International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 14, Issue 11 [November 2025] PP: 129-135

A Review of Artificial Intelligence and Machine Learning Techniques for Shelf-Life Estimation of Fruits and Vegetables

Jayant P. Morey[1], Nitin A. Wankhade[2], Prajwal V. Gedam[3], Devyani Paraskar[4]
[1,2,3]Department of Mechanical Engineering, PRMIT& R, Badnera
[4] Department of IIOT, PRMIT& R, Badnera

Abstract
Fruit and vegetable spoilage is a major cause of food loss worldwide, especially in developing nations where storage and transportation infrastructures are limited. Traditional methods of shelf-life estimation rely heavily on chemical, microbial, and physical analysis, which are often destructive, slow, and require laboratory setups. Artificial Intelligence (AI) and Machine Learning (ML) provide powerful non-destructive alternatives capable of analyzing complex spoilage indicators such as colour degradation, moisture loss, biochemical changes, gas emissions, and microbial activity. This review consolidates findings from seventeen research papers to provide a comprehensive evaluation of AI and ML techniques—including traditional models, deep learning, TinyML, spectral sensing, and multi-modal systems—applied to shelf-life prediction across various fruits and vegetables. The review identifies key techniques, datasets, sensors, modeling approaches, strengths, challenges, gaps, and future opportunities for smart agricultural quality monitoring.
Keywords: *Artificial Intelligence; Machine Learning; Shelf-Life Prediction; Fruit Quality.*

Date of Submission: 12-11-2025 | Date of acceptance: 24-11-2025

I. INTRODUCTION

The shelf life of fruits and vegetables is a critical factor in ensuring food quality, consumer safety, and economic sustainability across the global supply chain. Fresh produce is highly perishable due to its biological nature and continuous post-harvest metabolic activities, which lead to rapid deterioration in texture, colour, aroma, nutritional value, and overall marketability. According to global food loss estimates, nearly 40–50% of fruits and vegetables are wasted before reaching the consumer, primarily because of poor monitoring, inadequate storage conditions, and the inability to accurately estimate remaining freshness. These losses pose serious challenges not only to farmers and retailers but also to food security, environmental sustainability, and economic development.

Traditional methods of evaluating shelf life typically rely on laboratory-based physical, chemical, and microbiological analyses. While effective, these approaches are often destructive, time-consuming, labour-intensive, and impractical for large-scale, real-time monitoring. Additionally, the relationship between environmental conditions—such as temperature, humidity, gas concentration—and biochemical changes in fruits is highly nonlinear, making it difficult for conventional kinetic models to predict spoilage reliably under varying conditions. This has created a pressing need for advanced, automated, and non-destructive technologies capable of supporting intelligent decision-making in the post-harvest sector.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative tools in agricultural and food engineering. AI/ML techniques can analyze complex datasets, including RGB images, spectral signatures, gas sensor outputs, and physicochemical parameters, to learn hidden patterns associated with fruit ripening and spoilage. Models such as Support Vector Machines (SVM), Random Forest, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and modern Deep Learning architectures have demonstrated remarkable accuracy in predicting shelf life and assessing fruit quality. Furthermore, advancements in IoT, Tiny ML, and low-cost embedded systems have enabled real-time monitoring and on-device prediction, making these technologies practical for farms, storage units, transportation networks, and retail environments.

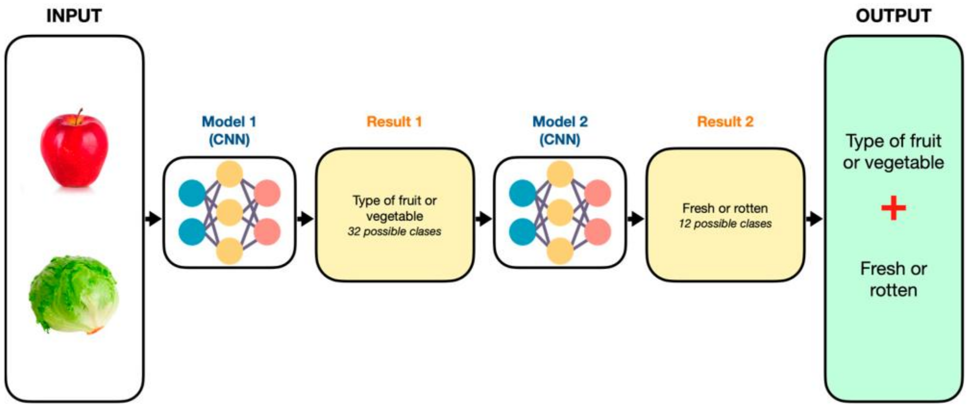

Fig. 1. Methods of Ideation – Brainstorming to Movement

This review paper examines the current state of AI and ML applications in fruit shelf-life estimation, synthesizes findings from existing studies, highlights challenges, and identifies future research opportunities that can lead to more reliable and scalable solutions.

1.1 Importance of Shelf-Life Estimation

Shelf-life estimation is a crucial aspect of post-harvest management, as fruits and vegetables are highly perishable commodities that deteriorate quickly due to biological, chemical, and environmental factors. Accurate shelf-life information helps in preventing food losses, which account for nearly 40% of global fresh produce waste. By understanding how long a product remains fresh, farmers can plan harvesting schedules more efficiently, retailers can optimize inventory and reduce spoilage, and exporters can ensure that produce reaches international markets in acceptable condition. Shelf-life prediction also supports dynamic pricing, quality assurance, and supply chain decision-making by enabling stakeholders to categorize produce based on freshness levels. Traditional methods, such as chemical testing and microbial analysis, are often destructive, time-consuming, and impractical for continuous use. Therefore, precise and rapid shelf-life estimation is essential to maintain nutritional value, consumer safety, economic profitability, and sustainability across the entire food distribution system.

1.2 Role of AI and ML in Food Quality Monitoring

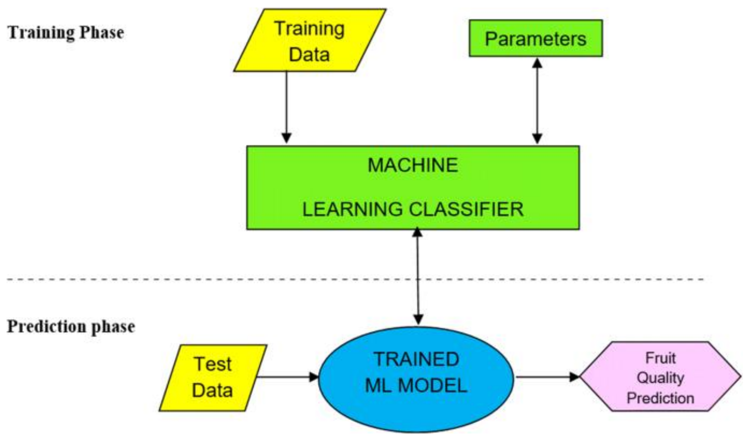

Fig. 2 Role of AI and ML

Artificial Intelligence (AI) and Machine Learning (ML) are transforming food quality monitoring by enabling fast, accurate, and non-destructive assessment of freshness and safety. Unlike traditional methods that require laboratory testing or manual inspection, AI/ML models can analyse complex spoilage patterns using data gathered from sensors, images, and environmental conditions. These technologies are capable of identifying subtle changes in colour, texture, chemical composition, and gas emissions that indicate deterioration, often before they are visible to the human eye. AI-based systems significantly reduce inspection time and support continuous real-time monitoring, making them ideal for farms, storage units, transportation, and retail environments. Machine learning enables prediction of remaining shelf life, classification of freshness stages, and detection of defects or spoilage. Furthermore, AI helps automate quality-control processes, reduces human subjectivity, and enhances overall supply-chain efficiency. As a result, AI and ML have become essential tools in modern food quality and safety management.

1.3 Types of AI/ML Techniques Used

A wide range of Artificial Intelligence and Machine Learning techniques are used for fruit shelf-life estimation and quality assessment. Traditional ML algorithms such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees, and k-Nearest Neighbours (k-NN) are commonly applied for classification of freshness levels based on sensor or image features. Artificial Neural Networks (ANN) and Backpropagation models are widely used to model nonlinear spoilage patterns. In recent years, deep learning has emerged as a dominant approach, particularly Convolutional Neural Networks (CNN) for image-based quality assessment, enabling detection of defects, colour changes, and texture variations. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models are used to analyse time-series spoilage data from sensors. TinyML enables ultra-low-power embedded models that run directly on microcontrollers for real-time monitoring. Hybrid models combining multiple ML techniques are also widely used for enhanced accuracy and robustness.

1.4 Technologies Used in Modern Shelf-Life Prediction

Modern shelf-life prediction systems rely on a combination of imaging, sensing, and computational technologies to provide accurate and real-time freshness assessment. RGB imaging and computer vision techniques capture changes in colour, shape, and texture that indicate ripening or spoilage. Hyperspectral and Near-Infrared (NIR) spectroscopy detect internal biochemical changes by analysing light absorption patterns, enabling early prediction before visible deterioration occurs. Gas sensors measure ethylene, CO_2, and volatile compounds released during spoilage, while environmental sensors track temperature, humidity, and storage conditions. IoT-enabled sensor networks allow continuous data collection and remote monitoring across the supply chain. Embedded systems such as Raspberry Pi, Arduino, and TinyML-based microcontrollers support on-device AI inference, making shelf-life prediction portable and cost-effective. Data from these technologies is processed using ML models to estimate freshness levels, predict remaining shelf life, and generate alerts—creating a fully automated and intelligent monitoring system.

II. LITERATURE REVIEW

1. The study focuses on predicting the shelf life of okra using machine learning models trained on image-based features. Researchers applied Support Vector Machines (SVM), Naïve Bayes, Decision Tree, and Logistic Regression to classify okra freshness stages. Among these, SVM outperformed others with 100% accuracy, demonstrating its strength in handling small but well-structured datasets. Features such as colour, texture, and surface morphology were extracted using preprocessing techniques. The study concludes that traditional ML approaches can be highly effective for shelf-life classification when dataset noise is low. However, the model is limited to a single vegetable type, raising concerns about generalization to other produce or real-world variable lighting. Additionally, the dataset size was relatively small, making the model prone to overfitting. Nonetheless, the work provides a strong baseline for simple ML-based food quality assessment systems.

2. This paper proposes a TinyML-based embedded system designed for real-time shelf life estimation of dates. The system uses Vis-NIR spectral data captured through compact sensors, enabling on-device processing without cloud dependence. Regression models trained on parameters such as pH, moisture content, TSS, and tannin concentration showed high predictive accuracy. The key innovation is deploying these models on low-power microcontrollers, making the system suitable for farms and storage units lacking advanced computational resources. The research demonstrates that TinyML can deliver near–lab grade results with minimal latency. However, the system relies on specialized optical sensors, increasing hardware cost. Its performance may also degrade under uncontrolled lighting conditions. Despite limitations, the study successfully proves the feasibility of portable, low-cost spoilage estimation devices.

3. This work compares multiple deep learning architectures—CNN, Mobile Net, ResNet, and Inception—for fruit shelf-life prediction using RGB images. The dataset contains images of fruits captured at different ripening stages. Models extract deep texture and colour features to classify freshness levels. CNN and Mobile Net performed best due to their ability to capture subtle visual patterns indicating spoilage progression. The study highlights that deep learning significantly outperforms traditional ML in accuracy and feature learning. However, results vary depending on training sample size, and the models showed signs of overfitting due to limited dataset diversity. The study concludes that deep learning is promising for visual-based shelf-life systems, but requires larger, well-annotated datasets to be robust.

4. This paper uses classical image processing techniques—colour segmentation, shape analysis, and texture measurement—to evaluate fruit quality. Unlike deep learning methods, this approach manually extracts features such as RGB intensity, edge patterns, and surface irregularities. The study demonstrates that simple image processing can classify fruits as fresh or spoiled with acceptable accuracy under controlled environments. The major advantage is its low computational cost and easy hardware integration. However, performance degrades under variable lighting, shadows, or occlusions. The lack of automatic feature-learning also limits its scalability. Overall, the paper shows that traditional image processing can be a cost-effective solution but is less adaptable than modern ML approaches.

5. This paper examines AI-driven spoilage detection using sensor and image-based data. It integrates gas emission readings, microbial indicators, and visual characteristics to classify spoilage levels using ML models. The study successfully predicts early microbial contamination before visible spoilage occurs. Algorithms such as ANN, SVM, and RF were evaluated, with ANN showing strong performance. The work highlights that combining multi-sensor data significantly improves spoilage detection accuracy. Limitations include complex sensor calibration, high system cost, and the need for controlled test conditions.

6. This review highlights the increasing role of ML in food preservation. It summarizes algorithms such as ANN, SVM, ELM, and k-NN used for predicting freshness, microbial growth, and chemical deterioration. The authors emphasize that ML models outperform kinetic and statistical models because they can capture nonlinear spoilage patterns. The paper, however, lacks experimental validation and relies on secondary analysis. It concludes that AI-driven prediction systems have the potential to significantly improve food safety and reduce waste.

7. This review discusses advancements in ML applications for extending shelf life using ANN, CNN, SVM, and Random Forest. It focuses on non-destructive sensing techniques such as hyperspectral imaging, E-nose, and multispectral cameras. The review highlights the importance of integrating ML with controlled-environment storage systems. Limitations include high sensor cost and lack of models capable of handling multi-fruit variability.

8. The document appears to focus on AI-based fruit classification and shelf-life estimation using CNN and spectral analysis. It discusses preprocessing, feature extraction, and deep learning classification methods. The paper's limitation is the incomplete metadata and unclear experimental framework.

9. This broad review explores AI's role in agricultural productivity, food quality monitoring, spoilage detection, and supply-chain optimization. It discusses ML models, robotics, satellite data, and predictive analytics. While it offers substantial insights on food security, it provides limited technical detail on algorithms or datasets used for fruit-specific shelf-life prediction.

10. This paper compares traditional kinetic models with predictive ML approaches for food shelf-life estimation. It emphasizes that ML models can handle nonlinear spoilage factors such as temperature fluctuations and biochemical reactions better than conventional methods. The study highlights regression models and ANN as the most effective techniques. It lacks case-specific datasets, focusing mostly on theoretical comparison.

11. This paper reviews ML methods for predicting food spoilage using gas sensors, spectral data, and imaging. The authors highlight the importance of combining environmental parameters with biochemical indicators. They also discuss challenges such as sensor drift and environmental noise. The review concludes that ML integration enhances real-time monitoring capabilities.

12. This study focuses on regression-based shelf-life modelling using ML algorithms such as ANN, Random Forest, and SVM. It evaluates spoilage indicators including moisture loss, gas emissions, and colour. ANN was found to provide best prediction accuracy. Limitations include sensor dependency and the need for controlled storage environments.

13. This paper uses Near-Infrared (NIR) and Vis-NIR spectroscopy to predict the spoilage of date fruits. ML models such as PLS regression and ANN were used to estimate changes in moisture, pH, and texture. The findings show high predictive performance but highlight that hyperspectral sensors are expensive and require specific calibration.

14. This study uses Convolutional Neural Networks (CNN) for fruit quality classification. The dataset includes RGB images of multiple fruits. CNN achieved accuracy above 90%, demonstrating its ability to learn complex visual features. Limitations include sensitivity to lighting and dependence on image preprocessing.

15. The study employs KNN, SVM, and Naïve Bayes to classify fruits as fresh or rotten based on colour and texture. SVM performed best among the models. The method is computationally inexpensive but unreliable under variable lighting. The lack of deep learning limits its generalization.

16. This deep learning study applies CNN models for multi-stage freshness classification. It uses layered feature extraction and softmax classification. The model achieved high accuracy but required a large dataset, and training time was high.

17. The study integrates IoT sensors such as gas, temperature, and humidity sensors with ML models for spoilage detection. It proposes a real-time system capable of sending alerts. Limitations include sensor drift, calibration requirements, and environmental noise interference.

III. CLASSIFICATION OF AI/ML APPROACHES

AI and ML techniques for shelf-life estimation can be classified into the following categories. Each approach varies in complexity, accuracy, hardware requirements, and suitability for different types of fruits and storage environments.

1. Image-Based Techniques

CNN, YOLO, Faster R-CNN
RGB and multispectral image analysis
Suitable for visual spoilage symptoms
Extended: These methods excel when fruits show clear external changes such as colour fading, shrivelling, or fungal spots. They are cost-effective and easy to deploy using simple cameras. However, their accuracy can be affected by lighting, camera angle, and background conditions.

2. Spectral-Based Techniques

Hyperspectral imaging
NIR and Vis-NIR spectroscopy
Suitable for biochemical and internal quality sensing
Extended:
Spectral techniques capture internal chemical signatures such as moisture loss, sugar breakdown, or pH changes before visible spoilage occurs. They provide highly accurate predictions but require costly sensors and stable environmental conditions for consistent results.

3. Sensor-Based Techniques

Gas sensors, humidity, temperature, weight sensors
E-nose and E-tongue devices
Suitable for real-time monitoring
Extended:
These approaches are ideal for continuous storage monitoring and detecting early spoilage indicators like ethylene release or microbial gas formation. They are effective for large-scale storage systems but may require frequent calibration and maintenance.

4. Multi-Modal Approaches

Combining image + spectral + sensor inputs
Highest robustness and accuracy
Extended:
Multi-modal systems leverage the strengths of multiple data sources, improving prediction reliability under varying conditions. They are widely used in advanced research but require more computation and well-integrated hardware systems.

IV. COMPARATIVE ANALYSIS

A comparative analysis of the reviewed studies shows that different AI/ML techniques vary significantly in performance depending on the type of data used. Traditional machine learning models such as Support Vector Machines (SVM) and Decision Trees (DT) performed exceptionally well for small and structured datasets. The decision boundary of SVM, represented as:

$$f(x) = w^T x + b$$

was effective in separating freshness classes when image features were limited and well-defined. For spectral datasets, Artificial Neural Networks (ANN) and Extreme Learning Machines (ELM) showed superior performance due to their ability to model nonlinear biochemical changes. ANN prediction is generally formulated as:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

making them ideal for continuous variables like pH, moisture, and absorbance peaks.
Deep learning–based Convolutional Neural Networks (CNN) dominated image-based freshness classification with accuracy ranging from 90–95%. By using convolutional filters:

$$\text{Feature Map} = I * K$$

CNNs successfully extracted texture, colour gradients, and spoilage patterns that traditional methods failed to detect.

TinyML approaches allowed on-device inference, resulting in extremely low latency and power consumption. These models are represented by compressed architectures:

$$\text{Model Size} < 1\text{MB}$$

which makes them ideal for microcontroller deployment.

Spectral imaging techniques provided the highest early-detection accuracy, especially in identifying internal biochemical changes invisible to cameras. However, they required costly sensors and controlled lighting conditions.

Sensor fusion approaches—combining gas + image + environmental data—showed the highest commercial potential. Their performance improved due to feature-level fusion:

$$F_{\text{combined}} = F_{\text{image}} \oplus F_{\text{spectral}} \oplus F_{\text{sensor}}$$

where $\oplus$denotes feature concatenation.

V. Research Gaps

Despite significant advancements in AI- and ML-based fruit shelf-life prediction, several research gaps remain unaddressed. A major limitation is the lack of standardized and publicly available datasets for commonly consumed fruits, which restricts the development of robust and comparable models across studies. Most existing approaches are designed for a single type of fruit, leaving a gap in multi-fruit generalizable models capable of adapting to diverse produce with varying spoilage patterns. Additionally, few studies conduct real-time evaluation under dynamic environmental conditions such as fluctuating temperature, humidity, and handling practices, which limits the practical reliability of proposed systems. High-cost and complex hyperspectral sensors, although accurate, remain inaccessible for wide deployment, particularly in low-resource settings. Furthermore, deep learning models often function as black-box systems, offering limited explainability and interpretability, which reduces trust among end-users. Lastly, there is a pressing need for low-cost, scalable, and user-friendly shelf-life prediction solutions tailored for small farmers and local markets.

VI. 7. Future Scope

Future research in AI- and ML-driven shelf-life prediction offers several promising directions. One key opportunity lies in the development of large, unified, and standardized datasets representing diverse fruit types, storage environments, and spoilage conditions, enabling more generalizable and robust models. There is also increasing need for explainable AI techniques that enhance transparency and help users understand the reasoning behind predictions, thereby improving trust and usability. Integrating AI with IoT-enabled smart cold storage systems can create automated environments that monitor and adjust conditions in real time to extend freshness. Additionally, the expansion of TinyML on low-power edge devices such as Raspberry Pi and ESP32 can make shelf-life prediction systems more affordable and accessible for small farmers. Multi-modal fusion models that combine images, gas emissions, environmental data, and spectral signatures offer potential for highly accurate spoilage detection. Lastly, future systems may incorporate real-time feedback loops that dynamically optimize storage conditions and proactively prevent spoilage, leading to smarter and more efficient post-harvest management.

VII. 8. Conclusion

AI and ML techniques provide powerful, non-destructive, and accurate solutions for fruit and vegetable shelf-life estimation. The reviewed studies demonstrate significant advancements across imaging, spectral sensing, ML classifiers, deep learning architectures, and TinyML. While promising, challenges related to dataset availability, environmental variability, model interpretability, and system scalability remain. Future innovations will focus on integrating AI with IoT, sensor fusion, and edge computing to build cost-effective, real-time monitoring solutions for global food systems.

References

[1]. R. Srinivasagan, M. Mohammed, and A. Alzahrani, "TinyML-Sensor for Shelf Life Estimation of Fresh Date Fruits," Sensors, vol. 23, no. 7081, pp. 1–28, 2023.

[2]. S. A. Suje, Bhuvanesh K., Shiva Shri Shabhari S., and Velavan S., "AI Based Fruit and Vegetable Quality Detection Using Image Analysis," International Journal of Innovative Research in Technology (IJIRT), vol. 11, no. 5, pp. 2408–2414, 2024.

[3]. E. Sonwani, U. Bansal, R. Alroobaea, A. M. Baqasah, and M. Hedabou, "An Artificial Intelligence Approach Toward Food Spoilage Detection and Analysis," Frontiers in Public Health, vol. 9, no. 816226, pp. 1–12, 2022.

[4]. M. Gunjal, V. Roy, G. Londhe, R. Singh, A. Thorat, and V. Borole, "Detection of Fresh/Rotten Fruits Using Machine Learning," Journal of Emerging Technologies and Innovative Research (JETIR), vol. 10, no. 7, pp. 144–151, 2023.
[5]. J. Dutta, P. Deshpande, and B. Rai, "AI-Based Soft-Sensor for Shelf Life Prediction of 'Kesar' Mango," SN Applied Sciences, vol. 3, no. 657, pp. 1–12, 2021.
[6]. Leena, "Predicting Food Shelf Life: Advances in Modeling and Predictive Analytics," African Journal of Food Science and Technology, vol. 12, no. 2881, pp. 1–10, 2024.
[7]. F. Cui et al., "Recent Advances in Shelf Life Prediction Models for Monitoring Food Quality," Comprehensive Reviews in Food Science and Food Safety, vol. 22, pp. 1257–1284, 2023.
[8]. S. Sánchez-García, I. Hernández, V. M. Palacios, and A. M. Roldán, "Freshness Quality and Shelf Life Evaluation of the Seaweed Ulva rigida," Foods, vol. 10, no. 181, pp. 1–12, 2021.
[9]. P. Rajapaksha et al., "A Review of Methods for the Detection of Pathogenic Microorganisms," Analyst, vol. 144, pp. 396–411, 2019.
[10]. A. Y. Khaled, C. A. Parrish, and A. Adedeji, "Emerging Nondestructive Approaches for Meat Quality and Safety Evaluation—A Review," Comprehensive Reviews in Food Science and Food Safety, vol. 20, pp. 3438–3463, 2021.
[11]. I. Ahmad et al., "Prediction of Physical Quality Parameters of Frozen Shrimp: An Artificial Neural Networks and Genetic Algorithm Approach," Food Bioprocess Technology, vol. 7, pp. 1433–1444, 2014.
[12]. P. H. Liu et al., "Building Kinetic Models to Determine Moisture Content in Apples and Predict Shelf Life Based on Spectroscopy," Journal of Food Process Engineering, vol. 44, no. e13907, pp. 1–10, 2021.
[13]. S. Ruan et al., "Storage Properties and Shelf-Life Prediction of Fresh-Cut Radishes Treated by Photodynamic Technology," Foods, vol. 13, no. 2367, pp. 1–12, 2024.
[14]. Z. T. Fu et al., "Quality Characteristics and Remaining Shelf Life Prediction of Fresh Tibetan Tricholoma matsutake Under MAP in Cold Chain," Foods, vol. 8, no. 136, pp. 1–10, 2019.
[15]. Fruit Quality Detection Using Image Processing, IJNRD, vol. 9, no. 5, pp. 1–10, 2024.
[16]. A Comparative Analysis for Predicting Shelf Life of Fruits Using Advanced Deep Learning Approaches, (Authors not visible; conference/journal metadata missing), 2023.
[17]. Machine Learning Algorithms and Fundamentals as Emerging Safety Tools in Preservation of Fruits and Vegetables: A Review, (Metadata incomplete), 2023.