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Cosmic AEGIS: An Intelligent Orbital Object Trajectory Prognostication and Proactive Risk Reduction Framework for Advancing Autonomous Spacecraft

Dr.M. Praneesh[1], T. Pradeep[2]
[1] *Assistant Professor, Department of Computer Science with Data Analytics, Sri Ramakrishna College of Arts & Science, Coimbatore, Tamilnadu, India*
[2] *Assistant Professor & Head i/c, Department of Computer Science with Cyber Security, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India.*

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Corresponding Author:
Dr.M. Praneesh

Abstract:
The escalating presence of orbital entities, including satellites, asteroids, and debris, highlights the pressing need for robust Space Traffic Management (STM) systems to preserve orbital integrity and sustainability. This research presents an innovative framework leveraging artificial intelligence (AI) and machine learning (ML) methodologies to enhance the accuracy of orbital object trajectory predictions and assess potential collision risks. By incorporating diverse image data sources, the framework generates probabilistic projections of object trajectories, enabling proactive risk mitigation measures. This paper focuses on the performance of object tracking-by-detection algorithm called YOLOv8. It explores a range of models and algorithms, spanning neural networks, computer vision techniques, and deep learning architectures, for trajectory prediction and collision risk evaluation. The effectiveness of the proposed framework is evaluated through metrics. The integration of AI technology will enhance spacecraft autonomy, facilitate independent navigation and maneuver in space with reduced human intervention. Continued advancements in algorithms for collision detection, avoidance, and celestial object tracking will enhance human spaceflight initiatives and lay the groundwork for future deep space exploration endeavors.
Keywords: Space-based Object Detection, Yolo Neural Network, Small-Size Objects, Space Debris, Feature Fusion

1. Introduction

The need for and complexity of collision avoidance functions between active spacecraft and debris (or another spacecraft) has increased significantly in recent decades due to the increasing number of orbiting satellites and significant fragmentation. Proliferation of objects in Earth orbit is already a critical threat to the safe and sustainable use of space and is expected to continue to grow due to recent developments in the space industry, such as reducing access to space for new launch experiments, the popularization of small, cubic, and nanosatellites as cheap but flexible platforms, and the large constellations offered by both established and start-up companies. Unseen is far more numerous: the presence of space debris poses a significant risk to operational satellites and spacecraft. With thousands of satellites orbiting Earth, along with defunct spacecraft and fragments from previous missions, the risk of collisions and their potentially catastrophic consequences have become increasingly pronounced.

Collisions with even small debris can result in catastrophic damage due to the high velocities involved, leading to the loss of valuable assets and generating even more debris in the process—a phenomenon known as the "Kessler Syndrome." The process of manual detection and classification is time-consuming. Recently, deep learning (DL) has become a very promising approach for computer vision (CV) tasks. To solve this problem, we use machine learning techniques to detect and monitor objects in space that can be applied to continuous real-time data. Research in this area has explored various AI-based approaches, including convolutional neural networks (CNN) for object detection and classification and reinforcement learning for decision-making in dynamic environments. These AI-based techniques have shown promise for improving the accuracy and reliability of space debris detection and tracking systems.

This paper evaluates the effectiveness of a widely employed DL-based object detection algorithm known as YOLOv8, a state-of-the-art object detection model that is a single-stage detector that predicts object labels and positions with a single pass of the image. It is an anchorless algorithm that directly predicts the center of the object rather than the deviation from a given anchor. Here we have performed the tasks using the YOLOv8m model variant algorithm, a medium-sized model that is suitable for most object detection tasks. It is based on a CNN architecture that learns to predict object labels and positions with a single pass of the image, and it is an extension of the YOLOv8 family of models. By harnessing the capabilities of YOLOv8, experts aim to improve the detection and characterization of space objects, thereby bolstering efforts to safeguard space infrastructure and mitigate collision risks.

2. Literature Review

In a study conducted by Moriba Jah, a renowned expert in the field of space research and his team at the University of Texas at Austin, researchers developed a novel approach for tracking space debris using a combination of ground-based optical telescopes and advanced algorithms. Published in the journal “Advances in Space Research” in (2020), the study focused on improving the accuracy of space debris tracking to enhance space situational awareness and mitigate collision risks. The research team utilized data from multiple optical telescopes to observe and track objects in orbit around the Earth. By employing machine learning algorithms, including deep learning techniques, the researchers were able to analyze and interpret the telescope images more efficiently, leading to improved object detection and trajectory prediction.

One of the key innovations of the study was the development of a probabilistic framework that accounted for uncertainties in the tracking data, such as measurement errors and atmospheric effects. This framework allowed for more reliable predictions of space debris trajectories and better assessment of collision risks for operational satellites and spacecraft. The study demonstrated the effectiveness of the proposed approach through extensive simulations and validation using real-world observational data. The results showed significant improvements in tracking accuracy and collision risk assessment compared to traditional methods. A study led by researchers at the European Space Agency (ESA), published in the journal “Acta Astronautica” in (2018), a novel approach for space debris detection using satellite-based sensors was proposed. The study aimed to address the limitations of ground-based observation systems and improve the accuracy of space debris tracking. The research team utilized data from ESA's Optical Ground Station (OGS) and various satellite-based sensors, including cameras and LiDAR (Light Detection and Ranging) systems, to monitor and track space debris in orbit. By combining data from multiple sensors, the researchers were able to enhance the resolution and coverage of space debris observation, enabling more precise tracking and characterization of debris objects.

Another Researchers at the University of California, Irvine, led by the Bosanac group, are focused on pioneering novel strategies for analyzing, designing, and predicting spacecraft trajectories amidst chaotic multi-body gravitational systems. Their interdisciplinary approach integrates dynamical systems theory, data mining, machine learning, and path-planning techniques to achieve this objective. Similarly, scientists at the California Institute of Technology and NASA's Jet Propulsion Laboratory have developed the motion primitive approach, employing clustering and graph search algorithms to craft spacecraft trajectories in intricate multi-body systems.

While various methods have been proposed and put into practice for orbital collision avoidance, such as pre-defined curves, cost functions, optimization problems, machine learning, and ballistic launches, they are encumbered by limitations encompassing accuracy, timeliness, complexity, uncertainty, and the degree of human intervention. Consequently, a critical gap persists in the current state-of-the-art, necessitating the development of a comprehensive framework capable of intelligently predicting orbital object trajectories, proactively mitigating collision risks, and augmenting spacecraft autonomy.

3. Methodology

This section discussed in detail about the methodology employed and performed in this study. The details are as follows

a) System Flow: The system flow outlines the sequential progression of tasks and interactions within a system to achieve its intended functionality or objective.

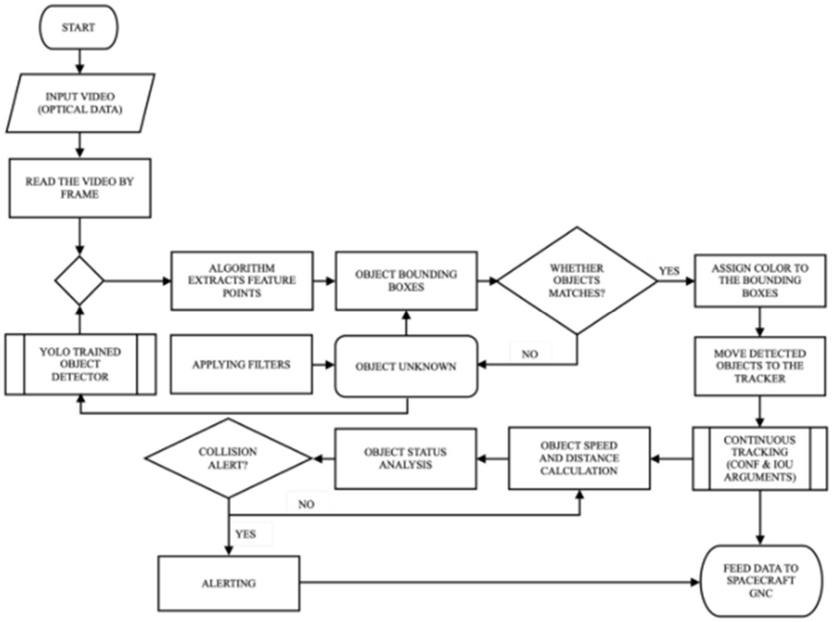

Fig-1 System flow of Cosmic Aegis

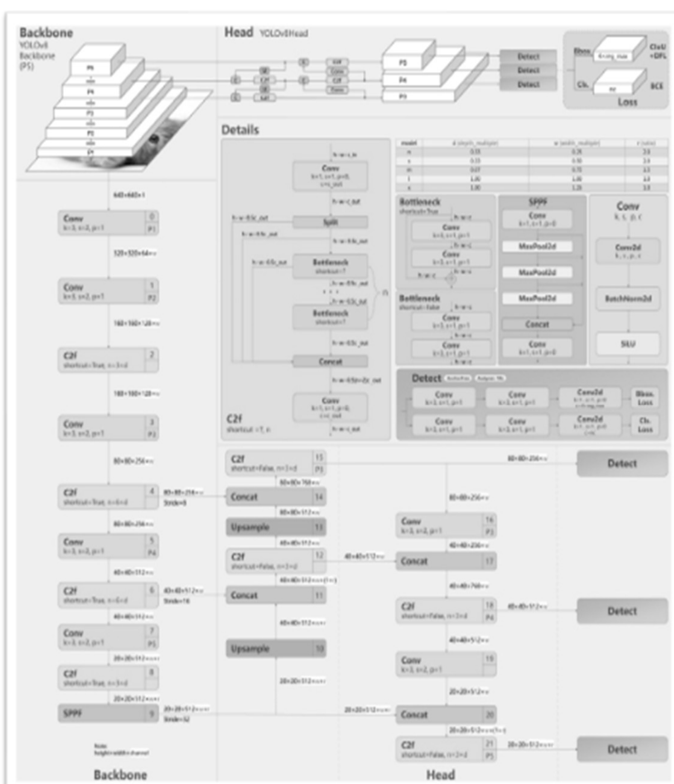

Fig-2 YOLOv8 Architecture

b) Proposed Algorithm

The YOLOv8 object detection algorithm process unfolds as follows:

1. Input Image: Initially, the algorithm receives an image as input, which could be a photo or a frame from a video.

2. Grid Partitioning: The image gets partitioned into a grid of cells, each tasked with detecting objects within its boundaries. The grid's dimensions are contingent on both the input image's size and the final convolutional feature map size of the network.

3. Feature Extraction: Every grid cell undergoes feature extraction via a pre-trained CNN. This CNN has learned significant features from extensive datasets, aiding in object recognition. These features encompass various attributes like contours, textures, and colors.

4. Object-ness Score: Each grid cell is assigned an "object-ness score," indicating the likelihood of an object's presence within it. This score is determined through a logistic regression function, calculating the probability of object presence.

5. Class Probability: If a cell predicts the presence of an object, it also assigns a class to the object along with its associated probability. A SoftMax function computes the conditional probability of the object for each potential class.

6. Bounding Box Prediction: In addition to object prediction, YOLO predicts bounding boxes encompassing detected objects. These bounding boxes are crucial for identifying and localizing objects within the image. They provide vital information about the object's position and size. The bounding box includes center coordinates (X, Y), representing the approximate center of the object within the grid cell. Width (W) and height (H) signify the dimensions of the enclosing

rectangle relative to the grid cell size. This adaptive nature allows bounding boxes to adjust to varying object sizes within the image.

7. Non-Maximum Suppression (NMS): YOLO employs NMS to remove redundant bounding boxes and refine detection accuracy. This process eliminates overlapping boxes with lower confidence scores, retaining only the most confident predictions.

8. Output: Ultimately, the YOLO algorithm produces a set of bounding boxes, each associated with a class and a confidence score. The confidence score reflects the model's certainty regarding the object's presence within the respective bounding box. Typically represented as a probability value, a higher score signifies greater confidence in the detection, providing crucial insights into the reliability of object detection within each bounding box.

4. Results & Analysis

In this section, we show the results obtained in our simulated environment. First, we define the metrics for measuring methods performance.

a) Data Set Description

The Source Data were collected from the well-renowned space agency portals such as NASA Jet Propulsion Laboratory, James Webb Space Telescope, Astroscale. These image data from satellites and optical observations captured and typically stored in petabytes in order to provide effective research and for real-world tasks. With the advancement of satellite technology and the increasing number of satellites launched into orbit, the volume of data generated has grown exponentially. This data includes high-resolution images of planets, astronomical observations, climate data, and much more. Totally the dataset consists of around 10,000 image data, under 12 different classes and the median image ratio (size) of 640px or higher. This dataset the Space Data only support FITS Format. The FITS (Flexible Image Transport System) file format is designed to store astronomical image data, including images from satellites and ground-based telescopes. These FITS format supports 8-bit (0-255) and 16-bit (0-65535) greyscale images. The size of a single FITS file can range from a few kilobytes to several gigabytes. FITS files, commonly used in astronomy, vary in size depending on image resolution.

Small FITS files, with low-resolution images containing a few thousand pixels, typically range from 1 to 10 MB. Medium-sized FITS files, housing moderate-resolution images with tens of thousands of pixels, occupy about 100 to 500 MB. Large FITS files, holding high-resolution images with hundreds of thousands of pixels, span approximately 1 to 5 GB. Very large FITS files, hosting high-resolution images with millions of pixels, can reach sizes of 10 to 50 GB. These sizes reflect the progressive increase in file size corresponding to the growth in image resolution. Converting these files into other formats to ensure the dataset to support the model to train, validate and test.

b) Results of the Study

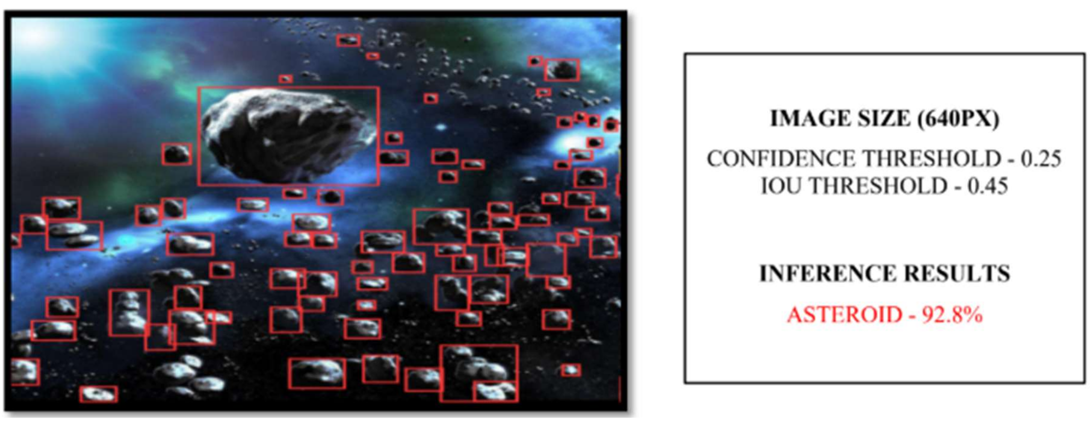

Fig-3 Multi Object Detection

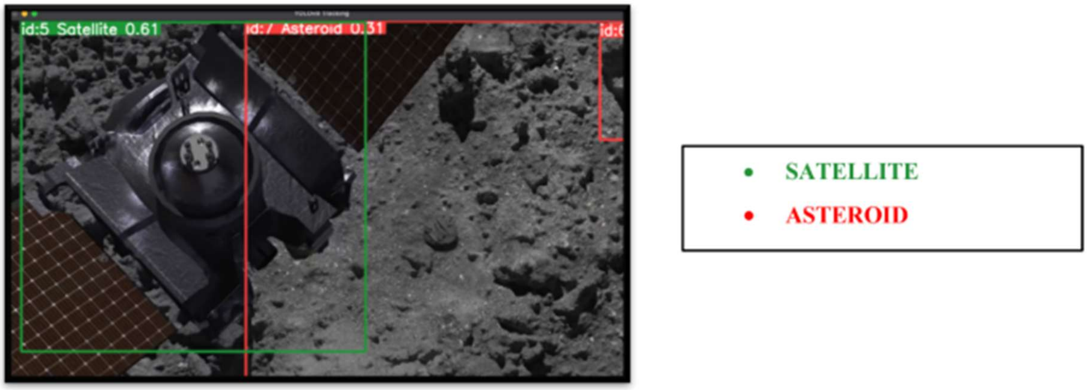

Fig-4 Multi-Object Tracking

c) Performance Measures

Performance metrics assess the effectiveness of a model in achieving its objectives. In the context of object detection, commonly used metrics include Precision, Recall, mAP Scores, Box Loss, Class Loss, Object Loss:

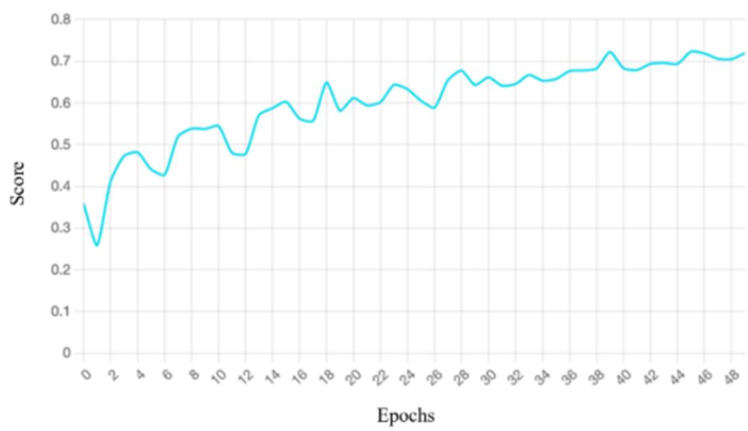

Fig-5 Results of Precision

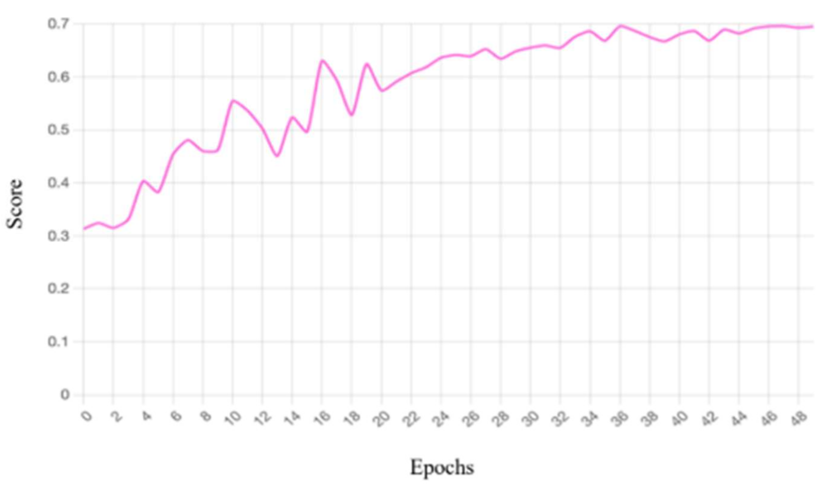

Fig-6 Results of Recall

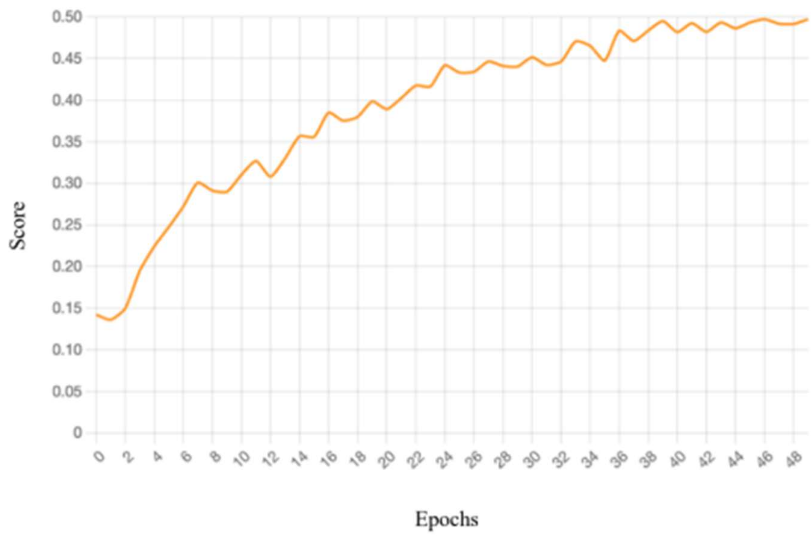

Fig-7 Results of Mean Average Precision (mAP)

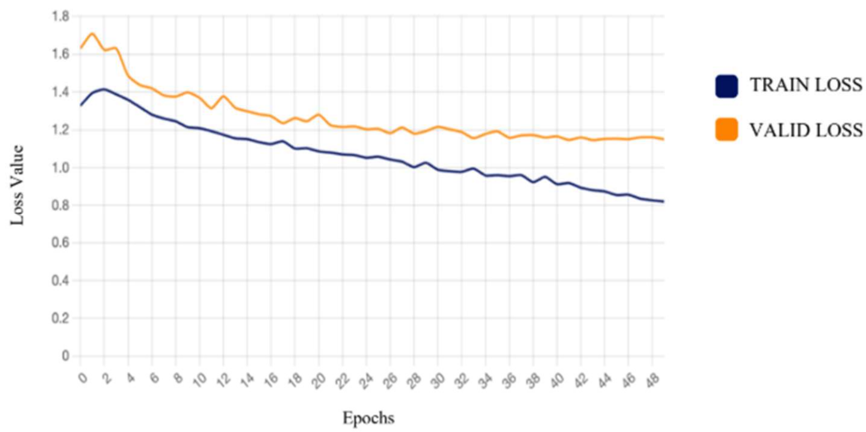

Fig-8 Results of Box loss

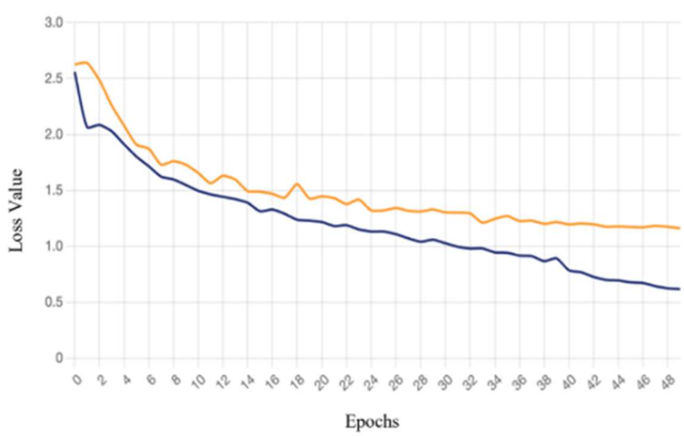

Fig-9 Results of Class loss

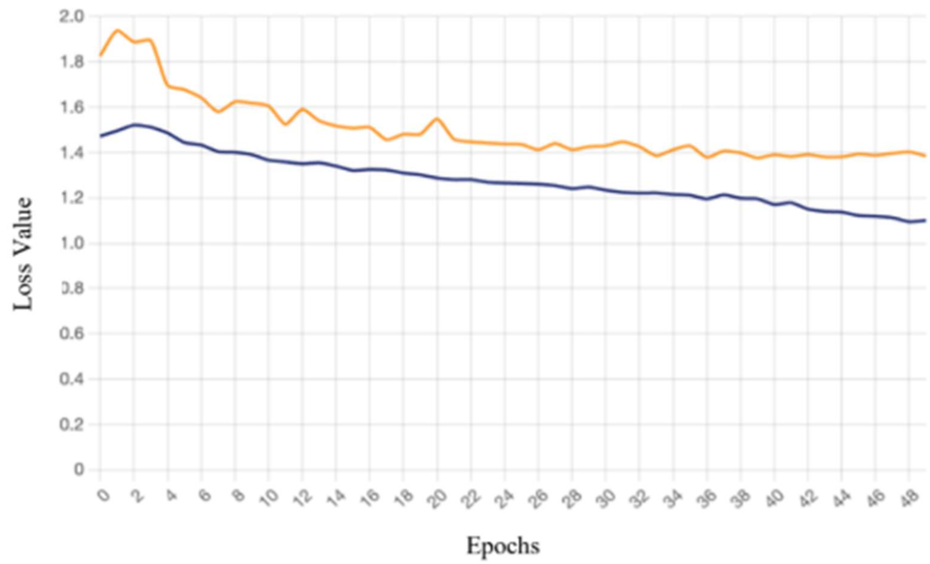

Fig-9 Results of Object loss

5. Conclusion

This paper introduces the incorporation of the YOLO deep learning method into space object detection and suggests a set of specific enhancements aimed at substantially improving the algorithm's ability to accurately identify faint and feeble space objects. Due to the continual expansion of satellites orbiting Earth, Space Situational Awareness has garnered heightened focus, underscoring the necessity of vigilance regarding space conditions and the imperative to devise novel algorithms to safeguard space assets like satellite constellations.

The algorithms have undergone training utilizing a dataset of space object photos comprising various space objects and bodies, including satellites and debris. Widely accepted metrics were used to evaluate the performance of the algorithm, including precision, recall, mean average precision (mAP), box loss, and class loss. The performance of YOLOv8 surpassed expectations across various measures, with a notable advantage observed in detecting tiny objects. Overall, this study demonstrates the capabilities of the DL algorithm in the context of space object detection and classification techniques. Continued research and development in this area hold the potential to significantly improve our understanding of space dynamics and contribute to the sustainable management of space activities in the future.

References

[1] Lou, Haitong, Xuehu Duan, Junmei Guo, Haiying Liu, Jason Gu, Lingyun Bi, and Haonan Chen. "DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor". Electronics 2023, 12, 2323.

[2] Tang, Qiang, Xiangwei Li, Meilin Xie, and Jialiang Zhen. Intelligent Space Object Detection Driven by Data from Space Objects. Appl. Sci. 2024, 14, 333.

[3] Xi, Jiangbo and Xiang, Yaobing and Ersoy, Okan K. and Cong, Ming and Wei, Xin and Gu, Junkai, "Space Debris Detection Using Feature Learning of Candidate Regions in Optical Image Sequences," in IEEE Access, vol. 8, pp. 150864-150877, 2020.

[4] Jiang, Y.; Tang, Y.; Ying, C. Finding a Needle in a Haystack: Faint and Small Space Object Detection in 16-Bit

Astronomical Images Using a Deep Learning-Based Approach. Electronics 2023, 12, 4820.

[5] H. Wang, C. Liu, Y. Cai, L. Chen and Y. Li, "YOLOv8-QSD: An Improved Small Object Detection Algorithm for Autonomous Vehicles Based on YOLOv8," in IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1-16, 2024.

[6] G. Jocher et al., Ultralytics/YOLOv5: v7. 0-YOLOv5 Sota Realtime Instance Segmentation, Honolulu, HI, USA: Zenodo,2022.

[7] Y.-F. Zhang, W. Ren, Z. Zhang, Z. Jia, L. Wang, T. Tan; Focal and efficient IOU loss for accurate bounding box regression Neurocomputing, 506 (2022), pp. 146-157.

[8] Massimi, Federica, et al. "Deep learning-based space debris detection for space situational awareness: A feasibility study applied to the radar processing." IET Radar, Sonar & Navigation 18.4 (2024): 635-648.

[9] Wang, C.Y.; Bochkovskiy, A.; Liao, H.Y.M. YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Vancouver, QC, Canada, 18–22 June 2023; pp. 7464–7475.

[10] T. Mahendrakar, S. Holmberg, A. Ekblad, E. Conti, R. T. White, M. Wilde, and I. Silver, “Autonomous rendezvous with non-cooperative target objects with swarm chasers and observers,” in 33rd AAS/AIAA Space Flight Mechanics Meeting (submitted), 2023.

[11] J. Cao, X. Weng, R. Khirodkar, J. Pang, and K. Kitani, “Observation-centric sort: Rethinking sort for robust multi-object tracking,” Mar. 2022.

[12] P. Dendorfer, H. Rezatofighi, A. Milan, J. Shi, D. Cremers, I. Reid, S. Roth, K. Schindler, and L. LealTaixé, “Mot20: A benchmark for multi object tracking in crowded scenes,” Mar. 2020.

[13] J. L. Goodman, “History of space shuttle rendezvous and proximity operations,” Journal of Spacecraft and Rockets, vol. 43, no. 5, pp. 944–959, sep 2006.

[14] R. Sun and C. Zhao, "A new source extraction algorithm for optical space debris observation", Res. Astron. Astrophys., vol.13, no. 5, pp. 604, 2013.

[15] J. Xi, D. Wen, O. K. Ersoy, H. Yi, D. Yao, Z. Song, et al., "Space debris detection in optical image sequences", Appl. Opt., vol. 55, no. 28, pp. 7929, Oct. 2016.

[16] J. Xi, "A maximum projection and particle filtering algorithm for space debris detection", J. Inf. Comput. Sci., vol. 12, no. 1, pp. 161-169, Jan. 2015.

[17] Du, Juan. "Understanding of object detection based on CNN family and YOLO." Journal of Physics: Conference Series. Vol.1004. IOP Publishing, 2018.

[18] Lee, Jinsu, Sang-Kwang Lee, and Seong-Il Yang. "An ensemble method of cnn models for object detection." 2018 International Conference on Information and Communication Technology Convergence (ICTC). IEEE, 2018.

[19] Dhillon, Anamika, and Gyanendra K. Verma. "Convolutional neural network: a review of models, methodologies and applications to object detection." Progress in Artificial Intelligence 9.2 (2020): 85-112.

[20] Pesce, Vincenzo, Andrea Colagrossi, and Stefano Silvestrini, eds. Modern spacecraft guidance, navigation, and control: from system modeling to AI and innovative applications. Elsevier, 2022.

[21] Silvestrini, Stefano, and Michèle Lavagna. "Deep learning and artificial neural networks for spacecraft dynamics, navigation and control." Drones 6.10 (2022): 270.

[22] Krishna, N. Murali, et al. "Object detection and tracking using yolo." 2021 Third International Conference on

Inventive Research in Computing Applications (ICIRCA). IEEE, 2021.

[23] Tan, Li, et al. "A multiple object tracking algorithm based on YOLO detection." 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE, 2018.