Chapter-II

2 Review of literature

This section includes a concise literature review on machine learning and its application in quality evaluation of agricultural produces. This review presents how machine learning coupled with non-destructive techniques has fueled automatic quality evaluation. Machine learning emphasizing more on deep learning for quality assessment is discussed thoroughly that enhances our understanding in deriving our targeted objectives.

2.1 Non-destructive quality assessment of agricultural produce

Food quality and safety is of upmost concern when it comes to health and well-being. Production of high quality safe agro-food has become a challenge in coming years. Food quality includes all the attributes like shape, size, color, texture, flavor including its nutritional content. It must meet the consumer's demand. Secondly, food safety refers to all of the risks that cause food to be harmful to human health. Safe food must be free of toxic components which are threatening to health of consumers (Fung et al., 2018). Non-destructive techniques are in favor of minimizing food waste. It helps pertain food quality and safety. Non-destructive techniques allow analysis of a product without causing much damage to it and reducing wastage. Thus, it excels the traditional technique of detection and assessment of components in food. The usefulness of non-destructive techniques comes from the fact that it allows simultaneous assessment of chemical as well as physical properties of food without the food being destroyed. Machine learning (ML) on the other hand gives the computing machines the ability to learn patterns in data without being explicitly programmed for each task. It is the technique that employs algorithms to parse, learn from past data and predict for unseen data. El-Mesery et al., (2019) mentioned one of the advantages of non-destructive techniques is that it provides qualitative and quantitative data simultaneously without separate analyses. Hence, non-destructive techniques in combination with machine learning is becoming one among the most popular preferred methods for quality evaluation of food with high accuracy (Quelal-Vásconezet al., 2019). Here AI coupled with non-destructive techniques in finding solution to agri-food problems is shown in Fig. 2.1.

Based on the data which is RGB image or spectral image, or signals acquired from non-destructive sources like NIR spectroscopy, hyper-spectral imaging, thermal imaging, e-Nose/e-Tongue, machine learning is able to make significant performance in recognition and classification (Zhu et al., 2019). The principles of working of the mentioned non-destructive techniques along with some of its application are discussed in Table 2.1.

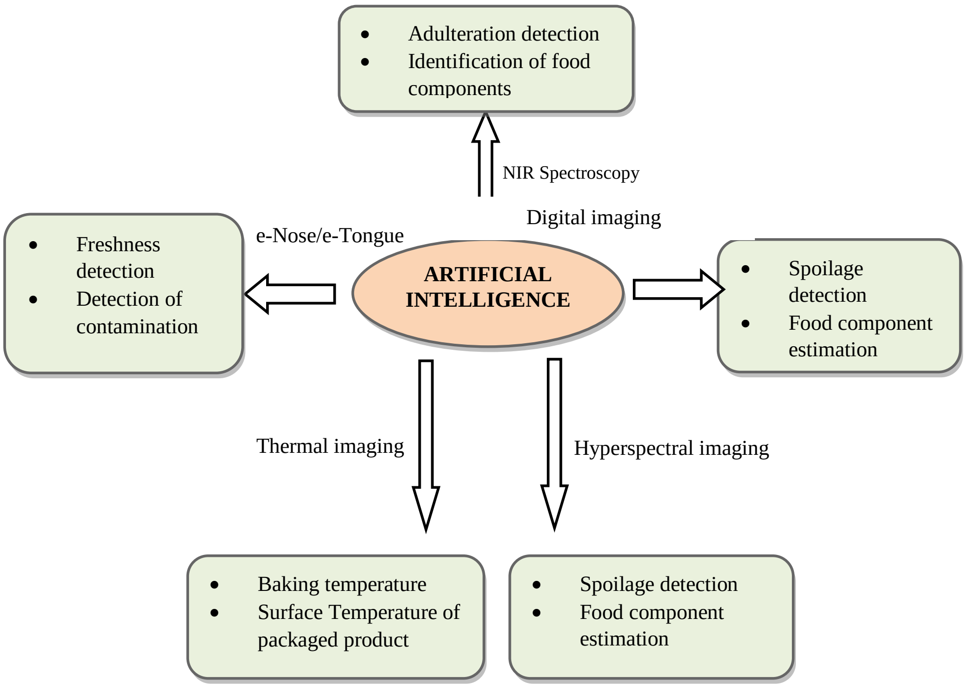
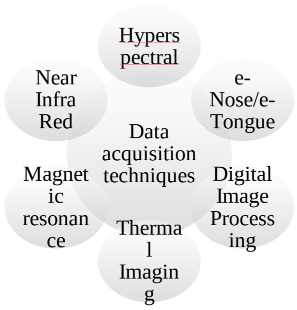


Fig. 2.1 Machine learning coupled with non-destructive techniques in food

Table 2.1 Application of non-destructive techniques in food

	Technique	Principle	Application	Reference
	NIR	Vibration of molecular bonds when light of range 750-2500 nm falls, generating spectrum of reflectance/absorbance	Storage quality of fruits, classifying food products, etc.	(Ortizet al., 2022)
	Hyperspectral Imaging	With relatively narrow band passes, measure the intensity of light diffusely reflected from a surface at one or more wavelengths. Capture spectral and spatial	On line detection of food quality most in a non-destructive	(Yao et al., 2022)

		information about an object at the same time.	way	
	Thermal Imaging	Emission of IR radiation subjected to temperature above the absolute zero	Bakery, meat and fish products	(Usamentiaga et al., 2014)
	eNose/ eTongue	Uses sensors to detect volatile compounds and convert it into electrical signals	Tea, coffee, wine, meat, fish etc	(Tan et al., 2020)
	Digital Image Processing	Enhancement of image for better information extraction ability on the basis of their pixel values in decision-making capability.	Food quality evaluation	(Patel et al., 2023)

2.2 AI-ML in quality inference of agricultural produce

It is evident from above that machine learning has given promising solutions to agri-food systems in quality inference based on (a) digital imaging (Meenu et al., 2021), (b) hyperspectral or multispectral imaging (Wieme et al., 2022) and (c) NIR, e-nose and e-tongue signals (Parastar et al., 2020 and Buratti et al., 2018). Hence, researchers have been motivated to use these applications for evaluation of quality level in fruits and vegetables during post-harvest in any of the following operation as shown in Fig. 2.2.

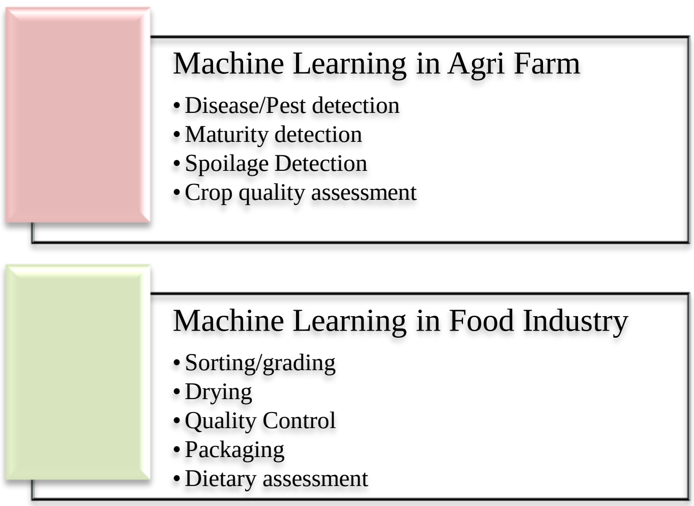


Fig. 2.2 Machine learning in food and agriculture

Assessing the quality of fresh food after harvest has been made easier by the use of grading, sorting, and disease detection (Tripathi and Maktedar, 2020). In the tea sector, machine learning has proven useful for a number of tasks, including grading-focused quality monitoring (Borah, 2005), illness recognition in tea leaves (Karmokar et al., 2015), detecting chlorophyll content in tea leaves (Sonobe et al., 2020), and categorizing tea leaves (Kamrul et al., 2020). Machine learning has been applied in the beverage sector to predict wine quality (Gupta, 2018), analyze fruit juice-alcohol combinations (Ordukaya and Karlik, 2016), and evaluate beer quality (Viejo et al., 2018). It was used in the bakery sector to forecast baking quality (Isleroglu and Beyhan, 2020) and to identify the ideal dough fermentation condition for bread manufacturing (Giefer et al., 2019). Additionally, machine learning has made inroads into the prediction of buffaloes' first lactation milk supply (Gandhi et al., 2012) and the determination of egg fertility (Onler et al., 2017). We cover the works of many researchers who have used various machine learning algorithms to the food industry. We presented some of the studies on image-based machine learning approaches for food or agricultural product categorization in section 2.2.1. By photographing items in the visible zone utilizing digital camera several real time difficulties linked to food quality and safety which has been explored here.

2.2.1 Application of digital image-based ML in quality inference of agricultural produce

In contract to image based machine learning solution in food and agriculture, other non-destructive techniques such as X-ray (Kotwaliwale et al., 2014, Yang et al., 2011), e-nose and e-tongue (Brezmes et al., 2005, Gómez et al., 2006, Oh et al., 2011) and IR spectroscopy (Bureau et al., 2009, Camps and Christen, 2009), are either very time-consuming or can only be achieved in a costly and labour-consuming manner. Moreover, data acquisition and pre-processing is easier in case of images. Numerous successful studies have been conducted on image-based machine learning techniques, some of which are discussed below.

Ireri et al., (2019) in their study proposed a quality grading system of tomatoes from RGB images. The proposed detection system classified tomatoes into defected and healthy class with an accuracy of 97.09%. Using ANN, Random Forest classifier, and RBF-SVM; GLCM texture, LAB color, and shape features were retrieved. The RBF-SVM surpassed the other three models, achieving the maximum accuracy of 97.09% in the categorization of defect-free and healthy tomatoes. Image attributes such as the combination of texture and color features demonstrated the greatest classification accuracy.

Qadri et al., (2019) proposed an algorithm for identifying leaf images of eight citrus varieties -Fuetrells, Moussami, grapefruit, Malta, Local lemon, Lemon, Kinow, and Malta Shakri in their work. Using a fused multi-feature dataset, four distinct machine learning classifiers— RF, J48, NB, and MLP—were utilized to compare the categorization of eight citrus plant kinds.

Wan et al., (2018) from their investigation suggested a maturity detecting method for tomatoes. Based on the color of their surfaces, development stages were divided into three maturity classes: green, orange, and red. This study took into account two tomato market kinds: the Roma and Pear varieties. The back-propagation neural network (BPNN) technique was used to retrieve the color value for the maturity stage classification. Image processing technologies was used to process the tomato photos. With the use of the tomato's maximum inscribed circle, the color feature extraction region was located. There were five concentric circles (sub-domains) created out of the color feature extraction area. The feature color values that best represented the samples' maturity level were derived from the average hue values of each sub-region. Subsequently, the five feature color values were loaded as input values into the BPNN in order to determine the tomato samples' maturity. With a standard variation of 1.2%, the average accuracy for identifying the three tomato maturity levels is 99.31%.

Surya and Satheesh, (2015) in their work used image processing techniques to construct a banana ripeness detecting system. Three categories for bananas were established: under-mature, mature, and over-mature. The colors and sizes of the objects were used to classify them. The accuracy of two classifier algorithms—the area method and the mean color intensity algorithm—was evaluated in terms of maturity detection. The histogram yielded the mean color intensity, and the calibration pictures' area, perimeter, main axis length, and minor axis length were retrieved based on the size values. The mean color intensity and area attributes were shown to be more relevant in predicting the maturity of banana fruit, according to an analysis of variance between each maturity stage on these variables. When identifying the ripeness of banana fruits, the classification accuracy of 99.1% was achieved as the highest value.

Ma et al., (2022), in their work, devised a method with 99% and 98% accuracy for food categorization and nutritional estimate, respectively. In this work, a new dataset termed as 134 k BFPD was gathered from the USDA Branded Food Products Database. It was modified, tagged with three food taxonomies and nutrient values, and turned into the largest dataset for machine learning purposes. They further trained the dataset using the Multi-Layer Perceptron (MLP)-TF-SE approach to reach the intended outcome.

Iorliam et al., (2021), in order to forecast the shelf life of okra, Blessing et al. (2021) used machine learning techniques such Support Vector Machine, Naïve Bayes, Decision Tree, Logistic Regression, and K-Nearest Neighbour. To precisely estimate the shelf life of okra, factors like weight loss, hardness, titrable acid, total soluble solids, ascorbic acid concentration, and pH were employed as inputs.

Arribas and Hortelano (2023) employed IoT technologies including MQ Telemetry Transport, MQTT, and Node-RED in their study to monitor beekeeping processes and increase honey productivity. Using spatial thermal data, real-time important information was gathered in the form of a 3D-grid that illustrates the location of the bees within the hive over the winter. In order to assist beekeepers make the best decisions possible to maintain the productivity of their hive, this technology disclosed unexpected bee behaviors, allowing for a more thorough examination of the health and vigor of a bee colony.

Azarmdel et al., (2019) created a machine learning system based on images to determine the ideal cutting sites for the head and belly of trout depending on its measurements. The pectoral, anal, pelvic, and caudal fin orientations of fish were detected by the algorithm. To segment the fins and obtain cutting points, each trout picture in this study was chopped into slices along its length. Overall fin detection results were 86.05%, 99.97%, and 99.87%, respectively, in terms of sensitivity, specificity, and accuracy. The overall accuracy of fin identification was 100% by correcting the line determination mistake in 8.24% of the samples and the additional object error in 4.12% of the samples. The head and belly cutting points' beginning and ending are determined by the removed fin areas, respectively.

Azarmdel et al., (2020) created a machine learning system for image processing that analyzed, assessed, and categorized mulberry fruit based on three different maturity levels: unripe, ripe, and overripe. An expert rated the mulberries, and an imaging system took the pictures. After that, each segmented mulberry's geometrical attributes, color, and texture were retrieved using two feature reduction techniques: the Consistency subset (CONS) and the Correlation-based Feature Selection subset (CFS). Mulberry fruit was classified using Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The accuracy of the ANN classification using the CFS subset feature extraction approach was 100%, 100%, and 99.1% respectively.

Fashi et al., (2019), created a machine learning model based on image processing to grade pomegranate fruit according to the size and color of the arils. An expert measured and took pictures of the 200 fruits' physical attributes, chopped and photographed the fruit skins, and took pictures of the arils before classifying the fruit into three classes. Three machine learning methods were used to process and classify the images: Response Surface Methodology (RSM), Adaptive Neuro Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN) Model. The results showed accuracy rates of 98%, 95.5%, and 75.5% for RSM, ANFIS, and ANN respectively.

Ma et al., (2019) developed an inference model that could forecast the temperature of raw milk storage, account for temperature fluctuations in raw milk refrigerated storage tanks, and sound an alert in the event that an anomaly occurred. BP Neural Network and Fuzzy Inference were utilized in data-driven modeling to tackle the raw milk storage issues through data collection, cleaning, and utilization.

Payne et al., (2013) developed a method for counting mango fruit from daylight photos of specific plants in order to estimate the crop production of mangos using machine vision. Strong correlation (R^2 = 0.91 for two sides) was found between manual picture counts and tree counts. Using color decomposition in the YCbCr and RGB color ranges and texture decomposition based on nearby pixel variability, 555 trees were photographed and separated into fruit and background pixels. To get a mango count for each picture, the blobs that resulted were tallied. A linear regression was performed on the machine vision count relative to the picture count over 555 photographs (mean ± standard deviation of fruit per tree of 32.3 ± 14.3). The regression coefficient was y = 0.582x 0.20, R2 = 0.74, bias corrected root mean square error of prediction = 7.7.

Sabzi et al., (2022) investigated the connection between the physical, chemical, and appearance features of apples at different stages of ripening. Additionally, they created an algorithm for assessing two physical parameters, firmness and soluble solid content (SSC), and three chemical values, titratable acidity, acidity, and starch. Four stages of ripeness were captured in videos of apples in orchards, and characteristics related to color and texture were retrieved from the samples. The hybrid artificial neural network-difference evolution method was used to correlate the observed physicochemical parameters (ANN-DE). The findings demonstrated that the physicochemical properties' coefficient of determinations (R^2) for the prediction models was more than 0.92. Furthermore, a hybrid multilayer perceptron based artificial neural network-harmonic search algorithm (ANN-HS) classifier with a classification rate (CCR) of 97.86% was used to evaluate the maturity degree of apples based on their physicochemical parameters.

Saad et al., (2016) used image analysis and chromaticity values at various stages of maturation to estimate the internal quality of tomatoes, including TSS, lycopene concentration, and color values. In their study, the a*/b* ratio showed a positive linear association with the average TSS, the entire class, and the lycopene content. A negative correlation was also found between the class average, h˚ and ΔE, and the average of TSS. In the meanwhile, the lycopene concentration was negatively correlated with h˚ and ΔE. However, there was a positive correlation found between the colorimeter and the chromaticity values obtained using image analysis technologies. When the average TSS, total class, and lycopene content were determined, the correlations were logarithmic with ΔE and linear with the a*/b* ratio. In the meanwhile, h˚ had exponential correlation for lycopene concentration and logarithmic correlation for the average TSS and class.

Arora et al., (2022), with an accuracy of 98.07%, created a mathematical model for the computation of a unique freshness coefficient, or Q-score, which was derived by combining the data from photos of pertinent focal tissues such the fish's eyes, gills, and skin.

2.2.2 Application of hyper/multi spectral image based ML in quality inference of agricultural produce

Hyperspectral imaging (HSI) is different from conventional imaging which just assigns the primary colours (RGB) to each pixel; instead it uses a wide range spectrum of light. In hyperspectral data, the spectral range can extend beyond the UV-Visible range to Infrared range. Some of the applications of hyperspectral in food coupled with machine learning are discussed below.

Lu (2004) measured the light backscattering patterns for five chosen spectral bands between 680 and 1060 nm using multispectral imaging of red apples in order to forecast firmness and soluble solid concentration (SSC). In order to predict fruit hardness and SSC, ratios of scattering profiles for various spectral bands were fed into a back-propagation neural network with one hidden layer.

Tziotzioset al., (2024) focused on physiological characteristics such as SSC, dry matter (DM), hardness, and tannins, which are frequently utilized as quality criteria, while evaluating the interior quality of kiwi fruit using a hyper-spectral imaging technique. The aforementioned quality variables were estimated using regression models, such as three-layered neural networks (TLNN), bagged trees (BTs), and partial least squares regression (PLSR). Software and experimental methods involving the use of the Specim IQ hyper-spectral camera were used to collect and analyze data. R squared (R2) values and the root mean square error (RMSE) were two statistical measures used to evaluate how well PLSR, bagged trees, and TLNN predicted the hardness, SSC, DM, and tannins of kiwifruit.

Cheng et al., (2016) used hyper-spectral images to predict and forecast K value, thio barbituric acid reactive substances (TBARS), and total volatile basic nitrogen (TVB-N) in grass carp fillet during chemical degradation. The established least-squares support vector machine (LS-SVM) and multiple linear regression (MLR) models performed exceptionally well for predicting TVB-N and K value with R2 P > 0.900 and RPD > 3.000, but performed poorly for TBARS value prediction. These models were selected using five successive projection algorithms (SPA) and six genetic algorithms (GA) as their wavelengths. The LS-SVM model, which used six wavelengths selected by GA and had good dependability, was determined to be the most effective model for concurrently calculating TVB-N, TBARS, and K value.

2.2.3 Application of other non-destructive techniques-based ML in quality inference of agricultural produce

In contrast to other spectral ranges, NIR spectra offer an advantage in food analysis since they can provide a succession of absorptions of varying intensities over a wavelength range while still conveying the same chemical information (Osborne, 2006). E-Nose and

E-Tongue are novel technologies which assess food quality using a collection of gas or chemical sensors. In conjunction with machine learning these techniques have demonstrated amazing results in the sector of food and agriculture, some of which are presented in Table 2.2.

Table 2.2 Machine learning in quality inference based on other non-destructive techniques

Authors	**Objective**	**Technique**	**Outcome**
(Behkami et al., 2019)	Classify milk on geo origin	Feed-forward MLP-ANN and NIR	Upon comparing the outcomes of the artificial neural network study, it was discovered that both of the suggested models had 100% classification performance, regardless of whether the spectra were from UV-Vis/NIR or single detector (FTNIR) devices.
(He et al., 2007)	classification of tea varieties	BP ANN and NIR	This model outperformed in predicting varieties of 40 unknown samples with 100% recognition rate.
(Badia et al., 2016)	compares packaging and estimates surface temperature over a pallet of apples	ANN and thermal imaging	The estimation using plastic and cardboard boxes has an RMSE of 0.41°C and 0.086°C, respectively, when using ANN through thermal imaging technology to monitor temperature. Using the surface temperature as a reference, results indicate RMSEs of 2.14 °C and 3.56 °C, for plastic and cardboard boxes respectively.
(Wang et al., 2012)	prediction of TVC in chilled pork	SVM and e-nose	SVM and PLS were used to create a correlation between EN signal responses and bacterial counts. The correlation coefficient was 0.94 for training and 0.88 for validation respectively.
(Rasekh et al., 2021)	identify and classify different volatile essential oils	LDA, SVM and e-nose	When chemometric data-analysis techniques including pattern recognition algorithms, PCA, and SVM were examined, the classification accuracy was found to be about 100%.
(Mamat et al., 2011)	classification of beverages such as blackcurrant, mango and orange juice	PCA, MLPNN and e-nose	To confirm the repeatability, a very strong correlation ($r > 0.97$) was discovered between the identical drinks. To confirm its repeatability, the prototype likewise showed highly correlated patterns ($r > 0.97$) in the measurement of beverages using several sensor batches.
(Haddi et al., 2013)	Characterize five types of virgin olive	SVM and e-tongue	When an enhanced low-level of abstraction combined with ANOVA was created, PCA, CA,

	oils based on geo area		and SVMs were able to perfectly recognize the five VOO geo regions.
(Hong et al., 2014)	Detect adulteration in cherry tomato juices	SVM, PCA, PCR and e-tongue	Discrimination and classification tomato juices adulteration by CDA and Lib-SVM were found better than PCA and LVQ.

2.3 Deep learning solutions in agri-food systems

Machine learning is based on evaluating increasingly complex data, such as surface patterns that correspond with certain features. Machine learning involves image pre-processing and then training in neural networks. However deep learning can process input data automatically and extract features drastically achieving excellent classification results for large data sets that are also used. Deep learning algorithms are multi-layered systems that draw inspiration from the human brain. The initial layers of the algorithm are responsible for extracting information, while the last levels handle categorization. Convolutional Neural Networks (CNNs) are widely utilized in many different disciplines and are the standard method for machine learning on image data.This approach results in development of CNN based an algorithm which finds application in various other fields of study. Second, most of the time it is not possible to train a deep learning model from scratch since doing so would involve a huge amount of labeled training samples, more processing power, and a great deal of trial and error to determine the ideal model configuration. This is where transfer learning is used. A model that has previously been pre-trained on a sizable broad data set is used, and its focused dataset is fine-tuned, as opposed to beginning from scratch. Performance of a deep learning model depends on the images in the dataset. There exist some popular food datasets that are available for performing food product classification. Those benchmark datasets include UNICT-FD889, Food 101, UEC FOOD 100 and UEC FOOD 256, Food-5K and Food-11.

2.3.1 Commonly used deep learning tools

There are some already available toolkits and libraries which helps a researcher to smoothly execute the deep learning operations. Selection of the appropriate tool depends on the expertise of the researcher on that tool. Here, a discussion is made on the commonly available toolkits namely TensorFlow, Theano, PyTorch, Pylearn2, Keras, Caffe, TFLearn, etc. Theano is an open source deep learning tool written in Python using Python’s Numpy library to perform complex mathematical operations. In the year 2007, Theano was developed at the University of Montreal (Al-Rfou et al., 2016). TensorFlow is one of the mostly preferred open source deep learning tools written with a Python API over a C/C++ engine that makes it work faster. Google built TF in 2015 aiming to replace Theano (Abadi et al., 2016). TF is considered one of the most efficient libraries with many industrial applications. PyTorch is a deep-learning library written in Python, C++ and CUDA. It was developed by Facebook AI Research and accelerates the journey from prototyping and product deploying. Pylearn2 is another deep learning library developed by LISA at University of Montreal is built on top of theano. Keras is a deep-learning library that uses either TensorFlow or Theano as backend. Created by Francois Chollet, in 2015, Keras is bestowed with an intuitive API written in Python. Developed by Berkeley Vision and Learning Center (BVLC) in 2017, Caffe is considered a mature deep learning tool. It is written in C++ while its interface in coded in python (Jia et al., 2014). TFLearn is another deep learning library built on top of TF written in python.

2.3.2 Image-based deep learning solutions

A digital image matches human vision. It almost captures all the surface information. Deep learning model has the ability to extract high-quality and representative features efficiently from image input boosting model's performance. Below are discussed some of the applications of deep learning in agri food systems emphasizing more on image based applications compared to other non destructive techniques.

2.3.3 Inference of wholesomeness of agricultural produce based on deep learning

Nithya et al., (2022), in their study, suggested a computer vision system based on deep learning for dividing tomatoes into excellent and defective varieties. The model was trained using kent mango photos from a publicly accessible dataset. Data augmentation techniques were utilized to resize the photos in the collection. To improve the raw photos, a preprocessing method called histogram equalization was applied. A machine with a CPU clocked at 2.83 GHz and 8 GB RAM is used to build the suggested CNN model using MATLAB. Ten epochs, an Adam optimizer, and distinct learning rates of 0.1, 0.01, 0.001, and 0.0001 were used to train the suggested CNN model. A batch size of 32 and a learning rate of 0.001 produced the best classification accuracy.

Shi and Wu, (2019), in their work, suggested an automated deep learning-based tomato flaw detection system. The Mask-RCNN architecture is trained for tomato feature extraction following the capture of pictures of tomatoes in various stages. To achieve the omni-directional identification of tomatoes, an omni-directional defect detection model of tomatoes was developed based on this. This approach will assist in tomato quality grading in fields that need uniformity, such food science and industry.

Chen et al., (2020), in their work, used transfer learning to identify leaf diseases in plants. The Deep CNN model for leaf disease identification was constructed using the VGG and Inception models, which were pre-trained on ImageNet. On the public dataset, the suggested method obtains a validation accuracy of at least 91.83%. The suggested method's average accuracy for classifying rice plant photos is 92.00%, even with complicated backdrop circumstances.

Noor et al., (2020) introduced a system and dataset for sheep faces that automates the categorization of normal (no pain) and abnormal (pain) sheep face photos using transfer learning with fine-tuning. The most recent state-of-the-art convolutional neural network(CNN) based architectures are used to train the sheep face dataset. The models have been prepared using L2 regularization, fine-tuning, and data augmentation. Using the VGG16 model, the experimental findings for the sheep facial expression dataset showed 100% training, 99.69% validation, and 100% testing accuracy. Using additional pre-trained models, we increased accuracy to 93.10% to 98.4%. As a result, it demonstrates that our suggested model is the best at accurately classifying sheep faces as normal or aberrant and is tested on a sizable dataset. It may also be utilized to save time and money, help other animals, and do so with great precision.

Da Costa et al., (2020) contributed an experiment on deep learning-based exterior fault detection on tomatoes. During this work, an unfiltered dataset including 43,843 photos with exterior faults was constructed. There is a notable bias in favor of the healthy class in the online dataset. Deep residual neural network (ResNet) classifiers were developed to detect external defects through feature extraction and fine-tuning. The findings demonstrate that, when enough data samples are available, fine-tuning performs better than feature extraction, highlighting the advantage of training extra layers. A ResNet50 with all of its layers optimized was the best model. On the test set, this model's average precision was 94.6%. With a precision of 91.7%, the best classifier retained a recall of 86.6%.

Xie et al., (2021), in their research, presented a deep learning and transfer learning-based approach for identifying faulty carrots. To identify faulty carrots, five traditional CNNs (Inception-V3, Densenet-121, VGG-16, VGG-19, and ResNet-50) were used. Also, these models were improved using a fresh dataset that contained 1330 faulty and 1115 normal carrots. Based on the experimental findings, ResNet-50's transfer learning model fared the best. In addition, the performance was improved by optimizing the hyper-parameters (batch size, fine-tuned layers, and learning rate) of ResNet-50. In order to enhance the identification rate of faulty carrots, the ultimate label was acquired by a selected ensemble utilizing several detection models' outcomes. Using an averaging technique, ResNet-50 was chosen as a fixed model in these ensemble models to be fused with any two of the other four models. According to the findings, the ensemble model utilizing ResNet-50, Densenet-121, and VGG-16 (R-D-V16) outperformed the others in terms of detection speed, F1-score, accuracy, precision, sensitivity, and specificity, with values of 0.09 seconds per picture, 99.53%, 94.62%, 99.62%, and 97.01%, respectively.

Hafiz et al., (2022) in their study provided an image-based application that self-monitors the nutritional content of soft drinks using a deep convolutional neural network (CNN) and transfer learning. First, contrast enhancement and noise reduction are used as preprocessing techniques. Next, using mean-shift segmentation and visual saliency, the position of the beverages zone is identified. After the backgrounds are eliminated and just the relevant portion of the image is separated, a deep CNN-based transfer learning model was employed for drink classification. In order to obtain the nutrition value from the nutrition fact table, the bag-of-feature (BoF) and distance ratio computation is used to determine each drink bottle's size. In order to conduct experiments, a dataset of the top 10 soft drinks drunk in Bangladesh is constructed through the use of online sources, self-capture, and photos from the ImageNet collection. The trial verifies that our technology has a 98.51% accuracy rate in identifying and detecting various drink varieties.

Taheriet al., (2020), in their research, presented an innovative and precise technique for detecting fish freshness that uses a deep convolutional neural network (CNN) and photos of common carp. In order to use the suggested method of classifying fish photos according to freshness, features from the photographs were first automatically extracted using the VGG-16 architecture. Then, fish photos were classified with a 98.21% classification accuracy using a designed classifier block made of dropout and thick layers.

Sharma et al., (2020), in their study, explored a possible method for diagnosing plant diseases by training convolutional neural network (CNN) models with segmented picture data. Testing using independent data that the models had not seen before, the S-CNN model trained using segmented pictures achieved 98.6% accuracy which is double as compared to the F-CNN model trained using whole images.

Wang and Xiao, (2021), examined the surface quality of ripe lychee, including any flaws or rot, a dataset of 3743 samples split up into three groups: rot, faults, and mature samples. There is a problem with the original dataset's uneven distribution. In order to solve it, a transformer-based generative adversarial network (GAN) was used as a data augmentation technique. This allows it to contribute additional and different samples to the initial training set, thereby rebalancing the three categories. Furthermore, for a comprehensive comparative analysis, three deep convolutional neural network (DCNN) models—namely, SSD-MobileNet V2, Faster RCNN-ResNet50, and Faster RCNN-Inception-ResNet V2—were trained in various configurations. The adoption of GAN-based augmentation yields consistent performance increases in mean average accuracy (mAP) for all three models, according to the results. Additionally, by lowering the inter-category disparity, the rebalanced dataset makes it possible to train a DCNN model uniformly among all categories. Furthermore, as seen by the qualitative results, models trained in the enhanced context are better able to recognize object boundaries and important areas, which improves mAP. Finally, the most affordable variant, SSD-MobileNet V2, is ideal for real-time detection in industrial-level applications because to its improved inference performance (102 FPS) and comparable mAP (91.81%).

2.3.4 Inference of ripeness stage of agricultural produce based on deep learning

Behera et al., (2021), in their research, created a revolutionary non-destructive maturity state categorization system for papaya fruits. The study proposed two techniques for identification of the maturity stage of papayas that are based on transfer learning and machine learning. Additionally, a comparison study using various machine learning and transfer learning techniques is conducted. Three hundred papaya fruit sample photos—100 from each of the three maturation stages—are used in the experiment. Three feature sets and three classifiers with various kernel functions are part of the machine learning technique. Local binary pattern (LBP), histogram of oriented gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and k-nearest neighbor (KNN), support vector machine (SVM), and Naïve Bayes are the features and classifiers used in machine learning methodologies, respectively. Seven pre-trained models, including VGG19, VGG16, GoogleNet, ResNet101, ResNet50, ResNet18, and AlexNet, are part of the transfer learning technique. With 100% accuracy and 0.099 s training time, the weighted KNN with HOG feature performs better than other machine learning-based classification models. Once more, VGG19 outperforms the other transfer learning approach-based classification models with 100% accuracy and a training duration of 1 minute and 52 seconds when early cease training is taken into account. Using a transfer learning methodology, the VGG19 suggested classification method for papaya fruit maturity classification obtained 100% accuracy, which is 6% better than the previous method.

Suzuki et al., (2022), using 1,080 RGB photos, investigated three distinct convolutional neural networks (CNN) to forecast the fast over-softening of "Soshu" persimmon fruits. With several criteria, a binary classifier and the date to fruit softening with > 80% accuracy were employed. Additionally, there was a correlation between the date to fruit softening and the prediction values, or confidence, in the binary categorization. Recent feature visualization techniques, also known as "explainable" deep learning, have made it possible to identify the pertinent areas in the original photos, even though the features for deep learning classification were previously believed to be in a "black box." Grad-CAM, Layer-Wise Relevance Propagation (LRP), and Guided Back-propagation (GBP) were utilized to identify early indicators for CNN's categorization of quickly softening fruits.

2.3.5 Inference of chemical composition of agricultural produce based on deep learning

Non-destructive estimation of physico-chemical properties of tomatoes is quite challenging. Although there is a few researches on evaluation of internal quality of agricultural products using machine learning techniques, but application of deep learning is very limited.

Xiang et al., (2022) created non-destructive methods based on hyper-spectral pictures and the associated deep learning regression model for measuring SSC and fruit firmness of tomatoes. A spectrum spanning from 400 to 1,000 nm is used to create hyper-spectral reflectance photographs of more than 200 tomato fruits. After correcting the obtained hyper-spectral pictures, the spectral information is recovered. We present and compare a novel one-dimensional (1D) convolutional ResNet (Con1dResNet) based regression model with the state-of-the-art methods. According to experimental data, our technology outperforms state-of-the-art methods in SSC by 26.4% and stiffness by 33.7% when a comparatively high number of samples are used.

2.3.6 Inference of shelf-life of agricultural produce based on deep learning

Tomato is a perishable agricultural produce and is highly affected by temperature variations. Estimation of shelf life of tomatoes at different temperature conditions becomes essential for its sustainability within the supply chain. Although there are various prediction models for shelf-life estimation of agricultural produces. Development of deep learning-based shelf life prediction models is quite challenging. Very limited research has been conducted for prediction of shelf life from its surface characteristics using deep learning.

Wang et al., (2018) used hyper-spectral transmittance data to identify internal mechanical damage of blueberries. In the study two deep convolutional neural networks (CNNs), namely Residual Network (ResNet) and its upgraded version ResNeXt were employed. For the deep CNN training, the initial hypercube size and structure are modified. Additionally, as comparative tests, five conventional machine learning algorithms—Random Forest (RF), Sequential Minimal Optimization (SMO), Bagging, Linear Regression (LR), and Multilayer Perceptron (MLP) are employed. In addition to accuracy, other assessment indicators such as precision, recall, and F1-score were utilized to evaluate the false positive rate. Moreover, ROC curves and Precision-Recall curves are displayed to show how well classifiers work. Average accuracy and F1-score of 0.8844 and 0.8784 respectively were obtained using the refined ResNet. Further, average accuracy and F1-score of 0.8952 and 0.8905 respectively were obtained using the refined ResNeXt. The F1-score of the classifiers SMO, LR, RF, Bagging, and MLP was 0.8268, 0.7796, 0.7529, 0.7339, and 0.7971 respectively. The average accuracy of the classifiers SMO, LR, RF, Bagging, and MLP was 0.8082, 0.7606, 0.7314, 0.7113, and 0.7827, respectively. Compared to conventional machine learning techniques, two deep learning models outperform them in terms of classification performance. The deep learning system shows significant potential for online fruit sorting, as each testing sample can be classified in just 5.2 ms and 6.5 ms for ResNet and ResNeXt, respectively.

Yakatpure et al., (2022) used DL model to forecast the pomegranate fruits' shelf life. The supplied MRI pomegranate pictures are first scaled to the correct size. After that, the DL S-ResNet-152 (Squeeze based ResNet-152) is applied to extract and classify the features. Fruits are categorized as healthy or harmful using this DL model. Furthermore, the metaheuristic optimization enhanced sandpiper optimization (ISO) by optimizing the layers and decreasing the loss function. Subsequently, the prediction procedure takes into account the fruits in good health. Here, the DL model is used to forecast the shelf-life of the pomegranate fruit. It is projected that characteristics like firmness and physiochemical and physiological loss in weight (PLW) would determine the fruit quality. The bidirectional gated auto network (Bi-GRU-AN) in the hybrid DL model uses these characteristics as input to forecast shelf life. The root mean square error of validation (RMSEV), root mean square error of calibration (RMSEC), and square of correlation coefficient (R^2) are used to evaluate the performance of the suggested classification and prediction results with those of other DL models.

Albert and Osman, (2022) investigated the application of active learning in grading 'Galia' melons according to their shelf life. k-Determinantal Point Processes (k-DPP), an entirely diversity-based technique was employed which enabled to have an impact on feature space exploration according to the selected subset k. When k is big, coequal outcomes is obtained for uncertainty-based techniques while also gaining a deeper understanding of the distribution of data. Even though the eigen decomposition method requires a runtime of O (n^3), rejection sampling allowed for further reduction to O (n poly(k)).

2.3.7 Deployment of deep learning models in app development

Among the most significant technologies for communication is the smart phone. With advancements in hardware and software, particularly in imaging and processing, its use as a measuring tool in horticulture and agriculture is growing. In addition to its low cost, smart phones provide other benefits including mobility and ease of use. For the purpose of predicting tomato shelf life, internal quality qualities, and ripening and spoiling stages, no all-inclusive smart phone application has been offered.

Ye et al., (2018) presented a unique, quick, and non-destructive approach for figuring out tomato lycopene concentration and fruit grade: using a smart device camera in conjunction with a new Android application. In order to create an efficient prediction model for lycopene estimate, the chromaticity values and lycopene concentration of sixty tomato fruits were determined. A color categorization system based on color differences was established, and an Android application for lycopene estimate and fruit grading was developed. Ultimately, an Android 4.2.2 tablet was used to assess the operation of the program.

Vesaliet al., (2015), in order to measure the chlorophyll content of a corn leaf, created an Android application. Using a smartphone's camera, contact imaging was utilized to take pictures of the corn leaves by capturing the light directly flowing through them. With this method, background segmentation and other pre-processing activities would be superfluous. Several features were taken out of each image to estimate the values of SPAD (Soil Plant Analysis Development). Subsequently, sensitivity analysis and stepwise regression were used to identify superior features. In the end, the chosen features were employed as inputs into neural network and linear (regression) models. The Minolta SPAD 502 Chlorophyll Meter was used to capture photos from a corn field west of Ames, Iowa, USA, in order to assess the performance of the models. For the linear model, the RMSE and R^2 values were 6.2 and 0.74, respectively. For the neural network model, the equivalent values were 5.10 and 0.82, respectively. Ultimately, these models were effectively integrated into the Smartphone app termed SmartSPAD. Following the installation of the created software on the smartphone, a fresh independent set of data that SmartSPAD directly obtained from maize plants within a greenhouse was used to reevaluate the models' performance. The SmartSPAD estimation and the matching SPAD meter data showed good agreement (RMSE = 4.03 and 5.96 for the linear model and neural network, respectively, and R^2 = 0.88 and 0.72). When there is a need for high availability, the created application could be viewed as a low-cost substitute for measuring the chlorophyll content.

Liu et al., (2024), created a deep learning and model-assisted labeling system that is mobile-based. Even in complicated backdrops, the user-friendly mobile application StripeRust-Pocket, which was created using deep learning models, reliably evaluates the severity of the illness in photos of wheat stripe rust leaves. StripeRust-Pocket also makes image capture, result storing, organizing, and sharing easier. StripeRust-Pocket uses an underlying model called StripeRustNet, which is a balanced lightweight 2-stage model. MobileNetV2-DeepLabV3+ is used in the first step for leaf segmentation, while

ResNet50-DeepLabV3+ is used in the second stage for lesion segmentation. By dividing the lesion pixel area by the leaf pixel area, the severity of the disease may be approximated. For leaf segmentation, StripeRustNet obtains 98.65% mean intersection over union (MIoU), while for lesion segmentation, it achieves 86.08% MIoU. A mean correlation of more than 0.964 with three expert visual assessments was shown in the validation process utilizing an extra 100 field photos. We provide a two-stage labeling pipeline that combines spatial complementarity, manual correction, and model-assisted labeling to overcome the issues with manual labeling. By using this pipeline, we can reduce the annotation time per image from 20 minutes to 3 minutes using our own dataset. Our approach gives wheat breeders and pathologists the ability to treat wheat diseases in a timely manner by offering an effective and realistic way for assessing the severity of wheat stripe rust. Additionally, it shows how to overcome the "last mile" difficulty in utilizing computer vision technologies for plant phenomics.

Sherafati et al., (2022) created an application called "TomatoScan" to forecast tomato fruit quality indices and ascertain the ripening stage. A total of 220 tomato samples from two storage and six ripening phases were utilized. The RGB smartphone camera captured contact pictures. Multilayer perceptron artificial neural networks were utilized to develop prediction and classification models after the stepwise regression approach was employed to pick the superior characteristics of contact photos. The combination of 650 and 532 nm lasers for L* (CIELAB color space), elasticity, and lycopene; 650 and 780 nm wavelengths for total chlorophyll; and white light for soluble solid content, a* (CIELAB color space), and titratable acidity yielded the best prediction performance. The optimum light source for classifying tomatoes according to their ripening stage was likewise discovered to be white light. TomatoScan is an Android smartphone application that was produced using the architecture, weight values, and bias of neurons of prediction/classification models created in MATLAB. The outcomes of the TomatoScan evaluation closely matched the outcomes of the MATLAB software while testing. The testing dataset yielded the following correlation coefficient (R) values: 0.964, 0.901, 0.664, 0.856, 0.824, 0.923, 0.816, and 0.792 for a*, L*, total chlorophyll, elasticity, carotenoid, lycopene, titratable acidity, and soluble solid content, respectively. The corresponding values for the mean square error were 13.485, 3.549, 14.070, 0.000, 0.065, 39.198, 0.058, and 0.259, respectively. Moreover, TomatoScan had an overall accuracy of 75.00% in determining the ripening stage of tomatoes.

2.4 Summary of chapter II

This chapter begins with a brief glimpse on the commonly used non destructive techniques such as spectroscopy, spectral and imaging techniques for providing various agricultural and food industry solutions. Next machine learning coupled with non destructive techniques is highlighted. In section 2.2, a detailed review is conducted on various non destructive coupled machine learning as a potential solution in food quality assessment. Machine learning a broader class of deep learning is emphasized at the beginning part of this survey. Various machine learning techniques used in feature extraction, classification and recognition tasks is primarily focused. It can be seen from section2.2, that image based machine learning has outperformed the task of spoilage detection and ripeness estimation with high accuracy. However, for estimation of internal quality attributes image based machine learning techniques are not very much familiar. For shelf-life estimation, hyperspectral imaging or infrared based solution are mostly preferred to image based solutions. In section 2.3.3, applications of deep learning as a potential solution in determining quality are reviewed. As discussed above image based deep learning finds way in prediction of current state of a given agricultural produce as defective or good along with its stage of ripeness. But there is lack of research in estimation of physico chemical attributes of tomato from its surface characteristics using image based deep learning. Also a shelf life estimation model based on its degradation kinetics stored at different temperature conditions is not developed so far for tomatoes. The models discussed in section 2.3.5 for estimation of physic-chemical properties and in section 2.3.6 for estimation of shelf-lifeuses hyperspectral and MRI techniques. There lacks image-based models that can predict internal quality parameters as well as shelf-life from surface characteristics. Lastly, in section 2.3.7, development of different apps for food quality assessment is discussed. However an android app that can estimate the shelf life of tomatoes from image input has not been developed so far. Therefore, this study involves development of image based deep learning models for prediction of quality and shelf-life of tomatoes. The developed models were then deployed into an android app. The methodologies involved in this study for conducting the experiments are discussed in chapter III.

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