Prediction of Remaining Shelf Life of Fruits

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***Abstract*—The accurate estimation of fruit shelf life is crucial for maintaining product quality and reducing food wastage. In recent years, advancements in deep learning and computer vision techniques have opened up new possibilities for non-invasive and efficient shelf-life prediction. This research aims to leverage deep learning and object detection methods to predict the shelf life of fruits.**

In the realm of perishable goods, such as fresh fruits, optimizing inventory management and reducing waste is an ongoing challenge. One critical factor that significantly influences consumer decisions in this context is the remaining shelf life of the product. This study aims to present a compelling justification for focusing exclusively on the variable of remaining shelf life to predict fresh fruit purchases.

In this study, we propose a novel approach that combines deep learning and object detection techniques to predict fruit shelf life. The proposed framework involves two main stages: fruit detection and shelf-life prediction. In the fruit detection stage, state-of-the-art object detection models are employed to identify and track individual fruits within images. Subsequently, the detected fruit images are fed into a deep-learning model designed to predict shelf life. The model takes into account various visual features such as colour changes, texture variations, and morphology, which are indicative of fruit ripening and deterioration. The integration of object detection and deep learning enhances the accuracy of predictions by capturing spatial and temporal information, enabling a comprehensive understanding of fruit conditions.

***Index Terms*—Deep Learning, Image Processing, object detection, remaining shelf life, feature extraction**

I. Introduction

The preservation and efficient management of perishable food items, particularly fruits, have emerged as critical challenges in the modern food industry. One of the key issues in this domain is the accurate prediction of fruit shelf life, which directly impacts product quality, consumer satisfaction, and the reduction of food wastage. Traditional methods of shelf life assessment often involve subjective judgment, which can lead to inconsistencies and inefficiencies in supply chain operations. These methods require highly structured and expensive sensory devices, sampling labs and data acquisition systems as inferred from [5]. In recent years, advancements in deep learning and computer vision techniques offer a promising avenue to address these challenges and provide objective, data-driven solutions.

Fruits undergo complex physiological and biochemical changes during their lifecycle, transitioning through stages of ripening, maturity, and eventual decay. These changes are often accompanied by alterations in colour, texture, and morphology. Accurate prediction of shelf life requires the ability to capture and analyze these subtle yet critical transformations. However, this task is inherently intricate due to the inherent variability in fruit characteristics, the influence of environmental factors, and the dynamic nature of the shelf life progression [6].

Conventional methods of shelf life estimation, such as sensory evaluation or chemical analysis, are time-consuming, labour-intensive, and may not be well-suited for real-time monitoring. Additionally, these methods may not capture the nuanced changes in fruit appearance that are indicative of shelf life. This presents a clear need for innovative and automated techniques that can comprehensively monitor and predict fruit shelf life in a non-invasive and efficient manner.

The integration of deep learning and object detection techniques has revolutionized the field of computer vision. Object detection models, such as Faster R-CNN, YOLO, and SSD, have demonstrated impressive capabilities in accurately identifying and localizing objects within images and videos [9]. By extending these capabilities to fruit detection, it becomes possible to precisely track individual fruits' conditions over time. Moreover, deep learning models, particularly convolutional neural networks (CNNs), and various traditional machine learning models have shown the capacity to learn intricate patterns from visual data, making them well-suited for predicting subtle changes in fruit appearance associated with shelf life progression.

In light of these considerations, this research endeavours to bridge the gap between traditional shelf-life prediction methods and the potential of deep learning and object detection techniques. By developing an integrated framework that leverages the power of computer vision and machine learning, this study aims to provide a more accurate, objective, and efficient approach to predicting fruit shelf life. Through the utilization of comprehensive datasets and robust evaluation metrics, the research seeks to validate the effectiveness of the proposed approach and contribute to the advancement of sustainable and informed practices within the food supply chain. Remaining shelf life is a dynamic parameter that directly influences the immediate purchasing decision. It also helps in Demand forecasting, routing and transportation, waste reduction, pricing strategies etc. Hence, incorporating the concept of remaining shelf life into supply chain management strategies for fresh produce offers a multitude of advantages.

II. Literature Review

In recent years, there has been an increased interest in using deep learning techniques to predict the shelf life of fresh food based on its physical characteristics, including food morphology. This approach shows potential for enhancing the prediction of fruit shelf life, leading to the discovery of innovative methods for extending storage periods and enhancing the quality of existing fruit preservation techniques.

The research work of [1] outlines the study's objective: predicting mango shelf life using cutting-edge non-destructive methods, specifically thermal imaging coupled with pre-trained models via transfer learning. This is grounded in the understanding that transfer learning is well-suited for high accuracy with limited image datasets. The study relies on specific hardware, including smartphones and Seek Thermal cameras. The performance and availability of such hardware might vary, potentially affecting the feasibility and accessibility of the proposed method. The paper focuses exclusively on the "Kesar" mango cultivar, which might limit the generalizability of the findings to other fruit varieties. Different fruits possess varying intrinsic characteristics that could impact the effectiveness of the proposed method on a broader scale.

Jiangong Ni, Jiyue Gao, Limiao Deng and Zhnogzhi Han introduced a transfer learning technique for identifying the banana fruit ripeness stage[2]. This research uses GoogleNet Network and achieved an accuracy of 98.92% for training. While the study mentions that transfer learning outperforms subjective judgment, it doesn't provide a comprehensive comparison with other state-of-the-art methods for freshness detection. Such a comparison would help establish the superiority of the proposed approach.

Shiv Ram Dubey and Anand Singh Jalal introduced various applications of image-processing techniques used in the recognition and identification of fruits and vegetables, used for identifying 5-7 distinct herbal plant varieties. The paper implements K means clustering to remove the background clutter, reflections and shadows in the image. Hence, the authors of [3] are able to reduce the complexity present in the scene.

Savakar (reference [4]) introduced a classification methodology that relies on an artificial neural network (ANN) for the discrimination of various fruit categories. The study encompassed five distinct types of fruits: Apple, Mango, Sweet Lemon, Chikoo, and Orange. A dataset of 5,000 images was compiled, with each fruit category contributing 1,000 images for analysis through the ANN model. The outcomes of the experiments revealed the model's commendable performance, achieving an accuracy rate of 94(%).

The literature review of [5] contextualizes the research within the broader field of object detection, classification, and deep learning. It highlights the transformative impact of deep convolutional neural networks (CNNs) and traditional machine learning methods on object detection and classification tasks, with a particular focus on the YOLO (You Only Look Once) architecture, known for its real-time capabilities. The relevance of fruit and vegetable categorization, especially for applications in the food industry and assistive technologies, is emphasized. The review sets the stage for the study's approach, emphasizing the significance of YOLOv4 and deep CNNs in addressing the challenges of fruit and vegetable classification and detection, as well as outlining future research directions for enhancing accuracy and expanding the scope of classification models and datasets. Although the proposed fruit categorization approach is efficient and useful in various applications, it does not provide much-improvised metrics, resulting in an AP of 73.5(%) and 72.6(%) on the fruit and vegetable dataset respectively.

AI-based fruit identification and quality detection [7] system by Kashish Goyal, Parteek Kumar Karun Verma. This paper proposes a fruit identification and quality detection model based on the YOLOv5 object detection system. The model works in two phases: in phase 1, fruit is identified, and in phase 2, fruit quality detection is performed. The paper compares the proposed method with several state-of-the-art detection methods and shows that it has high accuracy and efficiency. This paper compares four machine learning algorithms, namely, decision tree, random forest, support vector machine, and k-nearest neighbor, for apple fruit quality classification. The paper evaluates the performance of the algorithms based on accuracy, precision, recall, and F1-score.

The paper titled "Fruit Quality Evaluation using Machine Learning Techniques: Review, Motivation, and Future Perspectives" [8] by Bhumica Dhiman, Yogesh Kumar, and Munish Kumar provides a thorough examination of the integration of machine learning in fruit quality assessment. The authors conduct a comprehensive review of features extracted from fruit images, encompassing shape, size, colour, and texture, emphasizing their crucial role in automating and refining fruit quality detection processes. The paper extensively explores various machine learning methods, such as k-nearest neighbors, support vector machines, and neural networks, offering a nuanced understanding of their strengths and applications in fruit classification. Furthermore, the authors present a valuable comparison of different techniques proposed by researchers, elucidating the evolving landscape of machine learning in fruit quality evaluation. While the advantages include enhanced efficiency, rapid classification, and adaptability to diverse datasets, challenges such as the need for substantial labeled datasets and model interpretability underscore the nuanced considerations in leveraging machine learning for fruit quality assessment.

As per the current understanding of the researchers, the utilization of machine learning/deep learning methods for forecasting the shelf life of fruits via the latest object detection methods has not been explored in depth. Therefore, the primary motivation behind this study is to employ various machine learning techniques with the aim of predicting fruit shelf life for various types of fruits.

III. EXPERIMENTAL SETUP

A. Data Description

The dataset utilized as the foundation for our shelf life prediction model originates from Kaggle, specifically the 'Fruit and Vegetable Dataset for Shelf Life.' This dataset encompasses a total of 1533 images, carefully categorized into three distinct classes- apple, banana and carrot, all of which have been judiciously selected for training purposes. The dataset was partitioned into training and testing subsets using a ratio of 0.15, ensuring a robust evaluation of model performance, the dataset showcases an assemblage of high-quality images, ranging from 500 to 550 images for each species, thoughtfully organized into folders corresponding to the remaining shelf life of the items. This meticulous categorization allows our model to learn and predict the shelf life of various fruits and vegetables with precision.

To enhance the efficacy of machine learning and deep learning model training, deliberate efforts were made to diversify the dataset. This involved deliberately introducing rotations, tilts, and other augmentations to the images of fruits, thereby amplifying the model's capacity to generalize across various scenarios. By exposing the model to a wide range of variations in image perspectives, we ensure that it can make accurate predictions under real-world conditions.

Additionally, the dataset features images captured from a multitude of angles, further enriching the training regimen. The diversity in image angles empowers our model to handle the challenges of varying camera angles and viewpoints, making it well-prepared for deployment in different environments. This comprehensive approach to dataset preparation has significantly enhanced the model's ability to generalize and predict fruit and vegetable shelf life accurately in real-world scenarios.

Fig. 1. Apple with shelf life 1-5 days

Fig. 2. Banana with shelf life 10-15 days

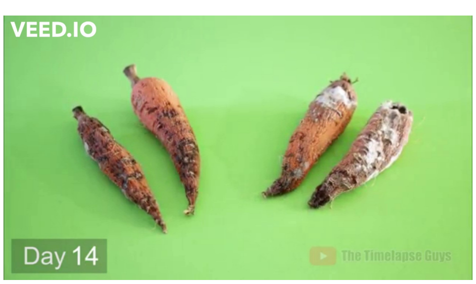


Fig. 3. Expired Carrots

In the context of our research investigation, we amalgamated three distinct datasets sourced from Roboflow, each formatted in the YOLO (You Only Look Once) framework, to form a unified dataset. This comprehensive dataset encompasses a collection of 1500 images, collectively represent instances from three distinctive classes. Our approach ensures the integration of diverse data sources into a cohesive repository, facilitating an enriched foundation for conducting object detection tasks.

Different datasets for object detection and shelf life prediction are used to provide a broader and more diverse range of data. This proves to be useful for training and testing the integrated framework, as it ensures that your model is exposed to a wider variety of real-world scenarios. Each dataset is selected to capture specific aspects of the problem more accurately and perform the specialized task.

B. Data Preprocessing

The high-quality images underwent various preprocessing steps described below:

1) Image Resizing and Pixel normalization: In deep learning, which encompasses a wide range of applications from object detection models like YOLO (You Only Look Once) to neural networks for tasks such as fruit shelf life prediction, image preprocessing steps hold a pivotal role in enhancing model performance and expediting convergence.

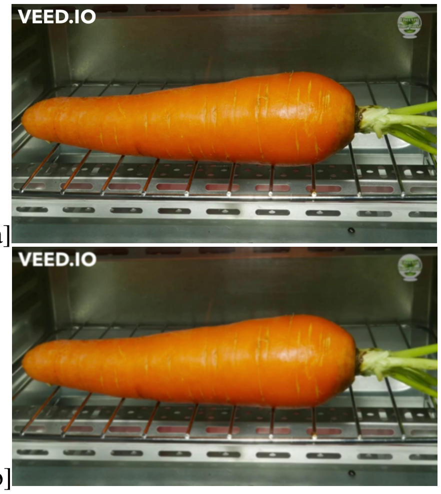
Image resizing, one of the fundamental preprocessing techniques, allows for uniformity in input dimensions. This ensures that models can effectively process images of varying sizes, making them more adaptable to real-world scenarios. Additionally, resizing reduces the computational burden, ultimately leading to faster training and inference.

Pixel normalization is another indispensable step. By scaling pixel values to a common range, often within [0, 1] or [-1, 1], we facilitate consistent and stable training. This prevents certain features or channels from dominating the learning process, promoting balanced and more efficient model training.

2) Guassian filtering: A Gaussian filter is a widely used image processing technique for reducing noise and smoothing images. It's a type of linear filter that's often applied to images to blur them, remove high-frequency noise, and retain important image features. The filter is experimented with numerous filter sizes, giving the most appropriate noise filtering for a 5X5 kernel.

Edge detection algorithms tend to work best on grayscaled images, whereas HSV colour space is needed to extract the colour-based features. Changing the colour space to the required format was implemented prior to feature extraction.

3) Background subtraction using K-means Clustering: Our approach for enhancing shelf life prediction accuracy through the integration of k-means clustering as a pre-processing technique in food product images represents a significant stride towards more accurate predictive models. By harnessing the intrinsic capabilities of k-means clustering to segment images into distinct clusters based on pixel similarity, we've unlocked a powerful tool for refining the initial image data.



[a]

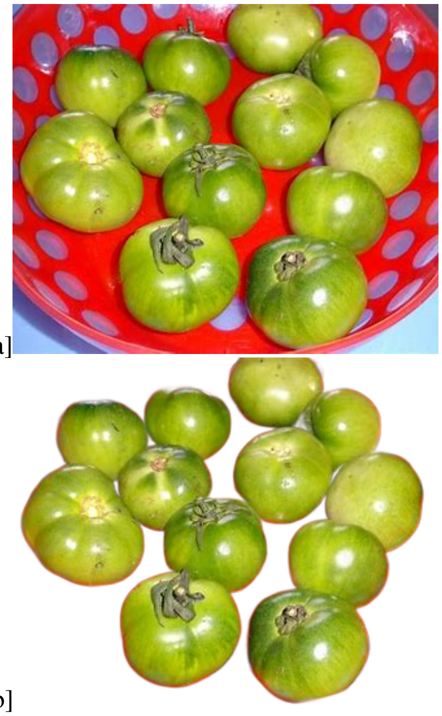
[b]

Fig. 4. Carrot(shelf life 4-8 days) (a) Original Image (b) Gaussian Blurred Image

The application of k-means clustering to the images is like separating signal from noise, enabling us to effectively isolate the product of interest from its background. This precise background subtraction is a pivotal step in improving the overall quality of feature extraction. By ensuring that the extracted features are now exclusively focused on the product itself, we've eliminated the potential influence of background artifacts, leading to more robust and relevant feature sets as shown in figures 5 and 6.
These refined features serve as the building blocks for training our predictive model. With their enhanced quality and relevance, our model is better equipped to make accurate estimates of the shelf life of the product. In essence, the quality of preprocessing directly impacts the predictive capabilities of the model, and k-means clustering has proven to be a valuable asset in this context.
Experimental results further validate the effectiveness of our proposed approach. Not only does it enhance the accuracy of shelf-life prediction, but it also underscores the versatility of k-means clustering in enhancing preprocessing techniques for a broad spectrum of image-based prediction tasks. This innovative fusion of clustering and predictive modelling promises to open doors to even more accurate and efficient solutions in the field of image analysis and predictive modelling.

4) Shadow Effect Removal: The objective of shadow removal is to enhance the visual quality of images affected by shadows, which can be particularly important in various computer vision and image processing applications. The image is initially transformed into the LAB colour space, wherein the 'L,' 'a,' and 'b' channels are extracted individually. Shadow removal is performed primarily based on the 'a' channel intensity, followed by the replacement of shadows with a constant pixel value. This technique has been found effective in improving image quality by mitigating the adverse effects of shadows.

In cases where an image contains multiple objects with complex shadows, the shadow mask is optimized for a channel with an intensity value of 138. Conversely, for single objects or



[a]

[b]

Fig. 5. Tomato with shelf life 25 days (a) Original Image (b) Background subtracted

[a]

[b]

Fig. 6. Banana with shelf life 1 to 5 days (a) Original Image (b) Background subtracted

isolated images, the intensity value used for shadow removal is adjusted to 124. The choice of intensity values is informed by empirical observations and experiments, aiming to strike a balance between shadow removal efficacy and overall image fidelity.

[a]

[b]

Fig. 7. Determination of region of interest mask with threshold 138 (a) Original Image (b) Mask

C. Feature Extraction

The essence of an image-based prediction task lies in the characteristics of shape, colour, and texture present in the data. Therefore, the process of feature extraction has been carried out post-preprocessing utilizing a variety of techniques.

Moving on to shape-related features, pivotal metrics such as area, perimeter, aspect ratio, and circularity have been computed. For the extraction of colour-based attributes, computations are centred around obtaining the mean and standard deviation of the RGB channels. Moreover, texture-based features are also obtained.

1) Texture based features: A key approach employed for the purpose of extracting the texture-based features is the calculation of Gray-Level Co-Occurrence Matrix (GLCM) based features of contrast, dissimilarity, homogeneity, energy and correlation. GLCM serves as a potent tool to extract intricate textural patterns that are imperceptible to the human eye, yet indicative of underlying changes within the fruit.

Through the utilization of GLCM, the relationships between pixel values at various distances and angles are meticulously examined. This matrix provides a comprehensive insight into the distribution of grey levels within an image, enabling the quantification of textural attributes like contrast, correlation, homogeneity, and entropy. Contrast quantifies the differences in brightness or intensity between neighbouring pixels within the image.

$$contrast = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

Correlation assesses the degree of linear interrelationship between the intensity values of pixels at distinct positions in the image.

$$correlation(r) = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Entropy gauges the level of information or disorder present in the texture of the image.

$$Entropy = -\sum_{i,j=0}^{N-1} P_{i,j} \ln P_{ij}$$

2) Shape based features: Edge detection algorithms tend to work best on the greyscale image. The shape-based features that were extracted, are obtained via contouring and thresholding features of open CV, which are the area, perimeter, eccentricity, aspect ratio and circularity. The aspect ratio serves as a shape descriptor obtained by dividing the length of the longer side of a bounding rectangle by the length of its shorter side. In mathematical terms, the Aspect Ratio (AR) can be expressed as AR = (Length of Longer Side) / (Length of Shorter Side). Area (A) signifies the number of pixels enclosed within the shape's boundary, while Perimeter (P) quantifies the entire length of the shape's boundary. Eccentricity, sometimes referred to as elongation, measures the extent to which a shape is elongated or stretched. It is determined by taking the square root of 1 minus the ratio of the minor axis squared to the major axis squared.

$$Eccentricity = \sqrt{1 - \frac{b^2}{a^2}}$$

Circularity quantifies how closely a shape resembles a circle. In the case of a perfectly circular shape, its circularity value is 1.

$$Circularity = \frac{4\Pi A}{l^2}$$

3) Color based features: The average colour of an image is computed by calculating the mean values of its red (R), green (G), and blue (B) channels. In mathematical terms, this is expressed as Mean(RGB RED) = (Sum of Red Values) / (Number of Pixels), and the same principle applies to the green and blue channels. The variation in colour values within an image can be measured by calculating the standard deviation of its red, green, and blue channels. Standard Deviation is computed as:

$$s_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}$$

4) Principal Component Analysis(PCA): PCA was performed and the best set of features were extracted. The figure below defines the percentage of explainable variance for each of the classes

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In [46]:  print(np.cumsum(pca.explained_variance_ratio_))

          [0.58800809 0.71179974 0.80844084 0.88119079 0.91286823 0.93507566
           0.95574397 0.9693202  0.97622039 0.98255531 0.98729154 0.99118982
           0.99392262 0.99653001 0.99790081]
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Fig. 8. Percentage of explainable variance for features

IV. Results and Discussion

1) Shelf Life Classifier Model: Incremental learning: For the deep learning model's application as a feature extractor, incremental learning refers to a process where a pre-trained deep learning model is further refined or expanded to accommodate new data or tasks while retaining the knowledge it has already acquired. This approach is particularly useful in scenarios where new information becomes available over time, and adapting existing models can be more efficient than retraining from scratch.

In this context, ”feature extractors” typically refer to the early layers of a deep neural network that learn to capture general patterns and features from raw data. These layers are often transferable to various tasks since they capture fundamental features that are relevant across different domains.

Here's how the incremental learning process for deep learning models as feature extractors might work:

Pre-trained Model: A deep learning model(namely Resnet-50) that has been pre-trained on a large dataset, for a general task like image classification is selected. The model's early layers serve as feature extractors.

New Data or Task: As new data is selected for a new task that needs to be addressed, instead of training a new model from scratch, you can fine-tune or update the pre-trained model. This involves exposing the model to the new data or task while keeping the weights of the early layers (feature extractors) relatively fixed.

Freezing Layers: Typically, you would ”freeze” the early layers during fine-tuning, preventing them from being updated much. This ensures that the previously learned general features are retained and not overwritten.

Fine-tuning: The later layers of the model, which are more task-specific, can be modified or replaced to suit the new task. These layers are responsible for making predictions or generating features specific to the new data or task.

Training on New Data: The fine-tuned model is then trained on the new data, with updates mainly affecting the task-specific layers.

Knowledge Transfer: By leveraging the features learned by the pre-trained model's early layers, the model can potentially adapt to the new task faster and with less data compared to training from scratch.

The extracted features are collected and stored in a comma-separated delimited file.

The research study employs ResNet-50 network as foundational feature extractor, facilitating an incremental learning framework. These networks serve as the basis for extracting high-level attributes, which are then fused with manually curated features.

Subsequently, Principal Component Analysis (PCA) is administered to distil an optimal feature set containing 1592 features earlier containing 2591, enhancing the discriminative capabilities of the dataset. These augmented features are then harnessed as inputs for diverse traditional machine-learning models. The 15 features that were extracted via morphological analysis are thus merged with incremental learning features to obtain a training-ready feature set. Each of the trained traditional classifiers was used to make predictions on the dataset's ResNet50 features. The following are the training results obtained for various machine-learning models:

Sr. No.	Algorithm	Accuracy(%)	Precision
1	Decision Tree	67.70	0.677003
2	Random Forest	0.9044	0.904393
3	SVM	37.73	0.377261
4	XGBoost	89.41	0.894057
5	Multi-Layer Perceptron	19.90	0.198966
6	FCN-28 Layer	93.48	0.95

TABLE I
PERFORMANCE METRICS

They are all trained on the same training data and evaluated on the same testing data for consistency. Furthermore, ImageNet is used to train the model on the image dataset. Predictions based on the raw image data are hence obtained with an accuracy of 92.48(%). Imagenet, Decision tree, random forest, FCN, and XGBoost were chosen for the ensemble due to their superior accuracy performance. The prediction is done using a voting ensemble technique. The class votes of each classifier are considered and the majority class is selected as the final prediction. The ensemble classifier gives an improved accuracy of about 95(%) and a precision of 0.89.

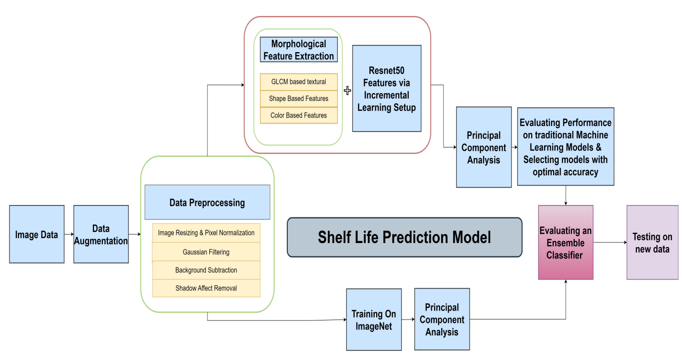


Fig. 9. Shelf Life Prediction Model

2) YOLO Based Object Detection: Furthermore, the investigation delves into object detection methodologies rooted in the ”You Only Look Once” (YOLO) paradigm. Remarkably, the performance of these YOLO-based object detection algorithms in the context of fresh food tasks aligns closely with that of comparable algorithms. Concurrently, a parallel endeavour unfolds, involving the fine-tuning of images on the ResNet-50 network through transfer learning techniques. These outcomes are harmonized through an ensemble approach, yielding predictions that effectively ascertain the most appropriate range for the residual shelf life of fruits.

YOLO-NAS is a new real-time state-of-the-art object detection model that outperforms both YOLOv6 and YOLOv8 models in terms of MAP (mean average precision) and inference latency. The models YOLO-NAS and YOLOv8 were trained on the concatenated datasets from roboflow and the MAP and latency for both were observed. The latest instalment of YOLO models, i.e., YOLO-NAS compared to the second-best YOLO model that is YOLOv8 was explored. The exploration and training details of these new models and their performance are covered in brief.

The YOLOv8 was trained on 225 layers, 3157200 parameters, and 3157184 gradients utilizing the ultralytics module while 79 gradients per iteration were updated for the YOLO-NAS trained on 3911200 parameters.

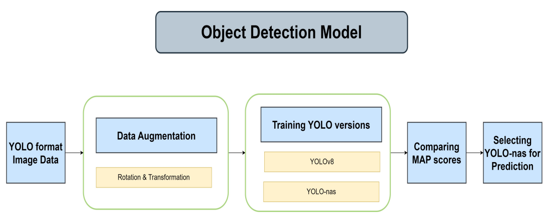
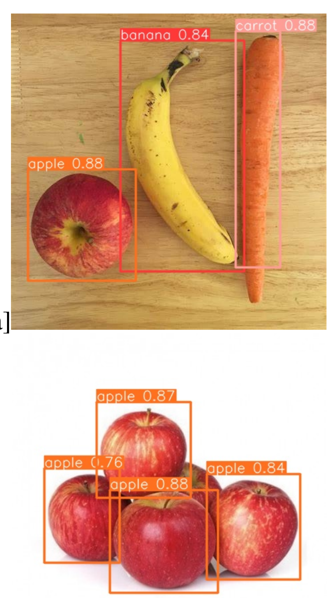


Fig. 10. Object Detection Model

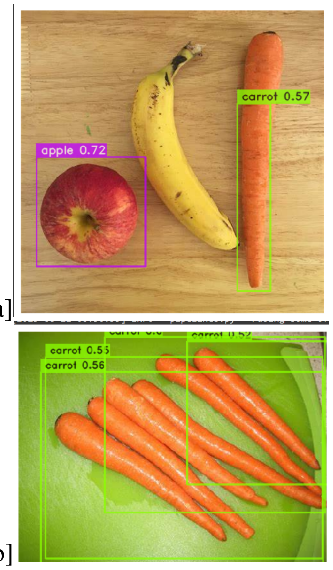
The results obtained are visualized as follows:

[a]


[b]

Fig. 11. YOLOv8 results (a) Heterogenous Classes (b) Homogenous prediction

The research paper presents a novel approach to enhance object detection performance, focusing on the integration of

[a]


[b]

Fig. 12. YOLO-NAS results (a) Heterogenous Classes (b) Homogenous prediction

three distinct object detection datasets from Roboflow. These datasets are thoughtfully amalgamated through a process involving rotation and transformation techniques, bolstered by rotation-based augmentations. This augmentation strategy introduces an element of translational invariance. Notably, the models are pre-trained using the most recent iterations of YOLO. The performance metrics for these variants were:

Sr. No.	Network	MAP	Latency
1	YOLOv8	50	6.5
2	YOLO-NAS	51.55	5.85

TABLE II
YOLOV8 AND YOLO-NAS METRICS

Moreover, the paper underscores the remarkable efficacy of YOLO-NAS and YOLOv8, which boasts an innate capability to surpass the performance of other YOLO-based models as well as alternative object detection model variants. The implementation of the neural architecture search (NAS) model, YOLOnas, has a discernible impact on refining the metrics referred to as Mean Average Precision and Latency in the original context. These advancements collectively underscore the innovation and effectiveness of the proposed methodology.

A single pipeline is built, and an input query image is fed into the pipeline, the input image is first segregated via the object detection module and each object is cropped and stored in a separate folder structure based on the class it belongs to. Hence it is able to work on both homogenous and heterogeneous objects in an image. Then the input query image is fed into the shelf life predictor and the remaining shelf life is thus determined for the fruit.

V. Conclusion and Results

The study's comprehensive approach, which harnesses advanced neural networks, innovative feature engineering, and

[a] 

Fig. 13. Results test image 1

[b] 

Fig. 14. Results test image 2

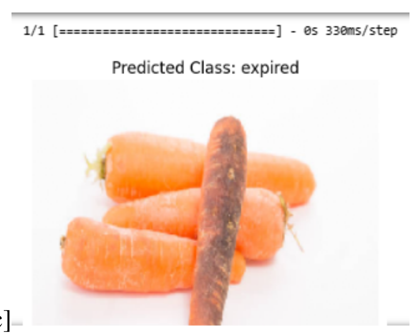
[c] 

Fig. 15. Results test image 3

a robust ensemble strategy, addresses the multifaceted challenges in fresh food analysis. This multifaceted approach results in an impressive accuracy enhancement of 95(%), achieved by amalgamating outcomes from deep learning and traditional machine learning architectures. Notably, the optimization of latency, reducing it from 6.5 to 5.85 for the YOLO-NAS model, significantly enhances computational efficiency, facilitating faster responses. These findings collectively contribute to the evolution of predictive models for shelf life estimation, underscoring their practical implementation in real-world scenarios and marking a significant step forward in the field of fresh food analysis. With a strong emphasis on accuracy and efficiency, this research sets a new standard for predictive modelling in food analysis.

Acknowledgment

The authors would like to thank...

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