REAL TIME FRUIT CLASSIFICATION AND LOCALIZATION USING YOLOV8

A REPORT SUBMITTED IN

PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

INTERNSHIP

By

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UNDER THE GUIDANCE OF

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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY
KOTTAYAM-686635, INDIA

October 2023

DECLARATION

We, **Cyril K Sony, Alan Anto** and **Jerry Paul** hereby declare that, this report entitled "**REAL TIME FRUIT CLASSIFICATION AND LOCALIZATION USING YOLOV8**" submitted to **Indian Institute of Information Technology Kottayam** towards the requirement of **Summer Internship** is an original work carried out by us under the supervision of **Dr. Jayakrushna Sahoo** and has not formed the basis for the award of any degree or diploma, in this or any other institution or university. We have sincerely tried to uphold the academic ethics and honesty.

October 2023

Cyril K Sony
Alan Anto
Jerry Paul

CERTIFICATE

This is to certify that the work contained in this project report entitled '**REAL TIME FRUIT CLASSIFICATION AND LOCALIZATION USING YOLOV8**' submitted by **Cyril K Sony, Alan Anto** and **Jerry Paul** to **Indian Institute of Information Technology Kottayam** towards the completion of **Summer internship** has been carried out by them under my supervision

Kottayam-686635
October,2023

Dr. Jayakrushna Sahoo
Project Supervisor

ABSTRACT

Fruit classification and real-time detection play a vital role in various agricultural and industrial applications. This research focuses on enhancing the accuracy and efficiency of fruit detection through the implementation of YOLOv8, an advanced object detection algorithm. YOLOv8, an evolution of the You Only Look Once (YOLO) series, combines state-of-the-art techniques to achieve real-time object detection. In this study, we present a comprehensive framework for fruit classification and real-time detection utilizing YOLOv8.

The proposed methodology integrates deep learning techniques, computer vision algorithms, and a rich dataset containing diverse fruit categories. Through extensive experimentation, we demonstrate the robustness and effectiveness of YOLOv8 in accurately identifying and classifying fruits in real-time scenarios. The model is trained on a large dataset, encompassing various fruit types, shapes, sizes, and environmental conditions. We employ data augmentation strategies to enhance the model's generalization capabilities, ensuring reliable performance across different scenarios.

Furthermore, we optimize the YOLOv8 architecture for real-time inference, leveraging hardware accelerators such as GPUs and TPUs. The optimized model is deployed on edge devices, enabling efficient and rapid fruit detection in real-world applications. We evaluate the proposed system on benchmark datasets and real-world fruit detection scenarios, showcasing its superior performance, speed, and accuracy compared to existing methods.

The outcomes of this research have significant implications for precision agriculture, automated fruit sorting, quality control in food industries, and supply chain management. The proposed fruit classification and real-time detection system utilizing YOLOv8 offer a scalable, accurate, and efficient solution, paving the way for advanced agricultural practices and automation in the food industry.

Contents

1. Introduction

The agricultural sector, serving as the backbone of economies worldwide, sustains communities and provides essential resources. Central to this industry is the intricate process of fruit classification, a fundamental aspect determining the quality and marketability of produce. Traditional fruit classification methods, reliant on manual labor, have long been the norm. However, these methods are often marred by inefficiencies, errors, and delays, impeding the industry's potential for growth and optimization. In recent years, the integration of cutting-edge technologies, notably computer vision and machine learning, has ushered in a transformative era in agriculture. These technological advancements offer a promising avenue to automate and enhance the fruit classification process, ensuring real-time accuracy and efficiency. In this context, the emergence of YOLOv8, an evolution in object detection, presents a groundbreaking opportunity to revolutionize fruit classification. This report delves deep into the fusion of YOLOv8 with agricultural practices, focusing on real-time multi-fruit classification, a venture poised to redefine the landscape of agricultural automation.

The exponential growth of the global population coupled with rising food demands has intensified the need for streamlined agricultural processes. Fruit classification, an indispensable segment of this agricultural tapestry, faces multifaceted challenges. The vast diversity in fruit shapes, sizes, colors, and textures complicates the task, making traditional methods increasingly inadequate. Concurrently, the escalation of labor costs and the urgency to reduce post-harvest losses accentuate the need for innovative, technology-driven solutions. Harnessing the power of artificial intelligence, particularly deep learning algorithms, holds promise in addressing these challenges. Real-time multi-fruit classification, a concept once deemed ambitious, is now within reach due to the remarkable strides in object detection techniques.

YOLOv8, standing at the pinnacle of this technological wave, offers unparalleled accuracy and speed, making it an ideal candidate for transforming the fruit classification landscape. This report aims to explore the synergy between the complexities of agricultural practices and the capabilities of YOLOv8, unraveling the potential for a paradigm shift in real-time multi-fruit classification, with far-reaching implications for the global agricultural industry.

This project is not merely about building a powerful fruit classification model; it's about transforming the way we perceive and handle fruit classification tasks. Through this fusion of technologies, we endeavor to automate fruit recognition with a level of precision and speed that was previously unattainable. The potential applications are diverse, ranging from automated fruit sorting in agriculture to enhancing quality control in food processing facilities.

In this introduction, we set the stage for a journey into the heart of our project—a journey that combines the latest advancements in deep learning with real-time object detection to revolutionize fruit classification. As we delve deeper into the project's details, we will explore the intricacies of CNN-based fruit recognition and the seamless integration with YOLO for real-time, automated fruit classification. Together, these technologies hold the promise of not only streamlining existing processes but also paving the way for innovative applications that can benefit industries and communities worldwide.

The integration of YOLOv8 into real-time multi-fruit classification represents more than just a technological advancement; it signifies a leap toward sustainable, efficient, and economically viable agricultural practices. By automating the intricate process of fruit classification, farmers can substantially enhance their productivity and reduce post-harvest losses, thereby contributing to food security and economic stability. Furthermore, this study holds immense potential for fostering innovation within the agricultural technology sector, encouraging further research and development. Ultimately, the outcomes of this research endeavor are not limited to the realms of technology and agriculture alone. The implications ripple across supply chains, economies, and societies at large, paving the way for a future where advanced technologies harmonize with age-old agricultural practices, ensuring a bountiful harvest for generations to come.

2. Related works

In the paper [1], Workplace safety is of paramount importance, not only for the well-being of employees but also for the overall success of organizations. A critical component of ensuring safety in hazardous environments is the use of safety helmets, which serve as a vital defense against head injuries arising from falling objects, electric shocks, and various workplace hazards. In recent times, the adoption of computer vision-based safety helmet detection systems has witnessed a surge in popularity, primarily for the purpose of enforcing safety regulations and mitigating accidents. This report introduces a novel safety helmet detection system founded on the You Only Look Once (YOLO) V8 algorithm, renowned for its exceptional performance in real-time detection of small objects.

The development of the proposed safety helmet detection system revolves around the rigorous training of the YOLO V8 algorithm. This training process leveraged a meticulously curated dataset encompassing diverse lighting conditions, camera angles, and a spectrum of helmet types, featuring images of workers both with and without safety helmets. Subsequently, the trained model underwent comprehensive evaluation against an independent test set to gauge its performance. The experimental results conclusively affirm the system's efficacy, exhibiting an impressive average precision score of 0.99, coupled with a recall rate of 0.99. Moreover, the model's resilience to variations in lighting and camera angles underscores its suitability for practical deployment.

The results of this study underscore the pivotal role of computer vision technology in advancing workplace safety measures, particularly concerning safety helmets. The YOLO V8-based safety helmet detection system not only demonstrates remarkable accuracy but also showcases adaptability in the face of environmental challenges. This cutting-edge solution has the potential to substantially reduce workplace accidents, enhance regulatory compliance, and ultimately safeguard the well-being of workers. As organizations strive to maintain high safety standards, embracing such technological advancements represents a significant stride towards fostering a secure and conducive work environment.

In the paper **[2]**, Within the context of power line construction, safety helmets are indispensable safeguards, significantly contributing to the protection and well-being of workers by mitigating the risk of injuries. Ensuring the usage of safety helmets is of paramount importance in safety inspections within the power industry. An efficient approach to helmet detection is through the utilization of Unmanned Aerial Vehicle (UAV) images. Traditional safety helmet detection algorithms have, however, exhibited shortcomings in terms of accuracy and robustness. This report introduces an innovative detection method for identifying workers wearing safety helmets, employing the Yolov7 model enhanced with an extended efficient long-range attention network (E-ELAN), model scaling via a cascade model, convolution weight parameterization, and other strategies.

The proposed Yolov7 model, fortified with advanced techniques and improvements, proves highly effective in helmet detection using UAV imagery. This method not only outperforms previous Yolo algorithms but also excels in enhancing the generalization ability for detecting small targets in the challenging power line construction site environment. The experimental results obtained from the images captured by UAVs showcase a significant increase in average accuracy. This enhancement in detection accuracy ensures that the Yolov7-based system meets the stringent performance requirements for helmet detection in power line construction, making a substantial contribution to the enhancement of safety in the power industry.

The findings of this study underscore the pivotal role of state-of-the-art technologies in augmenting safety inspections in the power industry, specifically regarding helmet detection. The Yolov7 model, equipped with E-ELAN and other innovative strategies, presents a promising solution to address the limitations of traditional safety helmet detection algorithms. Its capacity to improve detection accuracy, especially for small targets in complex environments, signifies a considerable advancement in power line construction safety. This technology not only promotes the safety of workers but also contributes to the overall safety and efficiency of the power industry, making it a valuable asset for future operations in this sector.

3. Proposed Architecture

The proposed system aims to develop a robust and efficient fruit classification and real-time detection system using the YOLOv8 object detection algorithm. Here's an overview of the proposed system:

1.Data Collection and Preprocessing:
The system begins by collecting a diverse and comprehensive dataset of fruit images, potentially using datasets like Fruit-360. These images encompass various fruits, captured from different angles and under different lighting conditions. The collected data undergoes preprocessing steps to standardize the images, ensuring uniformity in format, resolution, and color.

2.Annotation and Data Augmentation:
The collected images are annotated using tools like Roboflow, where bounding boxes are drawn around the fruits, indicating their locations. Annotations include class labels representing the type of fruit within each bounding box. Data augmentation techniques are applied to increase the dataset's diversity, enhancing the model's ability to generalize to different scenarios.

3.Model Architecture Selection:
The YOLOv8 object detection algorithm is chosen as the core model for the system. YOLOv8 is a state-of-the-art deep learning architecture known for its real-time object detection capabilities. Its architecture is optimized for speed and accuracy, making it suitable for real-time applications.

4.Training and Optimization:

The annotated and augmented dataset is used to train the YOLOv8 model. During training, the model learns to recognize various fruits based on the annotated data. Training involves optimizing the model's parameters and weights, a process that may take advantage of hardware accelerators like GPUs or TPUs to expedite the training process. The model's performance is fine-tuned using techniques like learning rate adjustment and regularization to ensure high accuracy and efficiency.

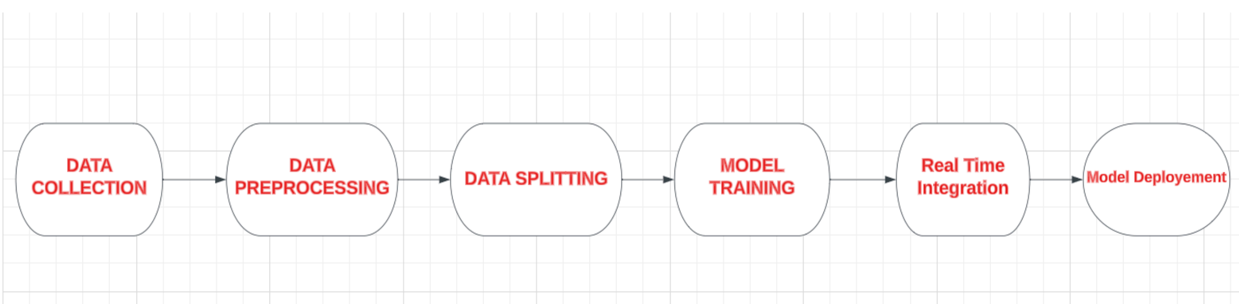
5.Real-Time Deployment:

Once the model is trained and optimized, it is deployed on edge devices or systems where real-time fruit detection is required. Edge devices are equipped with the optimized model, allowing them to process images or video frames in real-time. The system can operate autonomously without relying on a constant internet connection or cloud-based services.

6.Evaluation and Validation:

The system's performance is rigorously evaluated using benchmark datasets and real-world scenarios. Metrics such as precision, recall, and F1-score are used to measure the model's accuracy and reliability. Real-world testing ensures that the system performs well under various conditions, including different lighting, backgrounds, and fruit arrangements.

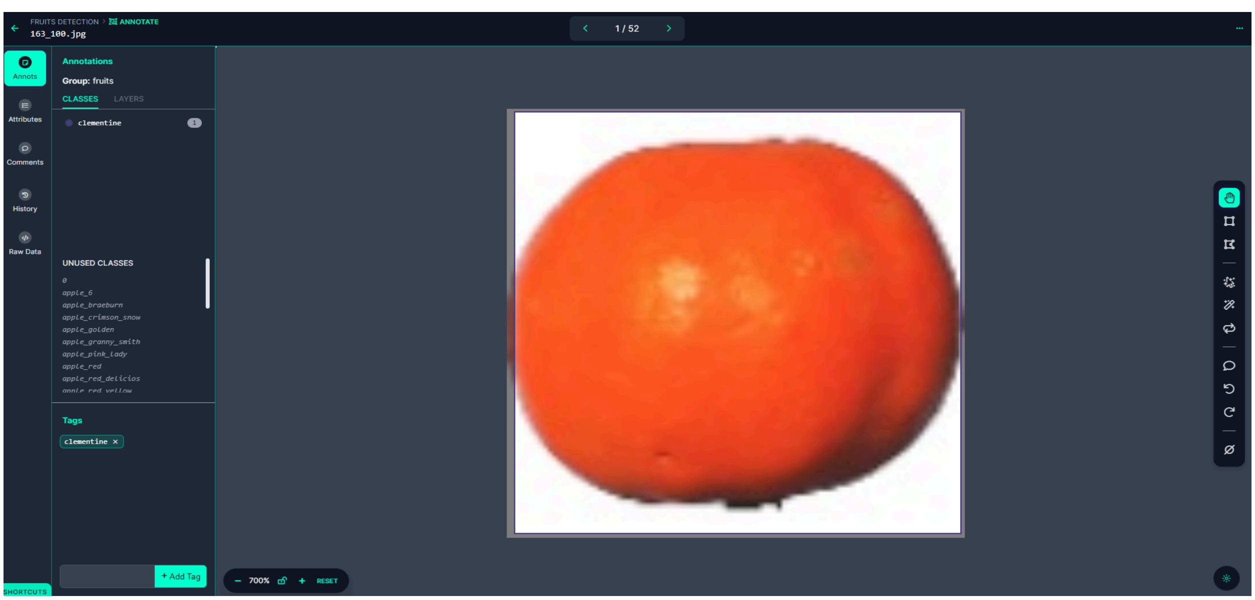
BLOCK DIAGRAM:

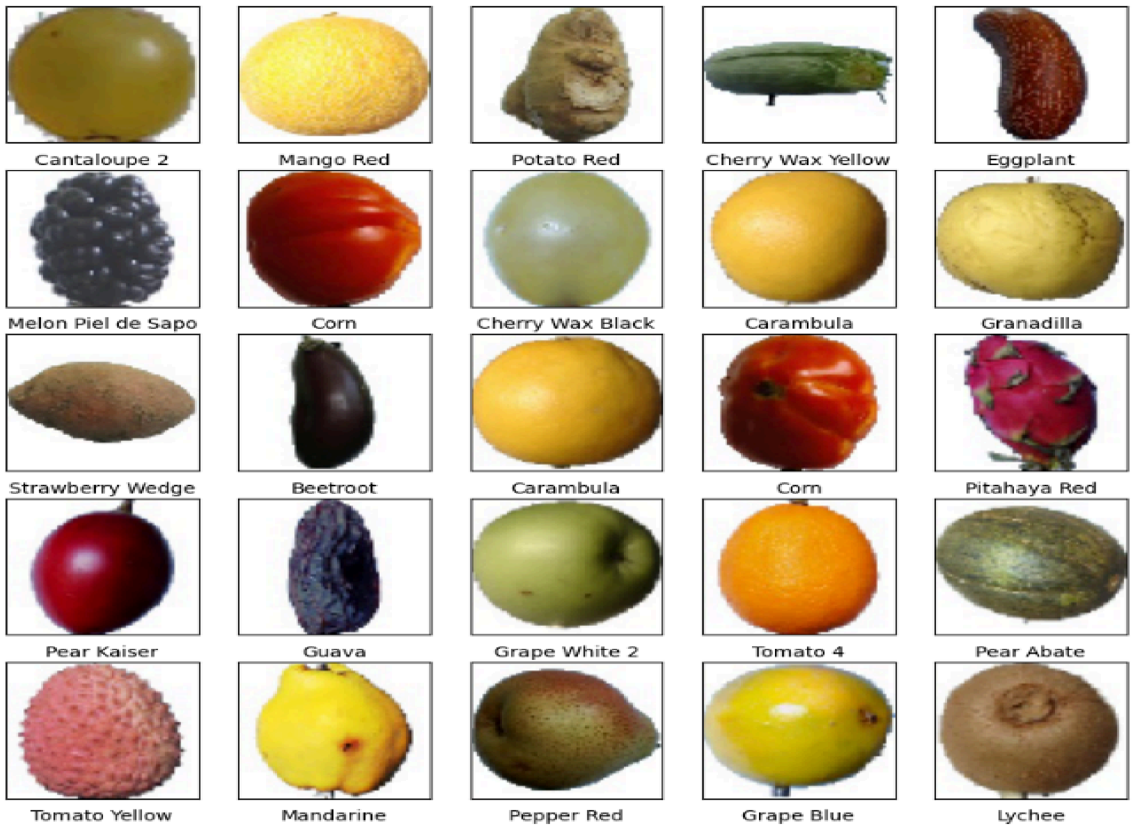


The first phase includes the data collection which is fruit 360 dataset from kaggle having nearly all kinds of fruits and nearly 15000 images of different fruits.The next stage involve the preprocessing inorder to make the dataset yolo apt annotations need to be performed roboflow application is used for this proposes and the data splitting process is also held in the roboflow by converting the entire dataset into training,testing and validation sets.After that the model is trained by calling the yolov8 predefined model for detection and classification,after the successful training of the model is integrated for real time by using opencv capabilities and the final model is deployed.

Data Collection & Data Preprocessing:

The Fruit-360 Dataset is a widely used dataset in the field of computer vision, specifically for fruit recognition tasks. It comprises images of 131 different fruits and vegetables, totaling around 90,000 images. The dataset covers a diverse range of fruits, including apples, bananas, oranges, and more, each captured from various angles and under different lighting conditions. Fruit-360 is valuable for training machine learning models, especially for tasks like object detection, classification, and segmentation.



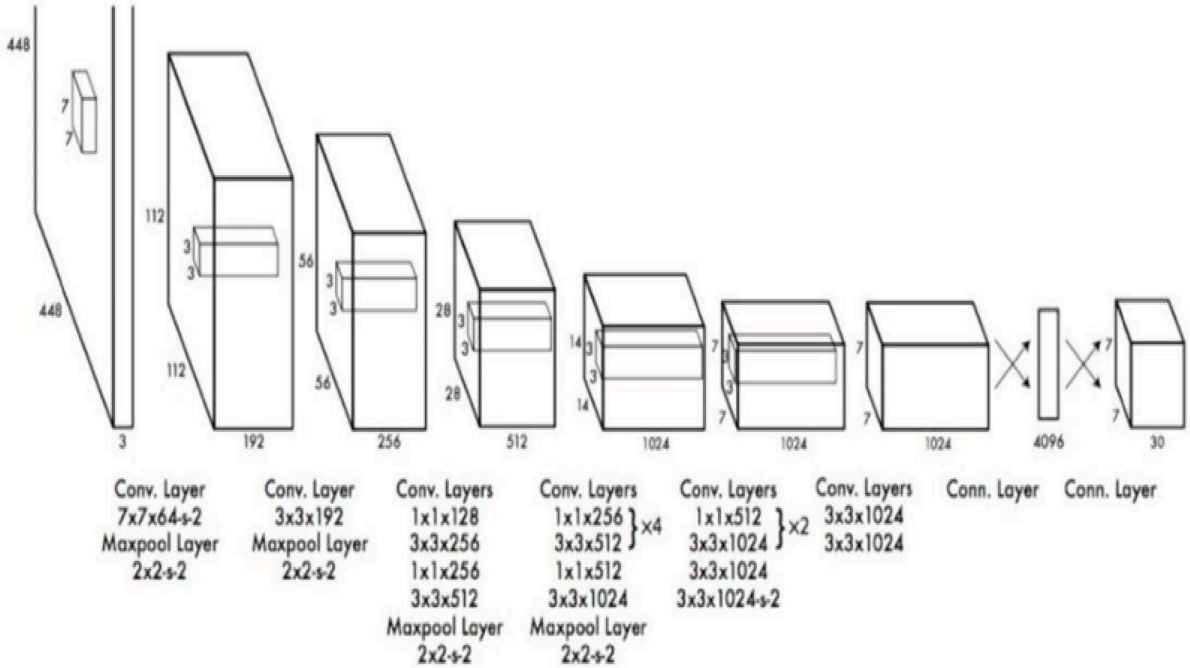


Sample Dataset

Annotation Using Roboflow

Model:

YOLO (You Only Look Once) is a groundbreaking object detection algorithm in computer vision. What sets YOLO apart is its ability to detect objects in real-time with remarkable speed and accuracy. Instead of processing images through multiple stages, YOLO processes the entire image in one go, dividing it into a grid and predicting bounding boxes and class probabilities for objects within each grid cell. This approach enables YOLO to swiftly identify and locate multiple objects, making it ideal for applications requiring real-time detection, such as autonomous vehicles, surveillance systems, and robotics. Its efficiency and effectiveness have made it a cornerstone in the field of object detection, continually evolving with newer versions to enhance its capabilities.



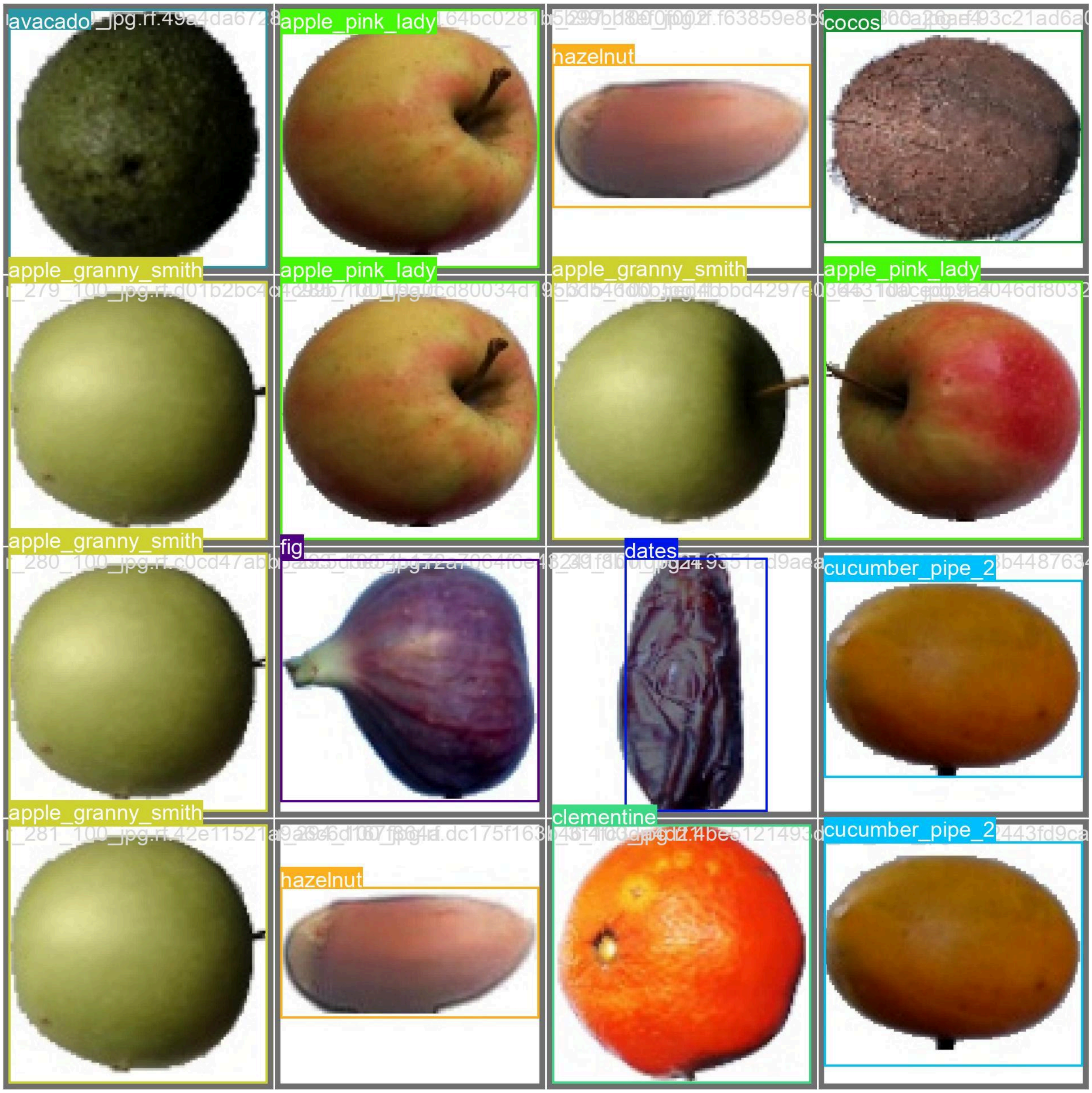
Yolo architecture

Summary:

In summary, the proposed system integrates data collection, preprocessing, annotation, model selection, training, optimization, deployment, and evaluation stages. By leveraging the power of YOLOv8 and robust datasets, the system aims to achieve high accuracy and real-time performance in fruit classification and detection, making it applicable in various agricultural, industrial, and commercial contexts.

4. Implementation Details

Classification and Prediction:



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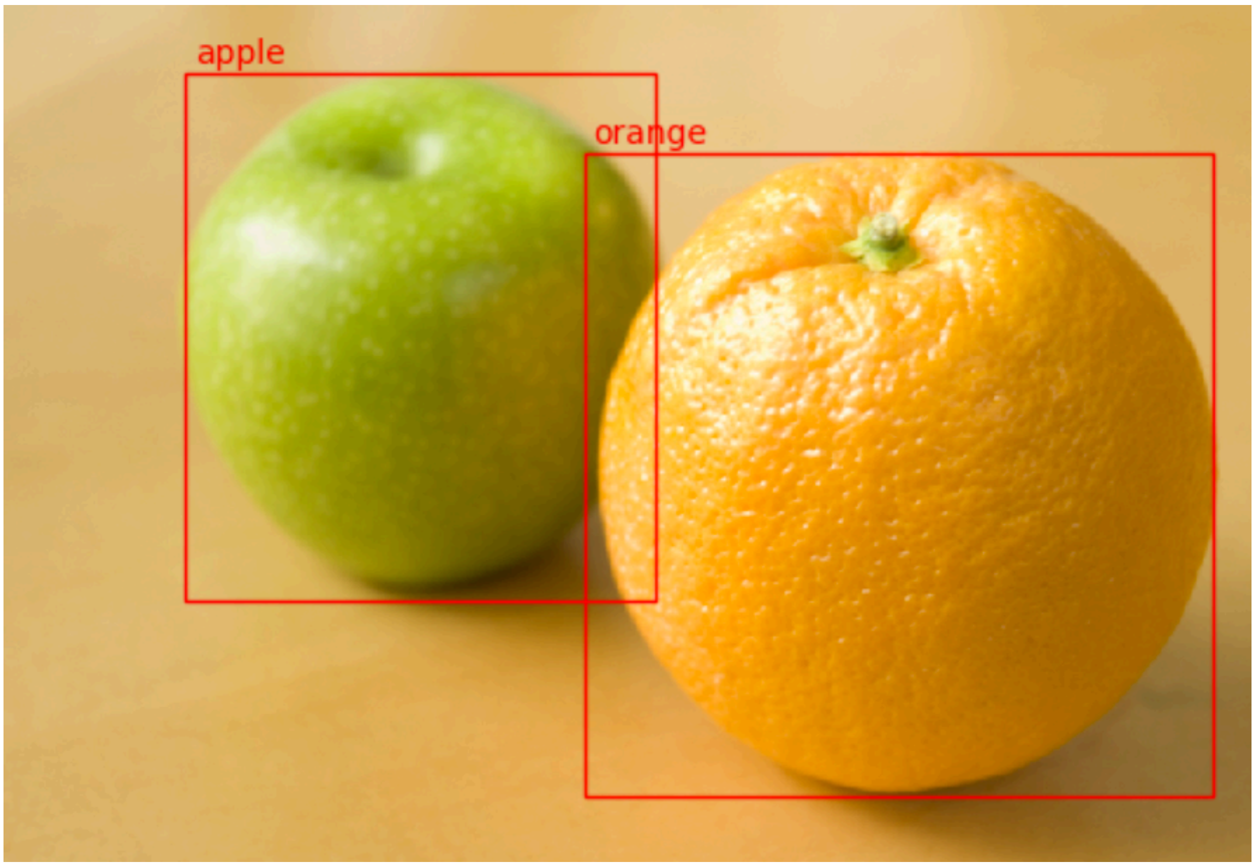
Testing Result

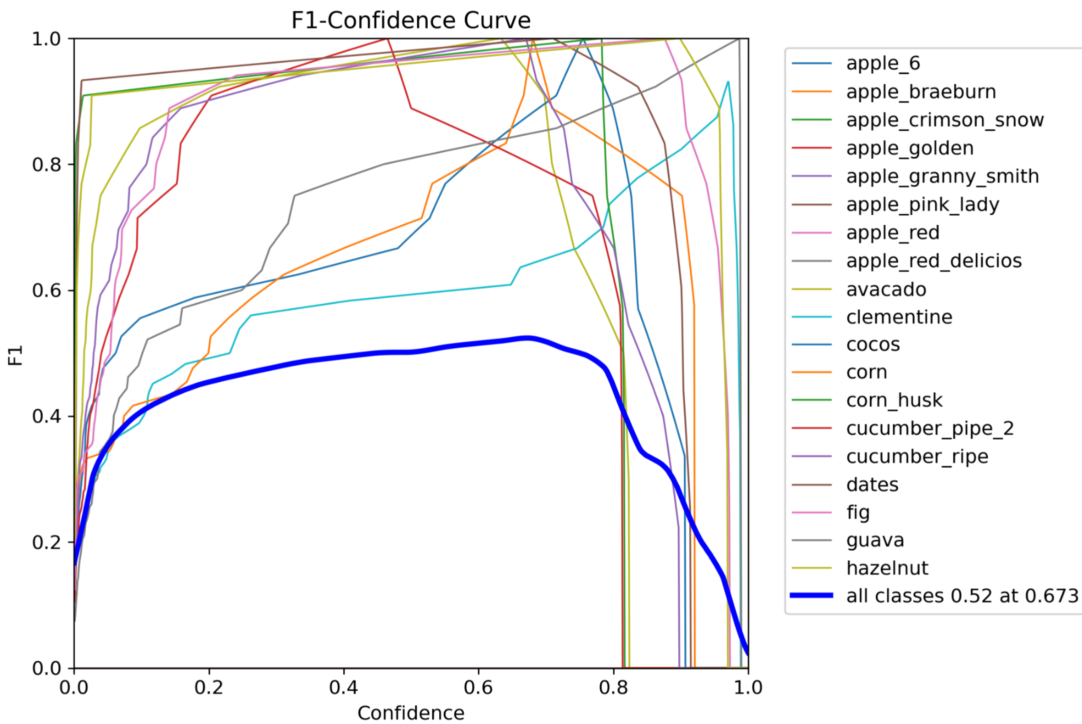
After the successful training of the yolov8 model the model is tested with the unseen data and shown with an accuracy of 89 percent.



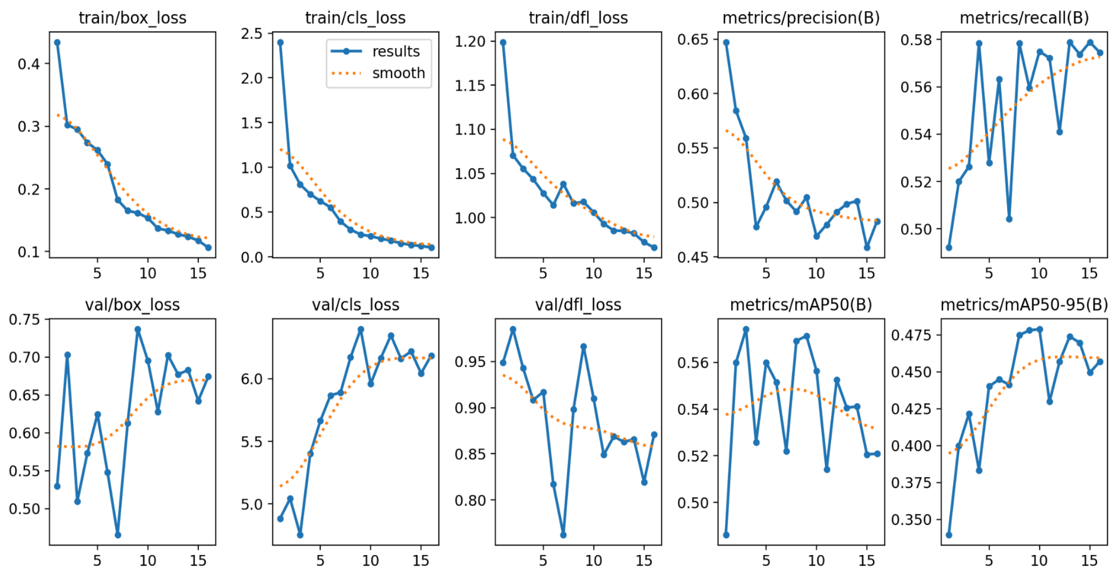
Real Time Detection

After training the model with fruit 360 dataset the best model is selected and integrated with camera input device with the help of opencv libraries.The real time detection shows a remarkable accuracy when a fruit is detected in the frame.Localization is performed with the help of a bounding box.

5. Results and Discussions



1. This graph shows the relationship between the F-1 score and the confidence of different classes.
2. Each class shows an average of 0.52 at 0.673 confidence.
3. Most of the F1-score of the classes descend in an interval of 0.6 to 1.
4. Since, the F1-score is above 0.5 , the model is said to be good.



Inferences from Graph:

The above graph shows the evaluation parameters such as mAP, precision, recall that are used to evaluate the performance of an object recognition model.The model was trained with sixteen epochs.At the end of sixteenth epoch, it is inferred that the model gained more accuracy with minimum loss. Even though the model shows slight variations, the model was able to detect and classify objects accurately.

6. Conclusion

In conclusion, this project successfully demonstrated the effectiveness of YOLOv8 in fruit classification and real-time detection. By harnessing the power of deep learning and computer vision, we developed a robust system capable of accurately identifying various fruit types in diverse environments. The project's significance lies in its potential to revolutionize the agricultural and food industry by automating tasks, improving efficiency, and ensuring the quality of produce.

Throughout the research, we observed that YOLOv8 not only excels in accuracy but also in speed, making it highly suitable for real-time applications. The project's outcomes provide a strong foundation for future advancements, paving the way for more sophisticated applications in precision agriculture, automated sorting, and supply chain management.

As technology continues to advance, the integration of additional sensors, fine-grained classification techniques, and adaptive learning methodologies will further enhance the capabilities of fruit detection systems. These developments will not only benefit farmers and agricultural industries but also contribute significantly to sustainable agriculture practices and global food security.

In essence, this project marks a significant step forward in the realm of agricultural automation, and its findings serve as a cornerstone for future research and innovation in the field of object detection, deep learning, and precision agriculture.

7. Future Scope

1. Multi-Sensor Integration: Integrate other sensors like infrared or hyperspectral cameras to enhance fruit detection accuracy, especially in challenging environmental conditions.

2. Fine-Grained Classification:Explore techniques for fine-grained fruit classification, distinguishing between varieties and ripeness stages, aiding in precise quality assessment.

3. Semantic Segmentation: Incorporate semantic segmentation to precisely outline fruit boundaries, providing more detailed information for analysis and sorting.

4. Dynamic Learning: Implement techniques like online learning and transfer learning to adapt the model to new fruit varieties and environmental conditions, ensuring continuous improvement.

5. Localization and Tracking: Extend the system to include fruit localization and tracking, enabling applications in automated harvesting and monitoring fruit growth stages.

6. Human-Computer Interaction: Develop user-friendly interfaces and augmented reality applications for farmers and workers, aiding in decision-making processes during cultivation and harvest.

7. Energy-Efficient Deployment: Investigate methods to optimize the model further for deployment on resource-constrained edge devices, ensuring energy efficiency in real-world applications.

8. Collaborative Systems: Develop collaborative systems where multiple edge devices can share information, creating a network for comprehensive agricultural analysis.

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