

APPLE FRUIT QUALITY DETECTION (GOOD AND ROTTEN) USING YOLOV5 METHOD

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ABSTRACT (10pt BOLD)

Fruit quality is an important factor that affects nutritional value, consumption safety, and market value of agricultural products. Apples, as one of the most widely consumed fruits, are prone to quality degradation due to spoilage, which is often difficult to accurately identify through human visual observation. Manual sorting of apples is subjective, time-consuming, and prone to errors. Therefore, this study aims to develop an automatic apple quality detection and classification system using the You Only Look Once version 5 (YOLOv5) deep learning method. Apple quality is classified into two categories, namely fresh apples and rotten apples, based on digital images. The dataset used in this study consists of 4,035 images obtained from the Roboflow platform, comprising 2,925 training images, 707 validation images, and 403 testing images. All images were resized to 640×640 pixels without data augmentation. The model was trained for 50 epochs using GPU acceleration on Google Colab. Model performance was evaluated using a confusion matrix on the testing dataset. The experimental results show that the YOLOv5 model successfully classified all testing images correctly without any misclassification, indicating excellent detection and classification performance. These results demonstrate that YOLOv5 is an effective and reliable method for automatic apple quality detection and has strong potential for application in agriculture and the food industry to improve efficiency and accuracy in fruit quality inspection.

Keywords: Apple quality detection, fresh apple, rotten apple, YOLOv5, deep learning, computer vision

1. INTRODUCTION

Apples are currently cultivated in most countries around the world, and due to having one of the most significant cultivar variations among fruit crops, they can grow well in regions with both the hottest and coldest climates on Earth. China is one of the largest apple producers in the world, and apples are also among the most widely consumed fruits globally. The development of the fruit production sector, particularly apple cultivation, strongly influences the growth of various inputs in the manufacturing sector, such as weed protection materials, mineral fertilizers, agricultural mechanization, packaging materials, and the construction of storage facilities [1].

The concept of smart farming has become increasingly popular along with the development of precision agriculture and information technology. China is one of the largest apple-producing countries in the world, and apple sorting has high economic application value. With the continuous growth of the economy, consumers now have higher demands for fruit quality [2].

Fresh fruits have their own definitions and characteristics. Therefore, it is important to have an appropriate method to distinguish fresh fruits from those that are not, so that the selected fruits retain their nutrients and vitamins. The nutrients contained in fruits can include antioxidants, which help protect the body from disease-causing viruses. The fiber and water content also assist in improving the metabolic system. For these reasons, everyone should be careful and more discerning when selecting and consuming fruits [3].

Convolutional Neural Network (CNN) is a deep learning algorithm that can be used for object classification (Iswantoro & UN, 2022). With current technology, image processing can be performed for classification using only image-capturing devices such as cameras or system galleries. CNN operates similarly to the way neurons in the human brain function based on visual perception. The development of CNN models for classifying fresh or rotten fruits designing the CNN architecture to enable the model to classify fruit types along with their freshness levels. Their study included apples, bananas, and mandarins, ranging from fresh to rotten, with the dataset obtained

from Kaggle. The dataset consisted of 10,900 fruit images, divided into 8,720 for training, 2,180 for validation, and 1,090 for testing. The study achieved a training accuracy of 98.20%, a validation accuracy of 99.22%, and a testing accuracy of 91.65% using 50 epochs [4].

In practice, the process of sorting apples into fresh and rotten categories is still largely done manually. This method heavily depends on human subjectivity, which can potentially lead to errors in assessing fruit quality. Furthermore, manual sorting is relatively time-consuming and inefficient when applied on a large scale, such as in the agricultural, distribution, or retail sectors.

With the advancement of technology, a system needs to be developed to assist in sorting fresh and rotten fruits. One of the technologies that can be used for implementing computer vision is machine learning, which involves computer applications and mathematical algorithms that learn from data and generate predictions for future outcomes [5]

Variations in lighting conditions, complex backgrounds, and diverse visual characteristics of apples pose major challenges in the fruit quality detection process. Therefore, a computer vision-based method that can operate reliably under various environmental conditions is required [6].

Based on these issues, this study aims to implement the YOLOv5 method for detecting apple fruit quality, specifically in classifying apples as either fresh or rotten. It is expected that this system will enable apple sorting to be carried out more accurately, quickly, and efficiently, thereby assisting both consumers and industry players in maintaining fruit quality, as well as improving the safety and nutritional value of the consumed fruits.

Although deep learning-based methods have been applied, there are still several limitations that need further investigation. Some previous studies focused on image classification without considering real-time object detection, while others did not optimize the feature extraction process to improve detection accuracy. In addition, the application of attention mechanisms in the YOLOv5 model for apple quality detection remains relatively limited. Therefore, this study proposes the development of a YOLOv5 model enhanced with a Coordinate Attention mechanism to improve feature extraction capability, detection accuracy, and model robustness in automatically detecting apple fruit quality. Despite various studies on fruit quality detection and classification, there is still room for further improvement [7].

2. METHOD

Manual fruit quality detection has limitations in terms of subjectivity and efficiency. Therefore, an automated system based on computer vision is required to accurately detect the quality of apples [8].

Several studies have shown that apple quality is influenced by various visual characteristics such as color, shape, size, and surface defects. Deep learning-based approaches, such as YOLOv5, are capable of automatically extracting these visual features from digital images without the need for manual feature extraction [9].

In this study, apple quality detection is treated as an object detection problem. The YOLOv5 model was used due to its ability to perform real-time object detection with high accuracy. YOLOv5 also possesses effective multi-scale detection capabilities, which are useful for identifying small defects on apples [10].

The selection of the YOLOv5 method in this study is based on its ability to detect objects quickly and accurately, as demonstrated in previous studies on fruit defect detection [11].

Several studies have been conducted on fruits, such as fruit image classification using an SVM classifier, which achieved an accuracy of 94%; meat-type image classification, which achieved an accuracy of 87.5%; automatic classification of fruit types and identification of rotten fruits using k-NN and SVM, which achieved an accuracy of 98%; and implementation of SVM for fruit type classification, which achieved an accuracy of 99.12%. Other related studies include the classification of fresh and rotten fruits using Hu-Moment, Haralick, and histogram feature extraction with the Random Forest algorithm, achieving an accuracy of 99.6%, and the implementation of Random Forest for classifying Palembang songket motifs based on SIFT, achieving an average accuracy of 92% [12].

This study aims to detect and classify the quality of apples based on their freshness level using the You Only Look Once version 5 (YOLOv5) algorithm, which is based on deep learning. Apple quality is classified into two classes: fresh apples and rotten apples, based on digital images. This method was chosen because YOLOv5 has fast and accurate object detection capabilities, making it suitable for implementation in an automated fruit

quality classification system.

The researchers used Google Colab and implemented the YOLOv5 method. YOLO is a network for object detection, while YOLOv5 is an advancement of the previous YOLO methods (Tan et al., 2021). The task of object detection is to determine the location of objects within an image and classify the types of objects present [3].

1. Dataset Collection

The dataset was collected by considering variations in image acquisition angles and lighting conditions to enhance the model's generalization ability in detecting fruit quality under different environmental conditions [13]. The dataset used in this study consists of images of apples obtained from the Roboflow platform. The dataset has been labeled according to the quality condition of the apples, namely fresh apples and rotten apples. Roboflow was chosen as the dataset source because it provides structured data and supports efficient annotation, management, and dataset splitting according to the requirements of the YOLOv5 model. The total number of images used in this study is 4,035. The dataset is divided into three parts: 2,925 images for training, 707 images for validation, and 403 images for testing. This division aims to ensure that the model can be trained effectively and is capable of generalizing to new data.

2. Data Pre-processing

Before training, apple images were preprocessed using noise reduction, enhancement, and color space conversion to improve image quality and facilitate feature extraction [14]. The data preprocessing stage was carried out to adjust the input images to meet the requirements of the YOLOv5 model. In this study, all apple images were resized to 640×640 pixels. This size was chosen because it is the standard input size for YOLOv5, which provides a balance between accuracy and computational efficiency. No data augmentation was performed in this study. The entire dataset was used in its original form without adding variations such as rotation, flipping, or changes in lighting. This approach aims to evaluate the capability of the YOLOv5 model in detecting apple quality based on the original conditions of the available images.

3. Detection and Classification Method

Several studies have shown that attention mechanisms can improve the performance of object detection models by focusing the learning process on the most relevant visual features and reducing the influence of irrelevant background information [15]. The method used in this study is the YOLOv5 algorithm, which is a one-stage object detector. YOLOv5 is capable of performing object detection and classification simultaneously in a single processing stage. In this study, YOLOv5 was used to detect apple objects in images while classifying their condition into two classes: fresh apples and rotten apples. The model was trained to learn the visual characteristics of apples, such as color, surface texture, and damage patterns, which differentiate fresh apples from rotten ones. The system output consists of bounding boxes around the apple objects, accompanied by class labels and confidence scores [16].

4. YOLOv5 Workflow for Apple Quality Detection

The YOLOv5 workflow for detecting fresh and rotten apples begins with image processing through augmentation and adaptive resizing. The model backbone extracts key features such as color, texture, and signs of damage, assisted by the Coordinate Attention Mechanism (CAM) to detect small or dense fruits. These features are then combined in the neck using PANet to improve accuracy, before the head generates bounding boxes, objectness scores, and apple quality classification, with NMS applied to remove duplicate predictions. This approach enables real-time apple detection with high accuracy and efficiency [17]. The first stage in the YOLOv5 workflow is the collection and preprocessing of apple image data. Each apple image is captured under varying lighting conditions and positions to represent the quality of both good and rotten fruits [18]. The YOLOv5 workflow is end-to-end, meaning that the system performs object detection and classification in a single image processing pass (single forward pass), making it faster compared to conventional methods such as two-stage CNNs.

The workflow stages are explained as follows:

5. Image Input

Apple image datasets (both fresh and rotten) are fed into the YOLOv5 model. Each image is divided into several grids of 19×19 pixels. Each grid is responsible for detecting whether an object (apple) is present in that area.

6. Bounding Box and Object Class Prediction

For each grid, YOLOv5 predicts a number of bounding boxes using anchor boxes. Each box has two main predicted values:

Confidence score → indicates the likelihood of an apple being present in the area.

Class probability → determines whether the apple is fresh or rotten based on color patterns, texture, and shape.

7. Detection Filtering (Thresholding)

Bounding boxes with low confidence values are removed so that the system retains only the most relevant and accurate detections.

8. Non-Maximum Suppression (NMS)

YOLOv5 applies Non-Maximum Suppression to eliminate duplicate detections (overlapping boxes), leaving only a single primary bounding box for each detected apple.

9. Detection Output

The final output is an image with labeled bounding boxes, showing the location of apples in the image and categorizing them as “Fresh Apple” or “Rotten Apple.” The model also displays the confidence score (%) indicating the detection certainty for each apple. With this workflow, YOLOv5 can automatically, quickly, and accurately detect apple conditions, even when multiple apples appear in a single image. This method can process images at an average speed of 0.1–0.2 seconds per image, making it highly efficient for real-time fruit quality detection applications [19].

10. Model Training Process

The model training process was carried out using the Google Colab platform, utilizing the available GPU to accelerate computation. The YOLOv5 model was trained using the dataset that had undergone preprocessing and data splitting. The training process of the YOLOv5 model for detecting fresh and rotten apples is carried out by preparing a dataset of apple images that have been labeled according to their respective classes [20].

The training was conducted for 100 epochs, where each epoch represents one complete learning cycle over the entire training dataset. The number of epochs was limited to 100 because increasing the number of epochs would also extend the time required for the training process [21].

After the training process was completed, the best model obtained from Google Colab was exported and run in the Visual Studio Code environment for local testing and implementation. Google Colab was chosen as the training environment because training the YOLOv5 model requires significant computational resources and would take much longer if conducted directly in a local environment.

11. Model Evaluation

To evaluate the performance of the proposed apple quality detection model, several commonly used object detection metrics were employed, namely Precision, Recall, and Mean Average Precision (mAP). These metrics were chosen because they effectively represent the accuracy, completeness of detection, and overall performance of the model in classifying apple quality [22].

Model evaluation was conducted to assess the performance of the YOLOv5 model in detecting and classifying apple quality. The evaluation process used the testing data, which were not involved in the training or validation stages. This approach aims to measure the model’s generalization capability on new data.

Precision measures the accuracy of the model’s predictions, recall evaluates the model’s ability to detect all relevant data, while accuracy indicates the proportion of correct predictions over the entire testing dataset [23].

The evaluation method used in this study is the confusion matrix, which is employed to analyze the model’s classification results for the two classes: fresh apples and rotten apples. Through the confusion matrix, information regarding the number of true positives, false positives, true negatives, and false negatives can be obtained, allowing for a more in-depth analysis of the model’s performance. The evaluation results are used to assess the accuracy and reliability of the developed apple quality detection system.

3. RESULT AND DISCUSSION

The training results in this study for detecting fresh and rotten apples achieved relatively high values, with an average precision of 0.995. The peak average recall reached 1.00 at a confidence level of 0.5. Recall represents

the ratio of true positive predictions to the total number of actual positive instances. From the recall value, it is also possible to determine the percentage of fruits predicted to belong to each class compared to the total number of fruits that actually belong to that category. The higher the recall value obtained from the training and validation data, the higher the accuracy of the developed system. A more detailed illustration can be seen in the following figure [3].

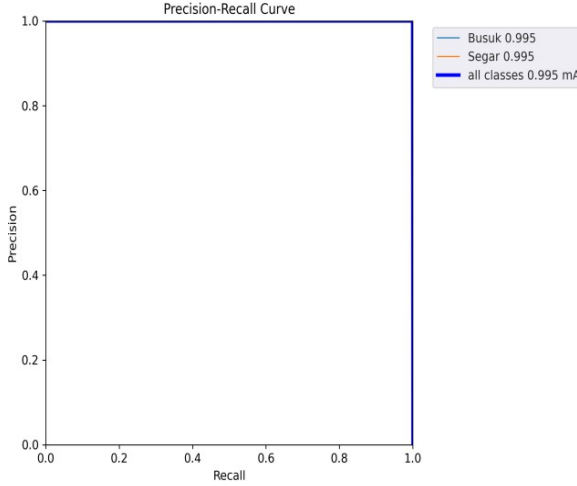


Figure 1. Curve showing the relationship between Precision and Recall

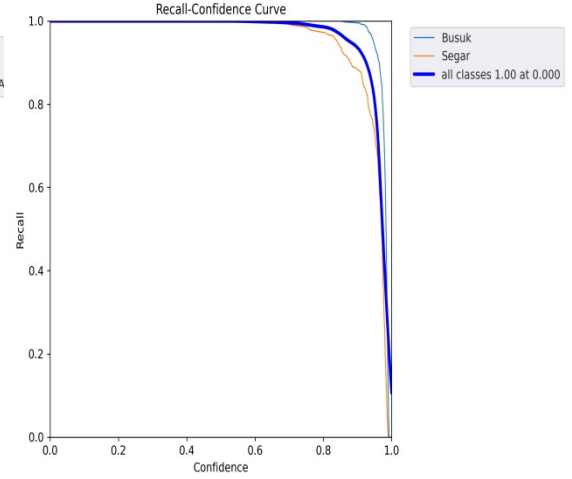


Figure 2. Curve showing the relationship between Recall and Confidence

In addition to the improvement in mAP values, the Precision-Recall curve results indicate that the model is able to maintain stable detection performance across various confidence levels. This suggests that the model has the potential to be used in real-time apple quality assessment systems, as applied in studies on apple grading based on defect detection [24].

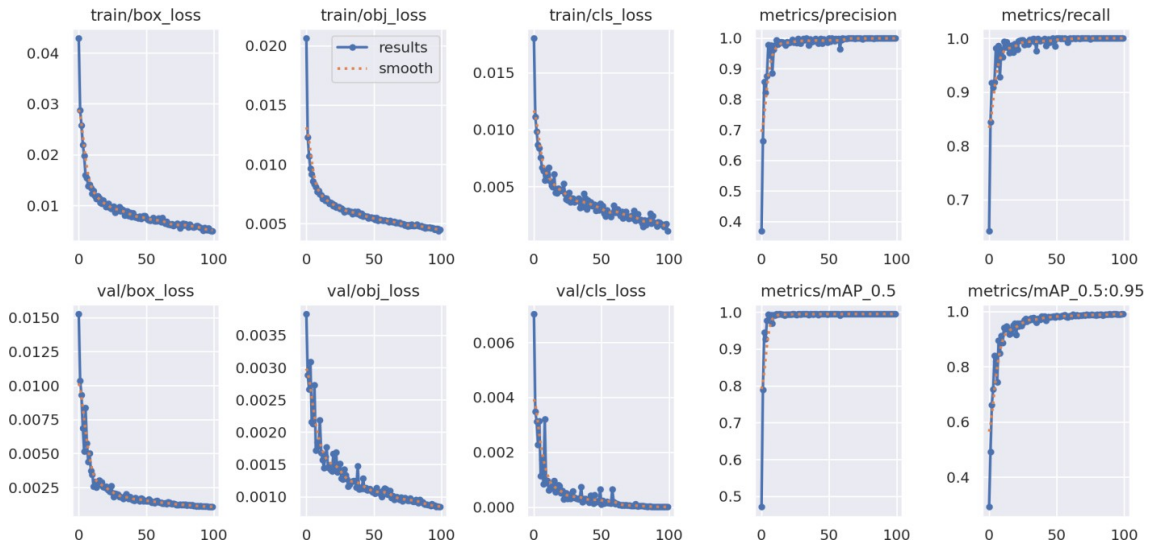


Figure 3. Evaluation results of the training data for both test and validation datasets

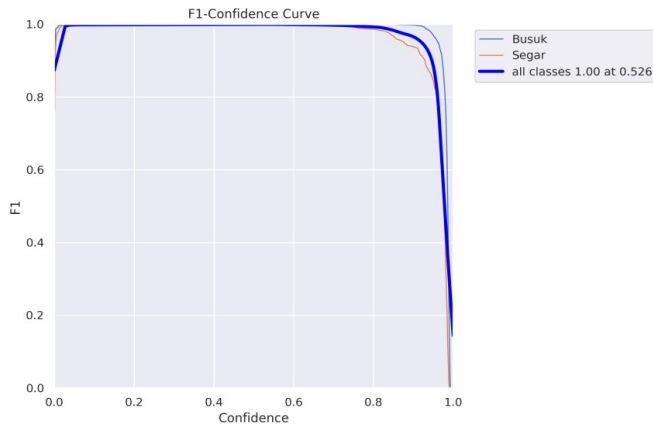


Figure 4. F1 score curve

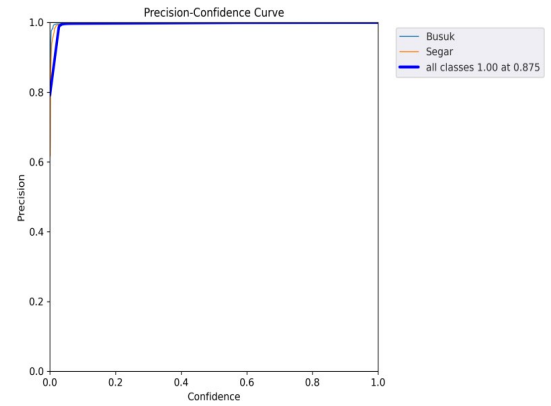


Figure 5. Precision curve against Confidence

a. Model Testing Result

The apple quality detection model was tested using 403 images from the testing dataset, which were not involved in the training or validation processes. The model's performance was evaluated using a confusion matrix to assess its ability to classify apples into two classes: fresh apples and rotten apples.

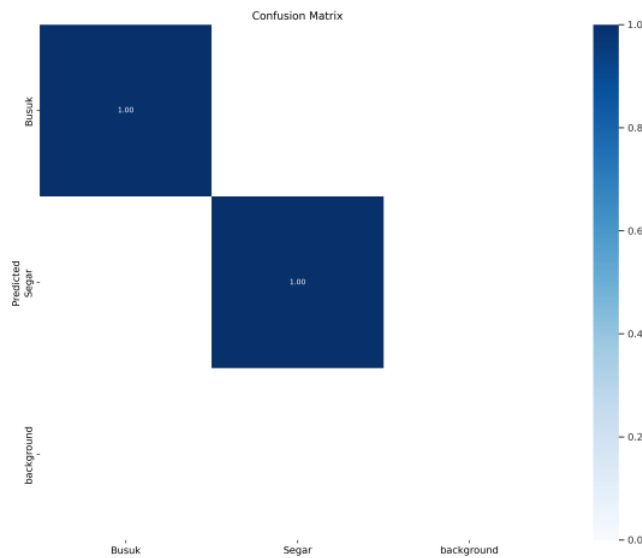


Figure 6. Confusion Matrix

Based on the testing results shown in the Confusion Matrix figure, all testing data were correctly classified by the YOLOv5 model. The values on the main diagonal of the confusion matrix are 1.00 for each class, indicating that no misclassification occurred between the fresh apple and rotten apple classes. Specifically, the model was able to detect all rotten apples as rotten and all fresh apples as fresh, without any cross-class prediction errors. Furthermore, no mispredictions were found for the background class, demonstrating that the model possesses excellent object detection capabilities.

Discussion

The results of the confusion matrix indicate that the YOLOv5 model exhibits highly optimal performance in detecting and classifying apple quality. The predictions being entirely on the main diagonal signify that the model has successfully learned the visual features that distinguish fresh apples from rotten ones. The model's success in achieving perfect classification results can be attributed to several factors. First, the quality of the dataset obtained from Roboflow was well-annotated and featured clear visual differences between fresh and rotten

apples, such as variations in color, surface texture, and the degree of fruit damage. This facilitated the model in accurately recognizing the visual patterns of each class.

Second, the use of an input image size of 640×640 pixels provided sufficient visual detail for the YOLOv5 model to extract important features from each apple image. With this resolution, the model was able to capture the texture and color characteristics of apples more effectively, thereby enhancing classification accuracy.

Third, the utilization of the end-to-end YOLOv5 architecture allows detection and classification to be performed simultaneously in a single stage. This not only increases detection speed but also improves the accuracy of apple object classification in the test images.

The experimental results show that the YOLOv5 model is capable of detecting and classifying apple quality with a high level of accuracy. These results are consistent with previous studies, which indicate that YOLO-based models outperform traditional classification methods. However, some detection errors still occur under suboptimal lighting conditions [25].

Although the testing results show excellent performance, it should be noted that these results were obtained from a dataset limited to certain conditions. Therefore, future studies are recommended to include more diverse datasets, such as varying lighting conditions, different image capture angles, and a wider range of apple types, to test the robustness and generalization ability of the model more comprehensively.

Several detection errors were still observed, particularly in images captured under suboptimal lighting conditions and in cases where the apples were partially occluded by other objects. This indicates that environmental factors remain a significant challenge in image-based apple quality detection systems [26].

The results of this study are consistent with previous research, which demonstrates that YOLOv5-based models achieve superior performance compared to traditional classification methods such as Support Vector Machines (SVM) [27].

4. CONCLUSION

Based on the results of this study, it can be concluded that the You Only Look Once version 5 (YOLOv5) algorithm can be effectively used to detect and classify apple quality into two classes, namely fresh apples and rotten apples, based on digital images. The developed model successfully learned the visual characteristics of apples, enabling it to accurately differentiate between the two classes. The dataset obtained from the Roboflow platform, consisting of a total of 4,035 images (2,925 for training, 707 for validation, and 403 for testing) contributed significantly to the success of the model's training and testing process. The preprocessing step, which involved resizing images to 640×640 pixels, was suitable for the YOLOv5 model requirements and helped improve detection performance. Evaluation using the confusion matrix showed that the YOLOv5 model performed excellently in classifying apple quality, with all testing data correctly classified without any prediction errors. This demonstrates that the model has very high accuracy and reliability in detecting fresh and rotten apples. Therefore, this study proves that the YOLOv5 method can serve as an effective and efficient solution for automated apple quality detection systems. The developed model has potential applications in agriculture and the food industry as a tool to assist in fruit selection and quality control processes. However, for further development, it is recommended to include a more diverse dataset and testing conditions to improve the model's generalization capability in real-world environments. The results of this study are consistent with the findings, which demonstrated the effectiveness of YOLOv5 in automated fruit quality classification. However, this study focuses specifically on applying YOLOv5 to apples, resulting in a more targeted detection system that can be directly implemented in apple sorting processes at the industrial level. Although the model demonstrates very strong performance, this study still has certain limitations, particularly regarding the variation of environmental conditions and the types of apples used. For future research, the structure of YOLOv5 can be optimized using lightweight modules such as ShuffleNet or depthwise convolution, as well as by implementing Coordinate Attention and SiLU Loss to enhance detection accuracy and computational efficiency, as applied in the EADD-YOLO model.

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