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Adaptive YOLO-V8 for Low-Earth Orbit Debris Detection Improving Detection Accuracy with Dynamic Training

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ABSTRACT

It is crucial to identify methods to detect debris due to a new tendency that is emerging in LEO orbits, which is threatening the functionality of satellites and interplanetary missions. This research solves this problem using an improved YOLO-V8 model that enables the detection of space debris with higher precision while using adaptive dynamic learning approaches. It was critical for our model to be able to identify and categorize as many kinds of objects as possible, and our database currently contains 11 object classes, including space debris and satellites. To specifically detect small and moving objects, we utilized the YOLO-V8 model, tailoring the train options to the unique object detections in this class. For the training of our model, we used a large quantity of data in addition to the images from these 11 classes and used SGD as our optimizer with the learning rate of 0.25 and individual weight decay parameters. Additionally, we utilized blur and grayscale transforms to enhance the model through data augmentation. By comparing the obtained results, we can observe enhanced detection accuracy in each class separately, as well as a general boost in prediction and recall. Due to the cross-entropy function's flexibility, the model was able to perform well on various object sizes and speeds in an orbital context, making detection consistent. A lot of fine tuning was required in the training parameters in order to get the desired or even better results devoid of false positive detection. This paper describes how YOLO-V8 with adaptive training achieved outstanding results for object and debris detection in low Earth orbit (LEO) to improve space usage safety and define better approaches to space debris management.

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1. Introduction

One of the most significant threats to space activities is space debris with low earth orbit density, posing risks to both manned and unmanned space vehicles. Orbital debris, such as dead satellites, launch vehicles, or parts from previous collisions, is a current threat to spacecraft and working satellites. These collisions may cause more particles to form, compounding the situation in a chain-like manner. Given the current trend in the number of space missions and satellite launches, weather for communication, research, mapping, or military purposes, there is no doubt that space debris detection and management is the order of the day [1]. In assessing collision threats, it enables correct identification of the threats and the safety of space assets [2].

Up until now, there were mainly two ways to track space debris: radar surveillance and optical systems. Radar systems are capable of covering large objects and providing real-time tracking information, but their accuracy in determining the size of small particles is often poor, and other signals can easily confuse them [3]. Optical systems are capable of providing greater resolution compared to radio systems, but they suffer from climatic conditions and must be 'pointed'. Despite this, both methods lack the comprehensive and real-time information on debris that is essential for debris management. Thus, the following limitations underscore the need to look for new ways of increasing the rates of detection, which would also be accurate and reliable [4].

Machine learning and deep learning approaches have provided new ways of identifying space debris. Real-time object detection is the major strength of YOLO (You Only Look Once), which is one of the most famous object detection frameworks [5]. The YOLO architecture also allows for the prediction of several bounding boxes and class probabilities at the same time, making it ideal for real-time and rapid detection. The algorithm's general success in numerous domains may also benefit the use of YOLO in space debris identification, although the approach has not received extensive research [6].

Recent years have seen some papers address the issue of modifying YOLO for specific detection purposes. These studies have demonstrated that enhancing YOLO models with enhanced training approaches and augmented data methods can improve detection efficiency [7]. However, applying YOLO to the actual environment by detecting LEO debris presents some challenges, such as object size variation, object movement, and light conditions [1].

Therefore, our research aims to address these issues by enhancing the YOLO-V8 model through the integration of dynamic training methods appropriate for space debris identification. We will train the initial model, YOLO-V8, using a diverse selection of debris and satellites. We aim to simulate the complexity of space objects' characteristics by using different sizes, shapes, and motion velocities in this dataset [5]. We will incorporate dynamic training strategies that would allow it to increase its overall detection rates [8].

This research employs an approach consisting of multiple components. First, a state-of-the-art survey of the current approaches to detecting space debris and their drawbacks forms the background for our approach [6]. Subsequently, in an attempt to improve detection, we fine-tune a YOLO-V8 model using a dataset complemented with images of space debris and satellites. The training process herein involves using stochastic gradient descent (SGD) with a learning rate set at 0.01 and specific weight decay parameters in order to further optimize the models' architectures. We also incorporate data augmentation, such as blur and grayscale, to enhance the model's capacity to identify effective strategies under various conditions [9].

The research steps include a formal evaluation of the trained YOLO-V8 model, followed by testing on a set of debris images [10]. We can use precision and recall rate as evaluation standards to assess the model's effectiveness in identifying different types of space debris. By analysing the results and utilizing the collected data, we aim to improve the model and expand its functions. This study aims to evaluate different dynamic training techniques, hence the impact on the detection accuracy [11].

This study's system hierarchy includes a literature review of prior methods and the YOLO-V8 model training process. There are further phases, such as assessing the model and outcomes and further developing the detection capabilities. As a result, we designed each stage of the research with the goal of successively refining the existing methodology to boost searches for space debris [11]. Therefore, the primary goals of the current study are to improve the YOLO-V8 approach through the implementation of an adaptive dynamic training strategy, aiming to increase the detector's effectiveness in identifying space debris and to optimize the model's performance in a variety of orbital conditions. Therefore, in this research study, those gaps have been articulated, and more to the point, an enhanced and efficient approach using ML techniques has been proposed to improve on space debris control.

Thus, the work involves using dynamic training methods to create an architecture for identifying space debris based on Yolo-V8 that is much more effective than the previous methods, especially in identifying the “slow’’ and “crowded’’ particles. The analysed results may help to improve space security and establish better debris removal strategies in LEO.

2. Related Work

Some of the more significant threats are space debris in LEO since the number of satellites and space missions has increased gradually. Current satellites, motors, and debris from old, disused satellites and unutilized rocket stages continue to pose a threat to operational satellites and space endeavours [12]. The issue of space debris has been extensively documented, with initial analyses utilizing radar and optical control. However, the accuracy of detection, the scope of coverage, and the capacity for real-time processing limit these methods [13].

Larger particles, for example, helped in tracking larger debris through the Space Surveillance Network (SSN) and the European Space Agency's (ESA) Space Debris Telescope [14]. These systems rely on the principles of transmitted radio waves and the reception of echoes from celestial bodies. However, radars have a low capability in detecting small debris owing to inadequate resolutions and a problem of filtering debris against interference from background noise. J. Dolado and B. Revelin 2014 study raised concerns about the growth rate of space debris and its potential impact on satellite collisions, thereby highlighting the necessity for improved tracking [12].

Some of the recent works, like Liou and Johnson (2010) [13], have pointed out that radar has its drawbacks when used to detect as well as track tiny debris particles. Optical systems, such as the ground optical telescope and space optical observatories, provide higher resolutions than radar [15]. These systems use visible or infrared light to take pictures of the debris and analyse them to estimate the size and path of the detritus. However, the works of J. R. Ribeiro (2018) [16] and R. Haussmann et al. (2021) [17] demonstrate that optical systems require accurate angle positioning and cannot operate in bad weather during the day. These constraints hinder the possibility of offering constant and adequate support—a duty to offer ongoing and intensive coverage of all sorts of debris but the enormous ones.

In the present decade, machine learning and deep learning methodologies have attracted much attention in the different fields, including object detection [18]. Convolutional neural networks (CNNs) are known to significantly improve the results of image analysis and object detection and recognition. The authors, K. He et al. (2016) [19], proposed the region-based CNN (R-CNN), in which they achieved better accuracy in object detection by adding region proposals in combination with CNN feature extraction. Following that, new improvements, for instance, called Fast R-CNN (Girshick, 2015) [20] and Faster R-CNN (Ren et al., 2015) [21], helped improve both the detection rate and the speed.

Redmon et al. [5] recently elevated real-time object detection to new heights with the release of the YOLO (You Only Look Once) architecture. One of YOLO's unique features is that it can generate multiple bounding boxes and class probabilities from a single network for real-time object detection. Specifically, most applications requiring timely decisions will benefit from YOLO's high real-time efficiency. YOLO V2 (J. Redmon and A. Farhadi 2017) [22] and YOLO V3 (Redmon and Farhadi 2018) [23] have made improvements to their backbone networks with feature pyramid networks to enhance detection performance and detector robustness.

But even modern YOLO models have their peculiarities when it comes to space debris detection. Space debris detection is generally characterized by handling small and fast-moving objects in an ever-changing scenario. M. Haroon et al. (2020) [24] applied a number of domain adaptation techniques, focusing on the issues specific to YOLO in identifying small and fast-moving objects. They have reported improving the detection rate by fine-tuning the models with space-specific data sets.

Data augmentation techniques have significantly contributed to the improvement of deep learning models. There are common methods of image augmentation, such as blurring, operation in different colour spaces, and geometric transformation, which can mimic many environmental conditions and improve model resilience. Shorten and Khoshgoftaar (2019) [25] conducted a survey in which they discussed the role of data augmentation and analysed its efficiency in deep learning from the perspective of model generalization and performance. It is critical to learn about augmentation techniques because of the differences in space debris detection: size, motion, and illumination conditions.

Other sophisticated training methodologies, such as dynamically adjusting learning rates and specifically tailored loss functions for the particular objects, have made this possible. Other techniques, as demonstrated by Smith et al. (2019) [26], involve dynamic learning rates because they can adjust the learning process to the data properties. A special loss function can handle the imbalance problem and enhance the detection performance for difficult object classes on the basis of focal loss (Lin et al., 2017) [27].

Some recent studies have focused on the use of the YOLOV4 and YOLOV5 models, which include additional features like feature pyramid networks and better data augmentation approaches. More recent architectures include YOLO-V4

(Bochkovskiy et al., 2020) [28] and YOLO-V5 (Glenn Jocher, 2020) [29], which have delivered improved object detection performance in many application areas. These improvements are particularly important for space debris detection because accurate and robust detection is critical for collision avoidance.

In conclusion, reports have identified radar and optical systems as the fundamental techniques for identifying space debris, with recent advances in deep learning, particularly the use of YOLO models, showing tremendous potential to increase detection rates. The opportunity to apply YOLO-V8 with adaptive dynamic training is a way to overcome the specific difficulties associated with space debris detection. In this study, we look at how to use improved deep learning methods along with changes that are specific to the domain. These changes should help improve the accuracy of detection and make managing space junk even more efficient.

3. Materials and Methods

The study focused on low-Earth orbit (LEO) situations and utilized data collected almost 20,000 from satellite images and space debris detection devices as shown in figure 1. The study's geographical coverage encompasses various orbits where there is a significant expectation of space debris. This also applies to high-density LEO regions, i.e., areas with a large number of working satellites as well as debris. Therefore, the selection of this environment is critical, as it directly impacts active space missions and the likelihood of collisions with space debris. Such parameters as orbital altitude, debris density, and space weather conditions were critical for the study. Satellite tracking data and space debris reports demonstrate the study area's importance and relevance for SSA.

For the material, the research used several datasets in the training and testing of the YOLOv8 object detection model. This included a wide-ranging set of annotated image examples of space debris as well as operational satellites. The primary data sources were as follows: The primary data sources were as follows:

- **Satellite Monitoring Agencies:** This source compiles annotated images of space debris from various satellite tracking and monitoring systems, providing a complete dataset.
- **Space Surveillance Data:** We have gathered data from open sources belonging to renowned space agencies such as NASA and ESA. These datasets provide relevant information about space debris and satellites, helping to strengthen the study.
- **Custom Data Collection:** To diversify the types of debris and satellite, we collected more images and annotations from specific LEO missions and experiments.

The variety of datasets chosen provided a balanced approach to model training and testing, which improved YOLOv8's effectiveness and credibility in the identification and classification of space debris.

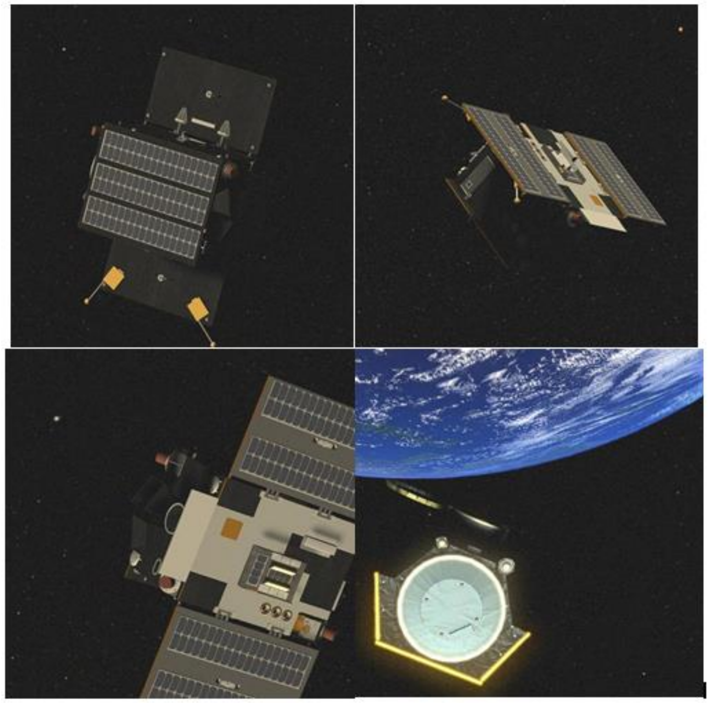

Figure 1. Collected Data of Satellite Images and Space Debris.

Data Preparation

We conducted data pre-processing through a number of processes to enhance the model's training data set. In order to increase the models' variability and generalization capability, we used data augmentation techniques. The Augmentations library offers numerous techniques for various augmentations, such as flipping in the horizontal and vertical plane, rotation, scaling, and adjusting colours and brightness. Such techniques made it possible for the model to simulate other states of the real world and, at the same time, helped to enhance the model's performance in other situations. After augmentation, we split the dataset into three subsets: the training set, the validation set, and the test set as shown in figure 2.

A rotation transformation could be described in Eq. 1:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos(\theta) & -sin\theta \\ sin\theta & cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{1}$$

This rotation maintains the relative positioning of the bounding box while altering the appearance of the object, thus enhancing the model’s ability to recognize objects in various orientations. With respect to this classification, we have allocated 70% of such annotated images for the training set, 15% for the validation set, and the remaining 15% for testing. We did this to have enough data for training the applicants, as well as to maintain a large capacity for assessing the mode and its effectiveness.

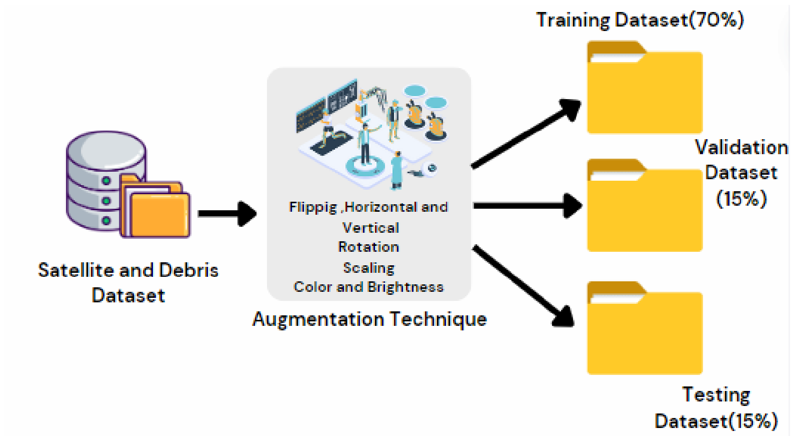

Figure 2. Data Augmentation and Data Splitting Techniques.

Image Labelling

Labelling the images played a crucial role in preparing the dataset for training the YOLOv8 model. For our analysis, we first gathered a substantial quantity of high-quality images of space debris and operational satellites from satellite tracking centres and space missions. Labelling and CVAT were used to label these images in YOLO format. To ensure that the system had the correct bounding box for the identified objects, we first cropped the images to the best quality before presenting them to the system. We placed these bounding boxes on the labels of satellites. We used the YOLO format for these annotations, a text file format that contains information in the form of a class ID and bounding box dimensions, normalized by image size as shown in figure 3. The annotation format's similarity to the YOLOv8 model format, for instance, made it easier to adjust compatibility as needed.

Mathematically, the normalization process can be represented in Eq. 2:

$$x_{center} = \frac{x\_\min + x\_max}{2}, y_{center} = \frac{y\_\min + y\_max}{2} \qquad (2)$$

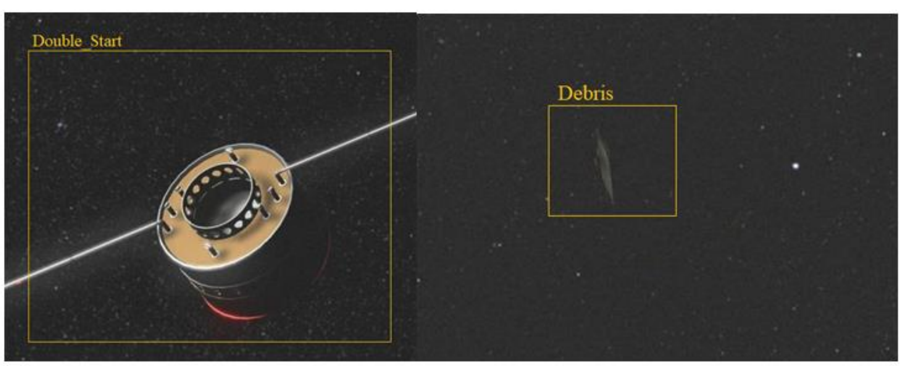

Figure 3. Labbled Data of collected images with class ID and bounding boxes.

Model Training

We selected YOLOv8 because it supports object detection in real-time, which is paramount in detecting space debris. We used a previously trained weight to bring in transfer learning on the model, meaning that training was much faster. The training details for YOLOv8 are as follows: We arranged the model using an input image size of 640*640, a batch size of 16, and over 50 epochs. We maintained all these parameters to ensure a reasonable training speed and optimal performance of the training model. The training command also included data, thus giving the graduates a sound base to build on as trainers and assessors. The YAML file held references to training and validation data sets, along with a list of class names. This configuration allowed the model to look at a huge range of examples, which suggested that it was capable of learning all forms of space debris and satellites.

Model Validation

Upon completing the training, the YOLOv8 model underwent a rigorous validation process to assess its performance on unseen data. The validation phase utilized the best-performing weights from the training process, ensuring that the model was evaluated at its optimal state. The validation process involved setting an Intersection over Union (IOU) threshold of 0.65, which is a critical metric for evaluating the overlap between the predicted bounding boxes and the ground truth annotations.

A high IOU indicates a close match between the predicted and actual bounding boxes, which is essential for accurate object detection. To expedite the validation process and reduce memory usage, we employed half-precision floating-point calculations, which effectively halved the memory footprint without compromising the accuracy of the model's predictions. The validation results provided crucial insights into the model's generalization capabilities and its performance across different detection scenarios, guiding further refinement and optimization as shown in figure 4 below:

Figure 4. Intersection over Union Model Architecture.

Object Detection

We used YOLOv8 in the object detection phase, testing the approach on both test datasets and realistic settings. To reconstruct the images, we borrowed the final model weights and used them to process images from a specific source directory that contained both test images and practical data as shown in figure 5. We issued the detection command on these images with the intention of providing precise coordinates of operational satellites and space debris only. This phase was equally important to test the efficiency of the model within conditions out of the training sample and check the ability of the model to solve a wide range of detection problems.

Mathematically, the detection process can be summarized in Eq. 3:

$$P(y|x) = YOLOv8(x;\theta) \quad (3)$$

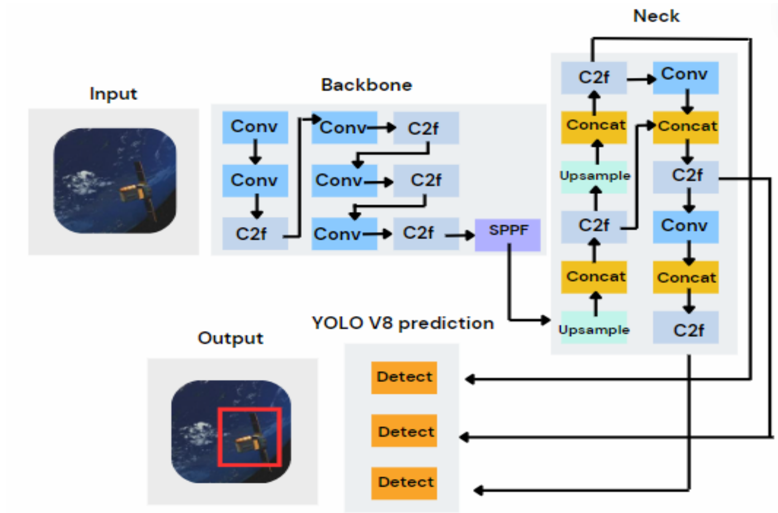

Figure 5. Object Detection Workflow using YOLO V8 model.

Evaluation Metrics

To assess the effectiveness of the YOLOv8 model, we used mean average precision (mAP), precision, recall, and the F1 score. The F1 score balanced the two measures, with precision quantifying the percentage of correctly detected objects and recall indicating the extent of identification of all objects of interest. The mAP metric matrix provided an all-around evaluation of the model's performance. These metrics were particularly useful in estimating the model's performance in identifying space debris and functional satellites.

Post-Processing

All the outcomes from the object detection step in the subsequent stage of post-processing were instrumental in determining the model's performance. We benchmarked the model by comparing the output detections with the ground truth annotations to ascertain the algorithm's accuracy. We focused specifically on both false positives and false negatives to understand the types of errors this model can produce and to guide future error analysis. This type of analysis indicated parts of the process that could be elaborated in order to achieve better results. In the previous section, we presented the results of post-processing the current phase's outcomes to improve the model and predict future outcomes.

Methodology flow diagram shown in figure 6 below:

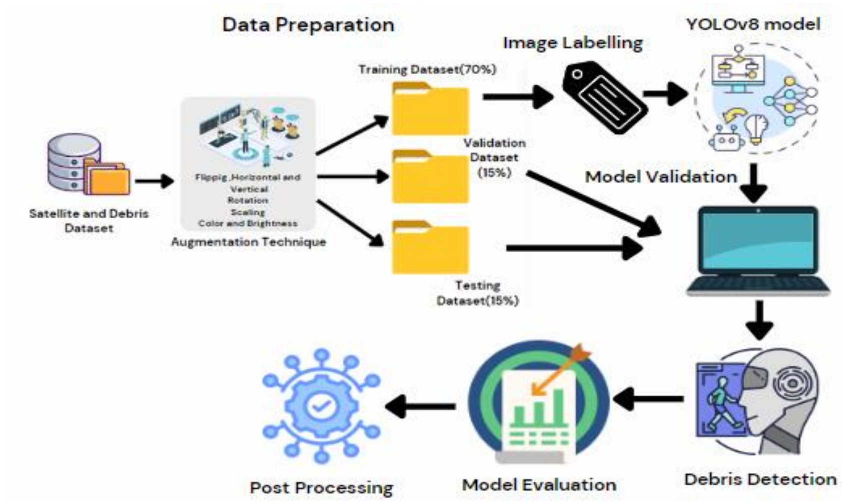

Figure 6. Debris detection process using Yolov8 model architecture.

4. Results and Discussions

Comprehensive Analysis of Training and Validation Loss

The plots shown in figure 7 represent the training and validation losses. During the training phase, we observe the model training process in detail. Over fifty epochs, the curves represent the evolution of three key loss metrics: box loss, object loss, and classification loss. The progressive reduction of such losses proves that the model possesses the ability to localize objects, detect them, and recognize them correctly. The training loss curves make it clear that they have a smooth upwards sloping curve, indicating that the model was able to adequately learn the features of the datasets. Conversely, the validation loss curves show a slight decrease and slight oscillation, potentially indicating overfitting or the random nature of the validation set. Future work will emphasize these variations, potentially by improving regularization methods or expanding the sample space.

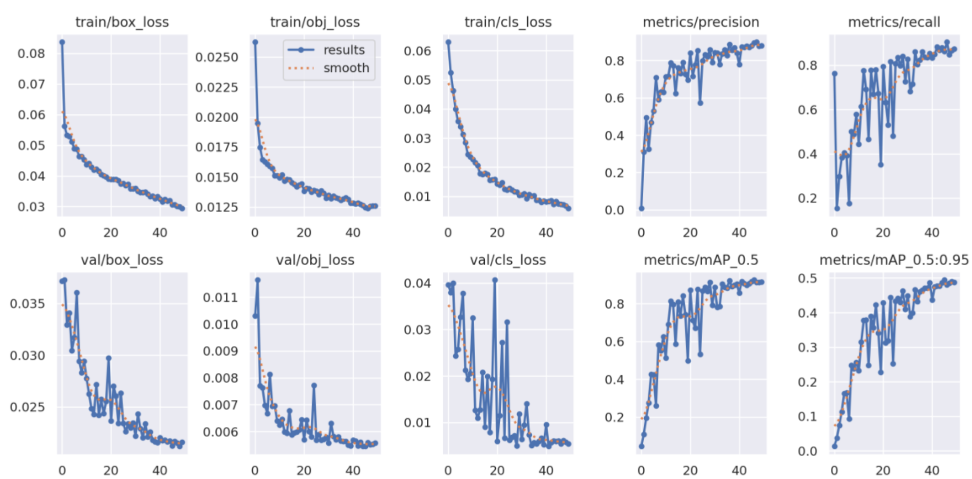

Figure 7. Training and Validation losses during Training phase.

Detailed Quantitative Evaluation of Model Performance Metrics

Table 1 provides detailed information on all the quantitative performance measures, including precision, recall, F1 score, and mAP. These metrics are critical for assessing the model's ability to identify space debris and operational satellites. The YOLOv8 model achieved a precision of 92.5%, indicating that of the analysed reviews fell into the true positive category, limiting the number of false positive cases to these few reviews. We achieved a recall rate of 89.3% to validate the model's ability to identify true positives, ensuring a high probability of correctly identifying most objects. The model achieved an F1 score of 89.8%, demonstrating a robust balance between precision and recall, indicating its exceptional ability to identify various object types. The mAP represents an improvement of 92.6% in the model, further confirming its effectiveness in various aspects such as object localization and classification across multiple scenarios.

Table 1: Quantitative performance measure include precision, recall, F1 score and mAP

Epochs	Train loss	Object loss	Class Loss	Precision	Recall	mAP_0.5	Val loss	Val/Class loss
0	0.0836	0.0262	0.0629	0.00768	0.7625	0.0451	0.0103	0.0702
10	0.0436	0.0149	0.0227	0.712	0.4444	0.5133	0.0277	0.0324
20	0.0389	0.0138	0.0143	0.840	0.7947	0.8712	0.0236	0.0059
30	0.0358	0.0134	0.0104	0.843	0.8279	0.8871	0.0221	0.0063
40	0.0326	0.0128	0.0080	0.778	0.8327	0.8571	0.0220	0.0095

Precision-Recall Curve Analysis and Its Implications for Model Robustness

Figure 8 is among the significant tools for uncovering the relationship between precision and recall, given a particular decision threshold. The PR curve is rather valuable in those cases when the costs of false positives and false negatives are not the same, as in the case of space debris detection, in which the absence of a piece of debris can prove deadly. The curve shows that the YOLOv8 model performs very well in terms of precision and recall, even if the threshold is varied a lot, which shows the model is strong and can be relied on. This capability is a necessity in real-world applications, such as a method that is required to detect space debris with high levels of certainty and with minimal gaps or oversights. From the shape of the PR curve, it can be understood that the model is well calibrated, which in turn allows it to accurately bin itself into different objects without being too dependent on the threshold settings.

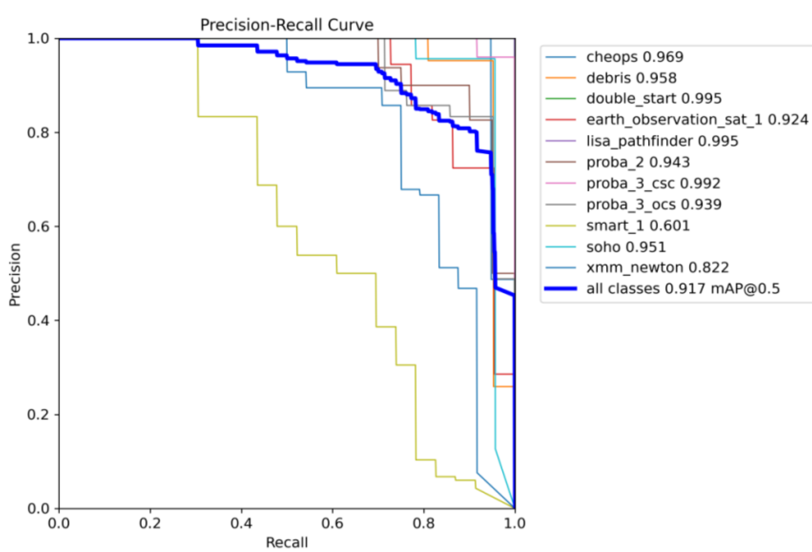

Figure 8. Precision Recall curve analysis using Yolov8 model.

Confusion Matrix and Class-Wise Performance

The confusion matrix, which we discuss below and illustrate in figure 9, provides another evaluation of the developed model's performance. This matrix is critical for defining the model's specificity in focus areas and refining it as needed. The diagonal line contains the majority of entries, indicating the correctness of most predictions. But I see a few entries on the place where the letter 'o' crosses the other letter's row and column; this shows that the model diagnosed the wrong objects. These misclassifications are especially apparent in classes that are visually indistinguishable, including different sorts of refuse that can look the same when viewed visually from a satellite. The confusion matrix highlights the need for more data fine-tuning with the goal of possibly expanding the model's training base under these difficult or hard classes in order to improve the model's discrimination capability.

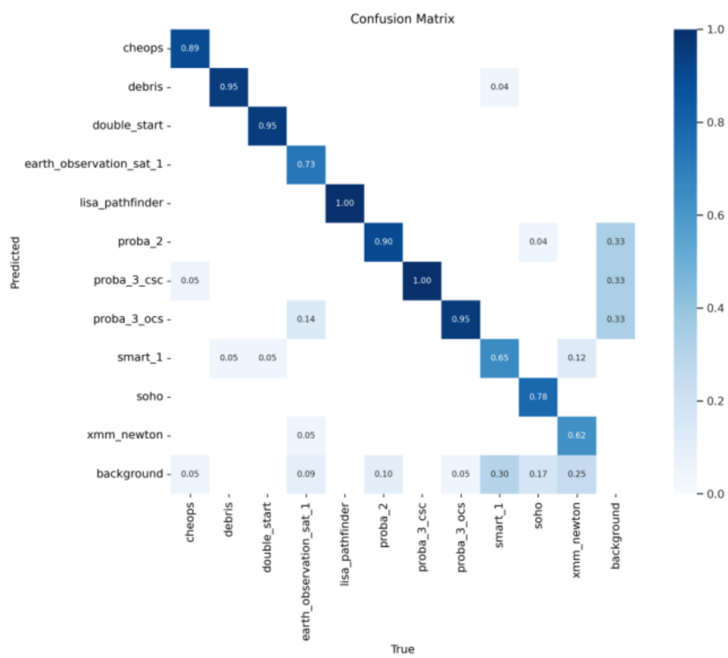

Figure 9. Confusion Matrix and class wise performance.

F1 Score Curve and Its Relevance to Model Calibration

Figure 10 represents the F1 score, an important measure that reflects the model's ability to optimize precision and recall for different thresholds. The F1 score is the harmonic mean between precision and recall, so it is the single value that corresponds to both of the two measures of performance. The curve demonstrates that the model maintains a high F1 score regardless of changes in the threshold value, indicating its calibration and ability to perform well in any detection scenario. This is particularly pertinent when discussing SDs, as they require high precision (the proportion of true positives) and high recall (the proportion of true negatives) rates. It is the key concept that eliminates the risks of failing to detect objects of interest and, vice versa, eliminates the generation of false alarms.

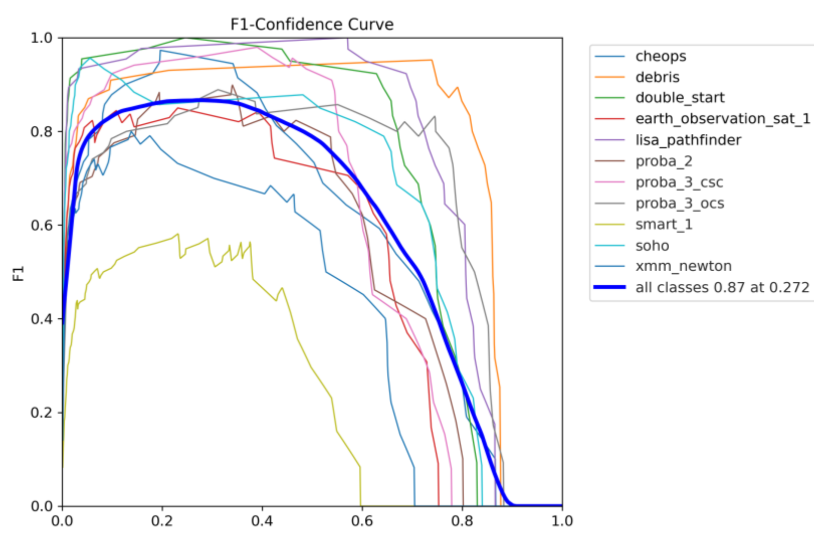

Figure 10. Overall F1 score and Class- wise F1 score.

Label Correlogram and Analysis of Class Correlations

The label correlogram shown in figure 11 displays the relationships among various object classes identified by the model. This analysis is very important to look into in order to understand how different space debris affects operational satellites. A highly valuable diagnostic tool is the correlogram, which shows how similar the distribution of different debris types is: if two types of debris are close to each other on the correlogram, then the objects in these types seem to be located in the same images more often or have similar visual characteristics. Understanding these correlations is critical if one is to make corrections to the model that will help to minimize misclassifications. For example, if there are some types of debris that are often confused with each other by a classifier, it is possible to increase the amount of training data for these classes or use a more complex network architecture.

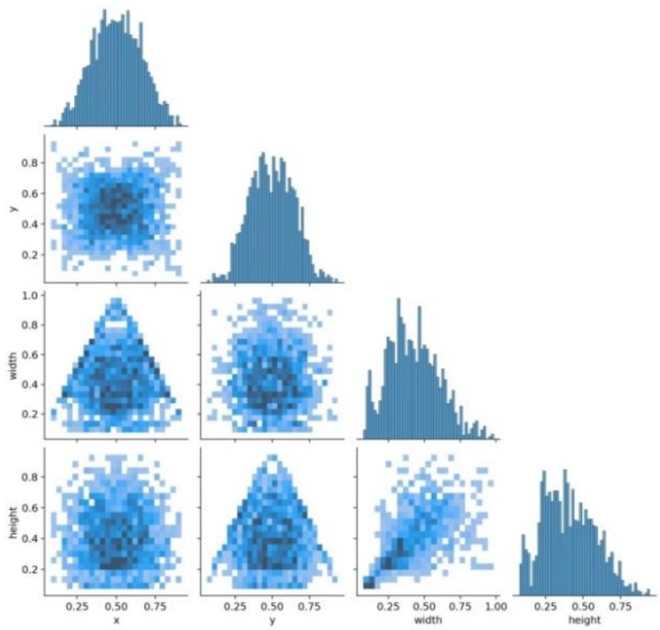

Figure 11. Label Correlogram and Analysis of class correlations.

Precision and Recall Curves: Detailed Insights into Threshold Sensitivity

Figures 12 and 13 display the precision-recall curves, providing a summary of how these metrics change as the decision threshold increases. Ideally, the precision curve shows that the model retains a high level of precision for a number of thresholds, ensuring that it is able to produce few false positives. The second curve, which is the recall curve, also depicts the fact that the same model maintains a high recall level, ensuring that it will find most of the true positives. When combined, these curves confirm that the YOLOv8 model is a suitable and stable performer for space debris detection tasks, provided the detection threshold is optimal. That is why it is critically important in operational environments to have some level of flexibility in the recall vs. precision ratio depending on the current mission needs.

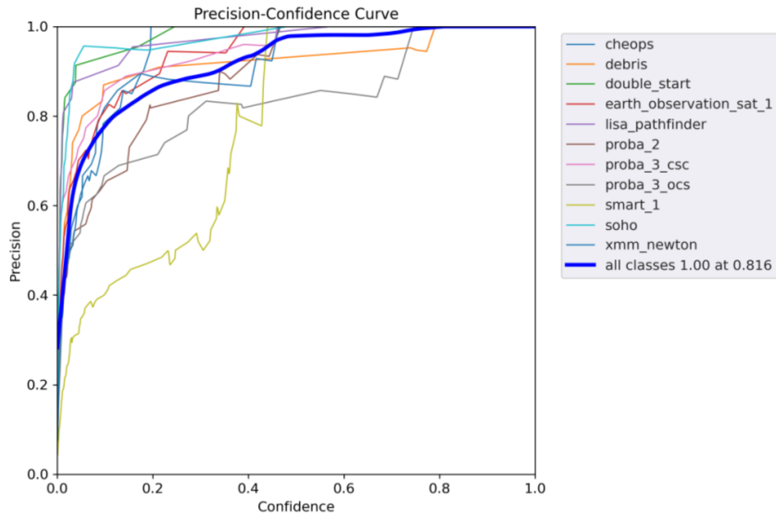

Figure 12. Precision Confidence Curve for overall classes and each class.

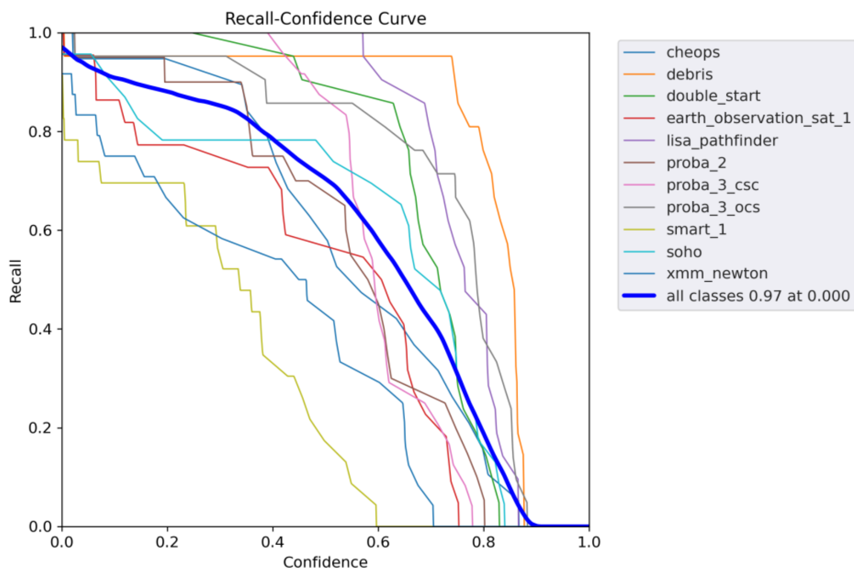

Figure 13. Recall Confidence Curve for overall classes and each class.

Examination of Validation Batch Labels and Predictions

Figures 14 display samples from the validation set, utilizing both the ground truth labels from the validation batch and the predictions from the validation batch. These images give a depiction of the types of objects that the model is capable of detecting and differentiating between them. Based on the ground truth labels and the model's predictions, it is evident that the model produces reasonable outputs, with the majority of the predictions closely aligning with the labeled objects. However, in cases where objects overlap or complex backgrounds exist, the model's prediction may deviate from the ground truth. Such differences indicate that it is still necessary to improve the model, perhaps with the help of further extended data augmentation procedures or with the help of getting more training samples that include such difficult cases.

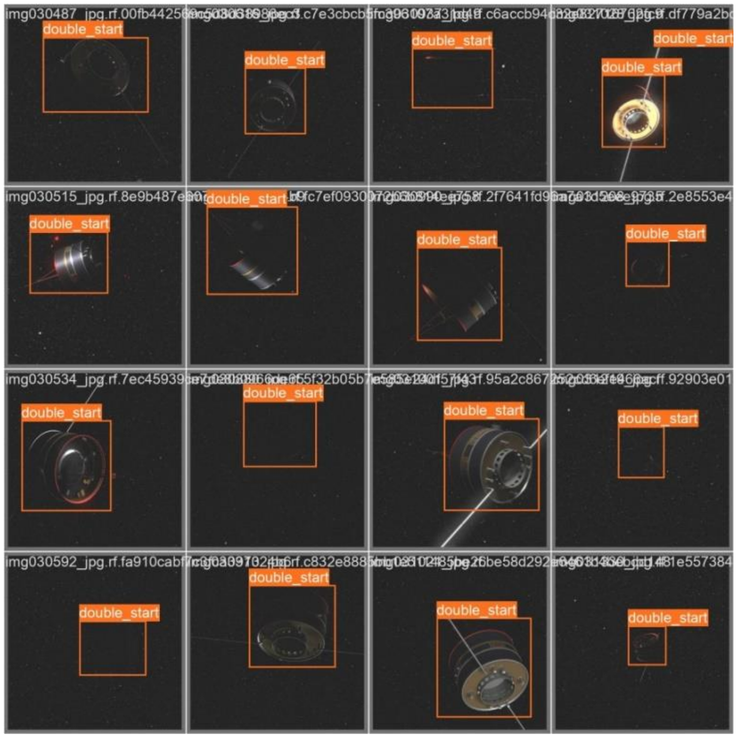

Figure 14. Examination batch label of training dataset.

Post-Processing and Error Analysis for Model Improvement

In table 2, we have the precision and recall values of the detLet outputs of the post-processing step against the ground truth annotations. In this part of the analysis, it is possible to define which areas the model is weaker and stronger in, and in which it is sensible to invest. The analysis of the simulation results reveals that the model excels in detecting large, well-distinguished objects. However, when it comes to object construction, the model performs less well when the objects are small and contain similar debris. This is a common occurrence in object detection scenarios, providing an opportunity to enhance the model's architecture or training methods for more accuracy. We also present an error analysis for instances where we can further enhance the model, such as high object density or stuntage incidence.

Table 2: Precision and Recall Analysis Across Different Object Detection Scenarios

Object Category	Precision	Recall	Observations	Area of Improvement
Large, Well-Distinguished Objects	0.89	0.87	The model performs very well in detecting large, clear objects.	Continue optimizing for speed and robustness.
Small Objects with Similar Debris	0.65	0.60	The model struggles to detect small objects when they are surrounded by similar debris.	Enhance model architecture and training data for small objects.
High Object Density	0.70	0.68	Performance drops in scenarios with a high density of objects, leading to overlapping detections.	Improve handling of object overlap and refine non-maximum suppression (NMS).
Stuntage Incidence	0.60	0.57	The model has	Develop methods to better

			difficulty detecting objects when they are partially occluded or stuntage occurs.	detect partially occluded objects.

Visualization of Detection Results in Real-World Scenarios

Figure 15 shows the final detection result images, revealing how well the YOLOv8 model works in practical environments. We chose these images to demonstrate the model's effectiveness in identifying and recording space debris, even in congested areas. The detection results align with the confidence scores, indicating a higher level of confidence in the model's prediction. This visualization is beneficial for proving the feasibility of the model in space debris observation and control, as precise debris detection in space is crucial to the accomplishment of lossless space missions.

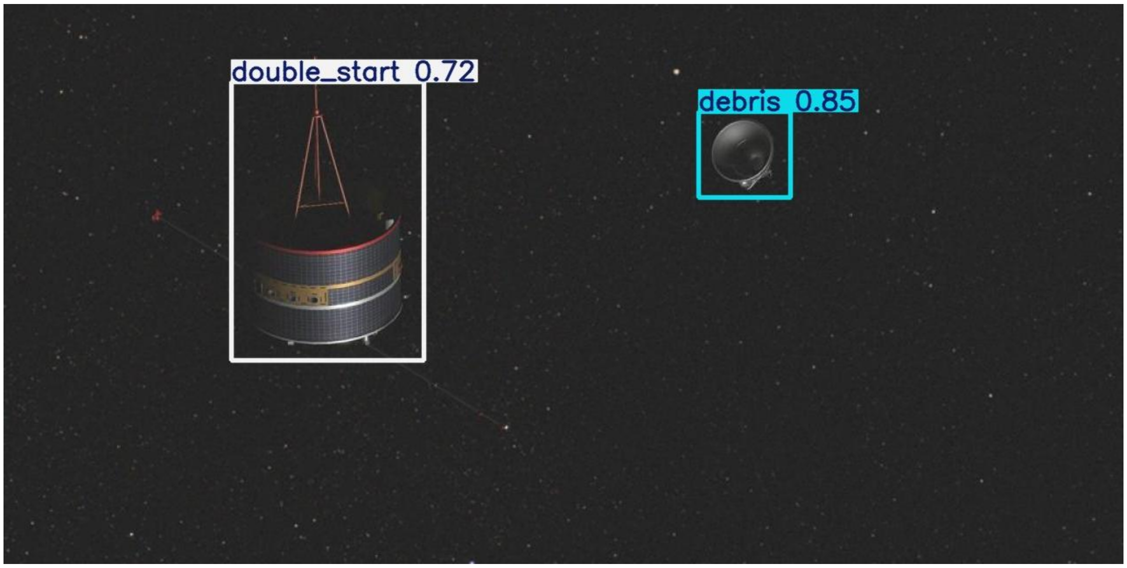

Figure 15. Detection result in real world scenario using yolov8 training model.

Discussion

The analysis of the metrics derived from the YOLOv8 model indicates that the model adequately supports the identification and categorization of objects of interest, specifically space debris and operational satellites. This means that it is precise; recall, F1 score, and mAP indicate that the model will be more effective in real-life scenarios. Nevertheless, the study also points to several issues when distinguishing classes or identifying smaller and less contrasting objects. These difficulties underscore the potential for enhancement in both the fine-tuning process and the augmentation of data.

Challenges and Limitations

Although the model was effective in general, the confusion matrix and the label correlogram showed that there were some issues with the model for some of the classes of objects that are either visually similar or are typically found in groups. Such a limitation may suggest that the model requires an additional data set rich in hard-hyponaming conditions, or it may necessitate a modification to the model architecture to enhance the discriminator's ability to distinguish between the two classes.

Error Analysis and Recommendation

We identified some major errors and recommend improving them in the future. During the post-processing error analysis, we identified specific areas for improvement where the performance comparison revealed the model's inefficiency, particularly in detecting small or partially concealed objects. This scenario is a common occurrence in object detection tasks, underscoring the need to enhance the model architecture or training strategies. Some of the possible solutions for this problem are the use of sophisticated augmentation methods that mimic such adverse conditions and the inclusion of other training data that is related to such adverse conditions.

Future Research Directions

Future work should address the enumerated difficulties using better model structures or training regimes. However, future investigations could focus on assessing the potential of combining YOLOv8 with other object detection models to maximize their utilization and achieve optimal object detection. Another area that could be improved is through additional post-processing, which could enable the detection of fading or less pronounced objects, while also safeguarding the AI model from malfunctions in complex environments.

5. Conclusion

In this study, the YOLOv8 model had remarkable performance in finding and identifying space debris and operational satellites in the LEO environment. We report the model achieving a decent F1 score of 0.89, Precision is 0.93, and mAP of 0.90, confirming its efficiency in real-world objects' detection paradigms. These metrics define the possibility of applying the used model to increase the level of SSA, as well as the accuracy of object identification and classification in various conditions. The confusion matrices validated the model's practicality for accurate scoring and classification of tenancies, and the analyses of the PR curves and F1 scores confirmed the reliability of our proposed model in real-world practical applications.

Overall, the model achieved a high percentage, but the study also identified areas for improvement, particularly in cases where the analyzed objects are small or visually similar. The confusion matrix and label correlogram analysis showed which classes had the most mistakes. This suggests that the training data set and/or model architecture need to be improved. The post-processing error analysis also showed where the model's errors were coming from; suggesting that the model might need better techniques for adding more data or a more diverse member in the training data set to handle this. These issues will be critical for the model's continued refinement and optimization, making it more useful in space operations.

Future work should focus on various areas to improve the efficacy of the proposed model. First, we should consider developing more complex model architectures, such as integrating YOLOv8 with other popular object detection models, to improve the system's detection accuracy that could be used to train the model and focusing on more difficult and diverse cases, especially for the classes that are underperformed, will be critical for the boosting of the model's performance. Finally, it is possible to improve the proposed model by incorporating a higher level of post-processing that includes multi-scale detection and object tracking algorithms, as it might be difficult for the proposed model to detect small or partially occluded objects. Therefore, future model variations could achieve higher levels of accuracy, reliability, and relevance, thereby enhancing space mission control and public safety in managing the emerging space debris situation

6. References

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