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AI Based Approaches for Fruit Freshness Detection: A Systematic Review

Mandip Bhattarai[1*] and Bhojraj Ghimire, PhD[2]

[1] *Asst. Lecturer, Janta Multiple Campus, Itahari, Sunsari.*

[2] *Asst. Professor, Nepal Open University, Nepal.*

** Email of Principal Author: mandip.itahari9@gmail.com*

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Principal Author:

Mandip Bhattarai

Email: mandip.itahari9@gmail.com

ORCID: *https://orcid.org/0009-0005-5422-7360*

Corresponding Author:

Bhojraj Ghimire, PhD

Email: dr.bghimre@gmail.com

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Itahari, Sunsari

Tel.: 025-81300

Email: rmcjantacollege@gmail.com

Abstract

Different AI models are the latest technologies for detecting fruit freshness. They are a promising solution for reducing harvest losses, improving food quality assessment, and supporting smart agricultural practices. This study systematically reviewed 27 peer-reviewed articles and conference papers published between 2020 to 2025 on AI-based fruit freshness detection, using PRISMA methodology. The review found that models such as ResNet, EfficientNet, and Transformer-based hybrid architectures achieved the highest classification accuracies, ranging from 97% to 99% under controlled laboratory conditions. The study also revealed that YOLO-based models generally demonstrated slightly lower accuracy but offered strong real-time performance, making them highly suitable for robotic and IoT-based agricultural applications. Furthermore, hybrid and multi-task learning frameworks were less frequently explored but showed significant potential due to their balance of accuracy, efficiency, and task diversity. This review also identified important limitations in existing studies. Controlled environments, homogeneous backgrounds, and stable lighting conditions are major characteristics of most datasets, which may limit the generalizability of these models in real-world scenarios such as farms, transportation systems, storage facilities, and marketplaces. Additionally, inconsistencies in evaluation metrics across studies make direct comparisons difficult. This review provides a comprehensive synthesis of recent advances and research gaps in AI-based fruit freshness detection. The findings suggest that the effectiveness of AI-based fruit freshness detection models depends on the application context and deployment requirements. Future research should focus on developing more diverse real-world datasets and adopting standardized evaluation protocols to improve the reliability and practical applicability of these systems

Keywords: AI models, fruit-freshness detection, IoTs-based systems

Introduction

The fruit's freshness is always a crucial parameter in the safety and quality of food. In the case of Nepal, it is an additional problem due to an open border trade with India. This makes it extremely hard to regulate the freshness and determine at the points of consumption (Bhandari**,** 2025). This is a major problem in the world platform, as it has a major impact on the health of the consumers, resulting in losses in wastages in post-harvest losses, consequently aiding the economic sustainability (Hussain et al.**,** 2025). According to the report released by the Food and Agriculture Organization in 2023, it is found that approximately 40% of the production on the international scale is either wasted or lost in the wake of the post-harvest, with huge economic losses and environmental pressures, due to which immediate measures are required.

Conventional quality evaluation techniques in fruits, including sensory analysis, microbiological analysis, and chemical identification, are widespread but frequently tiresome, bulky, and prone to human mistakes (Ogidi et al., 2025). Scalability is disadvantaged by such demerits, especially in quick consumer chains. One candidate to counter this issue as a potential alternative is the introduction of Artificial Intelligence (AI). Machine Learning (ML) and Deep Learning (DL)-centered algorithms such as convolutional neural networks (CNNs) and vision transformers are spectacular performers for fruit freshness and ripeness prediction with the accuracy more than 96% in the recent literature (Abayomi-Alli et al., 2024; Amin et al., 2023; Faisal et al., 2020; Sar et al., 2025).

These methods allow quick, automated and more reliable assessments compared to traditional procedures. Despite such advances, there are many resulting research gaps. Firstly, studies are conducted largely in simulated lab settings with minuscule or judiciously selected datasets, which is not appropriate for generalizability with real-world supply chains. Secondly, comparative studies are scarce between configurations of AI models in an attempt to explore accuracy-computation-scalability explorations for minimal-resource regimes. Thirdly, few studies involve cost-effectiveness evaluations or go beyond socio-economic and infrastructural barriers towards the implementation of fruit freshness detection by AI-aided mechanisms in emerging countries. Fourthly, fragmented literature forecloses aggregated knowledge regarding an integral appreciation for inbuilt technical progressions, methodological shortcomings, as well as practical revelations. The Following are the objectives of this systematic review: (a) To find out the trending AI models used for fruit freshness detection between 2020 to 2025. (b) To compare the performance and computational efficiencies of these deep learning models. (c) To measure the applicability of these models in different agricultural environments. And (d) To determine the research gaps and to provide recommendations for future studies on fruit freshness detection.

Methods and Materials

In this study, the researchers employed a systematic review as a research design. The systematic review method is a kind of research where studies are synthesized based on their relevance. Researchers follow the systematic process to collect, analyze, evaluate, and summarize existing literature on a particular issue in the systematic review. A systematic review begins with a research question. These research questions are raised to allow for focus and specificity (Hong & Brunton, 2025).

Different research designs are used for the systematic review, although we are using the Hybrid PRISMA–Meta-Analysis design as the research design. We are following the PRISMA 2020 guidelines in this systematic review. This framework will maintain transparency, replicability, and methodological purity through the systematic process of identification, screening, eligibility, and inclusion (Sharma & Laishram, 2025).

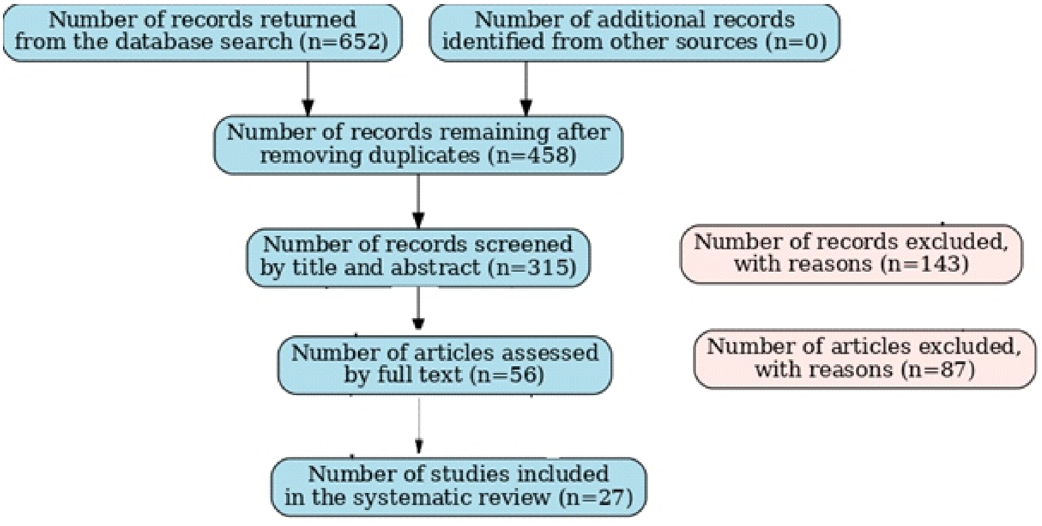
Data Extraction and Coding Procession

We have conducted a rigorous search on many repositories like Google Scholar, IEEE Xplore, and Scopus. We used the keywords and strings "*AI fruit freshness detection*", "*machine learning fruit ripeness*," and "*computer vision fruit quality*". This search generated 458 studies at the beginning, among them some from the reference list and some from the conference proceedings. The article focuses on the detection by AI, ML, or DL techniques for the freshness, ripeness, or quality of fruits through image-based, spectral, or sensor/IoT technologies.

Exclusions are applied when the studies: (1) are not concerned with fruits (or consider fruits as only a secondary set without individual results), (2) are concerned with disease detection alone, with no reference to freshness/ripeness/quality grading, (3) are review articles, editorials, theses, patents, posters, or preprints not going through the peer reviewing process, (4) omit extractable performance metrics or fail to present the dataset at all, (5) yield simulation results alone with no real images/sensor data,(6) replicate an already included study (previous or newer versions or overlapping datasets with no new analysis), or (7) are written in non-English or not publicly accessible as full-text. As well as the AI tool Grammarly has been used to make this article English grammar- and spelling-error-free.

Figure 1

Prizma Model



The extraction and coding process was organized according to the data extraction format prepared. All 27 eligible studies received a serial number (SN) and were coded into eleven categories. Methodological features were coded by determining data preprocessing techniques employed, such as steps involving the resizing, normalizing, segmenting, or augmenting of images, followed by the feature extraction or the type of model, like CNN, ResNet, EfficientNet, YOLO, or combined (hybrid) models. Dataset information was also noted with respect to the data size and the source to enable comparison of the performance of the models with respect to data availability. Performance was also measured through the reported percentages of accuracy with additional measures like F1-score, precision, recall, or confusion matrix. Source, such as a journal or conference, was also coded to determine the quality of the publication, and the reported results for each study were summarized in a short paragraph. The authors ' suggested future directions for the research were also noted for the identification of knowledge gaps. Each paper received a Q-level (Q1, Q2, Q3, or Q4) designation on the basis of the Scimago Journal Rank classification for the purpose of aligning with the standards for quality evaluation. This systematic extraction allowed for all the studies to be coded in the same uniform manner so as to make the studies appropriate for bibliometric mapping, identification of trends, and comparative synthesis.

Delimitation of the Review

Although this review has a major contribution in this field, some delimitation of this review exists. This study included articles published within 2020-2025 in English-language peer-reviewed journals and conference proceedings. The other weakness is the difference in performance measures. Other studies have reported only accuracy, whereas others have contained precision, recall, F1-score or processing speed, which makes them more challenging to compare. Lastly, there is no formal meta-analysis in the review because of the heterogeneity of datasets and outcome measures.

Literature Review

This section includes a review of the literature on various AI models used for the detection of fruit freshness. We have reviewed articles published between 2020 and 2025.

ResNet Family

ResNet models were one of the most widely used approaches to checking the freshness of fruits.ResNet skip connections prevent disappearing gradients and allow the model to learn higher-level features. Vijayakumar and Vinothkanna (2020) applied ResNet-152 to identify the level of ripeness of dragon fruit and achieved a precision of approximately 95 percent. This result is better than older VGG models. Kang and Gwak (2021) have applied ResNet-50 and ResNet-101 in a multi-task system to predict the fruit type and freshness, where the accuracy was 97.4 and 98.5%, respectively. This is a good indication of the importance of the ResNet model to be used in integrated frameworks. Also, in the course of the study, we have found that the joint application of

ResNet-18 and MobileNet to Hog Plum freshness classification achieved over 90 percent accuracy (Arunachalaeshwaran et al.,2022). These findings indicate that the ResNet types are versatile, very precise and can be used in a robust or weak resource environment.

VGG Networks

Even though the VGG architectures are quite heavy in parameters, they were successfully applied to freshness classification and grading. Mehta et al. (2021) compared VGG16, a combination of SVM, Decision Trees and Logistic Regression and detected that the SVM model showed the highest accuracy (99%). It emphasizes the importance of the hybrid power of deep feature extraction and standard machine learning. Shil et al. (2022) applied VGG19 CNN to a dataset of fruits in Bangladesh, they achieved a training accuracy of 99.86 and a validation accuracy of 98.08. This means increased accuracy of automated fruit recognition. Fu et al. (2022) applied VGG along with ResNet, GoogLeNet, and AlexNet, compared to a comparative framework, where VGG once again demonstrates better validation performance. Based on these research works, we can assert the VGG as a reference feature extractor. Nevertheless, the biggest problem of the VGG model is its efficient implementation on low-resource or mobile devices (Careem et.al., 2024).

YOLO Models

YOLO models were unique to real-time detection. They can be used in robotic harvesting and IoT-based freshness monitoring. Mukhiddinov et al. (2022) improved YOLOv4 with Mish activation and got 50.4% AP, which was lower than CNN classifiers but useful for real-time tasks. Xiao et al. (2023) applied an enhanced YOLOv5 based on ShuffleNet and CBAM with 91.5% mAP and 92% recall in detecting blueberry ripeness. This demonstrates a reasonable tradeoff between speed and accuracy. Liu et al. (2023) improved YOLOv5x with MobileNetV3 and CBAM, which has an 78.3% mAP. Through these studies, it is evident that YOLO is among the important models that can be used to detect the freshness of fruits in a fast and real-time manner, but when compared to other models, it is clear that YOLO is not as accurate as ResNet or VGG.

AlexNet and Transfer Learning Approaches

The reviewed studies indicate that the AlexNet can be considered as one of the credible algorithms to detect fruit freshness; it is more accurate and reliable when used with transfer learning. Amin et al. (2023) have combined AlexNet and transfer learning on three publicly available datasets of fruits. They not only got an accuracy of 98-99 percent, but they also got the faster computation, i.e. 8 ms of classification. Varshney et al. (2024) classified fruits and vegetables with AlexNet and VGG, as well as YOLO. The accuracy of these two studies is more than 90 percent in various conditions. These two studies demonstrate that AlexNet is incredibly simple compared to the current CNN, yet a good baseline for speedy image classification.

EfficientNet and MobileNet Variants

Several recent studies have adopted EfficientNet and MobileNet families due to their efficiency in the tradeoff between accuracy and computational cost. Aldakhil and Almutairi (2024) presented a same-domain transfer learning model based on EfficientNetV2 with an accuracy of 99 percent in multi-fruit classification and grading using the FruitNet dataset. MobileNet versions were frequently used with ResNet in lightweight versions, including in Arunachalaeshwaran et al. (2022), which were compatible with edge and mobile devices without much loss of accuracy. These results show the increasing relevance of efficiency-optimized architectures in practical agricultural contexts.

Multi-task and Hybrid Models

Models of hybrids and multi-tasks showed specific benefits in the integration of multiple goals and the exploitation of various sets of features. Kang and Gwak (2021) developed a multi-task ensemble with ResNet models that simultaneously predicted the fruit type and freshness, which enhanced robustness. Zhang et al. (2024) proposed a multi-task CNN to detect freshness and classify the type of fruits, achieving 93.2% freshness and 88.6% fruit type accuracy, indicating the benefit of shared feature learning. In the same way, Sar et al. (2025) proposed PapayaFreshNet, a hybrid CNN-Transformer architecture using SE blocks with 97.68% testing accuracy, which proves the advantage of integrating convolutional and attention-based methods. These papers point out that hybrid and multi-task strategies enhance flexibility and resilience in different fruit conditions.

IoT-Enabled CNN Models

Other researchers combined IoT sensors and CNNs to develop comprehensive freshness detection systems. Mudaliar (2021) trained CNN models on moisture and ethanol gas sensors to identify fruit spoilage with 96 and 89 percent accuracy, respectively, on rotten and ripe fruit. Studies explore that wider freshness monitoring is possible by the proper combination of gas sensing and vision data. Many supermarkets, storage systems and intelligent agriculture could benefit from these strategies.

Results and Discussion

We have discussed the various AI-based models to detect the freshness of fruits. Based on the above discussed 27 studies the following summary has been drawn. The summary of various models on the parameter accuracy, FPS and deployment suitability has been shown in the Table 1.

Table 1

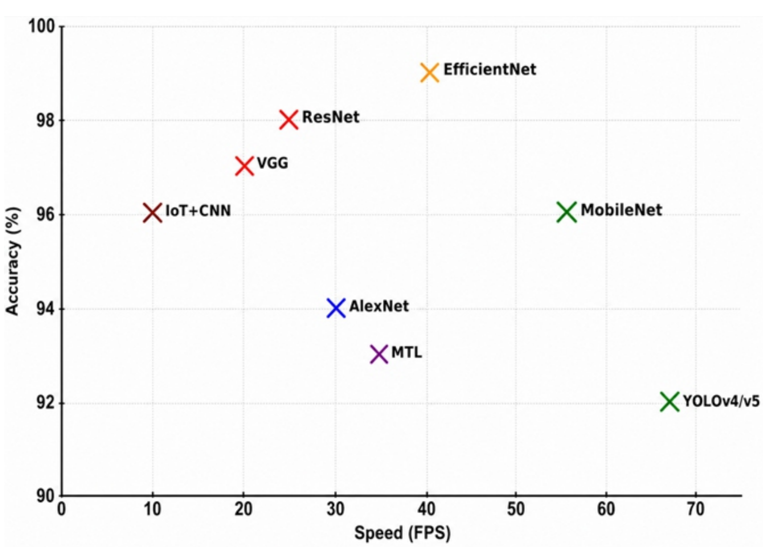
Comparison Table of Different Models

Model	Accuracy (%)	FPS (Speed)	Deployment Suitability
ResNet	~97–99	~25	High accuracy, but requires heavy compute resources (best for cloud/servers)
VGG (16/19)	~96–98	~20	Strong in feature extraction, but computationally heavy, less suitable for real-time edge use
YOLOv4/v5 (Improved)	~91–93 (mAP)	~60–70	Excellent for real-time freshness detection, highly suitable for orchard robots and edge devices
AlexNet	~94–96	~30	Lightweight baseline model, older but still effective for small to medium datasets
EfficientNet (V2)	~98–99	~40	Balances efficiency and accuracy, scalable for both edge and cloud applications
MobileNet (V2/V3)	~95–97	~50–55	Very lightweight, real-time IoT-ready, suitable for mobile and embedded systems
MTL (Multi-task Learning)	~92–94	~30–35	Robust in handling freshness + fruit type classification simultaneously, slightly slower
IoT + CNN Hybrid	~95–96	~10	Combines sensor data (gas/moisture) with vision, useful but highly hardware-dependent

The previously discussed models are further summarized in the above table. This comparison table is prepared based on the accuracy, speed (FPS) and deployment suitability of the various AI models. Models like ResNet and EfficientNet achieve very high accuracy of about 97–99% and 98–99%, but ResNet runs at around 25 FPS and requires heavy computational resources, so it is more suitable for cloud or server environments. VGG (16/19) also provides high accuracy of about 96–98%, but it is slower at around 20 FPS and computationally expensive, making it less suitable for real-time applications. In contrast, YOLOv4/v5 models have slightly lower accuracy of about 91–93% (mAP), but they are very fast at around 60–70 FPS, which makes them ideal for real-time tasks such as orchard robots and edge devices. AlexNet has a moderate accuracy of about 94–96% and runs at around 30 FPS, and although it is an older model, it is still useful for small to medium datasets. MobileNet (V2/V3) offers good accuracy of about 95–97% and speed of around 50–55 FPS, making it lightweight and suitable for mobile and IoT devices.

Figure 1

Comparative Performance of AI Models for Fruit Freshness Detection



EfficientNet (V2) balances both accuracy and efficiency with 98–99% accuracy and around 40 FPS, making it suitable for both edge and cloud applications. MTL (Multi-task Learning) models provide 92–94% accuracy and run at about 30–35 FPS, allowing

them to perform multiple tasks at the same time, although slightly slower.
The last model we discussed the IoT + CNN hybrid model has the 95–96% accuracy although it has a low speed of around 10 FPS, as this model is dependent on many IoT devices and components like sensor data and hardware. Overall, It is discovered that the models like EfficientNet and ResNet are best for high accuracy, while YOLO and MobileNet are more suitable for fast, real-time applications. The given result is shown in the Figure 1.

Conclusions

During this review, we discovered three broad trends has emerged. In comparing across models, three broad trends emerge. First, ResNet, Efficient and Transformer based-hybrid models are high capacity models and they are leaders in terms of accuracy i.e. 97-99% in the controlled dataset, although their practicability depends on the computational resources. Second, YOLO models are the real time models, they have slightly lower accuracy but very much suitable and important for robotic and IOT based applications as their accuracy is remarkable. As well as hybrid and multi-task frameworks are less common but shows great potential for future solutions because they have the good balance between accuracy, reliability and task diversity. The conclusion could be drawn that there is no single best model for every situation, controlled dataset or real-time dataset. The best model can be based on the working environment, such as high-accuracy laboratory grading, a fast scoring system or field robots with limited resources.

We found that most of the studies have very high accuracies, more than 95%. This figure can be interpreted with care. We noticed that most of the datasets were taken in laboratory or highly controlled settings where fruits were taken on a homogeneous background and under constant light conditions. These conditions are exceptional in real-time situations like farms, transportation, go-downs, and markets. This could be the reason for lower generalization of these models. Their performance may decrease when they are not used in curated datasets.

The researcher has some recommendation for the future researchers of this domain. To improve the accuracy and speed of the fruit-freshness detection, the future research should create large, open, and standard datasets with different fruit types and real-life conditions. Research with different technologies like thermal cameras, and sensors with improvised lightweight AI models could be explored to increase detection accuracy and make the system suitable for low-cost and real-time agricultural applications. Future studies should also investigate hybrid AI models and strengthen collaboration among researchers, industries, and policymakers to develop practical solutions that reduce post-harvest losses, improve supply chain efficiency, and ensure food security.

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