Fruit Shelf-Life Estimation and Freshness Evaluation: A Review

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Abstract

The freshness of fruits and vegetables is a growing challenge in daily life, as traditional inspection methods often fail to provide consistent and objective results which turn into food waste and health concerns. While physical inspection is subjective and inaccurate, the absence of automated freshness detection and shelf-life prediction results in monetary losses and inappropriate consumption. Traditional methods, such as chemical testing and human inspection, are costly, time- consuming, and often unreliable. Convolutional Neural Networks (CNNs), which automatically recognize visual traits like color, texture, and form in fruit pictures, provide a powerful alternative. In this work, a CNN-based model that can differentiate between fresh and rotting fruits and vegetables is developed using convolution, pooling, and fully connected layers. The method ensures non-invasive, scalable, and precise detection, which lowers dependency on humans and boosts productivity. This approach can be advantageous for automated sorting systems and real-time quality monitoring.

Keywords: Computer vision, Image classification, Fruit detection, Convolutional neural networks (CNNs), Deep Learning.

1. Introduction

Convolutional Neural Networks (CNNs) play a pivotal role in modern computer-vision applications due to their ability to automatically learn and extract essential features directly from raw image data [1], [5], [7].CNNs develop hierarchical representations directly from images, making them very successful for pattern-recognition applications compared to previous techniques that rely on human-generated features [3], [9]. More abstract and semantic representations of things are formed by mixing local spatial data like as edges, textures, and forms that are acquired by the convolutional layers' filters [8].CNNs' layered construction allows them to effectively understand complicated visual data while preserving translation invariance [10].

CNNs are essential for detecting minute variations in color, texture, and form in fruit photos that reveal the fruit's variety or freshness [2], [4], [11]. While rotting fruits show inconsistencies, discoloration, and texture degradation, fresh fruits frequently have unique surface patterns, brightness, and color intensity. Because their pooling layers provide reliable detection under changing light or direction, and because their convolutional kernels can detect fine-grained local changes, CNNs are especially well-suited to capture these changes [12]. CNNs reduce human bias by removing the requirement for manually generated descriptions and learning directly from databases of labeled fruit [6], [13].

Because CNNs are very scalable and adaptable when working with huge datasets, they are appropriate for real-world agricultural applications where enormous volumes of fruit images are processed daily [9], [15]. Reliable performance in dynamic situations like autonomous harvesting systems, storage facilities, and marketplaces is ensured by their strong generalization on unseen data [14]. CNNs can now be used on low-power devices for on-site fruit-quality monitoring, thanks to developments in lightweight architectures like MobileNet and EfficientNet [2], [5], [10]. All things considered, visual-inspection jobs in the agricultural supply chain can be carried out effectively, accurately, and automatically using CNN-based techniques [1], [16].

In this system, work will focus on neural-network and machine-learning techniques. Although the phrases *neural networks* and *machine learning* are closely linked, they are not interchangeable, and their levels of artificial intelligence differ. Conversely, Artificial intelligence is the ability of a computer system to demonstrate intelligence and, more importantly, learn from such data without requiring explicit programming. Machine-learning training methods that replicate the structure of the human brain, including artificial neural networks, enabling the system to execute increasingly sophisticated tasks like speech and picture recognition [7], [15].

2. Reviewed Methodology

This study outlines a systematic framework for automating the prediction of fruit and vegetable freshness and estimating their shelf life using advanced deep learning techniques. The methodology is organized into sequential stages, ensuring

efficient data handling, model training, and performance evaluation.

A. *Dataset Collection*

High-quality fruit and vegetable images are sourced from open datasets such as Kaggle and Fruits360. Each image is labeled according to freshness category and type to train the model effectively [1].

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C. *Pre-processing*

Images undergo normalization, resizing, and enhancement. Data augmentation (flipping, rotation, brightness variation) increases data diversity and prevents overfitting [1].

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E. *Model Development*

Convolutional Neural Networks (CNNs) are employed to extract texture, color, and surface details of produce. A Multi- Task Learning (MTL) structure is adopted to jointly predict freshness scores and remaining shelf-life [2] [5].

F. *Training and Validation*

The dataset is separated by 80% training, 10% validation, and 10% testing. Cross-entropy loss for classification and the Adam optimizer are used to optimize the model [3] [1].

Freshness Scoring

Model outputs are converted into a percentage-based freshness score (0–100%) reflecting current visual quality [4].

G. *Shelf-Life Prediction*

Regression layers estimate the remaining shelf-life (in days) using CNN feature embeddings [5] [2].

H. *Evaluation Metrics*

Accuracy, precision, recall, F1-score, and RMSE are used to assess the classification and regression results [6].

3. Approaches for Freshness Detection and Shelf- life Prediction

Fruit freshness detection and shelf-life prediction have evolved through various computational and deep learning techniques over the past few years. The evaluated papers show notable advancements in real-time quality assessment automation, scalability, and accuracy. Convolutional Neural Networks (CNNs), Decision Tree-based models, and Random Forest classifiers, Transfer Learning architectures, and Hybrid frameworks like CNN–BiLSTM. A brief overview of these approaches is presented below.

a. *Convolutional Neural Network(CNN)*

CNNs are deep learning models widely used for fruit freshness detection and shelf-life prediction because of their ability to automatically extract features from images [1], [3], [5]. Convolutional layers learn texture, edges, and color variations crucial for freshness scoring, , whereas pooling layers lower spatial dimensionality to prevent overfitting. Fully connected layers.produce the final classification labels such as fresh, medium, or rotten. Advanced CNN architectures like ResNet, VGG16, and DenseNet further enhance generalization and accuracy under varying lighting or background conditions [7], [15].

b. *Decision Tree Algorithm*

Decision Trees classify fruit quality based on feature thresholds such as color intensity, surface defect ratio, or texture variance [4]. Each node represents a test condition, and leaf nodes indicate the final class label. The algorithm uses impurity measures such as Gini Index or Entropy to recursively partition the dataset [9]. It is interpretable and effective for smaller datasets, making it suitable for initial experiments or baseline models [11].

c. Random Forest Algorithm

Random Forest is a collection of Decision Trees trained on random data and subsets of features via bootstrap aggregation [10]. It aggregates predictions from several trees to improve accuracy and prevent overfitting [17].In fruit freshness detection, Random Forest evaluates multiple color and texture features, providing robust classification even under noisy or diverse image conditions [8], [13], [16]. The algorithm also produces feature importance scores that help identify which visual attributes most strongly influence freshness prediction [12].

d. Transfer Learning (VGG16 / ResNet / InceptionV3)

Transfer Learning leverages pre-trained CNN architectures (such VGG16, ResNet50, and InceptionV3) trained on big datasets such as ImageNet and fine-tunes them for fruit freshness detection [2], [7]. This decreases training time and eliminates the requirement for large labelled datasets.The pre-trained layers extract general visual features, while the final layers are retrained to identify freshness- specific attributes such as discoloration and bruising.

e. Bidirectional Long Short-Term Memory (Bi-LSTM)

Recent works combine CNNs with Bi-LSTMs to capture both spatial and temporal dependencies in freshness detection [10]. CNN layers extract visual features, and Bi-LSTMs model temporal patterns that relate to progressive fruit ripening or decay. This hybrid model improves shelf-life prediction accuracy.

4. ANALYSIS OF EXISTING STUDIES

TABLE I.ANALYSIS OF EXISTING STUDIES

Sr. No	Name of the paper year	Technique Used	Advantages	Disadvantages
1.	Ensemble of multi-task deep CNN using transfer learning for fruit freshness classification, 2022 [7].	Ensemble (ResNet-50 + ResNet-101), multi-task learning, transfer learning.	High accuracy, effective with limited data.	High computation, limited to trained fruit types.

2.	CNN Ensemble Learning for Hyperspectral Imaging-based Blackberry Fruit Ripeness Detection in Uncontrolled Farm Environment, 2024 [8].	VGG16-based multi-input CNN, stack ensemble, VIS-NIR imaging.	High accuracy, Detects subtle ripeness, matches human sensory.	Needs special sensors, complex setup.
3.	Fruit Quality Assessment with Densely Connected CNN,2022 [9].	DenseNet CNN, transfer learning, deep feature reuse.	Very high accuracy (99.67%), Handles vanishing gradients, suitable for real-life use.	Computationally intensive, may require large datasets.
4.	An innovative approach to detecting the freshness of fruits and vegetables through the integration of CNN and BLSTM, 2024 [10].	CNN + BiLSTM fusion, deep feature extraction, parameter optimization.	High accuracy (97.76%), captures Complex correlations , better adaptability Than manual methods.	Computationally complex, may need large datasets and tuning.
5.	A Design of Deep Learning Experimentati on for Fruit Freshness Detection, 2021 [11].	CNN-based deep learning.	Automates freshness detection, reduces human error.	Accuracy depends on dataset quality.
6.	Measuring the Ripeness of Fruit with Hyperspectral Imaging and Deep Learning, 2021 [12].	deep neural network.	High ripeness prediction accuracy.	Requires expensive hyperspectral cameras.

7.	Fruits and Vegetables Freshness Categorizatio n Using Deep Learning, 2021 [13].	VGG-16 and YOLO deep learning models.	Multi-level freshness detection, high accuracy.	computational ly intensive for real-time processing.
8.	Canned Apple Fruit Freshness Detection Using Hybrid CNN and Transfer Learning, 2025 [14].	CNN with transfer learning, image processing, data augmentation.	High accuracy (up to 98%), outperform s other deep learning models.	Requires quality images, computational resources for multiple models.
9.	Fruit Freshness Classification and Detection Based on the ResNet-101 Network and Non-Local Attention Mechanism, 2025 [15].	ResNet-101 with Non-local Attention mechanism.	High precision and F1-score (~94%).	more complex than standard CNN models.
10.	Automatic Fruits Freshness Classification Using CNN and Transfer Learning, 2023 [16].	AlexNet-based DCNN, transfer learning, data preprocessing	computatio nally efficient (8 ms per prediction).	may require tuning for different fruit types.
11.	An extensive dataset for successful recognition of fresh and rotten fruits, 2022 [4].	Dataset creation for fresh and rotten fruits.	helps develop accurate and efficient detection models.	Does not propose a specific model.
12.	Complexity of Training ReLU Neural Network, 2022 [1].	ReLU neural networks, complexity analysis	Identifies conditions (fixed dimension, over-parameteriz ation) for efficient	NP-hard for general two-hidden-layer networks.

			training.	
13.	A deep learning- based approach for the detection of cucumber diseases, 2025 [2].	VGG19-based transfer learning.	High accuracy, early disease detection.	Needs large datasets, sensitive to image quality.
14.	Oil palm reconciliation in Indonesia: balancing rising demand and environmental conservation towards 2050, 2022 [6].	Geo- economic modelsand survival analysis.	Guides sustainable plantation planning.	Forest and peatland loss, higher costs.
15.	Vegetable and fruit freshness detection based on deep features and principal component analysis, 2024 [5].	Deep feature extraction using GoogLeNet, DenseNet- 201, ResNeXt- 101.	High accuracy (96.98%) and efficient.	Relies on pre-trained models and complex processing.
16.	Hyperparamet Er optimization of YOLOv4 tiny for palm oil fresh fruit bunches maturity detection using genetics algorithms, 2023 [3].	YOLOv4 computer vision model with GA-based hyperparamet er optimization.	Real-time, Accurate detection of oil palm fruit maturity.	Requires large labeled datasets and computational resources.

a. Review Summary and Observations

Fruit and vegetable freshness identification is now far more accurate and automated thanks to recent advancements in deep learning. Studies such as [1], [3], [5], [7], and [9] have used Convolutional Neural Networks (CNNs) and their variants including ResNet, VGGNet, DenseNet, and InceptionV3 to analyze color, texture, and shape features for distinguishing fresh from spoiled produce. Approaches

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involving Transfer Learning [8], [10], [11], [13] have helped achieve high accuracy even with limited data, while hybrid frameworks like CNN–BiLSTM and Multi-Task Learning (MTL) [4],[12] enhance adaptability by jointly predicting freshness levels and shelf-life. Some researchers have utilized hyperspectral imaging [2], [9] and feature fusion with Principal Component Analysis (PCA) [15] to extract deep spectral and structural cues, improving sensitivity to subtle freshness changes. Advanced ensemble and optimization techniques such as YOLOv4 with Genetic Algorithm tuning [16] and Random Forest classifiers have further improved detection performance. However, these models often depend on large labeled datasets, complex architectures, or specialized sensors, limiting their use in low- cost, real-time applications.

Traditional freshness assessment methods rely on human sensory judgement or laboratory tests like as spectroscopy and chromatography, which are subjective, expensive, and impracticable for large-scale deployment. Earlier machine learning approaches using SVMs and Decision Trees required manual feature extraction and lacked adaptability [6], [14]. Therefore, existing research still faces a gap in developing lightweight, scalable, and automated freshness prediction systems. The proposed FreshNet framework addresses this by combining deep learning-based image analysis with AI- driven shelf-life estimation for accurate and efficient fruit and vegetable freshness detection in real-world scenarios.

5. ALGORITHM-WISE PERFORMANCE OVERVIEW

TABLE II. ALGORITHM-WISE PERFORMANCE OVERVIEW

Sr. No.	Algorithm / Model	Evaluation Parameters	Observed Outcomes
1	CNN (VGG16, ResNet, DenseNet)	Accuracy, Precision, Recall, F1-score	Accuracy up to 99.67%; strong generalization under varied lighting [9], [15]
2	CNN + Bi-LSTM Hybrid Model	Accuracy, RMSE, F1-score	Achieved 97.76% accuracy; improved adaptability [10]
3	Random Forest	Accuracy, Feature Importance	Reliable detection with multiple color & texture features [17]
4	Decision Tree	Accuracy, Interpretability	Effective for smaller datasets; moderate accuracy [11]
5	DenseNet+ Transfer Learning	Accuracy, Loss	99.67% accuracy; robust against vanishing gradient [9]
6	ResNet-101+ Attention Mechanism	Precision, Recall, F1-score	94.7% precision, 94.24% F1-score [15]
7	AlexNet + Transfer Learning	Inference Time	Prediction time ~8 ms per image [10]

6. Conclusion

Food freshness detection remains a major challenge due to the limitations of manual and laboratory-based inspections, which are often subjective and time-consuming. This review analyzed recent studies on deep learning–based approaches for fruit and vegetable freshness detection and shelf-life prediction. Advanced models such as CNN, ResNet, DenseNet, Transfer Learning, and CNN–BiLSTM have shown high accuracy in capturing color, texture, and shape features, outperforming traditional techniques. Overall, these methods offer scalable, non-invasive, and automated solutions for real-world food quality monitoring. Future research should emphasize lightweight, real-time frameworks to enhance efficiency and reduce food waste.

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