Deep Learning-Based Intelligent System for Food Freshness Assessment in Smart Refrigerators

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***Abstract*—Maintaining the safety and freshness of foods and vegetables, especially perishables like fruits and vegetables, is now much more important than ever in today's hectic and busy environment. Using visual inspection and determination, touch, or smell to determine freshness is a traditional method that is typically subjective and unreliable. This task project represents how deep learning might offer us a more intelligent and trustworthy road to assess the quality of perishable food. We present a Convolutional Neural Network (CNN)-powered freshness detection system that focuses on transforming ordinary refrigerators into intelligent food tracking gadgets.**

This system examines pictures of fruits and vegetables to determine and convey us there freshness levels and it also makes conclusions of the results and will send out alerts instantly when in need. The performance of five deep learning architectures ResNet50, MobileNetV2, EfficientNetB3, VGG16, and YOLOv8 is compared in our analysis with a carefully chosen dataset of 9,300 labeled images from eight different classes of fruits and vegetables, which are divided into "fresh" and "rotten." We trained the models and evaluated the models in terms of accuracy, precision, recall, and F1-score by applying standard preprocessing, data augmentation, and transfer learning.

YOLOv8 proved to be the best for real-time use with the highest accuracy of 91.5% among them. EfficientNetB3 (91.0%) was second in demonstrating a better balance between computational cost and performance. In some cases, VGG16 and ResNet50 showed promising performance, however MobileNetV2 proved to be weak in this story. Going with the research deep learning can lead to improvement of our overall sustainability and health by lowering waste and improving how we handle our food. AI-assisted freshness determination is likely to become a important component of modern food management systems and smart Kitchen, with applications ranging from home kitchens to industrial food delivery systems.

***Index Terms*—data augmentation, transfer learning, Deep Learning, YOLOv8, EfficientNetB3, ResNet50, MobileNetV2, VGG16**

I. INTRODUCTION

Fresh and safe food, in today's world, is more critical than ever before both at home as well as throughout industries such as farming, the food supply industry, and the retail industry. Fruits and vegetables are some of the easiest foods to quickly spoil. If that occurs, not only is it causing substantial quantities of food to be lost, but there are also risks to health if they are still consumed. People used to determine if food was fresh by sight, touch, or smell. However, all these are very subjective and time-consuming. What may appear fresh to someone else may not appear that way to someone else and even with that, there's always a risk of missing signs of spoilage entirely. That is why there's a big need for a method that can analyze freshness in an efficient, trustworthy, and non-judgmental manner.[1]

This analysis shows us how deep learning models can be implemented to create a smart refrigerator system one that not only carry our food items, but keeps track of it. The refrigerator employs Convolutional Neural Networks (CNNs) to examine photos of vegetables and fruits and determine whether they're still fresh or are beginning to spoil or completely rotten. Even better, it will keep you updated in real time, monitoring what's their status, and alerting you when something's missing or runs out soon.

Here are just a few ways that this smart refrigerator simplifies your life: It checks the freshness of your food automatically, so you don't have to, It foretells spoilage, allowing you to consume something before it gets wasted, it keeps track of your fridge inventory, alerting you to what you have and what you're running low on. The objective is to offer a real-world, AI-based solution to day-to-day food quality issues that can function equally effectively in households as in supermarkets or supply chains. Aside from technology, it's also good to recall why food preservation is important in the first place: Occasionally, food just cannot be kept for too long it spoils, Reducing food waste and sourcing from local, seasonal ingredients is better for the environment, Saving money by buying in bulk or seasonally, Home cooking is preservative and additive free, It's really handy to have ready-to-eat food on hand, Preserved food sharing brings communities together—neighbors, families, co-workers and keeps traditions alive, It prepares us to respond to emergencies.[8] And let’s be honest there’s a special joy in creating something unique you can’t just buy at the store. A fully automated fruit freshness classification approach utilizing transfer learning with an optimized AlexNet CNN model was recently presented by Amin et al. (2023). The study achieved 99% accuracy on three publicly available fruit datasets by experimenting with different hyperparameters, such as learning rate and batch size, to enhance performance. The aim of their newly coming analysis is to enhance and expand this approach to additional fruit and vegetable classes and implement it on a cloud-based platform for practical application. This way gives a reliable and expandable way to evaluate the quality of food.

Owning to the recent advancements in IOT, our homes and particularly our kitchens are becoming intelligent. With Wi-Fi, cloud platforms, and mobile apps, we can manage appliances remotely with voice or text commands from any part of the globe. The kitchen, as the center of the home, has gained the most. IoT-enabled appliances such as smart refrigerators have revolutionized the way, making it easier and efficient to manage food. In agricultural exports, rapid fruit quality assessment is essential [6]. Recent systems using CNNs and image processing techniques automate the detection and classification of fruits and their diseases, significantly reducing the time and effort required for manual inspection. By integrating Raspberry Pi cameras and alert mechanisms, these models support real-time monitoring and can benefit farmers by minimizing post-harvest losses and streamlining the packaging process (Chandramma et al., 2020). With this, there has been fast development in computer vision and machine learning, which has presented in more intelligent and reliable tools that can determine and analyze objects automatically [6]. Fruits, particularly, are susceptible to fungi and viruses when left open. For farmers and vendors, this is a gigantic problem and a costly one. Manually sorting and inspecting fruits is not only time-consuming but also error-prone.[16]. That's why there has been a growing interest in automated fruit quality checking systems. Deep learning techniques such as CNNs and DNNs have been applied in the past few years to determine if fruits are fresh or not. These machines learn from thousands of images, identifying patterns and features that enable them to make the right judgments. This technology can even be applied to useful things such as multi-fruit identification for shopping malls or assembly lines minimizing human fault and maximizing efficiency. Freshness is not all visual it has an impact on how long the fruit will last and how healthy it will remain. For the consumer, this assists in making better purchasing decisions. For producers and retailers, this helps to ensure only the best makes it onto the shelves. And thanks to machine learning and transfer learning, the performance of these image-based systems continues to improve [1]. With a 99.9% accuracy rate on the FRUITS360 dataset and a considerable reduction in training time, MobileNetV3 was found to perform better than InceptionV3 in terms of both training efficiency and accuracy. Additionally, during real-time testing, our lightweight CNN model showed dependable performance, indicating its applicability for smart refrigerator applications (Jain et al., 2022).

Over the past many years, image and object classification research has been growing in rapid, particularly after 2014–2015. The initial attempts were based on conventional computer vision methods for testing the external quality of fruits and vegetables. Later, sophisticated methods such as hyperspectral and multispectral imaging were employed for testing both internal and external quality [17]. Scientists such as Baohua Zhang created algorithms from color, texture, and shape features for disease detection and sorting fruits.[14] Seema et al. (2015) focused on the relevance of color analysis, feature extraction, and recognition of shape during automatic fruit grading. Baietto and Wilson (2015) investigated electronic nose sensors that detect gases emitted by produce to gauge ripeness and quality important for storage, transport, and harvesting decisions. With the advent of deep learning, more recent models such as CNNs have made impressive progress. Zeng's system, incorporating saliency maps and VGG-based CNN, was accurate to 95.6% in fruit categorization. Chandramma et al. (2020) suggested a system based on CNN for speedy detection of diseases in fruits and vegetables, facilitating speedy packaging and transportation. A few recent research papers (Ni et al., 2020; Abayomi-Alli et al., 2023) have fine-tuned deep models such as EfficientNet and ResNet18 for freshness recognition. Nevertheless, they did not have multi-model comparison and experienced slower training time. In response to these shortcomings, this study introduces a novel, effective freshness detection method with pre-trained deep models having fewer parameters and accelerated training.

To help partially sighted or low vision people and for progress in automation in the food business, Mukhiddinov et al. progressed YOLOv4-based fruit and vegetable categorization system and determination was created to distinguish between fresh and rotten products. The enhanced model, which was trained on a dataset of 12,000 images in 20 classes, performed better than the conventional YOLOv4 with an average precision of 73.5% and shown resilience across a range of occlusion and illumination scenarios. In future call for hardware development and self-supervised studying, and this strategy shows guarantee for smart gadgets and supermarkets.[12]

II. DATASET

This dataset consists images of 8 items including fruits and vegetables, these are Apple, Banana, Carrot, Cucumber, Mango, Orange, Pepper, Potato, where each fruit and vegetable are divided into two categories: fresh and rotten. The dataset in total contains 9300 images, divided into folders test, train and valid. Fahad et al., represented large datasets are essential for training effective deep learning models in freshness classification. Some recent works have used over 60,000 images of fruits and vegetables to improve model performance and reliability. In line with such efforts, comparisons among object detection models like YOLO and classification networks such as VGG have shown valuable in determining and localizing freshness levels accurately [15]. Train folder contains 6499 images in total, which is divided into two folders of fresh with 3323 images and rotten with 3166 images. Valid folders contain 1849 images in which fresh folder contains 945 images and rotten contains 902. Test contains 945 in total, in which 483 of fresh folder, and 462 of rotten. To summarize, out of the total dataset, 70% of the dataset is used for training, 20% for validation, and approximately 10% for testing.

Fig. 1. Samples of vegetables and fruits in the dataset

III. METHODOLOGY

In this analysis, the models ResNet50, MobileNetV2, EfficientNetB3, Yolov8, and VGG16 are compared. This study uses a variety of CNN architectures to identify and determine the freshness of fruits and vegetables. It provides a thorough analysis of these models and compares all. An equivalent preprocessing pipeline was used for all models. Images of fruits and vegetables that were classified as fresh or rotten made up the data, which was separated into training and validation sets. Images were scaled to dimensions 224×224 pixels to match the input size required by most deep learning models. To strengthen the model, extensive data augmentation techniques like rotation, zooming, shift, flip, and shear were carried out using ImageDataGenerator. These techniques help the model learn from varied versions of the same image, reduce overfitting, and improve accuracy on new, unseen data. Test folder consists of variety of different fruits and vegetables some different from train folder. All the images were saved in a file, captured through the camera.

1) MobileNetV2: For the MobileNetV2 model, we used data augmentation to help the model generalize better by applying transformations like rotation, shift, shear, zoom, and horizontal flip to the images. The model is built on the pre-trained MobileNetV2 architecture, with additional layers (like GlobalAveragePooling2D, Dense, and Dropout) for binary classification—deciding whether the fruit or vegetable is fresh or rotten. We trained it for 25 epochs, with early stopping to prevent overfitting, and saved the final model for later use. To evaluate the model's performance, we plotted the training and validation accuracy over time.

2) EfficientNetB3: We used comparable data augmentation methods to EfficientNetB3 as we did for MobileNetV2. EfficientNetB3 serves as the foundation for the model, which also includes extra dense and dropout layers for classification. After training the model for five epochs with the base layers frozen, we unfrozen them and fine-tuned for fifteen additional epochs at a reduced learning rate. Early halting was used to minimize overfitting, and the best weights were restored during training. Following training, the model was saved, and the training log was preserved for future examination.

3) ResNet50: In order to add diversity to the data, the ResNet50 model also included data enrichment techniques like flipping and brightness variation. It uses bespoke dense layers for classification and is based on a pre-trained ResNet50 model, just as the others. Before storing the trained model for later use, we froze the base model and trained it for 15 epochs at a fixed learning rate.

4) VGG16: We also used shear and zoom transformations for data augmentation with VGG16. The design uses unique dense layers for classification and is based on VGG16. To enhance performance, we adjust the final four layers of a previously trained model if one is available. To prevent overfitting during training, we employed learning rate decrease and early halting. We stored the model for later use as soon as it demonstrated improvement on the validation data.

5) YOLO (You Only Look Once): For the classification job, we employed the YOLOv8 model for YOLO (You Only Look Once). After loading the dataset, the YOLOv8 model was trained on 224x224 pixel-resized images for 10 epochs. Following training, the model successfully identified and categorized fruits and vegetables.

IV. RESULTS

Model	Accuracy (%)	Precision (Fresh/Rotten)	Recall (Fresh/Rotten)
EfficientNetB3	91.0	0.97 / 0.86	0.85 / 0.97
MobileNetV2	21.1	0.29 / 0.06	0.37 / 0.05
ResNet50	62.0	0.82 / 0.57	0.33 / 0.92
VGG16	86.5	0.83 / 0.91	0.92 / 0.80
YOLOv8	91.5	0.99 / 0.86	0.84 / 0.99

TABLE I. Accuracy, Precision and Recall

Model	F1-Score (Fresh/Rotten)	Remarks
EfficientNetB3	0.90 / 0.91	Balanced and robust performance
MobileNetV2	0.32 / 0.05	Underperformed significantly
ResNet50	0.47 / 0.70	High recall for "rotten" class
VGG16	0.87 / 0.85	Strong overall performance
YOLOv8	0.91 / 0.92	Best test accuracy

TABLE II. F1-Score, Remarks

In the comparative assessment, of Table I. and Table II. of deep learning models for detection of freshness in fruits and vegetables, YOLOv8 proved to be the best-performing model, which recorded an impressive 91.5% test accuracy. It showed a fine balance between recall and precision for both fresh and rotten classes and is especially appropriate for real-time applications like smart refrigerators, supermarket checkout counters, or automated food processing unit quality control. Its resilience in maintaining high accuracy without sacrificing speed is a demonstration of its strength in high-throughput settings.

EfficientNetB3 was very close behind with a solid 91.0% accuracy. Along with its excellent performance, the model is also computational efficient and light, which makes it a perfect choice for deployment on resource-limited environments like mobile or embedded systems. It sustained balanced precision and recall, hence its consistency as a stable alternative when both efficiency and performance are needed. VGG16 also performed outstandingly well with an accuracy of 86.5% and consistently strong F1-scores for both classes. Though not competing with YOLOv8 or EfficientNetB3, it was an ever-reliable model in systems where image quality is uniform and under controlled environments. Its strong overall generalization indicates that it might be used effectively in lab-based analysis software or organized industrial inspections.

ResNet50, while having a lesser overall accuracy of 62.0%, showed strong strength in the detection of rotten produce, with a recall of 92% for the category. This indicates its potential in usage where the detection of spoilage is a greater concern than overall classification balance, such as early detection systems in supply chains or cold storage monitoring. In contrast, MobileNetV2 performed much worse, achieving only 21.1% accuracy. Although it has strengths in speed and model size, it did not generalize well across the freshness classes. Its low recall and precision indicate that, without extensive optimization or retraining, it is not currently appropriate for this specific classification task. Overall, YOLOv8 and EfficientNetB3 are the most likely models to be deployed practically in freshness detection systems due to their robust performance and flexibility. VGG16 and ResNet50 offer specific benefits based on particular application needs, whereas MobileNetV2 will need to be further developed to achieve acceptable performance levels in this area.

Fig 2. demonstrates how various deep learning models worked in identifying if fruits and vegetables were fresh or spoiled, using images taken via a system camera as well as some obtained from the internet. Each prediction has been marked accordingly—phrases such as "Fresh as Fresh" indicate that the model was correct in recognizing a fresh one, while "Fresh as Rotten" indicates that it made a mistake. Of the five models tested YOLOv8, EfficientNetB3, VGG16, ResNet50, and MobileNetV2. YOLOv8 reliably produced the most accurate output. It performed well with a large variety of inputs, producing correct predictions with high confidence. This indicates it's a viable contender for real-time freshness checking, particularly in real-world applications such as smart refrigerators or quality control systems. EfficientNetB3 was also generally good, though sometimes had issues with borderline instances. VGG16 and ResNet50 yielded a combination of correct and incorrect answers—usually good, but not perfect. MobileNetV2, although light and efficient, was least accurate among the bunch, often getting it wrong and with limitations in identifying nuanced freshness indicators. In general, the findings leave little doubt: where speed and accuracy are important, models such as YOLOv8 are more appropriately deployed, though easier models such as MobileNetV2 might have appeal for having lower computational requirements

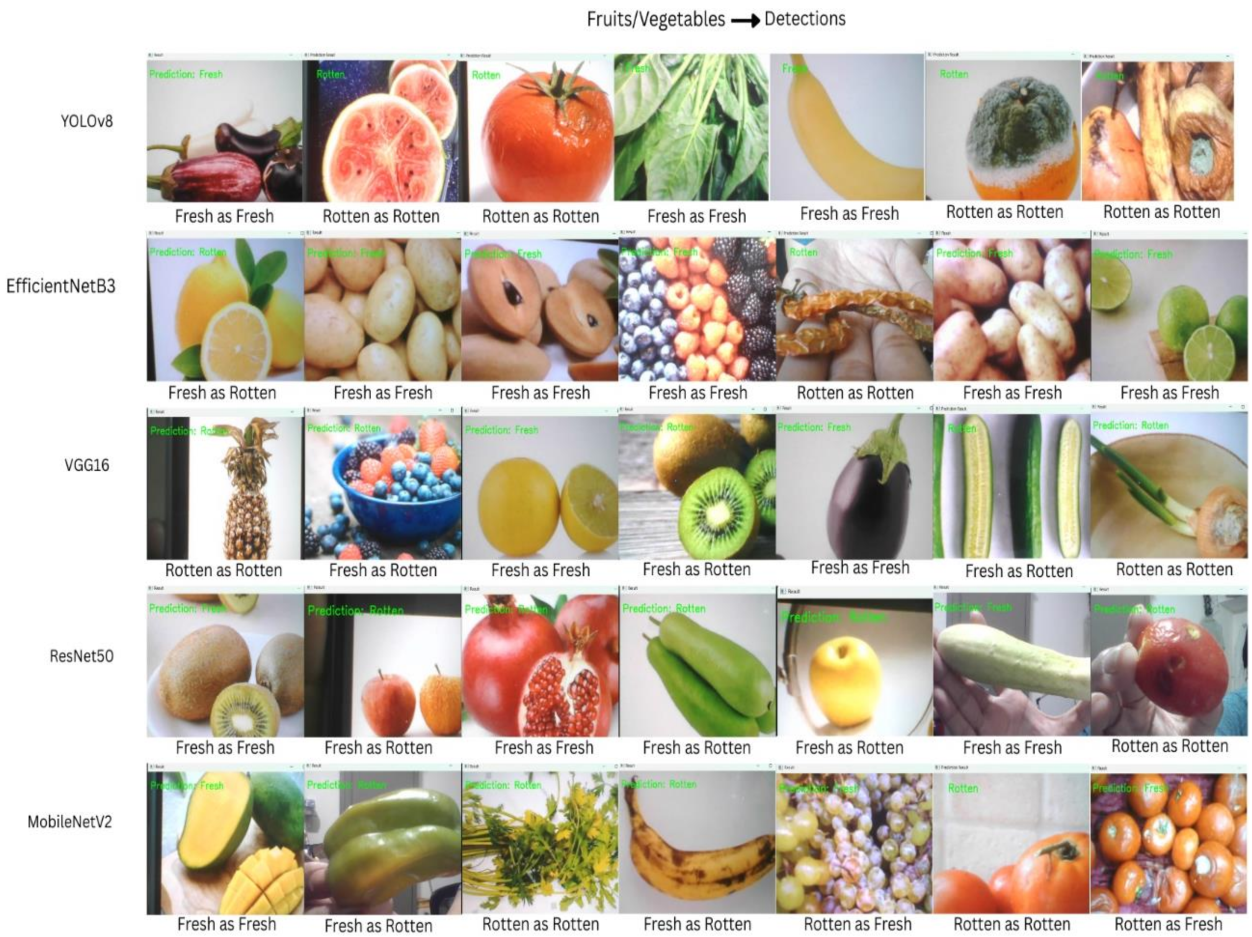

Fig. 2. Result of Detection as fresh and Rotten of images of fruits and vegetables

V. CONCLUSION

This work illustrates the high value of deep learning in creating intelligent food monitoring systems that can recognize freshness in fruits and vegetables. In assessing and comparing five of the leading CNN architectures—YOLOv8, EfficientNetB3, VGG16, ResNet50, and MobileNetV2—on a specially selected dataset of 9,300 labeled images, we discovered that YOLOv8 is the best-performing model with the highest accuracy (91.5%) and showing real-time applicability. EfficientNetB3 came close with a 91.0% accuracy, providing an ideal trade-off between performance and computational cost, making it effective for edge devices. Although VGG16 and ResNet50 were good for certain situations, especially in detecting spoilage, MobileNetV2 significantly lagged behind, indicating its inability to perform effectively in such classification tasks. This study demonstrates how deep learning can convert traditional refrigeration systems into intelligent, AI-based freshness sensors, minimizing food loss, enhancing health benefits, and enabling sustainable consumption. All the models made use of data augmentation and pre-trained models to help them perform better, and we fine-tuned them as necessary to improve accuracy. The models were evaluated based on their performance metrics, including accuracy, loss, precision, recall, and F1-score. The best performing models were saved, ready for use in real-time predictions or further analysis. Scope for future evaluations could involve incorporating gas sensors or multispectral cameras in gadgets to further bettering the robustness of freshness detection beyond visual inputs. Further research work on fruit and vegetable freshness detection through CNN models could deliver many promising directions for further improvement. IoT and smart gadgets integration can provide real-time freshness checking in houses and stores through edge-supported, embedded models.

Outside of visual hints, sensor combination (e.g., gas or temperature) with picture data can give more accurate and reliable freshness determination with multimodal solutions. Growing the dataset to get more types of fruits and vegetables in different lighting and packaging conditions will expand model robustness and generalization. Switching from binary classification to multi-stage grading (e.g., fresh, slightly spoiled, rotten) would offer more useful insights for users and businesses. Live video stream analysis would allow real-time monitoring in warehouses and stores. Combining freshness detection with supply chain systems may also minimize food waste and enhance logistics. Furthermore, actualizing augmented reality applications would enable consumers to scan produce in real time using smartphones and obtain freshness feedback. Adding continuous learning will enable the system to adapt to user-specific ratings and enhance over time. These directions of the future seek to advance the usability, precision, and effectiveness of freshness detection systems in becoming more intelligent, scalable, and beneficial across domestic, agricultural, and commercial settings.

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