JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1426-1438
https://publishoa.com
ISSN: 1309-3452

A Statistical Analysis of Fruit and Vegetables Quality Detection and Disease Classification for Smart Farming

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Abstract

The agricultural industry is the country's primary source of economic growth. Indian agriculture struggles with detecting and identifying fruit and vegetable defects. Fruit and vegetable faults can be spotted using their forms (i.e. colours and textures). Local markets struggle with fruit and vegetable flaws and infections because quality evaluations and classifications are time-consuming. By using the quality of fruit, we can determine how long it will last after purchase. Farmers can predict the best time to harvest fruit to avoid over-ripening. In addition, this will help farmers plan for harvest losses and increase their profits. For defect detection, image processing, machine learning (ML), and artificial intelligence (AI) tools have recently been presented. ML has established itself as cutting-edge technology with multiple applications in various fields. These methods have often been used to judge food quality in recent years. The present state of machine learning methods for estimating food quality and safety is examined in this paper. Product quality is an essential factor in determining the competitiveness of a manufacturing company. First, an introduction to the various approaches to machine learning is presented. Then, a complete comparison of the various methods for identifying the quality of various types of food is presented. To find answers to issues in the food industry, such as identifying the quality of fruits and vegetables, we looked through many research articles. This study found that machine learning techniques in the food industry are superior to more conventional ways.

Keywords – machine learning, fruit quality, smart farming, disease detection, classification

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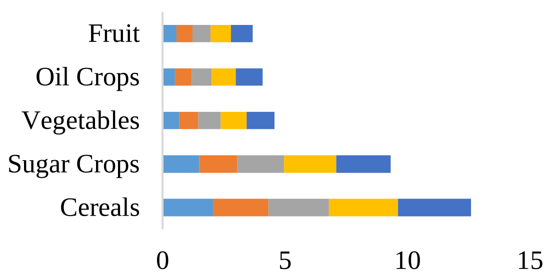
1. Introduction

Food waste affects the environment, economy, and food security. Globally, 1.6 billion tons of food waste are unfit for human consumption [1]. Over the last few years, the rate of food production has been gradually increasing. Figure 1 depicts the annual statistics of food production in billion tons. In addition to these food items, fruits and vegetables account for a substantial amount of output, and their proportion is increasing yearly (from 2015 to 2020). India is a developing country that grows fruits and vegetables. Figure 1 shows India's estimated top fruit production states in 2020 (source: Statista). In 2020, Andhra Pradesh was expected to produce 17 million metric tons of fruit. Maharashtra came in second with 11 million tons, followed by Chhattisgarh, which produced 2% of the country's fruits and ranked 12th overall, and the statistics are shown in Figure 2. The keywords in the graph CH, JK, AS, WB, BH, TN, KR, MP, GJ, UP, MH, and AP denotes Chhattisgarh, Jammu and Kashmir, Assam, West Bengal, Bihar, Tamil Nadu, Karnataka, Madhya Pradesh, Gujarat, Uttar Pradesh, Maharashtra, and Andhra Pradesh respectively. The country had a substantial export market for its low-cost fruits and vegetables.

Onions, mango pulp, fresh mangoes, dried walnuts, and grapes were exported. When categorizing physical food and the agricultural economy, images are the most basic classification technique. Evaluating fruits and vegetables is laborious, expensive, and prone to inconsistent evaluation and subjective results. Inspections and "best-if-used-before" dates determine market prices. Analyzing fruits and vegetables for multiple criteria is a constant task in this environment. Machine vision systems best serve conventional analysis and quality control. Pre and post-harvest crop analysis using computer vision systems and image processing is a growing research topic in agriculture. [2].



	Cereals	Sugar Crops	Vegetables	Oil Crops	Fruit
2000	2.06	1.5	0.68	0.51	0.57
2005	2.27	1.56	0.78	0.67	0.65
2010	2.46	1.91	0.92	0.83	0.74
2015	2.83	2.12	1.06	0.98	0.84
2019	2.98	2.23	1.13	1.1	0.88

2000 2005 2010 2015 2019

Figure 1: production volume of crops in billion tons worldwide (Source: FAOSTAT)

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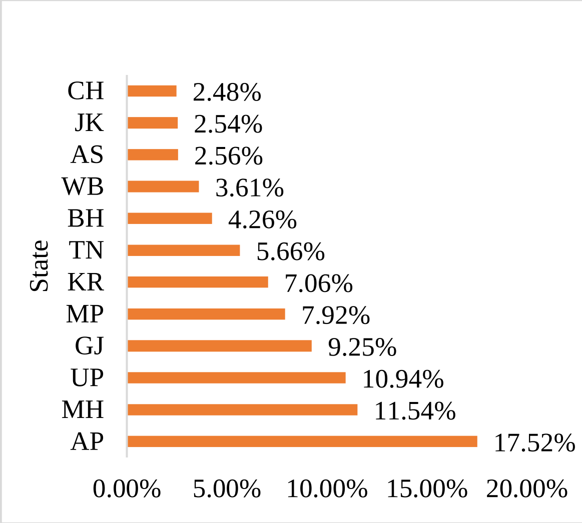

Figure 2: Production volume of fruits in India (Source: Statista -2020)

ML is a helpful paradigm that is now used in practically every field. It's simply putting what you've learnt in the past into practice. It has various applications in food quality inspection and subsequent product grading. As the demand for food commodities increases, it is inevitable that the need for food quality and safety will also increase. The ultimate purpose of high-quality goods is to make more money. Quality impacts processing, storage, pricing, and marketing costs. It took a long time to assess a food product's quality manually. Manual identification and sorting are challenged by inconsistency, discomfort, and a lack of knowledge. It all comes down to labour efficiency, which is influenced by several physiological factors. [3]. Food goods are graded, and defective products are sorted out during quality evaluation. Food quality and safety are also dependent on accurate and automatic detection of food properties. Type of food, compositions, nutrients, and processing style are all possible features. Extracting useful information from accessible data is a fundamental challenge for spectroscopy and spectrum imaging approaches. Modelling with ANN [4], Random Forest [5], SVM [6], CNN [7], and other techniques is crucial [8-10].

In a ML-based fruit and vegetable quality evaluation, handmade image attributes are used to determine food uniqueness. These occupations necessitate professional labour. Hence new algorithms or robust grading criteria are required. The remaining parts of the paper are structured as described below. In Section 2, we will discuss the traditional approaches to ML and the fundamental steps involved in developing an ML model that can determine the quality of fruits and anticipate diseases. Section 3 presents a statistical analysis of current efforts on quality and disease prediction in fruit and vegetables and discusses the problems and constraints posed by these endeavours. Section 4 concludes the paper.

2. Conventional Strategies of ML

ML is a blend of computer science and statistical analysis. Compared to statistics, computer science focuses on designing machines to solve problems. The effectiveness and feasibility of data processing algorithms and the performance measurements they produce are at the heart of ML paradigms. ML learns from prior experiences, like humans. ML algorithms use many human learning strategies to recognize patterns and form solutions. Five distinct categories make up ML. **Supervised learning** uses labelled data sets as input (i.e. classification and regression). The model is constructed based on the provided data and labels and can make predictions for future occurrences, as illustrated in Figure 3. **Unsupervised learning** lacks a clean dataset. It finds patterns and predicts output. In unsupervised learning, we offer unlabeled data and ask the system to detect hidden features (i.e. clustering). The input data teach the model, and it creates groups based on the similarities among the characteristics of each set of input data, as depicted in Figure 4.

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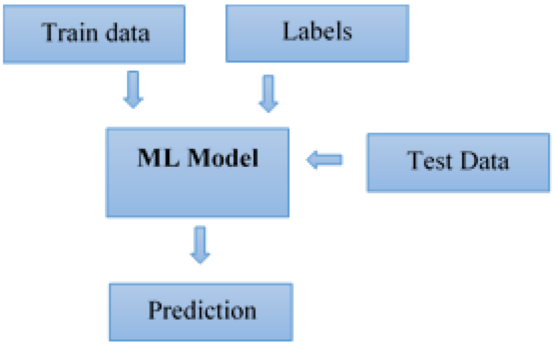

Figure 3: Supervised Learning

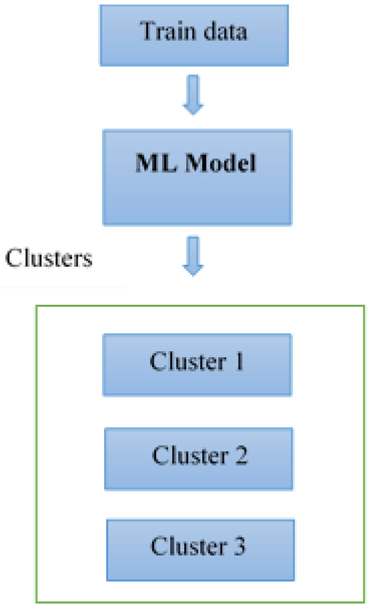

Figure 4: Unsupervised learning

Semi-supervised learning uses a training set that contains labelled and unlabeled data. It acts as a link between supervised and unsupervised methods of learning (See Figure 5). We can use reinforcement machine learning algorithms to automatically decide appropriate behaviour to maximize performance. The most critical aspects of **reinforcement learning** are trial-and-error searching and delayed reward. In this situation, estimated errors are rewarded or penalized, as shown in Figure 6. These incentives are pretty significant. If there is a large probability of making a mistake, the penalty will be significant, and the reward will be low. The penalty will also be minor if the offence is minor, while the prize will be substantial. The goal of **active learning** is to query the user interactively to identify new data points (test data) with appropriate labels. Figure 7 depicts active learning in action. Figure 8 depicts the five steps of image acquisition, pre-processing, image segmentation, feature extraction, and classification. Some imaging modalities in food applications include the camera, ultrasound, electrical, and computed tomography. CMOS and CCD image sensors are employed in the digital image generation process to produce the final image.

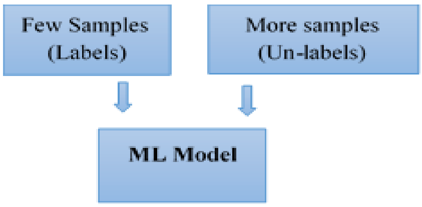

Figure 5: Semi-supervised learning

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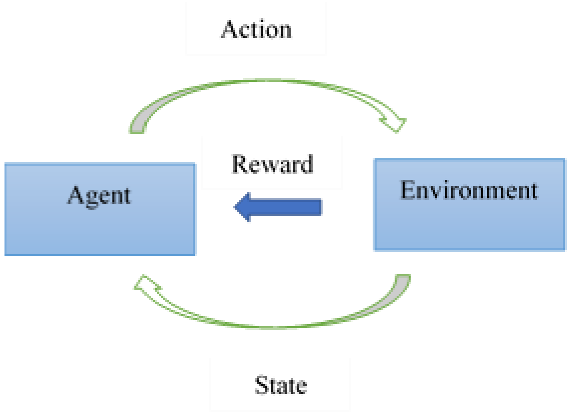

Figure 6: Reinforcement learning

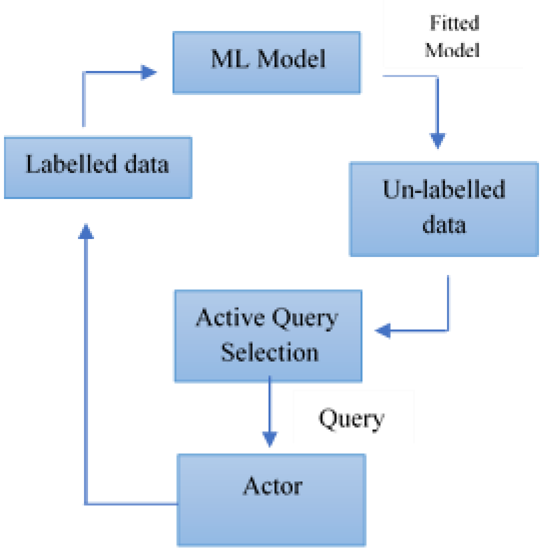

Figure 7: Active learning

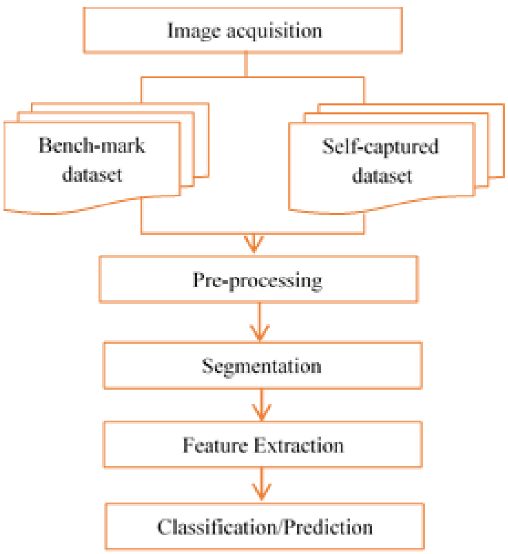

Figure 8: Fruit categorization or quality prediction block diagram

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For optimal results, the image must be filtered and polished. Image pre-processing includes scaling, noise removal, and enhancement. Digital photos may have noise issues. Poor capture makes thresholding difficult. Morphological actions can minimize noise. Gaussian filtering smooths images, whereas median filtering modifies pixel brightness. The noise was eliminated using a Gaussian filter. Gaussian filtering keeps image properties while averaging surrounding pixel intensities. This approach smooths the image while preserving its edges. Smoothed with cumulative standard deviation-based Gaussian kernels [12]. The standard deviation (s) and the Gaussian function G(x) are as follows:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{x^2}{2\sigma^2}} \qquad \text{Eq. (1)}$$

$$\sigma = \sqrt{\frac{\sum_i (X_i - mean(X))^2}{n-1}} \qquad \text{Eq. (2)}$$

Image segmentation splits a digital image into different sections after pre-processing. The primary function is to isolate the background for objective evaluation. Improper segmentation hinders image analysis and classifier performance. Agricultural and medical uses thresholding and clustering as popular segmentation techniques.

Image segmentation is followed by feature estimation. Because features provide data for image perception, interpretation, and classification, these features form the cornerstone of a computer vision system. To recognize input, extracted features are categorized. Feature vectors clearly define object shape. The recognition rate is improved by extracting attributes. These components provide data for the food industry's quality assessment and analysis. Colour, texture, and morphology examine fruit and vegetable flaws and maturity.

Classification is vital for evaluating food quality because it provides a mechanism for simulating human thought to help humans make accurate, immediate judgments. Image processing techniques can define fruits and vegetables by colour, size, shape, and texture. These features constitute a training set, and a classification algorithm extracts a knowledge base to decide a strange case. Food quality evaluation in computer vision systems uses KNN, SVM, ANN, and deep learning.

3. Recent Works

The research provides a wide range of diverse approaches that may be utilized to ascertain the fruit's quality and diagnose any disease. The most recent research works, along with statistical evaluation and comparison with other state-of-the-art approaches, are provided in this section.

Using ML, the researchers in [11] plan to establish a digital twin of banana fruit to monitor its quality. The thermal camera can detect changes in fruit's surface and internal structure as stored. SAP's intelligent technologies were used to train a model based on a dataset of four types of temperature data. A Deep CNN is trained to track the fruit's health using heat data. Thus, 98% of predictions were accurate, making this a potential strategy for developing fruit digital twins. Thermal imaging can create a machine-learning-based digital fruit twin to reduce food waste. The parameters used to carry out the task are detailed in Table 1.

Table 1: Parameters considered in the training process

Batch size	64
Learning rate	0.001
Epochs	150
Accuracy	0.99
Classes	4

The food traceability system that Wang et al. [12] designed includes an evaluation of food quality across the supply chain. It gives customers the knowledge they need to make informed food purchases. As a result, customers have a more positive shopping experience, and businesses can build consumer confidence in the food supply chain. Each food quality level was assessed using fuzzy classification, and an ANN algorithm was employed to assign a final grade. Iqbal et al. [13] described the role of image research and computer vision in evaluating agriculture and food product quality. Image analysis, automatic categorization, and rank-based ranking require this device's basic perception and computer vision capabilities. Improving agricultural production requires evaluating the efficacy and evaluation progression. The simulation recovered image colours. Iterative clustering with a median filter corrected impulsive noise-damaged images. This filter identified noisy pixels using three clusters. If a pixel falls below the previous iteration's center cluster, it is considered; otherwise, it is discarded. Uncorrupted pixels are unaffected by median filtering [14-17].

This article [18] describes the evaluation of food using segmentation and ML. It can distinguish between different types of fruits and detect rotten. Image noise is removed using Gaussian elimination. The images' quality is improved by histogram equalization and segmented using K-means clustering. Figure 9 demonstrates the results of utilizing KNN, SVM, and C4.5 to classify fruit images to detect damaged fruit.

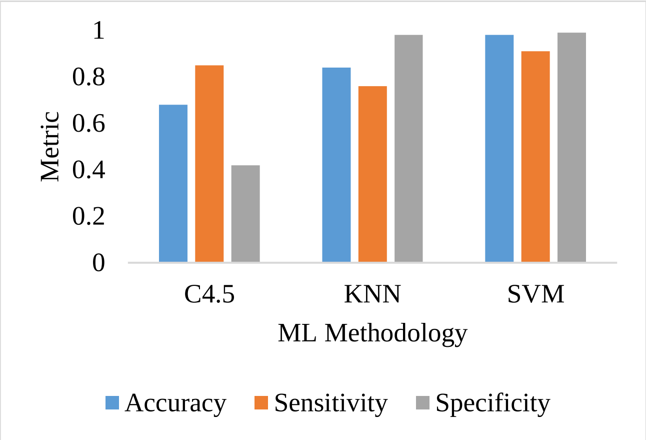

Figure 9: Different ML algorithms use evaluation metrics to detect the damaged fruit.

Using colour, texture, size, shape, and faults as criteria, this study [19] examines pre-processing, segmentation, feature extraction and classification methods for evaluating fruit and vegetable quality. Various fruit and vegetable inspection algorithms proposed by academics are examined in this study. The percentage of accuracy achieved by various approaches to the classification of fruits and vegetables is illustrated in Figure 10.

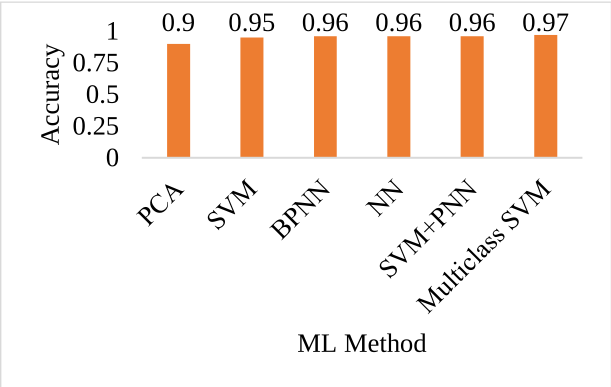

Figure 10: Efficiency of fruits and vegetable classification using numerous ML strategies

The authors in [20] outline a non-destructive method for assessing fruit quality. External and internal characteristics determine fruit quality. Orange and Banana are depicted in colour and x-ray. Image processing tools are utilized to analyze external and interior quality. The analysis includes 18 colours and 27 textural features. Orange and Banana colour and x-ray pictures are tested. The fusion algorithm detects three different fruit classes: 50% defective, 90% defected, and Normal class fruits. To determine fruit quality, SVM and ANN are used. This information determines fruit decay. SVM classifier's accuracy is higher than ANN's, according to experiments. The accuracy of classified fruits in evaluated articles [21-27] is compared, and the results are shown in Figure 11. True positive (TP), True negative (TN), False positive (FP), and False negative (FN) should be the lowest accuracy variables. The accuracy is defined as given in Eq. (3).

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$$\text{Accuracy} = \frac{TP+FN}{TP+FN+FP+TN} \qquad \text{Eq. (3)}$$

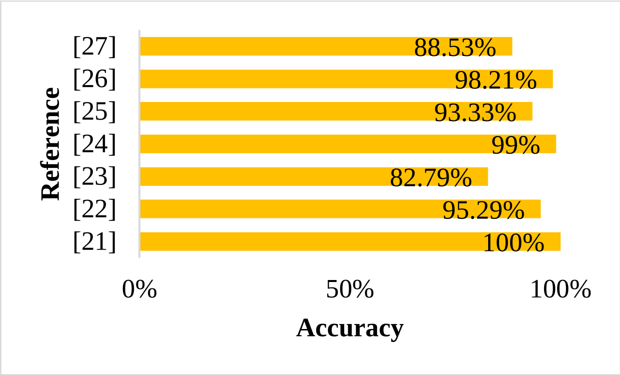

Figure 11: Quantitative comparison of different research in fruit quality detection.

In addition, the authors in [28] offered another method for classifying fruit diseases by employing a deep learning strategy on the plant village dataset and conducting statistical comparisons of the accuracy with other researchers currently working in this research [29-32]. The results are shown in Figure 12.

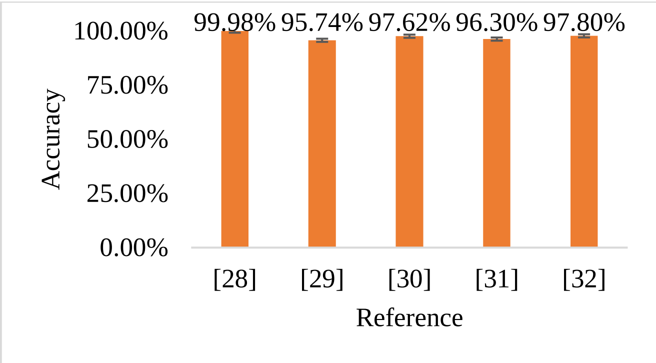

Figure 12: Objective results of disease classification by recent researchers

The authors in [33] provided a DNN model trained to detect disease regions with their severity levels utilizing citrus fruits tagged with four severity levels. VGGNet transfer learning classifies severity. The model predicts mild and high severity with 99% accuracy. The program detects healthy conditions 96% accurately and medium severity 97% accurately. The photos of the dataset were obtained by downloading them from PlantVillage and Kaggle, and Figure.13 illustrates the data distribution for training and testing purposes. Figure 14 illustrates the evaluation measures for four classes (healthy, HS –High Severity, MS- Medium Severity LS-Low Severity).

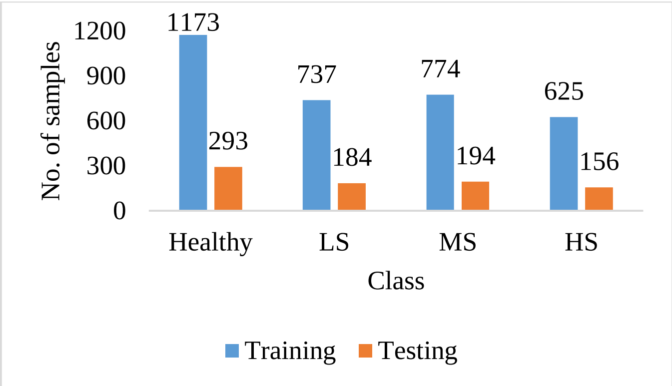

Figure 13: Data distribution over four different classes

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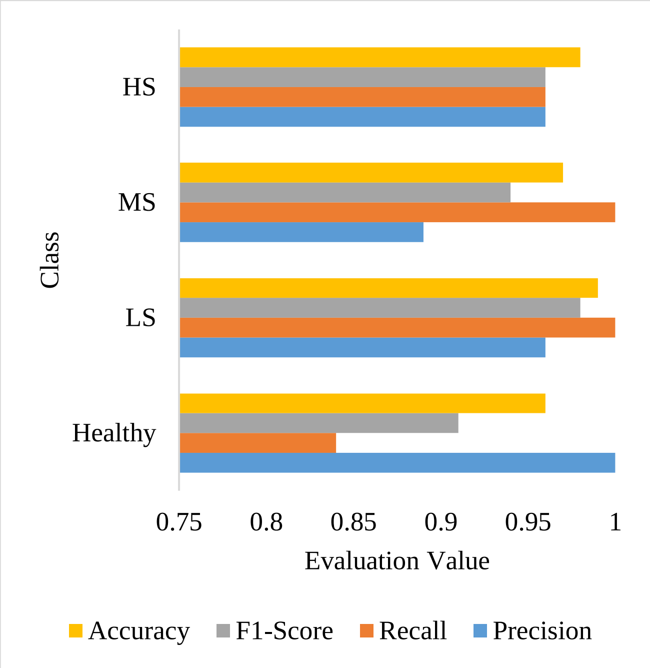

Figure 14: Evaluation Measures using the model.

Computer vision was used in this study [34] to build an architecture that can distinguish between fresh and rotten fruit. The VGG16 CNN model uses Apples, Bananas, Guavas, and Orange pictures to extract features. Extracted data can be classified using Decision Trees, SVMs, and Logistic Regression Models. Figure 15 shows the results of the Support Vector Machine's 99% classification accuracy. There are 13K photos of apples, bananas, and oranges in the dataset used to train and test the system.

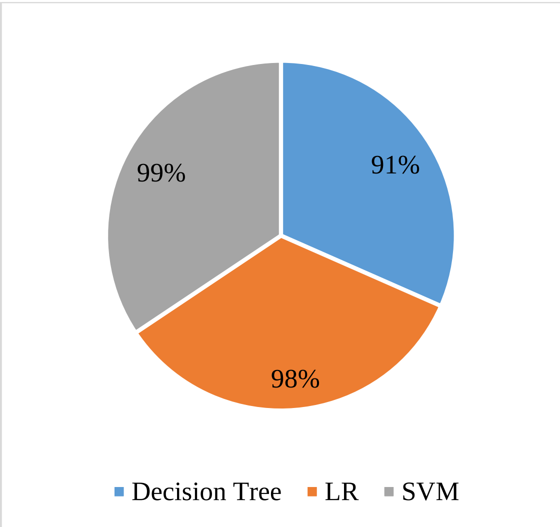

Figure 15: VGG16's performance on the fruit dataset, measured by three distinct machine learning techniques.

Using an ML algorithm and digital images, [35] authors predicted spinach freshness using FAST and BRIEF algorithms and models were trained to recognize freshness. Four colour features positively connected with the sensory evaluation score, while six local clusters had a negative association. The SVM classifier and ANN algorithm correctly identified spinach samples with 70% accuracy in 4-class, 77% in 3-class, and 84% in 2-class. The findings suggest that a model utilizing SVM classifiers and ANNs could replace non-trained freshness panels.

E-AlexNet is proposed for assessing strawberry quality. Then, laboratory and field strawberry photographs were augmented and balanced. The photographs were used to train E-AlexNet. The original AlexNet network's recognition accuracy is 84.5%, while the E-AlexNet network is 90.7%. AlexNet's recognition accuracy after augmentation is 89.34%, and E-AlexNet's 95.75%. E-AlexNet outperforms AlexNet before and after data augmentation. The recommended model is compared to traditional models, and experimental results show the upgraded method is practically applicable. Figure 16 shows the deep learning models compared with the E-AlexNet [36]. The graph's vertical bar shows the sum of square errors.

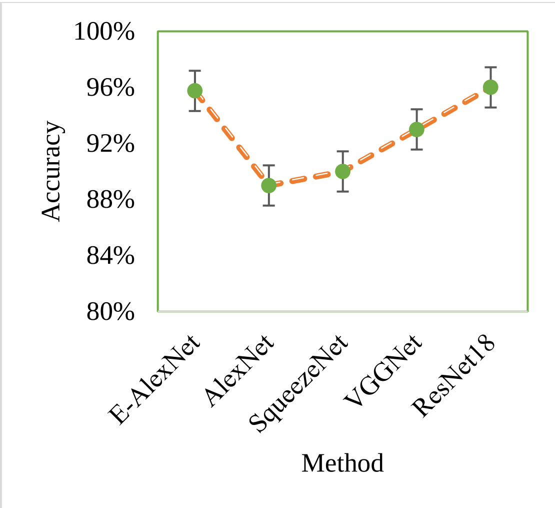

Figure 16: Comparison of [36] with other architectures.

This paper [37] implements an innovative way to evaluate six apple fruit varieties. First, grab-cut and fuzzy c-means images. Principal component analysis chooses statistical, textural, geometrical, discrete wavelet transform, oriented gradient, and Laws' texture energy features from feature space. K-NN, LR, SRC, and SVM categorize apples. Cross-validation with distinct k values verifies system performance. Table 2 shows how 'k' affects the model's performance. Feature selection and extraction increase performance. Advanced approaches are similar to its fruit algorithm.

Table 2: Performance evaluation for numerous 'k' values

k=5	K-NN	82.43
	LR	89.33
	SRC	91.28
	SVM	87.82
k=10	K-NN	84.57
	LR	92.83
	SRC	88.48
	SVM	95.48
k=15	K-NN	80.73
	LR	79.28
	SRC	89.82
	SVM	91.99

3.1 Challenges and Limitations

Image processing improves fruit and vegetable recognition, categorization, and illness detection in local markets. Vision-based technology is fast, persistent, and non-destructive. Fruit and vegetable detection resists lighting, capture positions, variability, cropping, and osculation. Some of the difficulties and constraints that may be encountered are listed below.

- Computer vision decreases the vegetables and fruits industry's effort, labour, and expenses. Computer vision for defect detection uses automatic processing, which decreases processing time.
- Identifying fruits and vegetables can be challenging for several reasons, including their unique appearance in size, shape, and colour.
- Using images from fruits and vegetables, we can classify flaw detection. Using a width multiplier and testing, it can classify fruits quickly.
- The existing approaches for computer vision have several significant shortcomings, one of which is that they require the preparation of a dataset, which is a process that takes a lot of time.
- Another problem is the extended amount of time spent processing an image with a vacillation effect, which can be rather costly.
- Vegetables and fruits are more susceptible to environmental factors. The same computer vision approach may produce varying degrees of accuracy on the dataset, making classifying these food items more difficult.
- Sometimes accuracy is impaired since the internal sections of fruits and vegetables aren't thoroughly investigated, increasing the chances of identifying faults and quality analyses.
- Flaws (brown spots) are more evident on yellow banana peels, for example. Therefore, more research is needed.
- New algorithms and methods for extracting, analyzing, and storing data that are more efficient and reliable than those now in use are being developed.
- Existing feature extraction methods can't collect spectral data from fruit regions. A multichannel spectroscopic system is needed to inspect apple defects in real-time.

4. Conclusion

This agricultural and food industry study mainly concerns image processing and ML. We analyzed and compared several ML and DL algorithms using multiple assessment metrics as part of the statistical investigation. The difficulties and restrictions that arise in the process of defect detection in fruits and vegetables and the quality assessment of various research efforts are discussed. The size, colour, form, texture, and flaws of agricultural products are quality features. Manual inspection is inconsistent and requires knowledge. Hence machine learning methods are utilized. The quality assessment and grading method is based on computer vision and includes four processes: image acquisition, pre-processing, segmentation, and feature extraction and classification, among others. This study compares existing research approaches. Many methods are assessed for fruit and vegetable quality, but a better ML system is needed. The survey shows that fruits and vegetables are only recorded from one direction. Multiple-angle photos must be considered. Researchers have employed numerous colour spaces for feature extraction. However, combinations and other colour spaces remain unexplored. Deep Learning techniques like CNN can be used and fine-tuned to improve the current results. We lack a system that counts, classifies, grades, and identifies defects in many fruit and vegetable categories.

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