Improved and Efficient Object Detection Algorithm based on YOLOv5

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ABSTRACT

Object detection is a fundamental and impactful area of exploration in computer vision and video processing, with wide-ranging applications across diverse domains. The advent of the You Only Look Once (YOLO) paradigm has revolutionized real-time object identification, particularly with the introduction of the YOLOv5 architecture. Specifically designed for efficient object detection, YOLOv5 has enhanced flexibility and computational efficiency. This study systematically investigates the application of YOLOv5 in object identification, offering a comprehensive analysis of its implementation. The current study critically evaluates the architectural improvements and additional functionalities of YOLOv5 compared to its previous versions, aiming to highlight its unique advantages. Additionally, it comprehensively evaluates the training process, transfer learning techniques, and other factors, advocating the integration of these features to significantly enhance YOLOv5's detection capabilities. According to the results of this study, YOLOv5 is deemed an indispensable technique in computer vision, playing a key role in achieving accurate object recognition. The experimental data showed that YOLOv5-tiny performed better than anticipated, with a mean Average Precision (mAP) of 60.9% when evaluated using an Intersection Over Union (IoU) criterion of 0.5. Compared to other approaches, the proposed framework is distinguished by significant improvements in the mean average accuracy, computational flexibility, and dependability. As a

result, YOLOv5 is suitable for a wide range of real-world applications, since it is both sophisticated and resilient in addressing present issues in the fields of computer vision and video processing.

Keywords-deep learning; object detection; deep learning;YOLOv5; computer vision

I. INTRODUCTION

Identifying and locating objects in images or videos poses a significant challenge within the domain of computer vision. This field of study has received considerable attention, primarily due to its extensive practical applications. These applications encompass experiences in augmented reality, autonomous vehicle navigation, robotic systems, and surveillance technology. Many algorithms designed for object identification face difficulties in accurately detecting small objects while maintaining satisfactory performance on larger ones. Small objects, defined by a limited number of pixels or a limited field of view in the input image, present challenges, such as limited visual qualities, restricted background information, noisy representation, unclear features, complex backgrounds, limited resolution, and significant obstruction [1]. Real-time object identification systems, while prioritizing computational efficiency compared to resource usage, often fall short in detection accuracy, making them inappropriate for numerous real-world uses [2]. Recognizing and identifying objects on the road is of paramount importance to ensure safety and efficiency in the field of autonomous vehicle systems [3, 4]. Traditional road object detection systems tend to exhibit lower accuracy in detecting small items, mainly because smaller objects occupy fewer pixels, making it challenging to extract meaningful information from representations with low resolution. This implies that models may erroneously classify diminutive objects as ambient noise, resulting in an inability to recognize or detect them [5]. Reliably identifying objects of different sizes poses a significant challenge in object identification [6]. Within the domain of self-driving vehicles, small items include traffic lights and road signage. Improving the representational ability of a network by increasing its depth and breadth has been proposed to potentially enhance precision [6]. However, it is imperative to admit that adopting this approach introduces increased model complexity and associated expenditures. Therefore, these approaches are not well adapted to the demands of the self-driving vehicles, which require real-time processing and have limited resources. Two primary deep learning categories are used to identify objects: one-stage and two-stage identification methods [7]. Although two-stage detection techniques offer higher accuracy, their increased complexity and slower speed make them less practical in driving scenarios. Recent studies have focused on improving the efficacy of one-stage techniques to develop detectors suitable for practical applications [1, 7].

This study focuses on version 5 of You Only Look Once (YOLOv5), a popular one-stage object recognition approach [6]. YOLO is a crucial and widely adopted technique for object identification. By treating object detection as a single integrated task, the YOLO algorithm has significantly advanced progress in this area and enabled real-time inference with impressive precision. YOLOv5 is characterized by a clearly defined and flexible architecture, with the main goal of achieving optimal speed and efficiency on easily accessible platforms. However, to improve efficiency, most YOLOv5 methods rely on conventional training techniques, normalization strategies, or parameter adjustments, often overlooking architectural changes. While YOLOv5 is a flexible object detector, it has not been specifically optimized for small-item recognition. Consequently, its relevance to real-world situations is constrained [8]. This study offers an in-depth examination of the structural elements of YOLOv5, with a certain focus on its backbone, neck, and head networks. These networks work synergistically to enable precise object detection and arrangement of objects in their respective locations. Furthermore, this investigation delves into the YOLOv5 training methodology, encompassing pivotal phases, such as data preprocessing, model refinement, and hyperparameter adjustment. Its principal approaches utilize a deductive procedure, including bounding-box forecasting and post-processing techniques (e.g., non-maximum suppression). This study aims to provide a comprehensive understanding of the core operations of YOLOv5 and its essential components in object identification. This can be achieved through a meticulous examination of its inherent properties.

II. OBJECT DETECTION USING YOLOV5

In the era of edge computing and the Internet of Things (IoT), there is a growing need for artificial intelligence techniques that can identify and recognize items in real time on devices with limited resources. This study is driven by practical uses, including areas, such as autonomous robotics, surveillance, and other scenarios in which embedded systems must make informed decisions based on visual information [9]. However, embedded systems often face constraints in memory, battery consumption, and processor power. Guided by these constraints, this study aims to develop an efficient object identification technique that can effectively operate within these limitations. This particular study primarily focuses on object detection inference and training using the YOLOv5-tiny model. In computer vision, object detection is crucial, as it allows customizing a model for improved performance, making it more valuable in real-world scenarios by tailoring the model to specific objects or domains [10]. This study employed the YOLOv5-tiny model, as shown in Figure 1, striking a reasonable balance between model accuracy and size. This simplified iteration approach works effectively in resource-constrained scenarios or for applications that require instant data handling.

A customized approach was employed throughout the training process. A dataset that included distinctive objects relevant to the chosen application was implemented [11]. The dataset contained images or videos with annotations, using bounding box annotations to represent the spatial locations of the items. This approach assists in accurately indicating the positions of objects within the dataset, thereby enhancing a thorough comprehension of their spatial relationships. This study involves supplying a substantial number of examples that cover a broad spectrum of item directions, alterations, and backgrounds. The YOLOv5-tiny model is fine-tuned using the custom dataset. The fine-tuning process begins by initializing with pre-existing weight values and subsequently trains the model on the selected dataset to obtain information specific to the task of object detection. Moreover, transfer learning techniques are employed to improve the training phase and efficiency of models by utilizing the knowledge gained during the pre-training phase on a large dataset. During the training process, a meticulous adjustment of hyperparameters, such as learning rate, batch size, and regularization techniques, is undertaken to achieve the best results. Furthermore, strategies for augmenting the data, like random cropping, rotation, and scaling, were implemented to strengthen the robustness and diversity of the training samples. This meticulous approach contributes to acquiring optimal results during the training phase of the model.

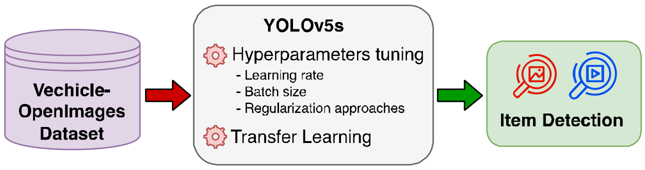

Fig. 1. The proposed framework for item detection.

Upon successful completion of the training process, the next phase involves a smooth transition to nuanced and intricate phases of inference. At this stage, the YOLOv5 tiny model, having completed a thorough training process, is employed to recognize and categorize objects within new and unobserved photos or videos. This crucial step marks the pinnacle of an extensive training task, where the improved capabilities of the model are applied to analyze and identify objects in visual data not previously encountered. The model systematically processes the input data to generate predictions related to the bounding boxes. Concurrently, it assigns the corresponding likelihood to each identified object belonging to a specific class, refining the precision and specificity of its analytical outcomes. Non-maximum suppression and related methodologies are adopted to mitigate instances of overlap or duplication, thereby ensuring the preservation of results characterized by high confidence and precision. The implementation of this distinctive item identification approach with the YOLOv5-tiny model brings various advantages. Tailoring the model to specific points of interest increases detection precision and enhances its applicability to real-world scenarios. Moreover, the compact size of YOLOv5-tiny enables efficient deployment on edge devices or in scenarios with limited computer resources [12]. These capabilities allow researchers to proficiently address challenges in item identification, enabling the formulation of highly accurate and effective results.

A. *YOLOv5-Tiny*

The YOLOv5-tiny object-detection model is a compromise between detection power and model size. Its main goal is to produce high-quality results at a lower cost than that of the bulkier YOLOv5 versions while maintaining excellent precision in identifying objects. The word "tiny" describes a reduced scale of the model, attained using a variety of network scaling techniques and architectural optimizations. These changes reduce the number of parameters and computing requirements, making it suitable for scenarios that require real-time performance or in devices with limited resources [6]. Even with its smaller size, the YOLOv5-tiny manages to retain all the important elements and ideas that are part of the original YOLOv5 design. The three networks of the system work together to recognize and pinpoint the exact position of items in images or videos. High-level features are extracted from the incoming data by employing the backbone network. The neck network then refines these traits even further. Ultimately, these improved characteristics are employed by the head network to predict the box boundaries and probabilities of classes of items that have been detected.

The YOLOv5-tiny training process follows the same methods as the other YOLOv5 versions, involving data preparation, model optimization, and hyperparameter tweaking [13]. A labeled dataset, comprising pictures or videos, is used with added bounding boxes to indicate object locations. YOLOv5-tiny learns to identify and classify significant objects by being trained on the dataset. To ensure reliable and accurate object detection during the inference process, YOLOv5-tiny deploys various methodologies, including a post-processing stage and bounding-box prediction techniques (e.g., non-maximum suppression). The real-time processing of the incoming images or videos results in bounding-box prediction as well as in the associated probabilities aimed at the recognized objects. From a broader perspective, YOLOv5-tiny stands out as a notably lightweight and efficient choice for detecting items, particularly compared to similar models inside the YOLOv5 framework. With precise detection capabilities, this model works effectively in situations with limited processing capabilities or the need for real-time performance. After adjusting the model to accommodate the specific dataset, the proposed YOLOv5 configuration features a complex structure with 214 layers. This detailed design includes a total of 7,033,114 parameters and gradients, demonstrating the model's ability to interpret data with precision. Additionally, the computational efficiency of the model was measured at 16 GFLOPs, confirming its proficiency in effective data processing and analysis.

B. *Dataset*

Vehicles-OpenImages [14] is a freely available dataset that specifically focuses on vehicles through intentional curation. The dataset is an extensive collection of photos with annotations for a wide variety of item classifications, and it was the source of the considered subset. The former constitutes a large collection of images that feature a wide range of vehicles including cars, trucks, motorcycles, and other forms of vehicles. The collection's bounding boxes are annotated with information regarding the exact locations of the vehicles within each image. Incorporating annotations into the dataset provides significant advantages for both developers and researchers, as it offers a strong basis for developing and evaluating object recognition algorithms, particularly those designed to identify vehicles. Experts can use this dataset to build and improve algorithms that can accurately recognize and locate vehicles in a variety of circumstances. This dataset is engaged in several fields, such as transportation studies, traffic surveillance, and autonomous vehicle technology. The particular dataset is a crucial resource for creating reliable algorithms for vehicle detection, which, in turn, aids in the creation of applications that require precise and effective vehicle tracking and identification.

Figure 2 presents a correlogram label, which is a visualization tool applied to explore the connections between labels within a multi-label classification context. This study provides valuable understanding of the correlations and interrelations between diverse labels within a dataset. Figure 2 demonstrates how labels are placed on the horizontal and vertical axes of a matrix or heatmap. This visual representation is crucial for a thorough comprehension of how different labels relate to each other and provides detailed insights into their patterns of co-occurrence within the dataset. Each cell in the matrix specifies a simultaneous occurrence, correlation, or a specific set of labels. Determining correlation often involves the use of statistical metrics, such as the correlation coefficient, the Jaccard index, and mutual information. These measures play a crucial role in evaluating the degree of association or similarity between the diverse elements within a dataset. For example, mutual information assesses the interdependence between variables, the Jaccard index gauges set similarity, and the correlation coefficient determines the magnitude and orientation of the linear association between pair variables. These reliable statistical methods improve the precision and dependability of the correlation analysis. Furthermore, the strength of the correlation between labels is visually conveyed through the intensity or hue of the cells. Higher-intensity or dark-colored cells are indicative of a strong positive correlation, suggesting a significant probability of concurrence among the corresponding categories. In contrast, lower-intensity or light-colored cells indicate a weaker or negative correlation, indicating a lower chance of co-occurrence among the five selected categories (trucks, cars, motorbikes, buses, and ambulances).

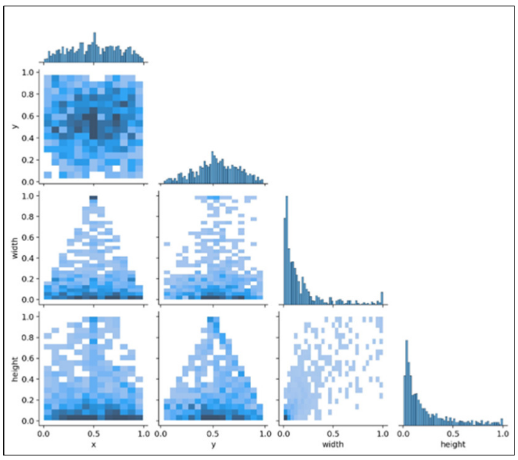

Fig. 2. Label correlogram of the various instances within the dataset.

Figure 3(a) portrays the quantity of annotations for each category in the dataset. Figure 3(b) provides an overview of the positions and sizes of the bounding boxes in the dataset. This study aims to get a sense of the arrangement patterns variation of the bounding boxes in the dataset. This guarantees that there is ample diversity in the object's placement and dimensions for successful detection by the model. This enhances model recognition and overall performance. Figure 3 (c, d) presents the statistical distributions associated with the placement and dimensions of the bounding boxes, offering valuable observations on their trends across the given dataset.

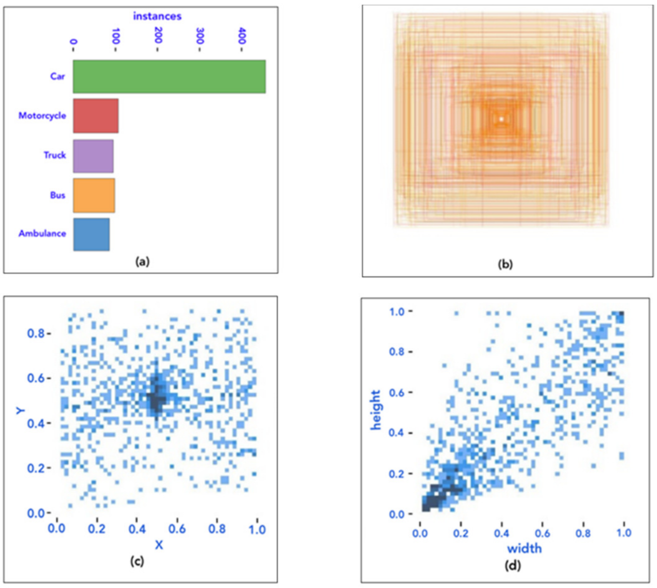

Fig. 3. (a) Visual illustration of annotation frequencies for each category in the dataset, (b) measurements and locations of individual bounding boxes, (c) statistical spread of bounding-box positions, (d) statistical distribution of bounding-box dimensions.

These graphs enable the assessment of whether there is a uniform distribution or if specific areas exhibit a greater concentration, which is essential for precise item identification, given the differences in object dimension and placement. Figure 4 depicts a subset of the dataset comprising 627 images, categorized into five distinct labels with diverse attributes.

Fig. 4. Example of vehicles (OpenImages dataset).

III. RESULTS AND DISCUSSION

A. Evaluation Metrics

The evaluation of the model is crucial and plays an important role in determining its effectiveness, ensuring that it efficiently aligns with the research objectives, and identifying areas for improvement. Different evaluation metrics can be used to identify factors associated with the precision, rapidity, and effectiveness of the model. The detection of items is primarily concentrated on evaluation criteria related to precision, as the model should be able to detect objects precisely. Recall (R) and precision (P) are frequently deployed as essential evaluation criteria [15, 16]. Recall represents the ability of a model to discern positive categorizations, providing precious knowledge of its performance. Other evaluation metrics, including mean Average Precision (mAP) and Average Precision (AP), are commonly applied in the domain of item recognition. AP measures the ability of the model to recognize relevant items precisely while ignoring irrelevant items. This determination involves plotting the precision-recall curve and calculating the area beneath it (AUC). In contrast, mAP represents the mean of the calculated APs for each class of an individual object noticed by the model and offers a more extensive performance evaluation by measuring precision across all classes rather than solely focusing on one [17]. The following equations represent these metrics:

$$P = \frac{TP}{TP+FP} \tag{1}$$

$$R = \frac{TP}{TP+FN} \tag{2}$$

$$AP = \int_0^1 P\,(r)\,dr \tag{3}$$

$$mAP = \frac{\sum_{i=1}^{k} AP_i}{k} \tag{4}$$

where *TP* signifies instances classified as True Positive, *FP* denotes occurrences identified as False Positive, and *FN* represents instances erroneously categorized as False Negative.

B. Training Results

The training procedure used random gradient descent with a 0.01 rate of learning and a batch size of 16. Training was carried out in 100 epochs on a training set consisting of 439 images and was validated on another set comprising 125 pictures. Figure 5 illustrates the training results of the proposed approach based on YOLOv5-tiny. Although the YOLOv5-tiny model can reach approximately 7 million counts, it has manifested a high degree of effectiveness in the results obtained. The entire training process was completed in approximately 0.41 hours, using a mid-level GPU. The model showed an mAP of 60.9% on an Intersection Over Union (IoU) threshold of 0.5, indicating its ability to detect and locate objects with significant precision. Additionally, when expanding the range of the IoU criteria from 0.5 to 0.95, the proposed YOLOv5-tiny model demonstrated an mAP of 44%. This implies that the proposed YOLOv5 model can maintain a consistently high degree of performance even when dealing with varying levels of overlap between the actual and predicted bounding boxes. These results demonstrate its effectiveness and competence to perform object identification tasks. Although smaller in size compared to the larger YOLOv5 versions, this model displays a high level of performance, making it suitable for real-time scenarios and applications with limited computational resources.

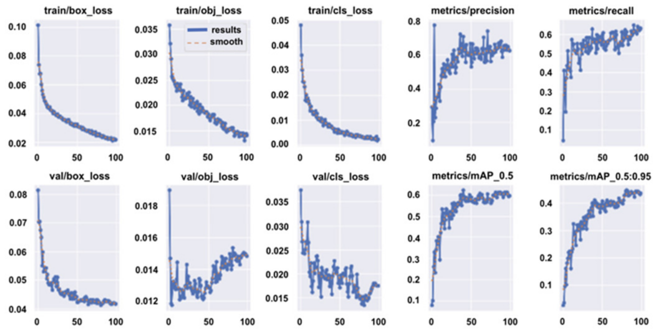

Fig. 5. Loss and mAP results.

Figure 6 presents the precision confidence for object identification at different confidence levels. The evaluation of object identification approaches commonly involves examining various confidence criteria to ensure the precision of identified objects. The precision-confidence results reveal that all classes achieved a precision score of 1 (100%) with a confidence criterion of 0.97, indicating high levels of accuracy. This denotes that the predictions with confidence exceeding 0.97 were either accurate or qualified as true positives. A precision value of 1 for a given confidence level indicates that there are no false positive detections for any class, establishing the model's reliability in making correct predictions when both the accuracy and confidence thresholds are high. This is particularly valuable in situations where minimizing false positives is crucial, signaling the model's ability to provide a highly reliable detection.

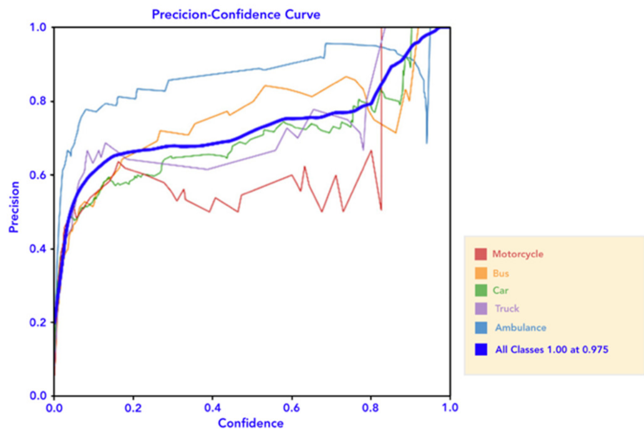

Fig. 6. Precision-confidence results.

Figure 7 presents the precision-recall curve for various thresholds. This curve is crucial to evaluate the model's efficiency at different confidence thresholds. Balancing accuracy and recall involves understanding the unique demands of the application, and the precision-recall curve provides insights into this trade-off. Higher accuracy suggests fewer false positives, while higher recall implies fewer false negatives. The identification of the most suitable balance varies depending on the situation and can be obtained from the characteristics of the precision-recall curve.

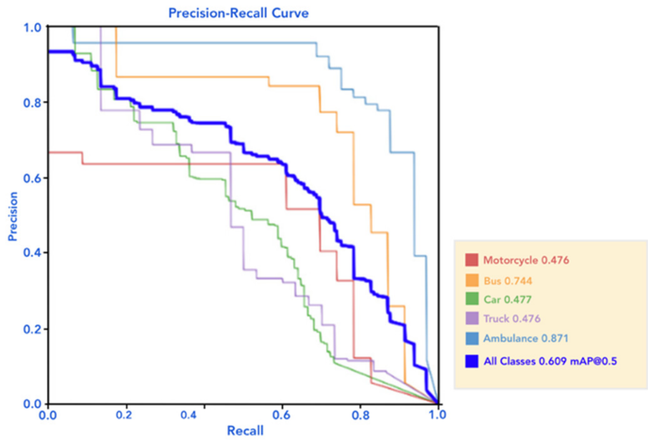

Fig. 7. Precision-recall results.

Figure 8 represents the correlation concerning the recall and prediction confidence in object detection. The recall metric evaluates the proportion of the TP identifications that the model detects accurately. Under a confidence threshold of 0.0, each class consistently demonstrated a recall rate of 0.82 (82%), as corroborated by the comprehensive recall-confidence findings. The model was able to precisely identify true positive instances across all categories, achieving an 82% success rate, regardless of the confidence threshold used. Furthermore, the recall-confidence curve can be employed to evaluate the precision of the model at various degrees of confidence. This aids in assessing how effectively different confidence degrees are represented in the balance between accurately identifying items and the occurrence of false positive detections.

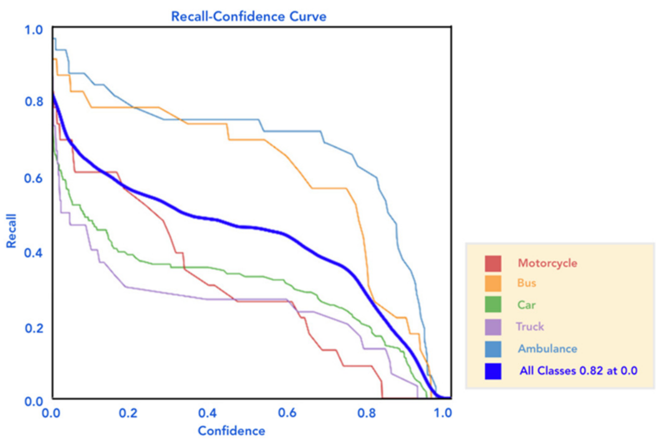

Fig. 8. Recall-confidence results.

Figure 9 shows the results of the identification process based on the proposed model.

Fig. 9. Object Detection findings.

IV. CONCLUSION

This study investigated the improvement of a custom item identification model implementing the YOLOv5-tiny framework, emphasizing its application to resolve unique challenges in autonomous driving. The primary goal was to develop a model that balances lightweight design, computational efficiency, and accuracy. The YOLOv5-tiny architecture achieved optimal results with respect to model size and computational demands. YOLOv5-tiny's architectural structure strikes a balanced harmony design between the complexity of the model and its ability to precisely detect objects, making it suitable for use in resource-constrained scenarios such as self-driving vehicles. The proposed item detection approach demonstrated a significant degree of accuracy in recognizing and determining relevant items related to autonomous driving activities. The effectiveness of this approach in performing these essential tasks was verified through a comprehensive evaluation procedure. The model's inherent lightweight design enables faster inference times, which is important in time-sensitive use cases, such as real-time video processing for security and surveillance systems, and autonomous driving. The limitations of this study include the need for additional diverse datasets, the spatial constraints of comprehensive comparative research, and the ongoing challenge of balancing real-time requirements with speed and accuracy. Future studies should address these limitations to further enhance the robustness and applicability of such models in real-world scenarios.

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