

Fruit Quality Detection with Deep Learning and IoT: A Comprehensive Review

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Abstract—Fruit quality detection is a crucial task in the agricultural industry. It impacts the overall market value and consumer satisfaction. Traditional methods for assessing fruit quality are labor-intensive and subjective, leading to inconsistencies and inaccuracies. This paper presents the comprehensive review of fruit quality detection methods such as conventional methods, IoT based methods and machine learning methods. It presents the statistical analysis of usage of these fruit quality detection methods in the related literature. Further, it discusses about the publically available benchmark datasets and their analysis. Additionally, challenges and future research directions are presented to the researchers.

Index Terms— Deep Learning, IoT, Machine Learning.

I. INTRODUCTION

Food safety represents a most important concern for public health and societal stability. The food safety crises can consume consumer trust, disrupt market dynamics, and potentially give rise to social challenges. Consequently, matters associated with food safety have garnered growing public awareness, emphasizing the increasing significance of research in this domain. In today's business landscape, numerous companies are integral parts of complex food supply chains that involve stakeholders before reaching the end consumer. This intricate network has exacerbated the severity and complexity of product quality issues. As supply chains expand with more participants, the potential for unforeseen cascading effects within operations grows. In the worst cases, a single unsafe product can trigger a food safety crisis, causing nightmares for all supply chain members. Another critical factor influencing the efficacy of product quality assurance is the lack of transparency in the supply chain. The surge in food safety incidents highlights the vulnerability of multi-tiered supply chains that lack visibility. Managers now recognize that the wealth of data within their systems can be a valuable asset in today's highly competitive market. Leveraging these data, the food traceability system can serve additional functions, enhancing enterprise competitiveness and fostering consumer trust. Simultaneously, consumer demand for food quality and process transparency is on the rise. Customers seek more scientific and professional information to aid their purchasing decisions, ensuring they acquire high-quality products that align with their preferences.

Fruit quality detection generally relied on traditional methods such as color analysis, size and shape measurement, texture analysis, visual inspection, near-infrared spectroscopy, ultrasonic and acoustic analysis, chemical analysis and manual grading. Color analysis assesses fruit ripeness and quality based on color using sensors or cameras. Size and shape measurement determine fruit size and shape to identify defects.

Weight and density measurement method deals with weighing and measuring fruit density to gauge internal quality. Texture analysis method evaluates firmness, tenderness, and juiciness using texture analyzers. The visual Inspection method deals with visually examining fruits for external defects by human experts. Near-Infrared Spectroscopy (NIRS) analyzes chemical composition non-destructively whereas ultrasonic and acoustic assess internal quality through sound characteristics. Chemical analysis method performs lab-based tests for contaminants, pesticide residues, and nutrients. The manual grading method performs sorting and grading fruits based on quality attributes whereas Gas Chromatography deals with analyzing volatile compounds for aroma and flavor. While these methods were useful for fruit quality assessment, they often required time-consuming manual labor, were limited in their ability to handle large volumes, and were subject to human subjectivity. Deep learning and machine learning techniques have significantly advanced the field by automating and improving the accuracy of fruit quality detection, making it faster and more reliable. The integration of machine learning with agriculture has brought about groundbreaking solutions for the detection of fruit quality. A series of research papers underscores the transformative influence of deep learning and computer vision on reshaping various aspects of fruit production processes. Using deep neural networks, researchers have developed systems capable of accurately identifying and quantifying fruits at different stages of growth. For instance, the "Deep Fruits" system exemplifies the precision of deep learning in fruit detection, accurately pinpointing and categorizing fruits within images. These principles also extend seamlessly to complex environments like orchards, facilitating automated fruit detection and orchard management. Over the years, several review articles are published on fruit quality assessment. Fig.1 depicts the analysis of review articles published in reputed journals.

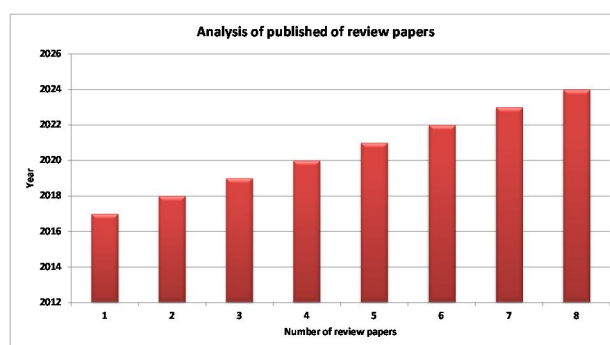


Fig.1. Analysis of review articles in past few years

Contribution of the paper is as mentioned below:

- Recent literature regarding the fruit quality detection is reviewed and analysed.
- Publically available benchmark datasets and their limitations are presented.
- Future research directions are provided to the budding researcher.

The rest of the paper is structured as follows. Section II, describes the various methods for fruit quality detection. The benchmark datasets and their limitations are discussed in Section III. Challenges are discussed in section IV. The paper is concluded in the section 5V.

II. METHODS FOR FRUIT QUALITY DETECTION

In order to determine fruit's quality, a variety of approaches have been developed over time. Traditional methods for fruit quality detection include a variety of approaches that have been utilized in agricultural and food processing for decades. These procedures normally don't involve the use of specialist tools and are non-invasive [1]. The methodology for fruit quality classification is multi-faceted and encompasses a diverse range of approaches, including Conventional Methods, Internet of Things (IoT) Techniques, and Machine Learning (ML) and Deep Learning (DL) Algorithms. Fruit quality assessment is essential for various applications, such as agricultural practices, food processing, and supply chain management. [2] This section discusses the methodology employed to achieve accurate and efficient fruit quality classification using these diverse techniques.

A. Conventional methods

Conventional methods for fruit quality classification typically involve manual feature engineering and expert domain knowledge [3]. These methods often rely on well-established image processing techniques, spectroscopy, and color analysis. These methods have shown notable results. However, they struggle to handle

the diversity and complexity of fruits and can be labor-intensive in terms of feature engineering. Given below are some of the conventional methods that are used in fruit quality detection and classification. The ultrasonic system consists of a programmable bipolar remote pulser unit, piezoelectric probes for transmitting and receiving ultrasonic signals, an oscilloscope, and a computer.[4] Concurrently, a machine vision system relies on image processing techniques to assess visual aspects, primarily size and volume. To calculate volume, the system captures five images of a fruit from various angles using high-resolution digital cameras. Despite the cost-effectiveness, speed, and practicality of these non-destructive methods, the study's experimental results suggest that they may not be as reliable as claimed before. Smart fingertip sensor is another method in which a novel texture sensor is designed with highly sensitive hair-like cilia receptors for automated fruit quality inspection. The sensor comprises magnetized nanocomposite cilia attached to a chip with magnetoresistive sensors, enabling rapid evaluation of fruit quality [5]. The research focused on scanning blueberries and strawberries at various ripeness stages. The sensor, upon contact with the fruit skin, provided qualitative data about the fruit's texture. Less mature fruits displayed lower peak voltages (0.14 mV for blueberries, 0.12 mV for strawberries), whereas overripe fruits showed higher voltages (0.58 mV for blueberries, 0.56 mV for strawberries). These findings were corroborated by sensory assessments, confirming the sensor's potential for accurate fruit quality control. Hyper spectral imaging (HSI) is a novel technology for simultaneously analysing the physicochemical components of fruits, including measuring and visualization capabilities. [6] Due to its ease of use, constant non-invasiveness, and affordability, this method has shown tremendous potential in assessing fruit quality. When utilizing HSI for quality estimation, however, the special qualities of fruits pose difficulties, such as difficulties with focusing, choosing scanning settings, image processing, data mining, and data analysis. Brix measurement is a critical tool in fruit quality detection, particularly for assessing ripeness and sweetness.[64] Brix measurement, expressed in degrees Brix ($^{\circ}\text{Bx}$), quantifies the sugar concentration in a liquid, typically the juice or sap of fruits. It is an important indicator of fruit ripeness and sweetness. [7] It provides a valuable assessment of fruit quality, but it focuses exclusively on sugar content and sweetness. Other attributes, such as texture, color, and aroma, are equally important for comprehensive fruit quality evaluation. The measurement can be influenced by factors like temperature and the presence of other soluble solids in the juice, so careful control and calibration are necessary for accurate results. The Laser doppler detection method to remotely sense ripening-dependent changes in fruit texture and the development of physiological disorders impacting texture. [8] The approach involves subjecting intact fruit samples to sine wave excitation across a frequency range of 5 to 2000 Hz using a vibration generator stage. It is capable of detecting internal defects in citrus fruit, suggesting its potential as a versatile remote sensing tool for assessing fruit tissue firmness and maturation. This method shows promising results but has potential flaws like detecting defects deep within fruits may not be accurately assessed, temperature and humidity can affect the results, and most importantly it is a costly method. All these methods show immense promise in evaluating fruit quality. However, the accuracy, calibration, and precision of measurement tools like refract meters and penetrometers might differ, producing conflicting findings. Also due to the time and labor involved, these procedures could not be practicable when working with huge quantities of fruits, which could postpone quality evaluations. Fig. 2 depicts the analysis of research work related to conventional methods of fruit quality detection.

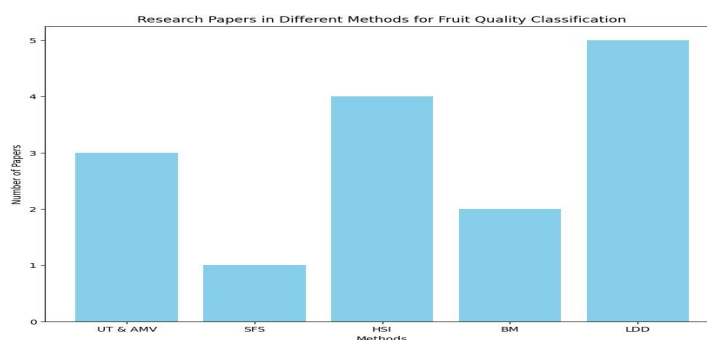


Fig 2. Analysis of research work related to Conventional Methods

B. IoT Based Methods

Internet of Things (IoT) technology can be employed for fruit quality detection and monitoring throughout various stages of the supply chain, from the orchard to the consumer. IoT-based fruit quality detection systems utilize sensors, data analytics, and connectivity to gather information about the fruit's condition, and then this

data can be analysed to determine its quality. [9] IoT-based fruit quality assessment leverages sensor data from various IoT devices placed in orchards, storage facilities, and along the supply chain. These sensors capture data related to environmental conditions, fruit attributes, and storage parameters.[65]

The collected data is transmitted to a central processing unit for analysis. IoT devices, including cameras, spectrometers, and environmental sensors, provide real-time data that enables continuous quality monitoring. The key advantage of IoT-based methods is their ability to capture real-world environmental

conditions. [10] However, challenges include ensuring data accuracy, efficient data transmission, network connectivity, and data security. Sensor technology, integrated with IoT devices, revolutionizes fruit quality monitoring throughout the supply chain.[61] Various sensors, including temperature, humidity, gas, color, image, weight, and ethylene gas sensors, continuously collect data on environmental conditions, ripeness, and defects. This data is transmitted to a central database for processing and analysis. [11] Machine learning

algorithms assess fruit quality based on factors like color, size, firmness, and sugar content, enabling real-time monitoring and quality control.[12] Additionally, IoT systems optimize supply chain management, ensure traceability, facilitate remote access for stakeholders, and provide feedback to growers for continuous improvement. Overall, IoT-enabled sensor technology enhances transparency, efficiency, and quality assurance in the fruit industry IoT-based data collection involves the use of sensors to track the performance of devices connected to the Internet of Things (IoT)[13][14][67]. Fig. 3 depicts the analysis of research work related to IoT Methods for fruit quality detection.

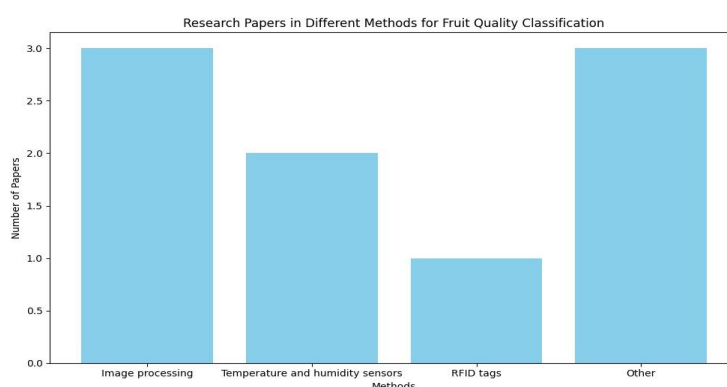


Fig 3. Analysis of research work related to IoT Methods

C. Machine Learning Based Methods

Machine learning methods play a pivotal role in fruit quality classification, offering efficient and accurate means of assessing the condition, ripeness, and overall quality of fruits.[15] These methods harness the power of algorithms and data-driven insights to analyze various attributes, such as color, size, texture, and external blemishes, enabling automated classification into categories like ripe, unripe, or even detecting defects like bruising. [16] Through the use of image processing and feature extraction techniques, machine learning models can make rapid and consistent judgments, contributing to enhanced fruit sorting processes in agriculture, reducing waste, and ensuring that consumers receive the highest quality produce. Random Forest is a popular ensemble learning technique used for fruit quality classification. One of its key advantages is its ability to handle both classification and regression tasks effectively.[17] It is robust against overfitting, thanks to its ensemble nature, and can handle large datasets with high dimensionality. However, one notable drawback is its "black-box" nature, which can make it challenging to interpret results and understand the decision-making process. Support Vector Machines have gained recognition for their ability to handle complex classification problems.[18] Their advantage lies in maximizing the margin between different classes, resulting in good generalization and classification accuracy. However, SVM can be sensitive to the choice of hyper parameters and may not perform optimally on noisy datasets. Fine-tuning is often required, which can be a time-consuming process. K-Nearest Neighbors is an instance-based learning algorithm suitable for fruit quality classification. Its simplicity is a significant advantage, making it easy to implement. KNN is non-parametric and adapts well to complex decision boundaries.[19] On the downside, it can be computationally expensive, especially with large datasets, as it requires computing distances to all data points for each prediction. The choice of the optimal value of "k" can also influence its performance. Naive Bayes classifiers are based on probabilistic principles and are particularly useful for text classification.[20][21] They excel in handling categorical data and work well with

high-dimensional feature spaces. However, their "naive" assumption of feature independence may not hold in real-world datasets, affecting classification accuracy. They might not be the best choice for highly correlated or continuous data. Ensemble learning, which combines the outputs of multiple ML algorithms, is a powerful strategy to enhance classification accuracy.[22] The main advantage of ensemble methods is their ability to reduce bias and variance, leading to more robust models. However, the major disadvantage lies in their increased complexity, both in implementation and interpretation. Fine-tuning ensembles may require significant computational resources and domain expertise. Semi-supervised learning, using Vision Transformers (ViTs), offers promise for fruit quality detection. [23][25] [26] Despite challenges, this approach has potential, particularly with limited labeled data, through careful implementation and experimentation. Fig 4 depicts the statistical analysis of research work related to Machine Learning Methods for fruit quality detection.

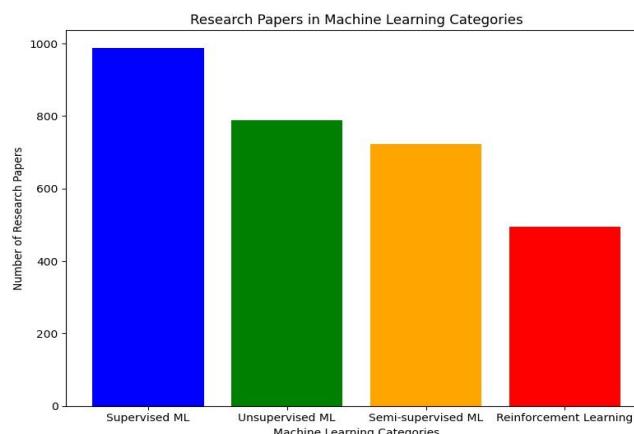


Fig 4. Analysis of research work related to Machine Learning Methods

D. Deep learning based methods

Deep learning has shown remarkable potential in solving complex problems across various domains. One of its critical applications is in the field of fruit quality classification. The need for deep learning methods in this context arises from the inherent challenges in manually assessing fruit quality. Traditional methods often require human intervention and are both time-consuming and subjective.[29] Deep learning techniques, on the other hand, enable the automation of fruit quality assessment through the analysis of high-resolution fruit images.[66] These methods can categorize fruits into different quality classes, such as 'high-quality' and 'low-quality,' by extracting and learning intricate patterns and features from images. By training deep neural networks on diverse and annotated datasets, these models become proficient at discerning quality attributes like color, shape, size, and defects.[30] Moreover, deep learning models have the advantage of scalability, allowing for the analysis of large volumes of fruit data quickly. In summary, deep learning methods have emerged as a promising solution for fruit quality classification, offering objectivity, speed, and scalability.[31] They can revolutionize the fruit industry by automating the assessment process, reducing human error, and enabling consistent and efficient quality control throughout the supply chain. The application of deep learning techniques holds the potential to enhance fruit quality assessment and contribute to improved fruit production and consumer satisfaction. Convolutional Neural Networks (CNN) have revolutionized image classification tasks, including fruit quality classification.[32] Their strength lies in automatically learning relevant features from images, eliminating the need for manual feature engineering. [33] CNNs are capable of capturing intricate patterns and hierarchies in images, making them highly effective. However, training deep CNNs may require large datasets and significant computational resources. The "black-box" nature of deep networks can also make interpretation and explainability challenging.[62] Recurrent Neural Networks are well-suited for sequential data like time series and sequences of images, making them applicable in monitoring fruit quality over time. [34] Their advantage lies in modeling temporal dependencies effectively. RNNs can capture information from previous time steps, enabling predictive analysis.[35] However, they are prone to vanishing gradient problems and may not perform optimally with very long sequences. This can be mitigated with Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks. Auto encoders are neural networks designed for dimensionality reduction and feature learning. They are beneficial for de-noising images and extracting relevant features for fruit quality classification.[36] Auto encoders' primary advantage is their unsupervised pre-training ability, which can help in reducing data noise and redundancy. However, choosing the right architecture and hyper parameters for auto

encoders can be a non-trivial task. Transfer learning, a technique where pre-trained models are adapted for a new task, has become popular in fruit quality classification. [37] This method's advantage is that it leverages knowledge learned from extensive datasets, resulting in improved classification performance, particularly with limited data. [38] One downside is that it may not work well if the pre-trained model's domain differs significantly from the target domain. Fine-tuning and domain adaptation are often needed. Using Generative Adversarial Networks (GANs) for fruit quality detection is an innovative approach that involves training two neural networks, a generator and a discriminator, in a competitive manner. [27] The process begins with collecting a diverse dataset of labeled fruit images. The generator creates synthetic fruit images based on random noise input, while the discriminator learns to distinguish between real and generated images. Once trained, the generator can produce synthetic images for quality assessment, potentially augmenting a limited dataset.[28] Challenges include ensuring data quality, addressing model performance issues, and ensuring generalization to unseen fruit types.

Possible approaches include conditional GANs and fine-tuning pre-trained models. Despite challenges, applying GANs to fruit quality detection shows promise for improving model performance and adaptability. Reinforcement Learning is suitable for scenarios where fruit quality classification involves sequential decision-making. It allows the model to learn the best actions to take over time. Its advantage is the adaptability to dynamic environments and optimal decision-making. However, reinforcement learning typically requires substantial data and time to train, which can be a limitation. Hyperparameters are crucial in fruit quality detection using machine learning or deep learning models as they significantly influence performance and accuracy. Key hyperparameters include learning rate, number of epochs, batch size, network architecture, regularization strength, dropout rate, optimization algorithm, initialization of weights, and image preprocessing. These parameters are tuned using techniques like grid search or random search to find optimal values. However, the best combination depends on factors such as dataset characteristics, fruit types, problem complexity, and model architecture. Experimentation and fine-tuning are essential for achieving optimal performance in fruit quality detection. Fig 5 depicts the statistical analysis of various deep learning methods for Fruit quality detection.

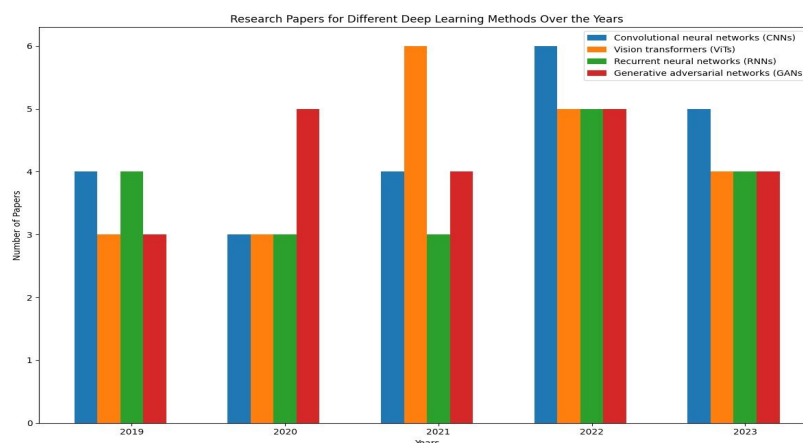


Fig 5. Analysis of research work related to Deep Learning Methods

II. 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 Data Port. The datasets include various fruits of different qualities, such as fresh and rotten, along with their labels. While deep learning has shown promise in fruit quality detection, several limitations persist that impact its efficiency in detecting fruit quality accuracy level. Fruit quality accuracy can be increased. The model was consuming more time thus time consumption can be reduced to a short span of time by scaling up to detect multiple fruits of different kinds at same time.[68] The models are only capable of detecting a quality of one fruit at a time. The smart fruit separator can also be upgraded to the next level like fully automated which can be controlled using a mobile phone. It is noticeable that there are several false negatives. If an object size in a testing image is significantly less than that of a triangle set, it misses the detection.

TABLE I

Dataset	No. of samples	Image Size	Classification			Utilization of this dataset in various fields		Reference
			Fruits	Classes	Test to Train	Method	Metric	
Rotten and Fresh Fruits (Apple, Banana, Orange)	11000	Variable	Apple, Banana and Orange	Fresh/ Rotten	50% Test, 50% Train	Gradient Descent Algorithm	Acc.=94.12%, Loss=16.78%	[45]
Deep Fruits	300	1296 × 964, 1920 × 1080	Rock melon, strawberry, apple, avocado, mango and orange	Well Ripened/ Rotten / Unripe	Variable Depending on availability	DCNN- Deep Convolutional Neural Network	F1 Score=0.83	[46]
Fruits 360, Kaggle	4000	100x100	Apples Mango Orange	Fresh/ Rotten	50% Test, 50% Train	YOLOv3(Map-90.03%), Improved Faster RCNN (90.72%)	mAP(%)=91	[47]
'Red Delicious' apples	12,81,167	227x227 x3	Apples	Good/Bad/ Mixed	70% Test, 30% Train	Impact response(Acc.:86.9%), AlexNet(Acc:91.11%)	Acc.=91.11%	[48]
FruitNet: Indian Fruits Dataset with Quality.	19526	256 × 256(72 dpi)	Apple, banana, guava, lime, orange, and pomegranate	Good/Bad/ Mixed	Variable Depending on availability	PCA, Multiclass SVM, BPNN, Neural Network, Probabilistic Neural network, SVM, Rule Based SVM+PNN	Acc.=96.00, Efficiency=96.47%	[49]

IV. CHALLENGES

The scarcity of high quality fruit data loss, Small fruit and fruit findings in agriculture fruit, light the size of the fruit detection model now poses a challenge in automatic fruit detection and recognition selection is based on deep learning.[41] The quality and size of the fruit dataset, the required development strategy, and the design model all have a major impact on research and knowledge work. For example, fruit data can be created by prior maintenance and processing. Improving fruit data can expand the data and make the data more diverse, thus reducing the dependence on special features and refining the structure. Fruit features fusion helps solve the problem of missing fruit features and improves results in small and large fruits [42]. To create a series of educational projects, the first source of fruit research is necessary to obtain more fruit knowledge through the process of connection with other subjects. In addition, the formation of an integrated network through multidisciplinary learning can improve fruit detection and recognition performance. The second level fruit detection and detection method is fast and lightweight while ensuring the accuracy of fruit detection. To examine the fruit at some level and know the development of the fruit, ensuring accuracy while maintaining the quality of search speed and sample size. Finishing the fruit more efficiently and the accuracy and speed of finding the fruit balance are the current development. [43]. Quality fruit identification using deep learning and the Internet of Things (IoT) has revolutionized agriculture and the food industry. However, like every new change, this brings its own challenges. One of the biggest problems is the complexity of fruit quality. The fact that fruits exhibit many features, from different shapes and forms to various colors and sizes, makes it difficult to create deep learning models. Training models that can focus on multiple fruit species and varieties require large and diverse datasets that can be difficult to understand and document. Another challenge is the need for urgent evaluation and decision making, especially in the context of supply chain management. The integration of deep learning and IoT means there is a constant stream of data from many sensors sent between devices, including agriculture, transportation and retail. Instant management and complete data entry to make timely decisions, such as identifying or delivering fruits under quality control, require the availability of energy and energy calculation tools. Latency in data transfer and processing can be a bottleneck in achieving the desired efficiency. [40] In addition, the use of IoT devices in agriculture creates problems with the connectivity and reliability of the network. Farms and remote areas may have limited internet connectivity, and sending data from these areas to a central location for analysis can be a big problem. Reliable and cost effective communication must be established between sensors, end devices and central offices to ensure that information is not compromised.[63]

Ensuring the security and confidentiality of the data generated by these systems is another challenge. As agriculture continues to expand, the risk of inaccessibility and data leakage increases. Securing the entire IoT ecosystem, from sensors to cloud based operations, requires strong encryption, authentication mechanisms, and adherence to stringent cyber security protocols. [44] Interpretation of deep learning models is an important issue, especially in applications where decisions such as classification and distribution of user parameters are directly related. Understanding why a model distributes fruit in a certain way is crucial to gaining confidence in the system. Deep learning models, especially structural models such as neural networks, are often considered "black boxes" due to their internal representations. Establishing a process to describe and explain the decision making process of this model is ongoing research to ensure clarity and accountability.[71] Scalability is a key challenge in implementing deep learning and IoT solutions in the agricultural supply chain. While small scale deployments may prove beneficial, scaling these solutions to large scale businesses requires careful consideration of factors such as cost, infrastructure, and technology changes in different agricultural practices. In addition, the economics of using this technology pose a problem, especially for small farms with limited resources. The initial investment in sensors, hardware, and software, combined with ongoing maintenance and repair costs, can be prohibitive for some stakeholders. Creating the best solutions that provide the best results for various agricultural businesses is important for widespread use.

In summary, the integration of deep learning and IoT in fruit quality analysis provides an unprecedented opportunity to improve operations, reduce waste, ensure food quality and solve related problems, while also being important for the success of the technology in business.[70] Agriculture and food industries are very important. Addressing these challenges will require collaboration among scientists, technologists, and industry partners to replace existing systems, create innovative solutions, and create robust systems that facilitate the integration of transformative technologies into critical agricultural systems.[39]

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This research paper delves into the domain of fruit quality detection through the innovative fusion of deep learning and Internet of Things (IoT) technologies. We conducted an extensive analysis of existing studies in this field and identified key gaps and limitations. Integration of cutting-edge deep learning techniques with IoT capabilities exhibits superior performance in discerning various quality parameters, including freshness, and defects [51][52]. By investigating edge computing we may improve real-time decision-making skills and drastically cut latency, fruit quality detection systems will be able to evaluate quality quickly and accurately[53]. A more thorough understanding of fruit quality can be made possible by incorporating numerous sensor data and fusion techniques, by which we will produce detection findings that are more accurate and trustworthy rather than relying only on the deep learning model [54]. By putting transfer learning strategies into practice, we can improve the model's adaptability and generalization capacity by facilitating the efficient transfer of knowledge from one fruit variety to another. Incorporating robust privacy-preserving mechanisms in IoT devices can ensure the security and confidentiality of sensitive data while facilitating seamless data sharing and analysis [55]. Implementing advanced data augmentation techniques like Generative adversarial networks and various autoencoders can increase the volume of the training data which in turn would improve the models capacity to generalize the fruits that are not yet known to the model[56]. Thereby enabling the model to concentrate on important features and areas, the integration of attention mechanisms into deep learning architectures improves the model's discriminative abilities and overall performance in fruit quality detection tasks. The model can prioritize pertinent data thanks to this attention-based methodology, which produces more accurate fruit quality evaluations [57]. By utilizing explainable AI approaches, including saliency maps and attention visualization, the model's decision-making process can be better understood. These methods help improve comprehension and confidence in the system's outputs by providing insight into the model's decision-making process. This is important for real-world applications where making decisions is vital. Online adaptation techniques and continual learning are used to achieve continuous model optimization [58]. Fruit quality metrics undergo dynamic changes over time. The model's long-term performance and reliability are enhanced by continuously learning from fresh data and adjusting its parameters, which better prepares it to manage changes and problems found in the real world. Through a comprehensive analysis of various studies on fruit quality detection using deep learning and machine learning methods, it is evident that the integration of IoT technologies and advanced deep learning architectures holds immense potential in revolutionizing the fruit industry's quality control and management practices. Our proposed framework, enriched with advanced data augmentation, attention mechanisms, and explainable AI techniques, significantly enhances the accuracy, efficiency, and robustness of fruit quality detection processes. Furthermore, by highlighting the importance of integrating edge computing,

multi-sensor fusion, transfer learning strategies, and privacy-preserving mechanisms, we anticipate a paradigm shift in the way fruit quality is monitored and managed, ensuring consumer satisfaction and market competitiveness.

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