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Leveraging Potential of Deep Learning for Fruit Quality Detection: A Review

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***Abstract*—Detection of the quality of fruits is essential for the health of humans as well as animals for sustainable agriculture. The quality of the fruit determines its price and directly impacts the agricultural sector thereby the economy. The early detection of the quality of the fruit can lead to the adoption of various techniques to further improve fruit quality, quantity and yield. Conventional methods include humans visually observing the fruit and checking for deformities. Moreover, IoT-based systems are used for this purpose,but satisfactory results have not been observed. Recent progress and research in deep learning methodologies have shown remarkable results for the aforementioned task which may lead to improvement in agricultural outcomes. However, the potential of deep learning methods for real-time fruit quality detection remains under-explored. This study aims to present a comprehensive review of widely adapted methods for fruit quality detection and provide future research scope and directions to the researchers as well as provide a clearer picture of quality determination using cutting-edge technologies.**

***Index Terms*— Deep learning, IoT, Machine learning.**

I. Introduction

The quality of a fruit has a great impact on its consumption. For instance, a ripe and crisp apple is preferred to an overripe soft one. In most cases, the external appearance of the fruit is a good indicator of its internals. India's government's ministry of commerce and industry reported that in the first quarter of 2022–2023, exports of fresh fruits and vegetables increased by 8.6% on a year-over-year basis. Fruit and vegetable exports brought in $642 million from April to June 2021, rising to $697 million in the equivalent months of the current fiscal year [40].
An AI-based quality assaying model is about to be implemented by the Telangana Government's IT department to evaluate the crops transported into the State's procurement centers [41]. Farmers who use this approach may find their farming methods to be improved. Based on the system's report, the farmers can alter their use of fertilizers or their crop rotation to increase yields. As consumers demand higher-quality fruits, fruit quality detection is getting special attention in today’s world. Several deformities are checked for fruit quality detection. For instance deformities like disease spots occurring due to excessive use of pesticides, mushy or slimy, unpleasant odor, color change, and mold present on the surface of the fruit, are commonly checked. Over the years techniques like image processing, machine learning, machine vision, IoT-based systems, and wireless sensor network-based systems are commonly adapted to solve these problems. Over the years researchers have explored numerous methods and published review articles on fruit quality detection. Fig. 1 depicts the year-wise distribution of recently published review articles.

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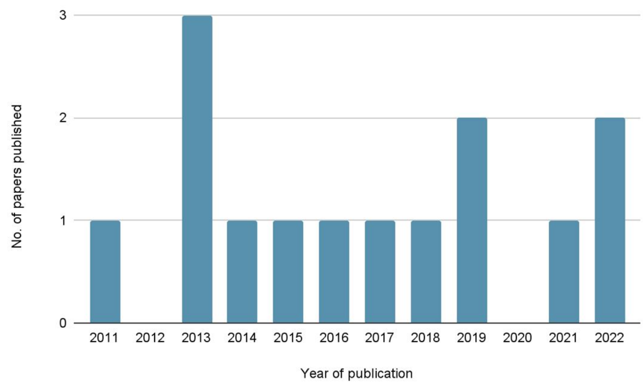

Figure 1. Various Fruit Quality Detection Methods

The analysis shows that most papers have concentrated on checking the external quality of the fruit. However, the growth of the computer vision system pertaining to fruit quality detection in the commercial sector is still at its nascent stage and is the motivation behind this paper. This paper presents a comprehensive review of various fruit quality assessment methods. The contributions of this paper are as follows:
This review article provides a comprehensive review of fruit quality detection methods.
This paper summarizes benchmark datasets published for fruit quality detection.
This paper discusses challenges and future research directions for researchers.
The rest of the review article is organized as follows: section II provides an analysis of methods commonly adapted for determining the fruit's quality. Section III discusses deep learning and its algorithms. Section IV explains recent research processes in deep learning pertaining to fruit quality detection. Section V analyzes different datasets for fruit quality detection. Lastly, Section VI concludes the paper.

II. FRUIT QUALITY DETECTION METHODS

A lot of research has been done to detect the quality of fruits. Several methods have been adapted to solve the aforementioned task. One of the most challenging aspects of hyperspectral image analysis is wavelength selection since there is so much data in a hypercube. A. H. Saputro [1] employed the modified CARS approach to determine the optimal wavelength and were able to predict the total solid soluble content of bananas with a relative error of 0.09 and a correlation coefficient of 0.97.
Another way for determining the quality of fruits is to create a biospeckle pattern with a He-Ne LASER and then determine the cross-correlation coefficients [2][3]. This approach is non-intrusive, non-destructive, and non-contact. Utilizing a radar-based microwave imaging algorithm to see the inside of the fruit is another non-destructive method [4]. The difference in the dielectric characteristics between the fruit and the seeds is used in this procedure, which is based on Huygen's principle. A high number of measurement points can slow the system down and harm the fruit. The number of measurement points is reduced by the Grey Wolf Optimizer to 106 from 12701 with 93% and 100% accuracy [5]. Dielectric spectroscopy technique was used to determine the fruit's quality using the mm-wave.The background of the image can have an impact on segmentation results. As a result, it needs to be eliminated, which the Active Counter Model (ACM) algorithm can do. This approach can be used in conjunction with the modified FCM (MFCM) algorithm to effectively find skin flaws in fruit color photos [6]. Kyamelia Roy [7] employed segmentation techniques such as Canny Filter, marker-based segmentation, and color-based segmentation. Out of these, the canny filter approach showed the most promising results because it is independent of the camera position and image pixel values.
In comparison to the Watershed approach, which results in over and under-segmentation, the K-Means method, which is prone to becoming caught in the local optima, and the Otsu's thresholding method is not compatible with variable illumination, the Gabor filter method produced a remarkably accurate result in [8].
It is insufficient to judge the fruit's quality solely by its outer appearance. It must also be tested for pesticides and artificial ripening agent content. The authors of [9] developed a system with three modules that each addressed a problem by employing an IR, Ethylene, and Electrochemical Sensor to detect the quality of the fruit, the presence of an artificial ripening agent, and the quantity of pesticide residue (organophosphate family) correspondingly.

It is crucial to estimate a product's shelf life because it has an impact on how long it can be consumed. These days, fruit and vegetable shelf life can also be predicted using Android apps. These applications have a 70% accuracy rate when using techniques like the SoftMax training method and the MobileNet Model [10].
Due to the narrow spectral resolution of grating base spectrometers (GS), it is challenging to get various aspects of gas absorption. Therefore, a broadband mid-infrared supercontinuum source and a Fourier transform spectrometer (FTS) can be used together [11] to measure volatiles released by fruit under various air conditions, which are signs of fermentation, ripening, and plant tissue decomposition.
Using a Raspberry Pi development board to build algorithms can be a good, independent, and affordable alternative [12]. Pre-harvest clustering thinning is a labor-intensive method for reducing crop burden to produce better wine quality. This viticulture technique will be more effective if it is automated. T. Kalampokas [13] offered a method for classifying grape berries as healthy or defective using Mask R-CNN, Wavelet Coefficient approach, local binary patterns, and Random Forest, with an IoU of up to 98.07%.
For fruit type categorization and quality estimation, numerous machine learning and deep learning models are available. However, because these models are used for general-purpose classification, their performance in terms of accuracy and precision is constrained. P. Nirale [14] employed multiple support vector machines (MSVM), adaptive Naive Bayes (aNB), varied depth random forests (VDRF), and interpolated k Nearest Neighbor (ikNN) to build an ensemble learning technique that was managed by a specialized Genetic Algorithm (GA) architecture. The model is particularly efficient for a range of classification applications because the internal parameters of each linear classifier are modified using GA and the input dataset. The model's accuracy ranges from 97.79% to 92.5% on average.
The ripening index for apples was calculated using an Arduino, resistor, gateway, IoT cloud, and probe [15], and the resulting data was stored in the cloud. Ohm's law was the basis for the study.
Various fruit quality detection methods are observed in the published literature. Fig. 2 depicts the analysis of the usage of existing methods for fruit quality detection. The aforementioned methods for fruit quality detection do not provide remarkable results.

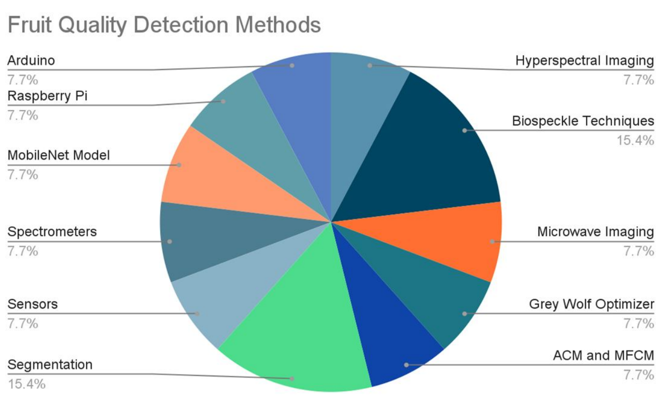

Figure 2. Various Fruit Quality Detection Methods

An ideal solution to detecting the quality of fruits should require minimal hardware and produce quick and accurate results. A solution that incorporates deep learning could provide quick results with minimal hardware. Deep learning would be preferred over machine learning as it is structured to handle large amounts of unstructured data. While deep learning requires high computational power to create and train the model, the final model can be deployed on relatively low-end hardware. Deep learning also requires less human intervention compared to deep learning. The accuracy of deep learning also improves with a larger dataset, while the accuracy of machine learning stagnates after a certain dataset size is reached. Commonly adapted deep learning methods are presented in the section below.

III. Deep Learning

Deep learning, a subset of machine learning, attempts to imitate the learning and thinking process of a human. Unlike machine learning which uses simpler concepts, deep learning uses artificial neural networks. With the recent boost in computing capabilities, neural networks have become larger and more complex. Deep learning is used in image classification, speech processing and recognition, language translation, and more. Deep learning uses Deep Neural Networks, which are networks in which each layer performs complex operations. Deep learning is preferred when the size of the dataset available is large. A key advantage of deep learning models is that their performance tends to improve with an increase in the size of the dataset. They scale with data, unlike a shallow learning model which plateaus after a certain amount of data is reached. The addition of more data may not result in improved performance in the case of shallow learning models. Recent research shows that deep learning methods like Convolutional Neural Networks and Recurrent Neural Networks are widely used. These methods are discussed below.

A. Convolutional Neural Networks

Convolutional Neural Networks (CNN) are deep learning techniques used in computer vision. They're generally employed in object detection, classification, and image enhancement tasks. A CNN includes convolution, pooling, and fully connected layers. The first few layers of a CNN may recognize simple characteristics, and the succeeding layers identify complicated features, leading to feature extraction in the initial layers. The classification task is achieved through the last layers. The ReLU, and leaky ReLU activation functions are commonly adapted in inner layers whereas sigmoid and softmax activation functions are adapted in the last layers.

$$S(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

$$f(x) = max(0, x) \tag{2}$$

Equation 1 and 2 presents the mathematical formula for the sigmoid and ReLU activation function. Several variants of CNN have been developed over time. These architectural versions include VGG (Visual Geometry Group) Net, ResNet[18], Dense Net, Inception Net, MobileNet, UNet [19], and Xception (Extreme Inception) Net.

B. Recurrent Neural Network

Recurrent Neural Network (RNN) is another type of neural network. Nodes in a recurrent neural network can create loops. The node's output can be its own input. RNNs can show temporal dynamics with this characteristic. RNN can remember past inputs and use them to generate output. This uses internal memory. Input and output lengths determine the types of RNNs. The types of RNN are one-to-one, one-to-many, many-to-one, and many-to-many. The tanh activation function is mostly used in hidden layers of recurrent neural networks. Equation no 3 represents the mathematical formula for the same. The aforementioned activation function takes hidden state and input as parameters.

$$tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3}$$

$$h_t = f(h_{t-1}, X_t) \tag{4}$$

$$h_t = tanh(W_{hh} h_{t-1} + W_{xh} x_t) \tag{5}$$

$$y_t = W_{hy} h_t \tag{6}$$

The term h_t stands for the current state, x_t for the input state, h_{t-1} for the previous state, W_{hh} represents the weight at the recurrent neuron, W_{xh} represents the weight at input neuron, W_{hy} represents the weight at the output layer and y_t represents the output. Equation (4) is the formula used for calculating the current state in RNN. Equation (5) depicts the formula of the activation function. Equation (6) depicts the formula for calculating the output. RNNs with simple architecture has short-term memory, making it hard to retain vast amounts of data. Simple RNNs encounter disappearing and exploding gradient problems. The vanishing gradient problem causes the algorithm to stop learning since updating parameters no longer works. The exploding gradient is the opposite of the vanishing gradient. As the gradient grows, the model becomes unstable. Advanced RNN designs like LSTM and GRU overcome the flaws of simple RNNs.

IV. Recent Progress In Deep Learning Applied To Fruit Quality Detection

Fruit quality detection has got special attention in the research community. J. J. Jijesh [16] used Convolution Neural Networks, Image Processing, and Transfer Learning Techniques to detect the quality of apples and divide them into three categories- RIPE: A (best), RIPE: B (raw or average) and RIPE: C (worst). Using the machine learning model, apples were pushed to their respective bins according to quality using Servo Motors which are

controlled by Arduino UNO. Further S. Bobde [17] trained a CNN using the Fruits 360 dataset to produce an accuracy of 95% after training for 50 epochs. The input image of fruit was classified as either "damaged", "good", or "raw". A train-test ratio of 4:1 was used. Fanli Lin[18] devised a non-destructive method that could estimate the sugar content of an apple using a mobile phone and a cardboard enclosure. The screen of the phone shines various colors on the apple while the front-facing camera takes photos. These photos were then used to estimate the sugar content of the apple. The model used was ResNet. It was trained for 100 epochs and a loss rate of 0.15 was achieved. Hajun Park [19] proposed an automated sorting and grading system for cherries using U-Net architecture. A training testing ratio of 70:30 was used. After training the model for 3 epochs, an accuracy of 99.486% was obtained.Raymond Erz Saragih [20] used two models, MobileNet V2 and NASNetMobile, to classify the ripeness of bananas into four classes: unripe/green, yellowish-green, mid-ripen, and overripe. MobileNet V2 achieved higher accuracy and faster execution time than NASNetMobile. The highest accuracy obtained was 96.18%. Sovon Chakraborty [21] collected the features of fruit using convolutional neural networks and used MobileNetV2 architecture to classify the fruits available in the dataset. The dataset, sourced from Kaggle, contained various classes of fruits like fresh apple, orange, banana, and their rotten counterparts. It was observed that after applying MobileNetV2 architecture, the accuracy improved significantly.
HongJun Wang [22] improved upon the MASK R-CNN by including a bottom-up connection path to precisely identify flaws on the surface of apples, pears, oranges, and peaches. Due to the inclusion of low-level feature information in the high-level feature map, the issue of imprecise target location at a wide scale and subpar network detection accuracy has been resolved. Based on the YOLOv3 neural network and their own dataset of 1193 photos, Olga A. Snatkina [23] assessed the freshness of bananas, oranges, and apples and achieved precision and recall of 90% and 96%, respectively. Using the UNet and En-UNet models, Kyamelia Roy [24] determined the quality of apples. The latter fared better than the former. The En-UNet earned a validation accuracy and best mean IoU score of 97.54% and 0.866, respectively, whereas the UNet achieved a validation accuracy of 95.36% and the best mean IoU as 0.66.

TABLE I. VARIOUS DEEP LEARNING METHODS FOR FRUIT QUALITY DETECTION

Reference	Method	Fruit	Evaluation
[16]	Convolutional Neural Network (CNN)	Fruits/Apple	Accuracy: 96.66%
[17]	Convolutional Neural Network (CNN)	Apple, Lemon, and Mango	Accuracy: 95%
[18]	Residual Networks (ResNet)	Apple	0.15 loss rate
[19]	U-Net	Cherries	Accuracy: 99.486%
[21]	Convolutional Neural Network (CNN)	Apples and Oranges	Average Accuracy: 92.5%
[22]	Mask Region-Based Convolutional Neural Network (R-CNN)	Fruits/Apple, Pear, Peaches, Orange	Accuracy: 97.79%
[24]	UNet and En-UNet	Apples	En-UNet and UNet: training and validation accuracy of 97.54% and 95.36% respectively

V. BENCHMARK DATASETS

Recently, deep learning has shown remarkable results in various fields including agriculture. However, deep learning needs huge amounts of data for getting good results. Several datasets have been published recently. Table II depicts the datasets available from Kaggle and IEEE DataPort. The datasets include various fruits of different qualities, such as fresh and rotten, along with their labels.

VI. CONCLUSION

Agriculture sector is a pivotal element of the Indian economy. Quality and quantity of fruits is essential to meet with high demand for fruits and vegetables. In this paper, various fruit quality detection techniques that assess the fruit's quality both within and externally have been mentioned. Initially IoT based methods and machine learning based methods and its drawbacks are discussed. It is observed that these methods have few limitations. Deep learning methods are non-intrusive and require relatively less hardware. Recent progress in deep learning applied to fruit quality detection is discussed further.Deep learning algorithms generally give better results when

TABLE II. VARIOUS FRUIT DATASETS

Reference	Fruit	Dataset	Count	Deformity	Resource Link
[23], [24], [17]	Apple	Fruit Recognition, Fruits 262, Fruits fresh and rotten for classification, FRUITSGB, Fruits 360	Fruit Recognition(5024) Fruits 262: (1203) Fruits fresh and rotten for classification: Fresh Apple(2088) Rotten Apple(2943) FruitsGB: Fresh Apple(1000) Rotten Apple(1000) Fruits 360: Over 4000	Spots, discolouration, mold.	https://www.kaggle.com/datasets/chrisfilo/fruit-recognition, https://www.kaggle.com/datasets/aelchimminut/fruits262, https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification, https://ieee-dataport.org/open-access/fruitsgb-top-indian-fruits-quality, https://www.kaggle.com/datasets/moltean/fruits
[23], [24]	Orange	Fruits fresh and rotten for classification, FruitsGB	Fruits fresh and rotten for classification: Fresh Orange(1854) Rotten Orange(1998) FruitsGB: Fresh Orange(1000) Rotten Orange(1000)	Mold, dry skin	https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification, https://ieee-dataport.org/open-access/fruitsgb-top-indian-fruits-quality
[23], [24]	Banana	Fruits 262, Fruits fresh and rotten for classification, FRUITSGB	Fruit 262: (1162) Fruits fresh and rotten for classification: Fresh Banana(1962) Rotten Banana(2754) FruitsGB: Fresh Banana(1000) Rotten Banana(1000)	Discolouration, overripe, partially peeled and dry skin, mold	https://www.kaggle.com/datasets/aelchimminut/fruits262, https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification, https://ieee-dataport.org/open-access/fruitsgb-top-indian-fruits-quality
[17]	Guava	Fruits 262, Fruits 360, FruitsGB	Fruits 262: (1024) Fruits 360: (656) FruitsGB: Fresh Guava(1000) Rotten Guava(1000)	Spots, discolouration, mold.	https://www.kaggle.com/datasets/aelchimminut/fruits262, https://www.kaggle.com/datasets/moltean/fruits, https://ieee-dataport.org/open-access/fruitsgb-top-indian-fruits-quality

applied on huge data. Publicly available datasets are analyzed for deep learning. Most of the work is observed on determination of external issues. Identifying defects in fruit from the inner side using deep learning is underexplored and has huge research potential. We conclude that usage of deep learning methods for fruit quality detection outperforms the conventional method.

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