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Pineapple Ripeness Detection Using YOLO v8 Algorithm

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Abstract
Pineapple is a tropical fruit that has various benefits for human health. However, determining the ripeness of pineapple is not easy, especially for inexperienced consumers. This study aims to develop a computer vision system that can automatically identify the ripeness of pineapple based on its peel color and texture. We use the YOLO v8 algorithm, a state-of-the-art object detection model, to detect and classify pineapple images into three categories: unripe, ripe, and overripe. We collect and label our own dataset of 1386 pineapple images with different ripeness levels. We train and test the YOLO v8 model on our dataset using Google Colab. We evaluate the model's performance using accuracy. The results show that the YOLO v8 model achieves an accuracy of 84.75%. These results indicate that the YOLO v8 model can effectively detect and classify pineapple ripeness with high accuracy and speed. This system can be useful for consumers, farmers, and retailers to select and purchase high-quality pineapples.

1. Introduction

The demand for pineapples is increasing in the international market due to its high nutritional content and health benefits [1]. However, smallholder farmers face various challenges in marketing their harvest, particularly concerning market information, transportation, price fluctuations, market distance, and limited product shelf life [2]. To enhance pineapple sales, it is crucial to understand consumer preferences, especially regarding the age and color of the fruit. According to [3], these aspects play a key role in determining the attractiveness of pineapples in the market. Therefore, addressing the challenges faced by small farmers while comprehensively understanding consumer preferences can contribute to the development of effective marketing strategies, fostering sustainable growth in the pineapple industry.

Several studies have tackled the challenges associated with determining the optimal time to harvest pineapples and assessing their color, offering solutions through object detection. [4] and [5] utilized machine learning and deep learning methods, respectively, to detect and quantify pineapples, with Syazwani achieving an impressive 94.4% accuracy in fruit counting. In a related effort, [6] developed a convolutional neural network (CNN) to classify pineapple maturity, demonstrating exceptional accuracy rates of 100% for both unripe and fully ripe stages and 82% for partially ripe ones.

This research aims to develop a computer vision system utilizing YOLO v8 object detection to automatically detect the ripeness levels of pineapples. The objective is to enhance efficiency in the pineapple harvesting process, with a specific focus on accurate maturity level detection. The use of YOLO v8 in this system is expected to provide more precise and responsive results in identifying various ripeness stages, including unripe, fully ripe, and partially ripe pineapples. By harnessing the high-level object detection capabilities of YOLO v8, this research endeavors to contribute to the advancement of technology supporting the agricultural industry, particularly in improving the quality and efficiency of pineapple production.

2. Methodology

The YOLO algorithm, including variations like YOLOFruit, YOLOX-EIoU-CBAM, and YOLOv4, has exhibited promising results in the detection of fruit ripeness. [7] and [8] both achieved notable accuracy rates in their detection, with Widyawati additionally showcasing real-time processing capabilities. Building on this foundation, [9] and [10] further refined the YOLOX and YOLO-V4 models, respectively, specifically for detecting ripeness in sweet cherry and cherry fruit. Notably, Gai's work achieved a higher mAP value, emphasizing the continuous improvement and adaptability of the YOLO algorithm in fruit ripeness detection. These studies collectively underscore the considerable potential of the YOLO algorithm, especially when enhanced by advanced techniques and refined models, in the accurate and efficient detection of fruit ripeness.

Therefore, recognizing the significant potential of the YOLO algorithm in fruit ripeness detection, this research endeavors to harness its capabilities further. Considering YOLO's positive performance in previous studies on fruit ripeness detection, we plan to adopt a similar approach. Our goal is to implement object detection for pineapple ripeness using the latest version, YOLO v8. Through this approach, we hope that the outcomes of this research can contribute to the agricultural industry, particularly in enhancing efficiency and quality in the harvesting and marketing processes of pineapples.

2.1 Workflow

This research employs the AI project cycle methodology, commencing with problem scoping, followed by data acquisition, data exploration, modeling, and evaluation. The workflow diagram for this study is presented below.

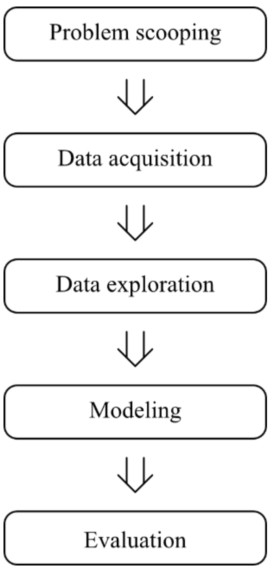

Fig 1. Workflow

2.2 Dataset

The utilized dataset comprises images of pineapples categorized into four classes: underripe, ripe, raw, and overripe. The total number of images in the dataset is 1386, distributed among 1204 training datasets, 122 validation datasets, and 60 test datasets.

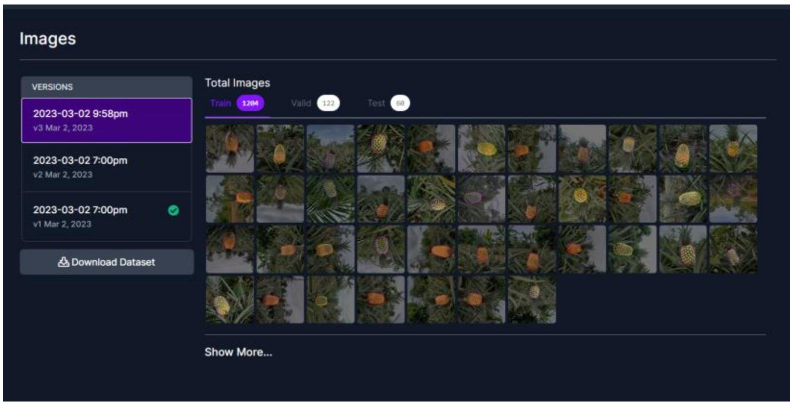

Fig 2. Dataset

3. Results and discussions

3.1. Training Model

The data training process was conducted on Google Colab, utilizing the API provided by Roboflow for YOLO v8 object detection. The designated number of epochs for training was set at 600, taking into consideration the constraints imposed by the usage limitations. This extended training duration allowed for a comprehensive exploration of the model's learning patterns and convergence toward optimal performance. The utilization of Google Colab, coupled with the advanced capabilities of YOLO v8 and the integration of the Roboflow API, facilitated an efficient and effective training process, ensuring the model's proficiency in detecting pineapple ripeness across various classes.

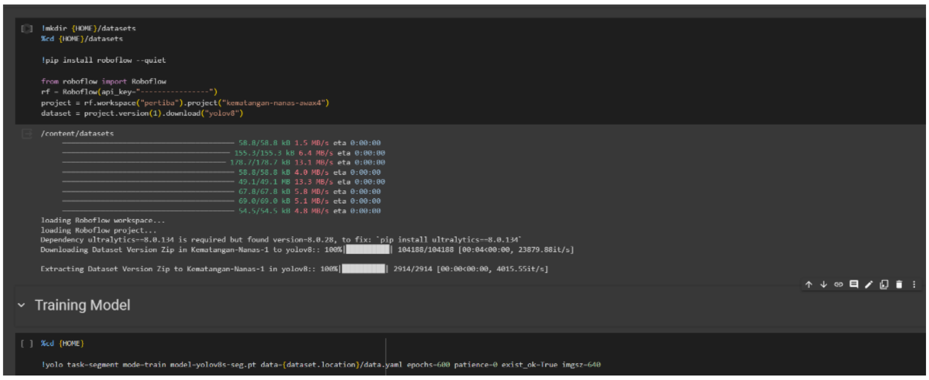

Fig 3. Training on google colab

3.2. Accuracy

Following the completion of the training process, an overall accuracy of 84.75% was achieved in detecting pineapple ripeness levels. However, it is crucial to note that the accuracy varies across individual classes, with underripe class accuracy at 81%, ripe class at 69%, raw class at 95%, and overripe class at 94%. Disparities in accuracy among these classes can be attributed to the uneven distribution of datasets for each class, introducing inherent challenges in achieving balance during training. Additionally, the observed variations in accuracy could be influenced by the relatively limited number of epochs employed in the training process. The nuanced nature of accuracy across classes underscores the importance of addressing data imbalances and optimizing training parameters to further enhance model performance and ensure robustness in pineapple ripeness detection.

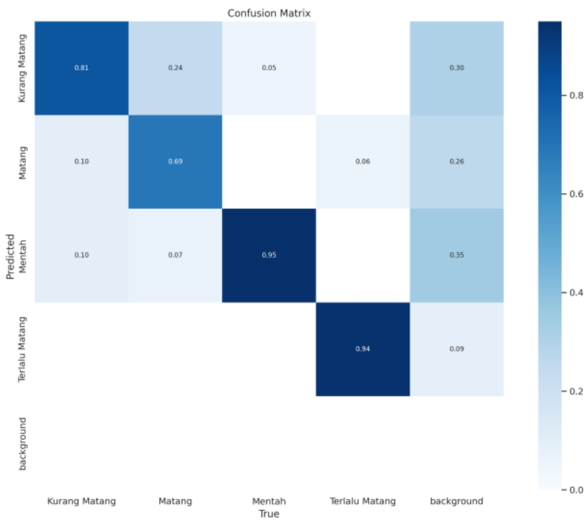

Figure 4. Model accuracy

3.3. Result

Post-training, the model underwent a comprehensive testing phase, evaluating its efficacy in detecting pineapple ripeness through analysis of several pineapple images. This assessment aimed to gauge the model's generalization performance and ascertain its ability to accurately discern ripeness levels in diverse scenarios. The testing process involved presenting the model with a variety of pineapple images representative of different lighting conditions, angles, and backgrounds. The objective was to assess the model's robustness and reliability in real-world scenarios beyond the training dataset.

Fig 5. Detection result using YOLO v8

4. Conclusion

The escalating demand for pineapples in the international market presents both opportunities and challenges for smallholder farmers. Challenges such as marketing, transportation inefficiencies, and limited product shelf life were identified, emphasizing the necessity for innovative solutions to enhance the efficiency and sustainability of the pineapple industry.

The literature review highlighted the promise of the YOLO algorithm in fruit ripeness detection, as demonstrated by various studies. Motivated by these findings, this research aimed to develop a computer vision system utilizing YOLO v8 object detection for automatic pineapple ripeness detection. The training process, conducted on Google Colab with the Roboflow API, resulted in an overall accuracy of 84.75%. However, the nuanced variations in accuracy across individual classes underscore the importance of addressing data imbalances and optimizing training parameters. The comprehensive testing phase showcased the model's potential for generalization, contributing valuable insights into the application of YOLO v8 in pineapple ripeness detection. This research represents a significant stride towards improving the efficiency and quality of pineapple production, with the potential to drive advancements in agricultural technology and support sustainable practices.

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