Chapter-I

1 Introduction

1.1 Preamble

Food quality and food security have been contentious issues of human civilizations for ages. At present day world, with the increase in income and raise in education, quality has grabbed a wide position among the demographics. Quality is a broad term comprising of physical attributes as well as nutritional content involving grading of food products and sorting out of defected ones. Quality degradation prior to harvest and during storage is one of the greatest concerns for maximizing agricultural productivity. Evaluating the quality of a food product is tedious if manual (Meenu et al., 2021). In experience, fatigue, and inconsistency are factors that affect the process of sorting and grading of food products. It simply depends on labor efficiency, which is influenced by several physiological parameters. Recently, quite a lot of work has been done on rapid and non-destructive measurement of fruit and vegetable quality, using artificial intelligence techniques. Nondestructive sorting and grading using machine learning techniques helps in maintaining quality by minimizing food losses (Zhou et al., 2023). This technology is thus adopted in the field of food and agriculture to meet the demand for food which is an important agenda of Agriculture 4.0. Digitalization in agriculture is a smart solution in this regard, maximizing agricultural productivity from farm to fork. This has already been dubbed the "Digital Agricultural Revolution" (Trendov et al., 2019) by the United Nations Food and Agriculture Organization, which combines cutting-edge technology such as the Internet of Things (IoT), Big data, Artificial Intelligence (AI), and Cloud computing (Rose and Chilvers, 2018). Recent developments in the field of smart devices have made it possible to capture and handle large data from targeted sources using smart phones and AI. Meanwhile tomato is a perishable product which is in high demand and market value being dependent on quality. Tomato, while undergoing spoilage, entails drastic changes in colour, surface texture, flavor, etc. Also, tomatoes being sensitive are vulnerable to physical treatment, loads, vibrations etc., (Alsamir et al., 2021). An accurate, rapid and non-destructive spoilage detection technique will be very much helpful in this regard. Deep learning is one of the machine learning techniques that has been able to set Gold Standard in the artificial intelligence community by outperforming its predecessors (Alzubaidi et al., 2021). So, the present work focuses on nondestructive quality assessment of tomato using deep learning.

1.2 Inference of wholesomeness

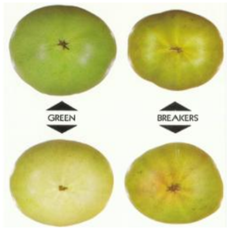
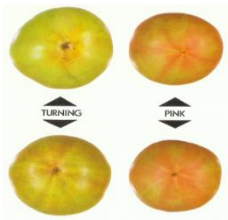
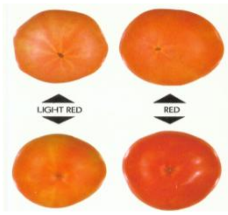
Inference is a conclusion that is drawn about some things by experiencing them first-hand and acquiring knowledge about it through learning. Quality inference can help minimize the food losses suffered pre and post-harvest (Delgado et al., 2021). These losses can occur at the farm level or after harvest, in supply chain, storage, handling and processing. Quality assessment by trained human investigators is performed by feeling and seeing (Bhargava and Bansal, 2021). Images are the most basic digital representation of what one feel and see (Furht, 2008). Image based quality inference is an emerging technique that provides authenticity and traceability in recognition and identification problems. This is achieved by extracting data and information from digital images subjected as input to a given technique. With the rapid growth of information science, computer vision-based image processing will be a viable solution to this data recognition problem. Due to its learning capability from data, deep learning is becoming most widespread in complex cognitive quality inference, matching or even beating those provided by human inference. Deep learning coupled with image processing can be an effective tool in this regard. This study is thus an attempt to predict the quality of tomato using the deep neural networks.

1.3 Standard based quality inference

According to the National Horticulture Database (Nhb, D. A. C., 2019), which was released by the National Horticulture Board in 2019–20, India is the world's second-largest producer of fruits and vegetables, including tomatoes. Because tomatoes are an excellent source of vitamins and minerals, especially lycopene (60–90 mg/kg), they play a significant role in human diets (Kaur et al., 2013). When it comes to the nutritional value of vegetables with high biological activity that is consumed by humans, it comes in at first place. The tomato is becoming more and more significant as the most affordable source of antioxidants due to its abundance in carotenoids, β-carotene, total polyphenol content, and ascorbic acid (Abera et al., 2020). But owing to its perishable nature it is very much prone to spoilage leading to huge loss in the production sector. The post-harvest losses are the highest in tomato (12.44%) followed by onion (8.2%) and potato

(7.32 %) (Tiwari et al., 2021). To minimize these losses continuous monitoring and evaluation of tomatoes is required right from harvest till processed. Spoilage may occur at any stage and in different forms during the life cycle of tomatoes. Spoilage may include cuts, bruises, and rotten spots as described by USDA defect standard. Thus, spoilage detection of tomatoes is an important quality activity for quality assurance. Accurately identifying the current state of tomatoes as edible or spoilt thus becomes necessary when it comes to quality inference. The presence of defects affects the price, making food look worse. Secondly, defect is an indicator to spoilt or infected foods (Da Costa et al., 2020). An automatic, rapid, non-destructive technique in this regard will prove to be very effective. The deep neural network models have the potential to overcome this challenge of spoilage detection. Secondly, maturity stages affect the quality of tomatoes. Identifying the congruous maturity stage is important to retain superior quality tomatoes. Tomatoes plucked at an early stage of maturation are subject to shriveling and mechanical damage creating poor flavor and taste despite lengthy shelf life. Again, tomatoes harvested at an advanced stage of maturity produce good taste and flavor but have short shelf life. Thus, the knowledge of the current maturity state becomes essential in decision making. Manual tracking the ripe tomatoes is time consuming as well as labor intensive. Artificial intelligence-based technologies can thus help users optimize the process of monitoring the maturity stage of tomatoes. To this end, a ripening stage prediction model is proposed that can detect mature green, intermediate and advanced tomatoes based on the USDA colour classification standards as shown in Table 1.1. In our study, the six USDA classes of tomatoes is sorted to three classes- mature green, intermediate and advanced based on their surface appearance (Table 1.1). This categorization is done following the research reported by Saad et al., (2016). Taking into consideration the above two factors; the first objective of this work is to identify the current state of tomato as- i. edible or spoilt and ii. mature green, intermediate and advanced. The quality of tomatoes is assessed in terms of its physico-chemical attributes and its shelf-life during processing and storage. Tomato colour and firmness are the most important quality attributes in context of consumers' acceptance. Lycopene and Total Soluble Solids (TSS) are mostly responsible for colour and flavour of tomato. Organic acids are utilized as substrate to respiration. Thus, colour, firmness, TSS, lycopene content, Titratable Acidity (TA) and pH are the most widely used indices for tomato quality assessment. However, estimation of this quality attributes manually is time consuming and involves use of chemicals. Machine learning technologies show outstanding performance in image recognition based on colour, texture and surface characteristics. Focusing on this if a model is developed that can predict the composition of a given tomato at any time from its surface characteristics, it would be beneficial to users. This can be achieved by mapping the physico-chemical properties of tomato with its surface characteristics, establish a relationship and thus develop a model. Image processing is a technique by which surface characteristics of a product can be captured and then can be related to its quality (Barbin et al., 2016). The second objective of this study is thus to predict the physico-chemical properties of tomato from its surface characteristics using deep learning. Thirdly, estimation of shelf-life of tomatoes becomes crucial to maintain its quality. The quality attributes pertaining to shelf-life of tomatoes include colour, firmness, TSS, TA, lycopene content, PME, PWL (Tsouvaltzis et al., 2023). The degradation kinetics of the mentioned quality attributes can be modeled and predicted for its shelf-life, selecting the appropriate order of kinetics i.e., zero, first and second. The reaction rate can be assessed using Arrhenius and Eyring model. Based on the values of activation energy, enthalpy and entropy, the most critical parameters are to be determined. The results obtained can be trained against the respective image and establish a deep learning model. To assist this, a deep learning based predictive model is developed to estimate the shelf-life of tomatoes, which is the third objective of this study. Combining all the three objectives, a robust deep learning-based quality estimation model of tomatoes is developed. As smart phones have reached every nook and corner of the country and most of our farmers are familiar with its use, to make the developed model handy and easily assessable, a smart phone-based application is developed. A smart phone-based application will work as a real-time quality inference for the users. The fourth and final objective of this study is smart phone-based application development for quality inference of tomato based on its surface characteristics.

Table 1.1 Ripening categories for tomatoes

<table>
<tr><th>USDA classification category (Ripening Stage)</th><th>USDA description</th><th>Representative images from USDA unofficial Tomato Visual Aid</th><th>Class</th></tr>
<tr><td>Mature Green</td><td>“Entirely light-to dark-green, but mature”</td><td rowspan="2">
</td><td rowspan="2">Mature green</td></tr>
<tr><td>Breaker</td><td>“First appearance of external pink, red or greenish-yellow; not more than 10%”</td></tr>
<tr><td>Turning</td><td>“Over 10%, but not more than 30% red, pink or orange-yellow”</td><td rowspan="2">
</td><td rowspan="2">Intermediate</td></tr>
<tr><td>Pink</td><td>“Over 30%, but not more than 60% pinkish or red”</td></tr>
<tr><td>Light Red</td><td>“Over 60%, but not more than 90% red”</td><td rowspan="2">
</td><td rowspan="2">Advanced</td></tr>
<tr><td>Red</td><td>“Over 90% red, desirable table ripeness”</td></tr>
</table>

1.4 AI in quality inference

Artificial intelligence (AI) is making machines intelligent in order to automate decision making and operation. Intelligence in machines are stimulated by adequate training with algorithms to mimic the human brain in information processing and making decisions, and thereby, making the machines capable of carrying out tasks similar to the human brain as shown in Fig. 1.1. Machine learning (ML), subset of AI uses algorithms to learn input data predicting patterns, while making decisions. Hence, ML-based AI is gaining more acceptability in handling the complex problems of agri-food systems. DL, being subset of ML uses neural network to learn from large data and automatically extract features out of it. The emergence of deep learning technology has led to the development of many models for automatic image recognition for quality evaluation purposes finding applicability in this study.

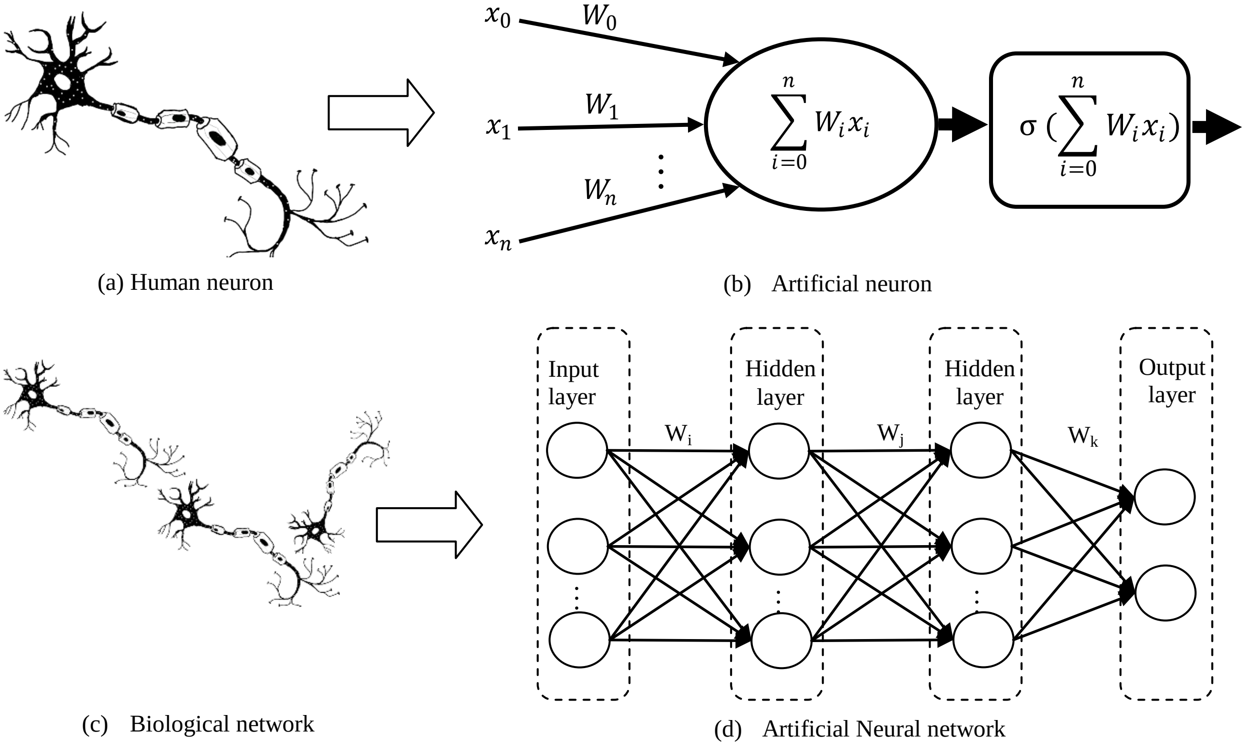


Fig. 1.1 Biological neuron inspired artificial neural network

A CNN is a typical representative of deep learning that is powerful in image processing. CNNs are designed to learn and extract features within an image (O'Shea and Nash, 2015). CNN architectures are hierarchical comprising of set of layers as shown in Fig. **1.2**. The input layer is followed by convolutional layers, pooling layer and fully connected (Fig. **1.2**). In the CNN architecture, convolutional layers and pooling layers are responsible for extracting hidden characteristics out of image pixels while the fully connected layer is responsible for classification (Nag et al., 2023). Numerous research findings have demonstrated that a CNN is capable of automated feature extraction and high recognition performance in addition to its great learning capacity.

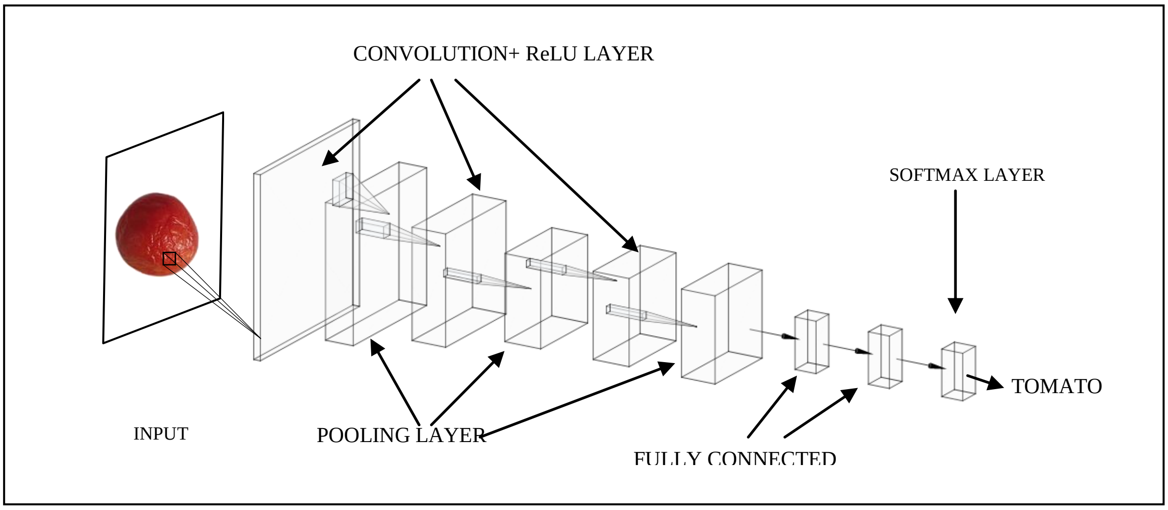


Fig. 1.2 Deep Learning Architecture

Performance of Deep learning architecture is typically dependent on -

Dataset: Dataset is a collection of data in the form of images, texts, audio, videos, etc. stored in a digital format. Building a data-driven model for classification requires a lot of data (LeCun et al., 2015).

Architecture: A deep learning architecture often consists of convolutional layer, pooling layer, normalization layer, regularization layer. The number of layers in a deep learning model depends on the data and the task being performed.

Hyper-parameters: Both parameters and hyper-parameters are present in deep learning architecture. Hyper-parameters are variables that aid in fine-tuning the precise model, whereas parameters are variables that are part of the model itself. Hyper-parameters are usually established prior to training, and model parameters are learnt during training. Hyper-parameters control a model's learning process, its capacity to learn new things, and its out-of-sample performance. The performance of machine learning models on unseen, out-of-sample data is significantly influenced by hyper-parameters. Determining a model's optimal selection of hyper-parameters has a significant impact on performance findings. Some of parameters and hyper-parameters during training CNN architecture are:

Weights: In deep learning, weights are learnable parameters that represent the strength of connections between neurons. Weights are analogous to synapses in biological neural networks as shown in Fig. 1.1.

Bias: Bias in deep learning is the difference between the expected and predicted values, or the error that occurs due to a model's assumptions.

Epoch: One epoch is when an entire dataset is passed forward and backward through the neural network only once. However, we split "one epoch" into many smaller batches because it is too large to provide to the computer all at once.

Batch size: The total quantity of training samples in a given batch.

Iteration: The number of batches required to finish an epoch is known as iterations.

Gradient Descent: In machine learning, the optimal outcomes (minima of a curve) are found by an iterative optimization procedure. The learning rate, cost function, and loss function are the hyper-parameters of the gradient descent. In machine learning, a cost function is a technique that yields the inaccuracy of the complete training example's expected and actual outcomes. In contrast, the mistakes made by the model on the entire training batch are used to calculate the loss function in DL. The number of steps the model takes during gradient descent—the method used to reduce the loss function—is known as the learning rate.

Hardware: During training a model on datasets, intensive computer processes undergo and to perform more computations in lesser time GPU is preferred over CPU. Compared to traditional machine learning, DL involving intensive algorithms is run on GPU-assisted high-performance computers (Coelho et al., 2017).

Feature Engineering: Feature engineering involves extracting features from raw data. Here comes the advantage of DL over other ML techniques, extraction of high-level features from the raw data is done by the model itself (Deng and Yu, 2014). As a result, DL reduces the time and work needed to build a feature extractor for every issue.

1.5 Applicability of deep learning models in quality inference

Deep learning approaches have been implemented in a wide range of quality evaluation problems such as- classification of dates (Albarrak et al., 2022), detect and classify spoilage in mangoes (Pugazhendi et al., 2023), quality evaluation of apples (Li et al., 2021), real-time pineapple quality evaluation (Huang et al., 2022) and so on. The architectures developed can be used as a tool in solving real life problems in food and agriculture. These models can further be deployed in android phones for on-site image acquisition and quality inference. In contrast, transfer learning is a two-phase method of training DL models that includes pre-training and fine-tuning phases where the model is taught on the intended task. These architectures are such that the weights of the layers are pre-trained on standard image datasets. The pre-trained models are used as feature extractors. The extracted feature out of these models 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. AlexNet, LeNet, VGG, Inception, Resnet etc are some of the popular pre-existing CNN architectures that are trained on more than a million images from the ImageNet database. Since, deep transfer learning attempts to reduce training of models on extensive training data (Nag et al., 2023), decreasing training costs and time and high recognition accuracy (Zhu et al., 2019), it has motivated many researchers to deploy transfer learning in solving problems related to food and agriculture like- surface defect detection of fresh-cut cauliflowers (Li et al., 2022), real-time strawberry detection (Zhang et al., 2022), classification of mango varieties (Ratha et al., 2024) and so on.

1.6 Motivation

Quality evaluation of agricultural products in minimizing food losses is an important agenda of agriculture 4.0. It has become very essential to identify the state of a product to make decision in maintaining quality. At the same time, a tool that indicates its physico-chemical properties as well as its shelf-life based on its surface characteristics will be more beneficial. Deep learning can assess tomato quality automatically and non-destructively with high accuracy. Moreover, transfer learning relaxes the tedious task of handling large data and development of model from scratch.

1.7 Research gap

Food and agriculture are lagging behind to a greater extent when it comes to digitalization. Development of techniques for quality evaluation of wholesome food using digitalized computer-based models is very less done. Moreover, non-destructive techniques that are mostly used for quality assessment are hyper-spectral imaging, NIR, X-ray imaging, NMR imaging. Deep-learning based image processing solutions are very less implemented for estimation of internal quality attributes as well as for determination of shelf-life.

1.8 Objectives

As discussed above, the focus of this work is inference and prediction of quality of tomato using deep learning. To achieve this, the following objectives are accomplished:

Objective 1: To apply deep learning-based image processing technique for classifying tomato with physiological attribute-based validation

Objective 2: To map the pixel-level colour values with physico-chemical properties of tomato using a multi-class classification model

Objective 3: To develop image processing based multi-class classifier for estimating the shelf-life of tomato

Objective 4: To deploy the developed model as application tool for non-destructive on-site assessment of quality and shelf-life of tomato

1.9 Justification

1. Deep learning-based models have outperformed in the AI community in classification and regression problems, proving it to be a promising tool in quality assessment.
2. Transfer learning relaxes the tedious task of data collection and model development.
3. A tool that indicates its physico-chemical properties as well as its shelf-life from image input will be very beneficial to industries and researchers.
4. The developed mobile application is automatic, fast and cost-effective with high recognition accuracy.

1.10 Summary of chapter I and arrangement of the thesis

This chapter gives an introductory view on non-destructive quality assessment of food in minimizing food waste in support of Agriculture 4.0. On a digitalization front, the advantages of machine learning with emphasis on deep learning have been highlighted. Tomato classification standards and its assessment in the food supply in setting the objectives of this study are discussed. In the later part of this chapter deep learning is discussed in an elementary manner.

The thesis is divided into five chapters. Taking into account the objectives of the study, the chapters have been divided into several sections, as shown below:

Chapter I (Introduction): This chapter presents an introduction on the topic of this study, its problems and setting out the objectives. Tomato being the focused commodity is discussed in context of its quality evaluation. Also, the motivation behind the application of deep learning in quality evaluation of tomato is highlighted in this chapter. Lastly deep learning is discussed in detail citing few examples.

Chapter II (Review of literature): This chapter presents a concise literature review that enhances our understanding on the applications of machine learning emphasizing more on deep learning for quality assessment in Food and Agriculture. The methodologies adopted in classification along with the classification accuracies achieved are also reported.

Chapter III (Material and Methods): This chapter gives a detailed description of all the materials and methods used and implemented to fulfill all the objectives of this study.

Chapter IV (Results and Discussions): This chapter is the detailed discussion on the observation and output obtained from following the methodologies mentioned in chapter 3. The chapter is divided into 5 subheadings of the 4 objectives.

Chapter V (Summary and Conclusions): This chapter summarizes all the works and findings of the proposed methods with respect to the objectives of the thesis. It puts forward the potential outcome of the proposed methods to carry out our research on prediction of quality of tomato using deep learning.

1.11 References of chapter I

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