SMART FRIDGE

Mehmet Erkut Erdem[1], Can Ali Ateş[1], Emre Çoban[1], Abdullah Enes Ergün[1], Baha Kırbaşoğlu[1]
[1]Hacettepe University, Department of Artificial Intelligence
https://smartfridgehacettepe.github.io/

Abstract

Food waste is a significant global issue, impacting both the environment and the economy. The "Smart Fridge" project addresses this problem by monitoring the condition of fruits and vegetables stored in household refrigerators, thereby preventing spoilage and reducing waste. Using the YOLOv8 object detection algorithm, the system classifies produce as either fresh or rotten, with rotten items further analyzed by a ResNet-101 model to determine the extent of decay. Our integrated approach has shown high accuracy in differentiating and estimating decay, promising to cut down food waste and encourage sustainable consumption. Future improvements will enhance accuracy, expand the dataset, and integrate additional sensors for comprehensive monitoring.

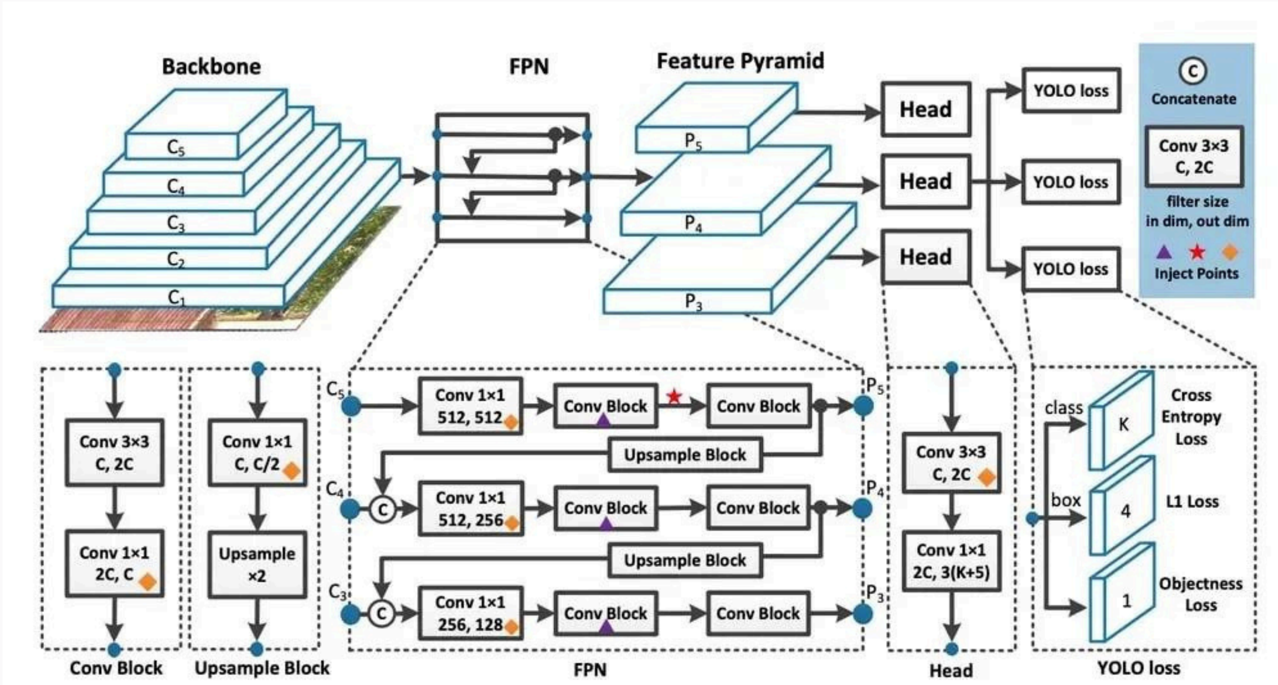
Dataset

The dataset contains five different types of vegetables and fruits. Hacettepe University Food Engineering Department is provided to fresh and rotten images. The distribution of these images are as follows:

- Peach: 307 fresh, 252 rotten
- Lemon: 132 fresh, 195 rotten
- Mandarin: 196 fresh, 220 rotten
- Tomato: 253 fresh, 225 rotten
- Cucumber: 105 fresh, 39 rotten

Methodology

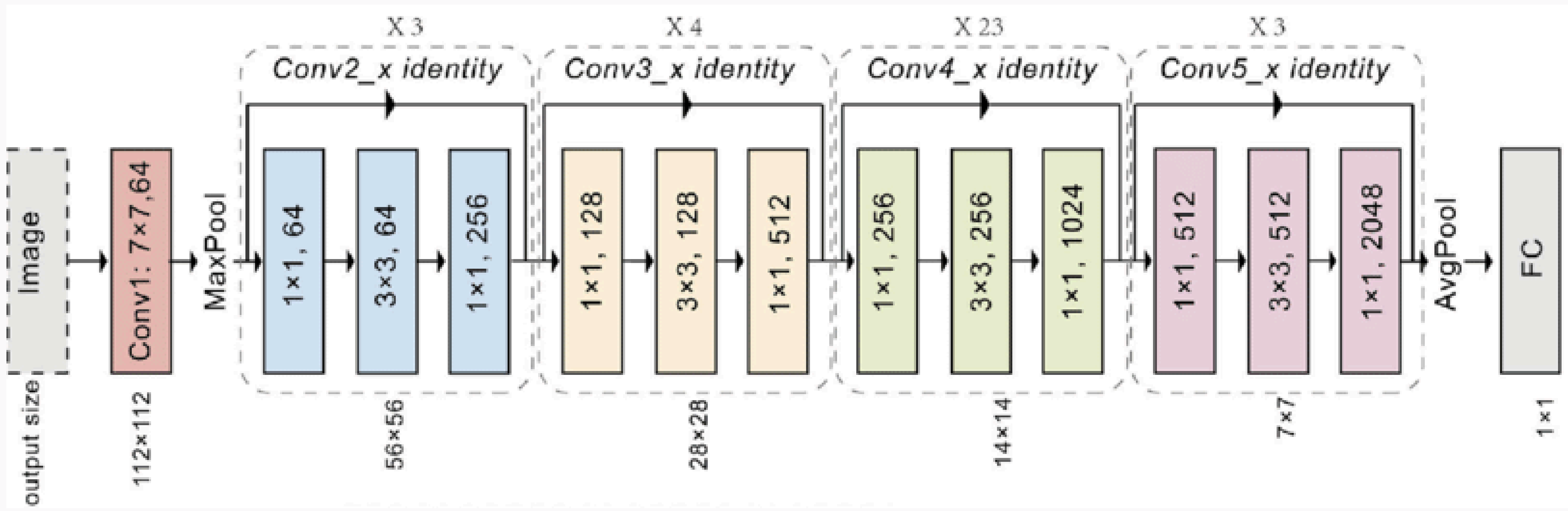
Fruit and Vegetables Detection with YOLOv8



YOLOv8 (You Only Look Once, version 8) was selected for object detection due to its superior performance in speed and accuracy. As a single-stage detector, YOLOv8 predicts bounding boxes and class probabilities simultaneously, making it suitable for real-time applications. The small version (YOLOv8-s) was deemed sufficient for the task. Each image in the dataset was annotated with bounding boxes around the fruits and vegetables, labeled as either fresh or rotten, and the annotations were stored in a format compatible with YOLOv8. During training, the YOLOv8 model was initialized with pre-trained weights, and data augmentation techniques such as resizing, random horizontal flipping, random rotation, and normalization were used to enhance the model's ability to generalize to unseen data. The model was trained for 60 epochs with early stopping based on validation loss with an AdamW optimizer with 0.000714 learning rate at 38 batch size.

Decay Estimation with ResNet-101

For estimating the percentage of decay, the ResNet-101 model was utilized after items were identified as rotten by YOLOv8. Chosen for its depth and superior performance in image classification tasks, ResNet-101's ability to extract complex features was leveraged. The model was initialized with pre-trained weights from ImageNet, and three fully connected layers were added: the first layer with 2048 input features and GeLU activation outputting 512 features, the second layer with 512 input features and GeLU activation outputting 64 features, and the final layer with 64 input features producing a single output node representing the percentage of rot (0-100).



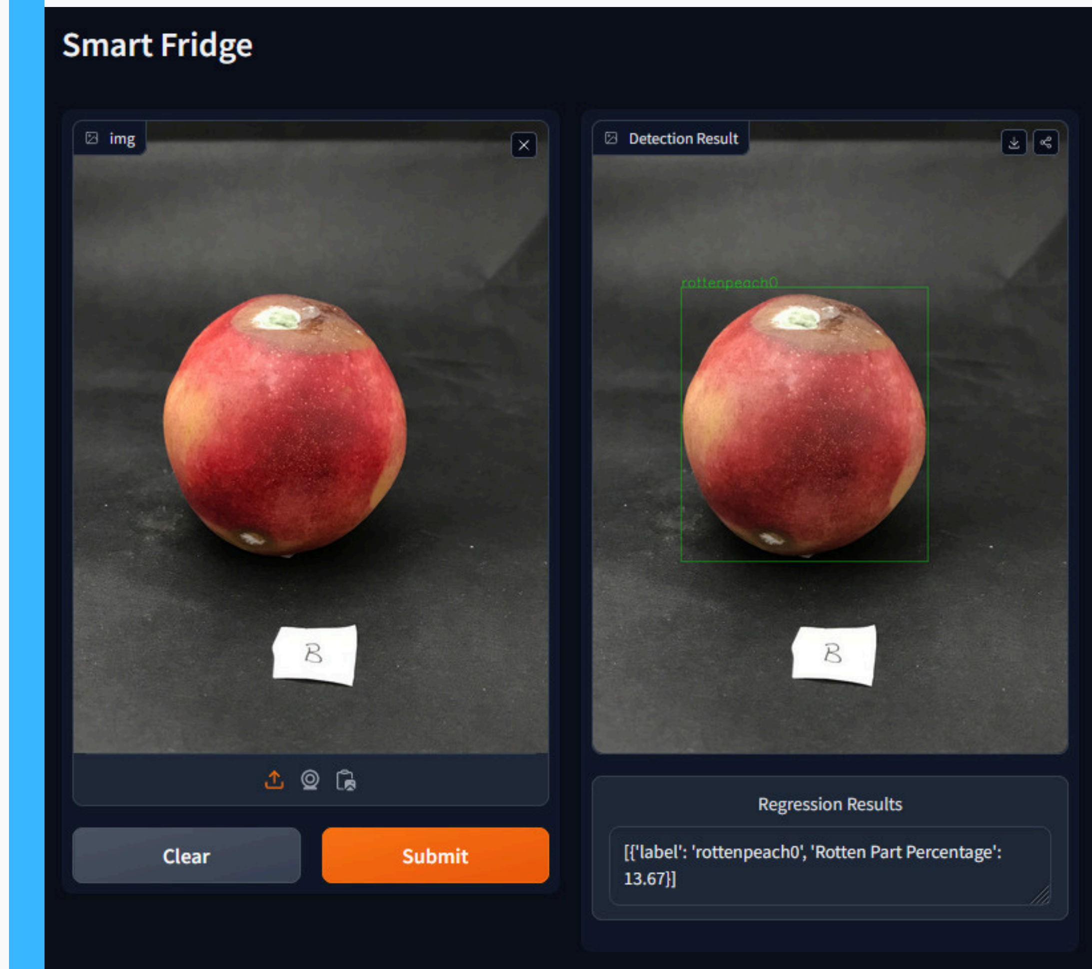
Training & Evaluation

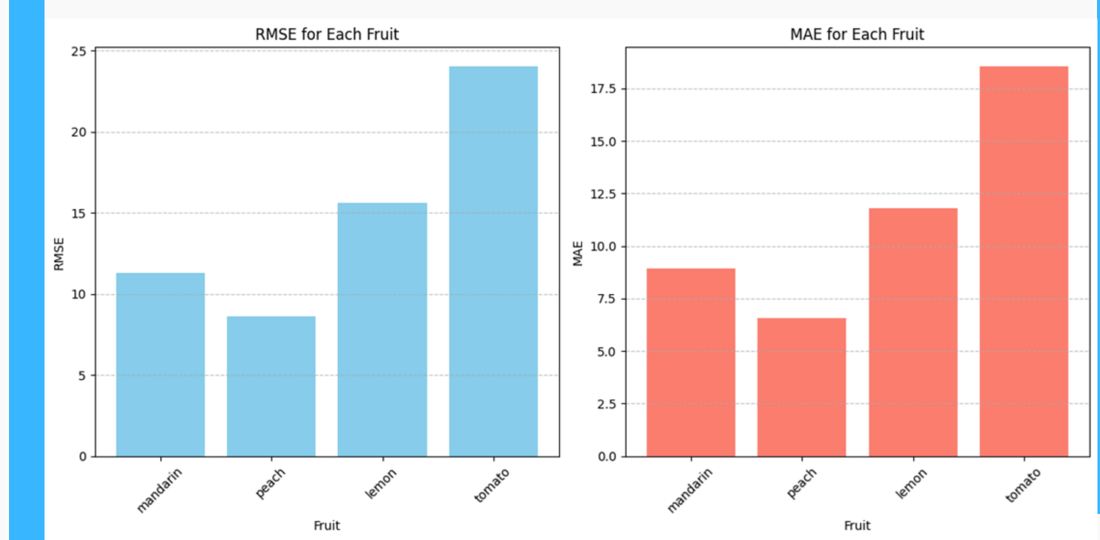
- Dataset Preparation: Images were annotated with bounding boxes labeled as fresh or rotten.
- YOLOv8 Training: The YOLOv8 model was trained with pre-trained weights and data augmentation techniques over 100 epochs, with early stopping based on validation loss to prevent overfitting.
- ResNet-101 Initialization: ResNet-101 was initialized with pre-trained ImageNet weights.
- ResNet-101 Configuration: Three fully connected layers were added to predict the percentage of rot.
- Training Environment: Training was conducted using an NVIDIA RTX 3060 GPU in a high-performance computing environment.
- Optimization: Mean Squared Error (MSE) loss and the Adam optimizer with an initial learning rate 1e-4 were employed.
- Early Stopping: Applied based on validation loss to enhance performance.

The effectiveness of both models was assessed using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

Results & Conclusion

Overall, the YOLOv8 model achieved impressive performance across all classes, with mean Average Precision (mAP) scores exceeding 0.95 for each category. The integrated pipeline demonstrated the ability to accurately differentiate between fresh and rotten items and estimate the decay percentage with a Mean Absolute Error (MAE) of approximately 10-15%.





In conclusion, the Smart Fridge project represents a transformative approach to mitigating food waste through the application of advanced image recognition and deep learning techniques. By enhancing household food management practices, the system not only provides economic benefits to consumers but also contributes to environmental sustainability by reducing the amount of organic waste in landfills. The integration of this technology into smart home ecosystems offers a competitive advantage for manufacturers and valuable insights for future innovations. With ongoing improvements in decay detection accuracy and the incorporation of additional sensors, the Smart Fridge can deliver even more precise assessments of produce conditions. Moreover, the development of a complementary mobile application could enhance user engagement and efficiency in food utilization. Ultimately, the Smart Fridge project has the potential to play a pivotal role in achieving sustainability goals and revolutionizing the way households manage their food resources.