 9*(46), 1-6. https://dx.doi.org/10.17485/ijst/2016/v9i46/99733

He, K., Zhang, X., Ren, S., Sun, J. (2016). Deep residual learning for image recognition. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770–778. https://doi.org/10.1109/CVPR.2016.90

Khalid, S., Hassan, S. A., Javaid, H., Zahid, M., Naeem, M., Bhat, Z. F., Abdi, G., & Aadil, R. M. (2024). Factors responsible for spoilage, drawbacks of conventional packaging, and advanced packaging systems for tomatoes. *Journal of Agriculture and Food Research*, *15*, Article 100962. https://doi.org/10.1016/j.jafr.2023.100962

Li, F., Yan, L., Wang, Y., Shi, J., Chen, H., Zhang, X., Jiang, M., Wu, Z., & Zhou, K. (2020). Deep learning-based automated detection of glaucomatous optic neuropathy on color fundus photographs. *Graefe's Archive for Clinical and Experimental Ophthalmology*, *258*, 851–867. https://doi.org/10.1007/s00417-020-04609-8

Ma, T., Wang, H., Wei, M., Lan, T., Wang, J., Bao, S., Quain, G., Fang, Y., & Sun, X. (2022). Application of 237 smart-phone use in rapid food detection, food traceability systems, and personalized diet guidance, 238 making our diet more health. *Food Research International*, *152*, Article 110918. https://doi.org/10.1016/j.foodres.2021.110918

Magwaza, L. S., & Opara, U. L. (2015). Analytical methods for determination of sugars and sweetness of horticultural products—A review. *Scientia Horticulturae*, 184, 179-192. https://doi.org/10.1016/j.scienta.2015.01.001

Pongnumkul, S., Chaovalit, P., & Surasvadi, N. (2015). Applications of smartphone-based sensors in 243 agriculture: A systematic review of research. *Journal of Sensors*, *2015*, Article 195308. https://doi.org/10.1155/2015/195308

Poojary, R., Raina, R., Mondal, A. K. (2021). Effect of data-augmentation on fine-tuned CNN model performance. *IAES International Journal of Artificial Intelligence*, *10*(1), 84-92. http://doi.org/10.11591/ijai.v10.i1.pp84-92

Raiola, A., Rigano, M. M., Calafiore, R., Frusciante, L., & Barone, A. (2014). Enhancing the health-promoting effects of tomato fruit for biofortified food. *Mediators of inflammation*, *2014*, Article 139873. https://doi.org/10.1155/2014/139873

Ranatunga, C. L., Jayaweera, H. H., & Ariyaratne, T. R. (2008). Evaluation of fingerfeel firmness as a subjective measurement of tomato quality degradation in the retail market. *Topical Agricultural Research*, *20*, 134-142. http://www.pgia.pdn.ac.lk/files/Annual_congress/journel/v20/13_Ranatunga.pdf

Ranganna, S. (1995). *Hand book of analysis and quality control for fruits and vegetables.* Tata Mc Graw Hill.

Ranganna, S. (1986). *Handbook of analysis and quality control for fruit and vegetable products*. Tata McGraw-Hill Education.

Saad, A. G., Jaiswal, P., & Jha, S. N. (2014). Non-destructive quality evaluation of intact tomato using VIS-NIR spectroscopy. *International Journal of Advanced Research*, *2*(12), 632–639.

Shehata, S. A., Abdelrahman, S. Z., Megahed, M. M., Abdeldaym, E. A., El-Mogy, M. M., & Abdelgawad, K. F. (2021). Extending shelf life and maintaining quality of tomato fruit by calcium chloride, hydrogen peroxide, chitosan, and ozonated water. *Horticulturae*, *7*(9), Article 309. https://doi.org/10.3390/horticulturae7090309

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for largescale image recognition. *arXiv preprint arXiv:1409.1556*. https://doi.org/10.48550/arXiv.1409.1556

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2818–2826.