Development of an image-based android application for quality inference of tomato

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Abstract: The objective of this study is to develop a real-time quality evaluation toolfor quality inference of tomato from image input. Recent advancements in deep learning tools such as Tensorflow Lite, have assisted in building a light weight real-time android-based application for tomato quality inference. Availability of smart phones and its developmental prospects can meet the growing concern of consumers for quality foods from image. Deep learning has significant potential on image identification and hence an image-based application is thus opted. This work is an effort to develop an image-based artificial intelligence (AI) tool for quality inference of tomatoes. To execute the task of application development, an extensive study on the quality attributes of tomato is done and different state-of-the-art Convolutional Neural Network (CNN) models are trained on tomato images for quality prediction. The proposed CNN models after being trained on tomato image dataset are then deployed in an android application for the following quality inferences: (a) prediction of current state of tomatoes as edible or spoilt, immature or partially mature, or fully mature (b) prediction of physico-chemical properties and (c) shelf-life estimation. Experimental results indicate high classification accuracy of 99% and 97% respectively for spoilage detection and maturity detection respectively from tomato images. In addition to the high recognition rate, the TFLite models in android application consumes very less computation time and is able to make prediction in real-time (<0.67 sec).Thus, this application can be considered as a viable solution in tomato quality inference.

Keywords: Tomato; quality; app development

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1 Introduction

Quality is the utmost concern of consumers when it comes to health and well-being. Consumers often tend for foods that are healthy and safe.Quality can be based on various parameters such as the current state of food product, its physico-chemical composition and most importantly its shelf-life (Galanakis, 2019). Quality inspection during production, storage and processing becomes tedious if done manually. With the evolution of AI tools these challenges can be overcomed. Deep learning models such as CNN has outperformed various traditional machine learning models based on manual feature extraction. It overcomes the tedious task of manual feature extraction from image(Mohanty et al., 2022). Hence, in this work, CNNs are used to develop models to accomplish the objective of food quality inference. Additionally, mobile phones have reached every nook and corner of India making everything easy and accessible. In order to accomplish the objective of this study, an image-based application is developed keeping in view the needs of farmers and industrialist.

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The major contributions of this work are investigation of quality indicators of tomato and develop CNN models. The models are deployed to an android based application for mobile devices. Deploying these CNN models on smart phones is beneficial in making them accessible to everyone especially those dealing with tomato production, processing and storage. This work thus aims to automate the quality inference of tomatoes based on its surface characteristics. While developing the application the quality aspects taken into consideration are-its current state, its physico-chemical properties and its shelf-life. The physical properties-color and firmness and biochemical properties-Total Soluble Solids (TSS), Titratable Acidity (TA), pH, lycopene content, weight loss during tomato ripening are mainly considered to correlate with its respective tomato maturity stage. This study begins with accomplishment of first objective to predict the current state of tomato as edible or spoilt, and maturity stage as; immature, partially mature and fully mature. The experiment begins with preparation of dataset. Spoilage dataset is prepared based on the USDA defect detection standard whereas maturity class classification is done based on USDA color classification standards. To assist this, sensory evaluation was performed to identify consumer's perception on the same tomato. Following the second objective, an effort has been made to predict the physico-chemical properties of a given tomato. To accomplish this objective physico-chemical properties of tomatoes are mapped against its respective image and thus a model is developed. Finally the third objective is accomplished by studying the degradation kinetics of tomatoes stored under different temperature condition and then kinetic models are developed for shelf-life estimation. The estimated results are then trained in a deep transfer learning model to predict the shelf-life of tomatoes. The obtained models were then deployed into an android application that can estimate the quality of tomato and its shelf-life as presented in Figure 1.

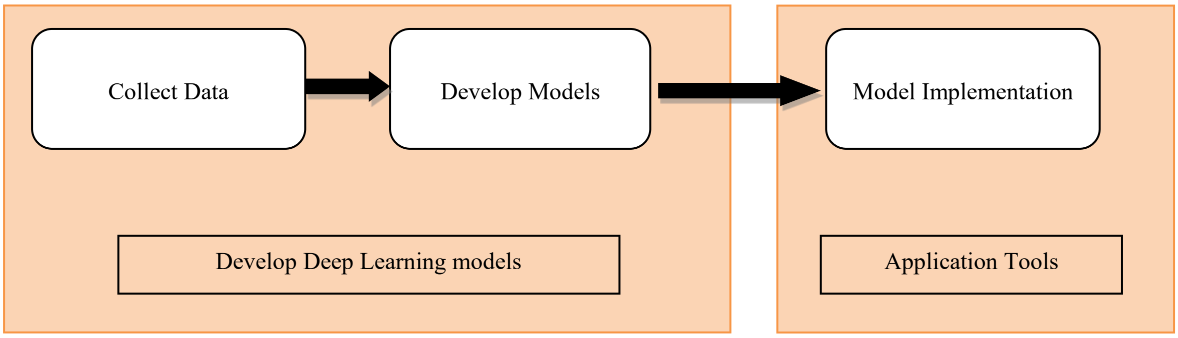


Figure 1 The graphical representation of model implementation

The major contributions of the presented work are as follows:

(1) Develop CNN models to accomplish the target of application development;

(2) Datasets preparation for training the CNN architectures;

(3) Extensive experiments with the customized CNN model and transfer learning models-VGG, inception and ResNet to assess the effectiveness of the model in capturing relevant features for accurate maturity stage classification and to compare their performance against each other.

(4) The developed CNN models are then deployed in the mobile application.

A Real-time android-based tomato quality inference application is developed.

To date very few comprehensive studies have been conducted on smart phone based application development to evaluate the quality of tomato from image input. Sherafati et al.(2022) in their work developed an android based application namely '*TomatoScan*' for determination of tomato quality indices as well as its maturity estimation. Quality indices includes L^*, a^*, elasticity, total chlorophyll, carotenoid, lycopene, TA and TSS.The application successfully estimated the maturity stage of tomatoes with overall accuracy of 75.00%. Ye et al.(2018) in their work developed an android based application for lycopene content estimation of tomato. Additionally the app identifies the grade of tomatoes. Debnath et al.(2023) in their work deployed transfer learning models for tomato leaf disease detection in smart phones and online apps. Transfer learning model 'EfficientNetV2B2' identifies different illnesses in tomato with a classification accuracy of 100%. Tata et al.(2022) developed an application for classifying fruits according to their appearance as a quality parameter. Principal Component Analysis (PCA) and deep learning is used to achieve the classification task. Srivastava et al.(2014) developed a novel system for disease classification in tomatoes using Zigbee Module and different soft computing techniques with an accuracy of 92%.Tian et al.(2024) developed a model TF-YOLOv5s for detection of tomato flowers and fruits in natural environments. To achieve this, a C3Faster module is introduced to reduce the number of parameters and calculations while maintaining detection accuracy.

2 Materials and methods

Collection of tomatoes: The experiment started with collection of tomatoes (variety PUSA 120) from a local farmer of Tezpur (Assam). Tomatoes of uniform size and maturity were selected, washed, kept in laboratory condition of Tezpur University, Assam, India (Latitude: 26.7003° N, Longitude: 92.8308° E, Elevation: 80.89 m) and made ready for image acquisition and physico-chemical analysis.

Preparation of image dataset: The dataset of edible and spoilt tomatoes was prepared from the acquired images following the USDA defect detection standards as shown in Figure 2. Tomato images were taken during the whole process until the tomatoes get spoilt. During the experiment, the images were further randomly splitted into training and test sets in the ratio of 7:3 i.e. training set contains 70% images and test dataset contains 30% images. For classifying tomatoes into edible and spoilt, the dataset is trained in a customized CNN model.

Figure 2 Tomato dataset prepared for spoilage detection

Similarly, for classifying tomatoes into their maturity classes, dataset containing immature, partially mature and fully mature tomatoes were prepared from the acquired images as shown in Figure 3. The prepared dataset is then trained in pre-trained transfer learning models-Inception V3, VGG 16, VGG 19, ResNet 101 and ResNet 152. The model giving the highest classification efficiency was then considered for maturity class detection of tomatoes.

CNN model for spoilage detection: The architecture of the customized CNN to classify the tomato images into edible and spoilt is shown in Figure 4. The architecture consists of three 2-D convolutional layers with a kernel size of 3×3 for spatial feature extraction. Further, each convolution layer used rectified linear activation function (ReLU). The use of 3×3 kernel and ReLU activation in this work is inspired by various models in the field of computer vision. The feature maps for the three 2D convolutional layer is set to 32,64, and 128 respectively. After each of the convolutional layers, there is a maxpool layer which uses a filter of size 2×2 and slides over the channels in the feature map and calculates the maximum, or largest of the features points in the region lying within the filter. After the last maxpooling layer, a dropout layer with 25% dropout rate is applied. After that, the output from the dropout layer is flattened to obtain a 1D feature vector. The 1D feature vector obtained is given as input to a dense layer having 256 neurons and ReLU activation function. A dropout layer with 40% dropout is also used to prevent the model from over fitting. Another dense layer having 256 neurons and ReLU activation function is again applied. Then again a dropout layer with 30% dropout is applied on the output of the dense layer. Finally, the output of the dropout layer is given as input to the last layer i.e., the output layer. In the output layer, a single neuron with sigmoid activation function is used to classifying the tomatoes images into two classes: edible and spoilt.

CNN model for maturity detection: The pre-trained transfer learning model,VGG19,showed superior performance over VGG16, InceptionV3, ResNet101 and ResNet 152on ImageNet for three class classification of tomatoes as reported in our previous study (Begum and Hazarika, 2022). Therefore, VGG 19 is considered for classification of tomatoes based on maturity classes. The VGG19 model has 19 deep layers out of which 16 layers are convolutional layers and 3 layers are fully-connected layers. The convolutional layers are used for feature extraction from image and the fully connected layers are used for classification. The model architecture of VGG 19 is shown in Begum and Hazarika (2022). The pre-trained VGG19 model provides an advantage of extracting features from smaller sized datasets in less time. The pre-trained VGG19 model is further augmented with a dense layer having 256 neurons and a output layer with three neurons and softmax activation for classification of three maturity stages: Immature, Partially mature, and Fully mature.

Figure 3 Tomato dataset prepared for maturity detection

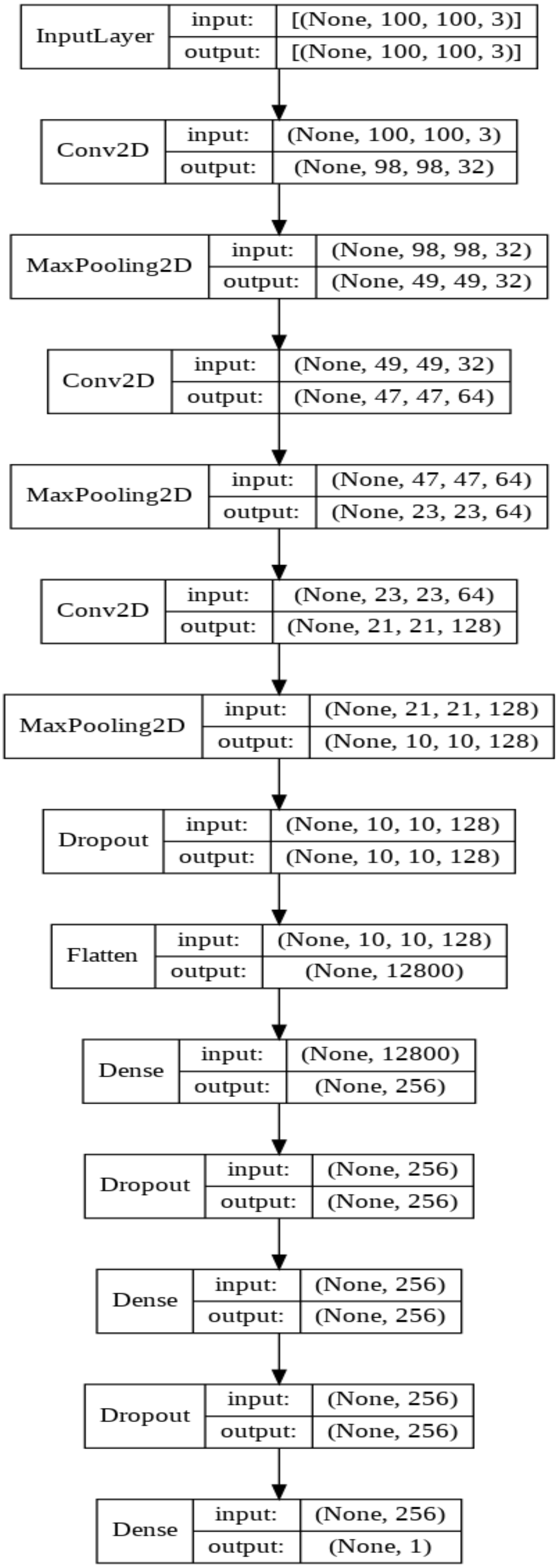


Figure 4 The proposed CNN architecture to classify edible and spoilt tomatoes

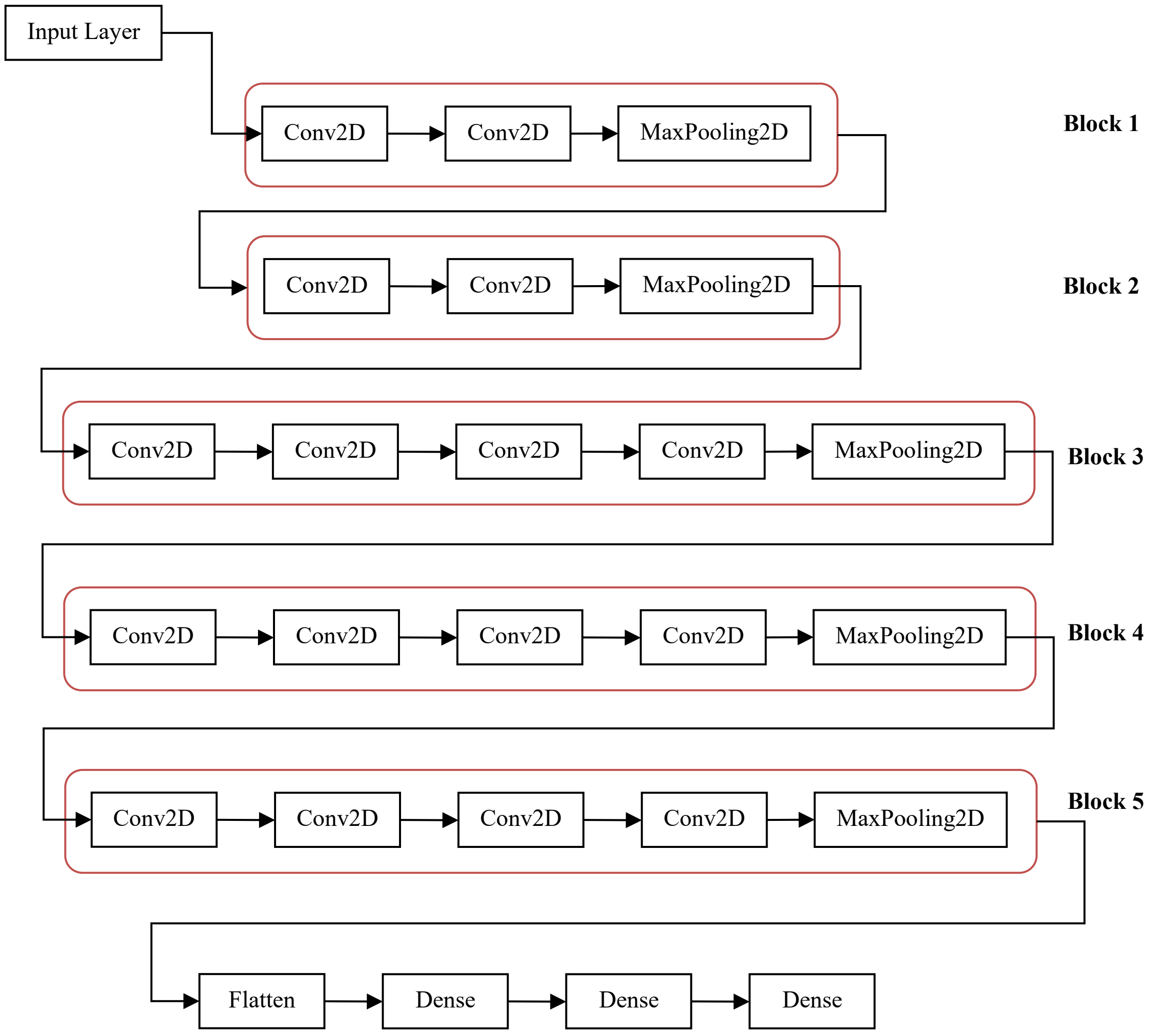


Figure 5 Layers in VGG19 architecture

In the similar way two different models were developed for prediction of physico-chemical properties as well as shelf-life of tomatoes from its surface characteristics.

Android application development: Smart phones have strong mobility and can meet real-time monitoring requirements (Pongnumkul et al., 2015). With the introduction of user-friendly operating systems, applications, high-quality cameras, cloud computing, and many more;smart phones are becoming more like micro-computers that can assist in performing complex functions, such as sample detection and data processing (Ma et al., 2022).Developments in android phone digital cameras have assisted in capturing images to provide real-time input to the models. However, it is very challenging to directly deploying Tensorflow based CNN models in less computationally intensive mobile devices. In this regard, Tensorflow provides a mechanism to convert a tensorflow model to a lesser computationally intensive model using TensorFlow Lite(TFLite). TFLite is a collection of tools to convert and optimize TensorFlow models to run on mobile and edge devices. The proposed pre-trained CNN models for quality inference in this work are converted to TFLite models using TFLite. These TFLite models are then used to build an android application for tomato quality inference. The build application can capture image from the onboard camera or load image from the directory. The image is then preprocessed 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 Figure 6.

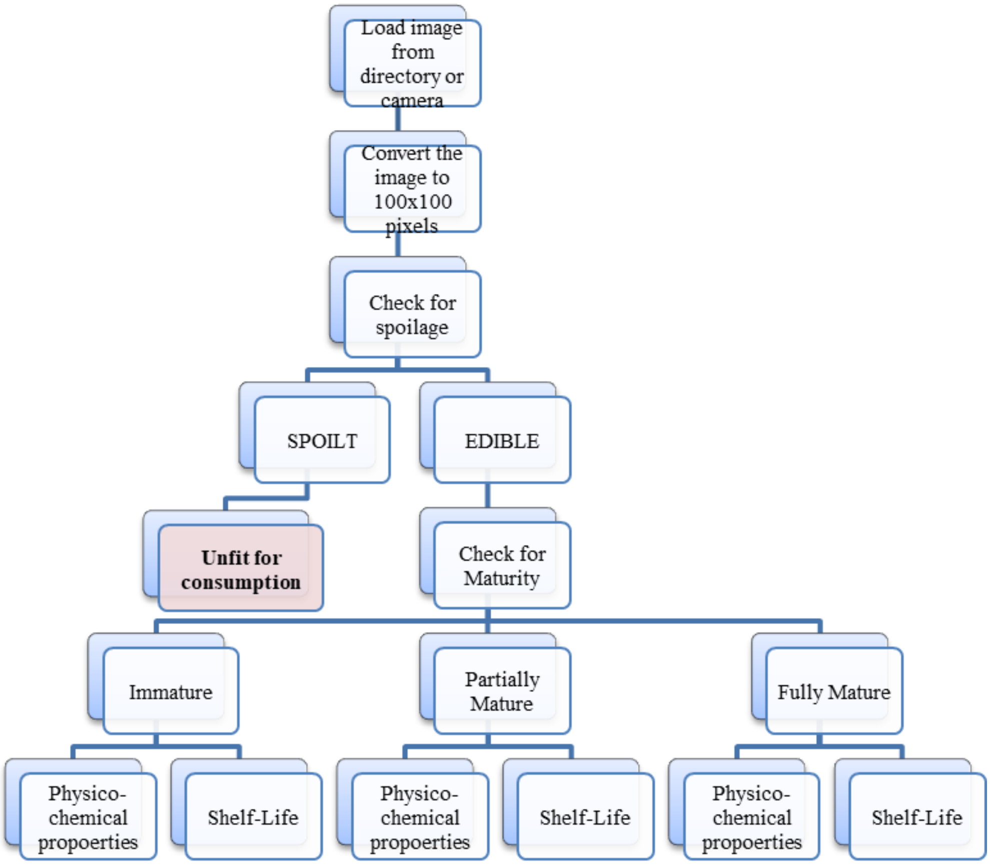
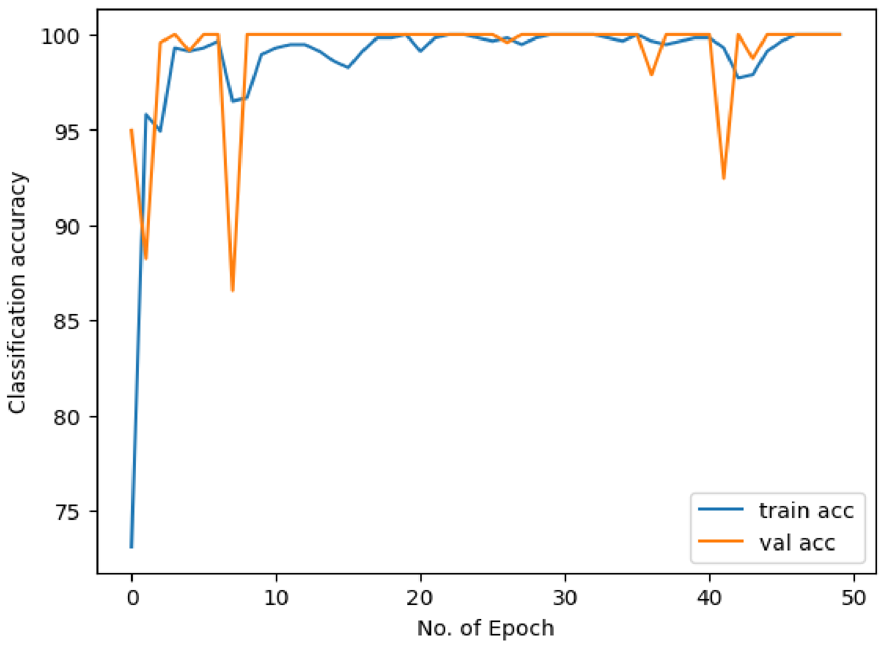
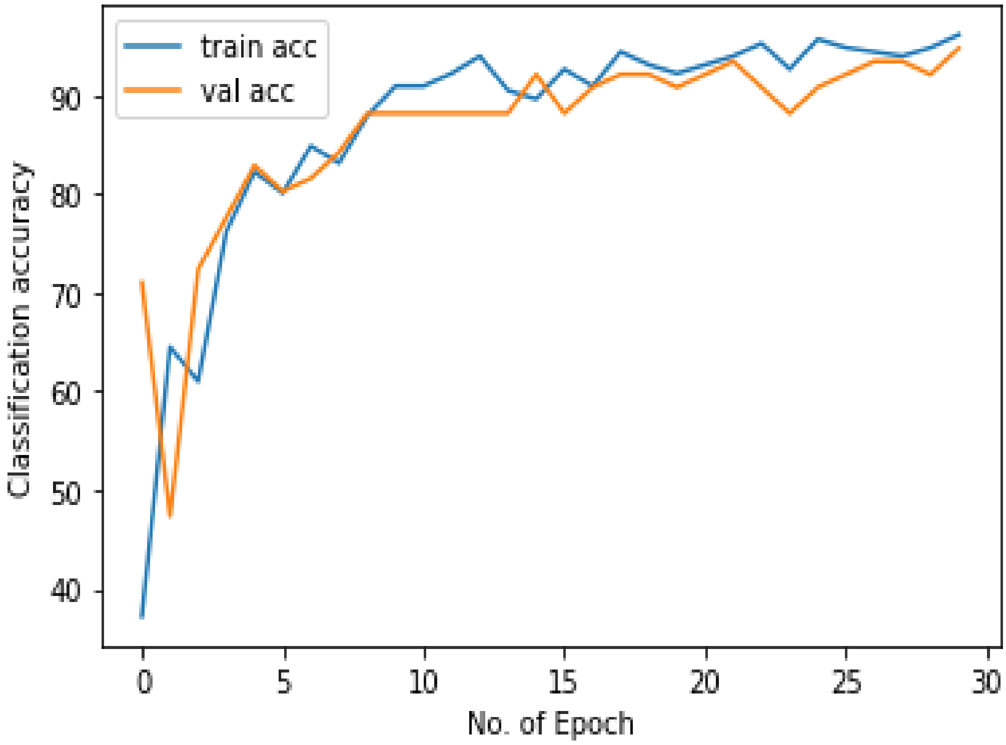


Figure 6 Flow diagram of the android application

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 immature, partially mature and fully mature. 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.

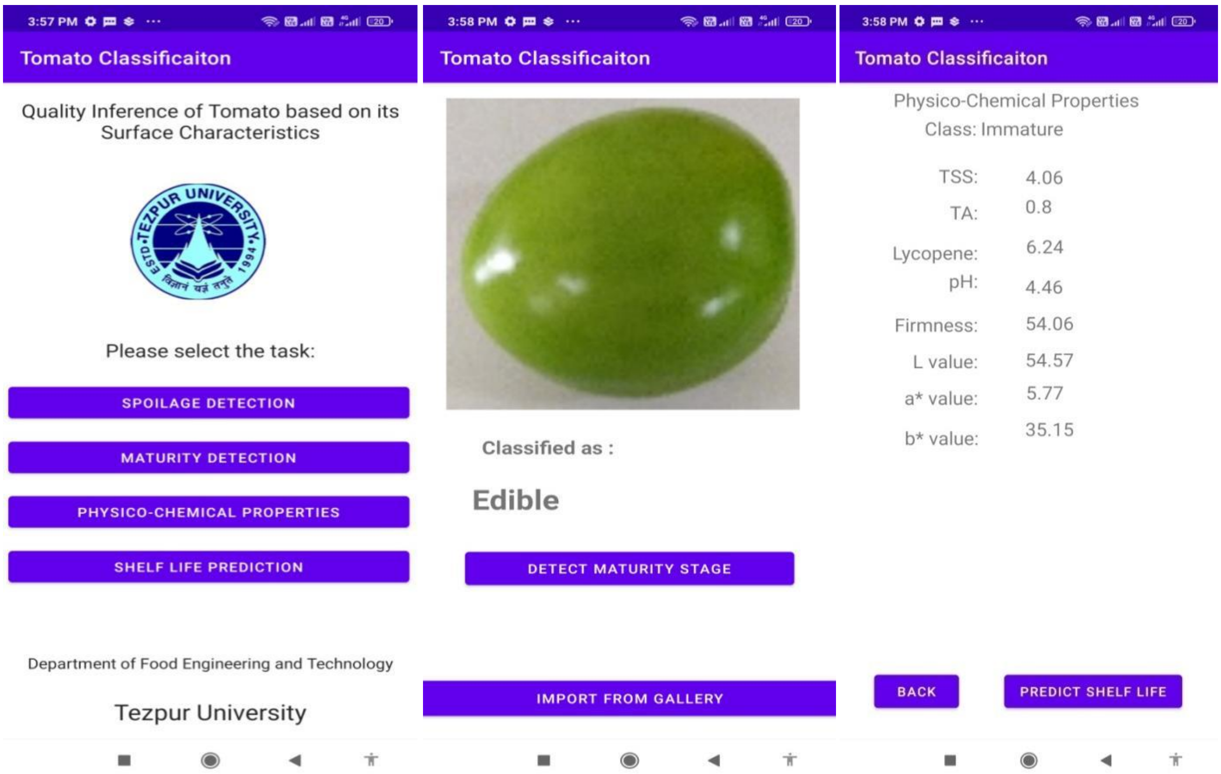


(a) Training and validation accuracy of customized CNN model



(b) Training and validation accuracy of VGG 19 model

Figure 7 **Training and validation accuracy of the models implemented for app development**



(a) Initial interface of the application, (b) Spoilage detection interface, and (c) Interface for display of physico-chemical properties

Figure 8 Performance of the developed app on test samples

3 Results and discussion

Performance of the CNN models: The training of the CNN model was carried out iteratively with varying epoch and batch sizes to evaluate its accuracy. Overall classification accuracy obtained was above 95% for epoch between 10 and 30 as well as batch size between 8 and 64. The highest classification accuracy of the CNN model was achieved at 20 epoch and 32 batch size. Thus, at the aforementioned hyper parameters, the architecture of the CNN model showed an accuracy of 99.70% as shown in Figure 7 (a)

Secondly, the pre-trained VGG 19 model was trained iteratively with varying epoch and batch sizes its accuracy was evaluated. The highest classification accuracy of the VGG model was 97.37% at 50 epoch and32 batch size as shown in Figure 7 (b).

Performance of application: 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 Figure 8 (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 Figure 8 (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 Conclusion

This work proposes a deep CNN-based android application to help tomato users to make an inference on its quality. The motivation behind this work is the ongoing digital revolution of India with the advent of Artificial Intelligence. Smart phones have almost reached every nook and corner of India and 5G also has already started rolling out. Smart phones have become an indispensable communication tool for interpersonal communication as well as rapid response to any problem. Future scope of this application is to integrate more vegetables and fruits in the existing application.

Conflict of interest

We declare that we have no conflict of interest.

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