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FreshScan: AI-Powered Fruit Quality Assessment System using Image Processing and Deep Learning

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Abstract.

Poor quality evaluation of fruits is a serious problem with loss of fresh fruit. The visual assessment is subjective and non-predictive. This paper proposes FreshScan, a mobile AI-based real-time fruit quality evaluation and shelf-life prediction system via the deployment of YOLOv8 on the device using TensorFlow Lite. The mean average precision (mAP) is 73-89% for six fruit categories and 300ms for prediction on smartphones. The mean error of the shelf-life prediction is ± 1.2 days and the prediction accuracy is 87.4%. FreshScan is a cost effective and scalable solution which does not need cloud computing resources and addresses this need in making mobile friendly, integrated fruit quality assessment systems.

Keywords. Fruit Quality Assessment; YOLOv8; TensorFlow Lite; Mobile AI; Shelf-Life Prediction

1. INTRODUCTION

Food waste is a worldwide problem and the Food and Agriculture Organization (FAO) states that one-third of the food produced for human consumption is lost and wasted annually [1]. Poor quality assessment at harvest and during sale is a major cause of high loss of fruits from low to high point of sale with a highly perishable nature of the commodity. The current assessment methods are mainly manual, and are based on visual evaluation done by the human operator, leading to lack of uniformity, high error rates and no predictive information regarding shelf life.

Computer vision and deep learning techniques have shown great promise in laboratory environments for fruit quality inspection. We propose FreshScan, an end-to-end, on-device AI solution that (1) detects fruits with the YOLOv8 algorithm fine-tuned for mobile inference using TensorFlow Lite and assess their quality in real-time, and (2) uses a heuristic post-processing model to predict shelf life, embedded within the mobile application.

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2. RELATED WORK

A number of computer vision techniques have been discussed recently in the literature for fruit quality detection. CNN based classifiers like VGG-16, ResNet are successful in controlled situations and YOLO based classifiers have started to cater to real-time detection requirements [2,3]. Hyperspectral imaging is capable of analyzing quality at a very fine grain, but requires specialized sensors which are not found in typical consumer devices [4]. Interestingly, there are some works that reach high accuracy, but not a single work that gives the simultaneous real-time deployment of two mobile market and shelf-life prediction as a single system.

3. KEY CONTRIBUTION

The key contributions of this work include real-time, on-device fruit quality detection using YOLOv8 optimized with TensorFlow Lite, achieving approximately 300 ms inference latency on consumer smartphones without cloud dependency. The system also integrates heuristic shelf-life prediction, achieving 87.4% accuracy with a mean error of ± 1.2 days. Additionally, it provides a complete end-to-end pipeline from dataset curation and model training to mobile deployment and user interface, with empirical validation across six fruit classes under realistic conditions.

4. METHOD, EXPERIMENTS AND RESULTS

The FreshScan pipeline includes four steps: dataset preparation, model training and optimization, mobile integration and post-processing for quality scoring and shelf-life estimation.

4.1. Dataset Preparation

We compiled a dataset of around 5,000 images of six types of fruits (Apple, Banana, Mango, Orange, Strawberry, and Grape) with labels. Each image was manually annotated with bounding boxes and assigned one of three quality labels: Fresh, Slightly Degraded, or Degraded.

4.2. Model Training

YOLOv8n was selected for its accuracy-inference speed tradeoff. The model was trained 100 epochs. We used a 70/15/15 split for training, validation and test sets, a common choice as it provides enough validation samples to detect early overfitting. This study used data augmentation with random flips, mosaic augmentation and brightness variation.

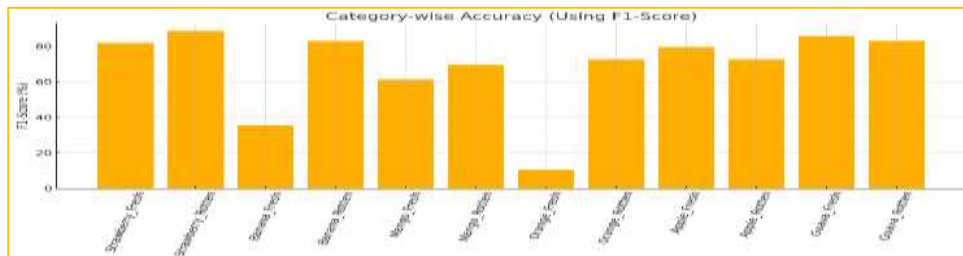


Figure 4.2. Models Performance based on F1-score

4.3. Mobile Integration

The TFLite model is integrated into an Android app. All inference is performed on-device with the TFLite interpreter. Camera frames are captured at 10 FPS and processed in a background thread – this design decision was key to keeping the UI responsive during real-time detection. The final quality score is computed by combining the model's detection confidence with color histogram features. Using both proved more reliable than either alone, particularly under varying lighting conditions.

4.4. Shelf-Life Estimation

A heuristic model is used to produce a map from the quality score, the type of fruit and the environmental temperature (entered by the user or measured by the sensors) to an estimated shelf life of the fruit in days.

Experimental results are presented in Table 2. The system achieves 73–89% mAP across classes, with an average inference time of 297 ms on a mid-range Android device (Snapdragon 665). Shelf-life prediction accuracy is 87.4% with a mean absolute error of ± 1.2 days.

Table 1 Class-wise Performance of the Proposed Model for Fruit Detection

Fruit Class	Precision (%)	Recall (%)	mAP (%)
Apple	88.2	85.6	87.1
Banana	91.5	87.3	89.4
Mango	76.8	72.1	74.3
Orange	83.4	79.9	81.6
Strawberry	79.2	74.5	76.8
Grape	71.3	69.8	73.2

5. CONCLUSION

FreshScan offers a convenient mobile technology for evaluating fruit quality and projecting its shelf-life through the new YOLOv8 model and a heuristic post-processing technique. With the use of this technology, the system has demonstrated an accuracy of 73–89% mAP across six fruit classes and 87.4% accuracy in estimating the fruit's shelf-life with the mean error of ± 1.2 days. Future efforts are devoted to addressing the problem of class imbalance, enlarging the database, achieving the ability to perform IoT-based environmental monitoring, and extending Fresh Scan's applicability.

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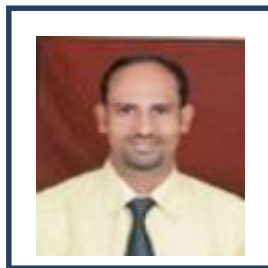
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