17th International Conference on Space Operations, Dubai, United Arab Emirates, 6 - 10 March 2023.

SpaceOps-2023, ID # 101

An Onboard AI-based Space Debris Detection and Localization System

Yaqoob Alqassab[a]*, Aysha Alharam[a], Reem Senan[a]

[a] *National Space Science Agency, Bahrain*
* Corresponding Author

Abstract

Space debris is a term used to describe a collection of malfunctioning artificial objects orbiting the planet. The advancement in space technology has resulted in the increase of space debris. With the ever expanding coverage area of space debris, in-orbit catastrophic occurrences have resulted in an exponential increase in space pollution over time. Space debris are classified based on their size, where space debris larger than 10 centimeters are classified as large space debris, between 10 centimeters and 1 millimeter as medium debris, and smaller than 1 millimeter as small space debris. Small space debris are the highest in terms of quantity, where their number is approximately 128 million. In addition, space debris smaller than 2 millimeters cannot be detected from the ground. Therefore, this research paper proposes an AI-based onboard space debris detection and size classification with Keplerian elements calculation in the Low Earth Orbit (LEO). The proposed system will analyze the image for object detection using deep learning. If debris are detected, a flag will be raised, and the image can be downloaded along with the analysis results, such as the object's width, height, time, and location. The output of the proposed system can be utilized by ground processing to calculate all orbital parameters of the space debris and predict its motion and risk associated with it. The proposed system shows a promising result contributing to the world effort in tracking space debris and collision avoidance.
Keywords: Space debris, Detection, AI-based algorithm, Images, Deep Learning, YOLO

Acronyms/Abbreviations

3U	Three Units
AI	Artificial Intelligent
CNN	Convolutional Neural Network
ESA	European Space Agency
EVA	Extravehicular Activity
FN	False Negative
FP	False Positive
GPS	Global Positioning System
IADC	Inter-Agency Space Debris Coordination Committee
ID	Identification
IOU	Intersection Over Union
LEO	Low Earth Orbit
ML	Machine Learning
NASA	National Aeronautics and Space Administration
SBRC	Space-borne Radar and Communications
TN	True Negative
TP	True Positive
VOC	Visual Object Classes
YOLO	You Only Look Once

1. Introduction

Space debris is a term used to describe a collection of malfunctioning artificial objects orbiting the planet. They range from tiny flakes of paint sizes to enormous dysfunctional spacecraft orbiting around the Earth for various years. The advancement in space technology has resulted in the increase of space debris. This increase in space debris has become a concern to space-faring countries, as the sustainability and access to space will be compromised. With the ever-expanding coverage area of space debris, in-orbit catastrophic occurrences and collisions have increased exponentially in space pollution over time.

According to the European Space Agency (ESA), as of August 2021, Space Surveillance Networks are regularly monitoring about 29,210 pieces of debris. However, statistically, the figures are probably far higher. There are about 34,000 artificial objects larger than 10 cm in length and around 900,000 debris between 1 and 10 cm in orbit around the Earth. Whereas, about 128 million debris objects are between the sizes of 1 mm and 1 cm [1], which is considered a huge amount. Thus, there is a high risk of seriously damaging operational spacecraft due to the sheer volume of these debris that are now in orbit and their tendency to collide with other objects at speeds of up to 7 Km/s.

Space debris are generally classified based on its size, space debris that is larger than 10 cm is classified as large space debris, between 10 cm and 1 mm as medium debris, and smaller than 1 mm as small space debris, which in terms of quantity are considered the highest. However, space debris that are smaller than 2 mm cannot be detected from the ground.

The National Aeronautics and Space Administration (NASA) initiated efforts to combat this issue in the 1990s through their orbital debris mitigation policy and guidelines. These efforts have continued today to mitigate the space debris issue through monitoring, tracking, and ensuring that the creation of additional space debris is reduced through safe disposal and end-of-life of deployed spacecrafts after a mission. The Inter-Agency Space Debris Coordination Committee (IADC) in the year 2002 put in place the first internationally recognized standard consensus on orbital debris mitigation guidelines.

Holger Krag, head of the ESA's space debris office in Germany estimated that the guidelines are only abided by half of all space emissions [1]. More effort and focus are put on access to space and its sustainability by all space-faring countries and entities. Thus, the strict monitoring and tracking of the accumulated space debris are crucial to alleviate the risk of collision and aid in reducing the debris.

Recently, there have been various studies about the feasibility of utilizing CubeSats in detecting space debris in orbit. The use of CubeSats is advantageous due to its low cost as a result of standardization and the short duration of manufacturing. However, their limitations as a result of their small size restrict the complexity of the computation and equipment used onboard. CubeSats can provide a suitable platform that can be used for furthering space debris detection for space asset protection and situation awareness.

This study proposes an Artificial Intelligent (AI) based onboard space debris detection and estimation of the debris size for Low Earth Orbit (LEO) to aid in the tracking, monitoring, and collision avoidance efforts of space debris, as well as the sustainability and access to space for all space-faring countries. The proposed system will analyze captured images for object detection using deep learning. If debris were detected, a flag would be raised, and the image can be downloaded along with the analysis results, including the estimated object's width, height, time, and location.

2. Related work

There are numerous studies regarding detecting space debris using existing ground equipment and ground-based technology [2], [3], [4], [5], [6]; however, the detection of space debris of smaller size (1 cm and less), as stated previously, cannot be detected using ground equipment. There is still a lack of space-based detection for smaller space debris to characterize the space environment and debris accurately and reliably. There is also a lack of information regarding these smaller space debris particles, nonetheless, their damage is very high a 0.01 cm in diameter particle has caused the space shuttle to replace the windows, whereas a 0.02 cm particle has pierced Extravehicular Activity (EVA) suits of astronauts [7]. The collision of small-sized space debris with a spacecraft can cause the functionality of a spacecraft to be reduced considerably. There is a lack of in-orbit detection and monitoring of small space debris to enhance the detection accuracy of orbiting debris. In LEO the trajectories of the debris are not stable, and this entails continuous updates of the trajectories of space objects [8]. The accuracy of the trajectory prediction models for collision avoidance and mitigation relies heavily on the updated detection data provided through various sources. Hence, there is an increase in research in monitoring and tracking space objects of sizes smaller than 1 cm using space-based radars or optical measurements [9], [10], [11]. Using space-based detection enhances the prediction accuracy for space object trajectories, as having more data for smaller size space debris will increase the accuracy of debris predictions and the measurement of the number of space debris, as well as reduce the current data gaps. In orbit, real-time detection and monitoring of space debris provide more precise data for collision avoidance and debris mitigation approaches. Additionally, space-based technologies are less sensitive to the atmosphere and its distortions, the sunlight, and the high signal path losses.

K. M. Brumbaugh et al. [7] have studied the significance of researching these small particles of space debris by utilizing CubeSats. The study addressed the feasibility of a 3U CubeSat mission for space debris detection using a piezoelectric dust detector as its main case study. Using a 3U CubeSat as the main source of debris detection has shown that it is a valuable and cost-effective method for expanding the knowledge of space debris and its database for 1 cm and lower sizes of debris, still, there are currently not many active space missions that are dedicated to detecting space debris as their main payload/mission.

In 2021, A. Anttonen et al. [8] proposed a Space-borne Radar and Communications (SBRC) concept for detecting space debris using readily available satellite constellations from available operators such as SpaceX. This concept uses the communication systems onboard the satellite by employing the communication signals to act as radar signals which can be used to increase space environment awareness. However, this approach requires a high-density constellation to reduce the limitations of this approach (large detection space, and speed of space objects) and the acceptance of an available satellite operator to integrate this in their constellation. Most research has been done to test the feasibility of using space systems/spacecraft to detect small space debris, however, as of yet, a very limited number of space-based systems are used to detect space objects. Simakov and Belokonov [12] developed an onboard algorithm based on random samples of triangulated points taken from a pair of simultaneous stereo images for space debris motion determination using nanosatellites equipped with stereo images taken by a video system onboard. The estimated probability of the effectiveness of the proposed system was tested using the Monte Carlo method. This study proposed a way to determine the spatial orientation of space debris, however, it assumed that the velocity of the debris is low, whereas, in reality, it can reach a relative speed of around 15 km/s [8], as well as did not address the limitation of the size of the object detected. Hence, the effectiveness, complexity, and accuracy of the system to be applied onboard a nanosatellite has not been addressed.

This paper proposes a space detection approach using onboard processing and AI by analyzing captured images onboard an Earth observation CubeSat. The detection of space objects will be done using deep learning You Only Look Once (YOLO) algorithm to process the image to obtain the detected object's time, location, width, and height. The proposed system can be used in any CubeSat mission as a secondary payload/function to support space debris awareness and mitigation approaches, as well as be utilized by ground processing to calculate all orbital parameters of space debris and predict its trajectory and associated risks.

3. AI-based space object detection

The deep learning algorithm used to detect space debris is the YOLO algorithm. YOLO is considered one of the most popular object detection algorithms [13]. Various YOLO algorithms are developed, such as YOLO, YOLO V2, YOLO V3, YOLO V4, YOLO V5, and YOLO-LITE [14]. However, this study used the standard YOLO algorithm for detecting space debris. With this technique, detection is modeled as a regression issue. A single neural network simultaneously predicts multiple bounding boxes and class probabilities for those boxes for each box. The input picture is divided into a $S \times S$ grid via YOLO. A grid cell is in charge of detecting an object if its center falls within that grid cell. The B bounding boxes, confidence ratings for those boxes, and C class probabilities of the grid are predicted by each grid cell. These predictions are represented by the tensor $S \times S \times (B \times 5 + C)$. Equation 1 shows the YOLO algorithm in the test process where it multiplies the individual box confidence predictions and the conditional class probabilities, which provide us with class-specific confidence scores for each box [15].

$$\Pr(\mathrm{Class_i}|\mathrm{Object}) \times \Pr(\mathrm{Object}) \times \mathrm{IOU}_{\mathrm{pred}}^{\mathrm{truth}} = \Pr(\mathrm{Class_i}) \times \mathrm{IOU}_{\mathrm{pred}}^{\mathrm{truth}} \qquad (1)$$

The IOU term used in Equation 1 means the Intersection Over Union. The scores encode both the likelihood of that class being in the box and how well the projected box fits the item. Five predictions, namely x, y, w, h, and confidence, make up each bounding box. The centroid of the box in relation to the boundaries of the grid cell is represented by the (x, y) coordinates. According to the entire picture, the width and height are predicted. Hence, the YOLO algorithm calculates the tensor using $B \times 5$. Normal values for $S = 7$ and $B = 2$ are used for evaluating YOLO on a Pascal Visual Object Classes (VOC). There are 20 identified classes in the Pascal VOC. The final tensor predicted by YOLO is $7 \times 7 \times (5 \times 2 + 20) = 7 \times 7 \times 30$. Moreover, 98 bounding boxes are used instead of the 2000 in Selective Search for each image. 24 convolutional layers precede 2 fully linked layers in the YOLO network. YOLO merely employs a 1×1 reduction layer followed by a 3×3 convolutional layer, similar to Lin et al [16], in place of the inception modules used by GoogLeNet. YOLO processes pictures at 45 Frames Per Second (FPS) on Pascal VOC2007, which is two to nine times faster than Faster R-CNN. Fast YOLO, in particular, has achieved an incredible 155 FPS. Quick YOLO is a fast variant of YOLO created to test the limits of fast object recognition.

4. Proposed system

The model starts with processing the image captured through the YOLO algorithm, where predictions of bounding boxes are made for the objects detected in the image. The estimated size of the object detected is found from the bounding box predictions. The size is calculated using the coordinates of the bounding box from the detection to obtain the estimated width and height of the debris. Afterward, the detected object will be saved with an Identification (ID), its size, time stamp, and the location from the Global Positioning System (GPS) onboard the satellite. The flowchart of the proposed system is shown in Figure 1.

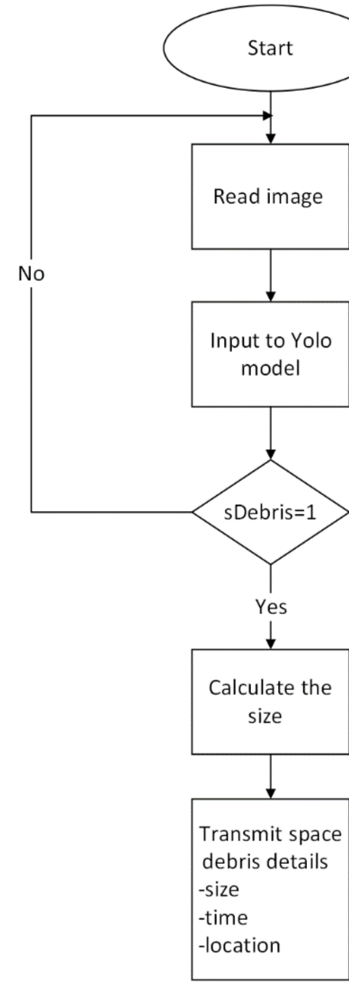

Fig. 1. The proposed system flowchart

Further system validation of the results obtained can be done on ground to get the IOU to obtain the localization accuracy and calculate the localization errors in the model by using the ground truth bounding box. This can be done by using the intersecting area between the two bounding boxes corresponding to the same object. Then, the total area covered by both boxes 'Union' and the area of overlap between them 'Intersection' is calculated. From these, dividing the intersection by the union gives the ratio of the overlap to the total area, which provides a good accuracy estimate of the prediction model.

4.1 Data description

The dataset used in this study are simulated space debris images combining two previously done datasets [17], [18]. The number of images used for training the AI model is 19,200, while the number of images used for testing is 4,800. Figure 2 shows a sample from the dataset used in this paper. There are some assumptions made in preparing the dataset. First, the optical imager that will be used to capture the images shall have a predefined focal length and spatial resolution so that it does not detect very far space debris. Moreover, it was assumed that the size of the images captured is 1920x1080 pixels. Based on these assumptions, the model can detect space debris of size 1 cm and lower.

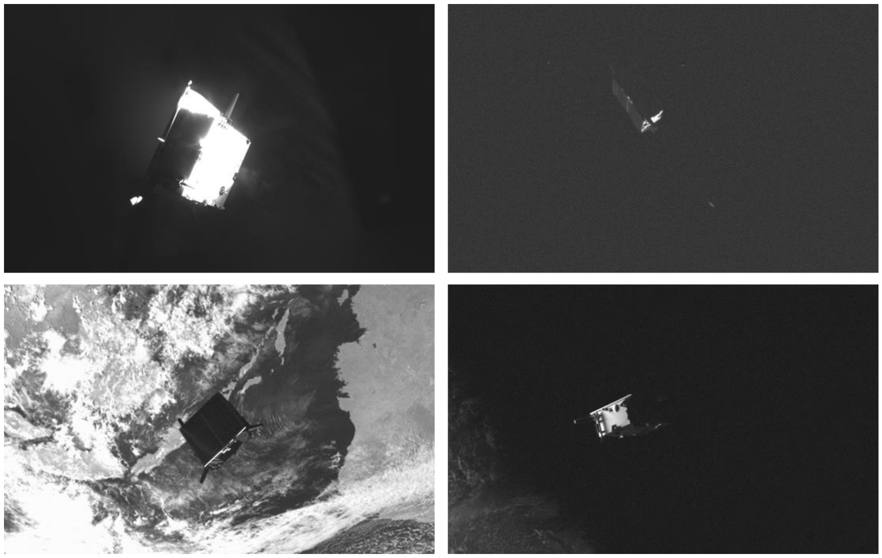

Fig. 2. Sample of the used dataset

5. Preliminary results and discussion

The deep learning YOLO algorithm was used to come up with the results of this study. Figure 3 shows the overall process where a boundary box surrounds the space debris in the final output image. The precision and the recall- are used to evaluate the model's results. The term "precision" refers to the percentage of accurately predicted "True" labels in all the predicted "True" labels and ranges from 0 to 1. For space debris detection, the high precision showcases the high confidence of space debris that has been detected. On the other hand, recall, which ranges from 0 to 1, is the percentage of properly predicted "True" labels in relation to the total number of real "True" labels. For space debris detection, a high recall indicates that the algorithm can fully recognize space debris in the dataset. Recall and precision were calculated using equations 2 and 3, respectively.

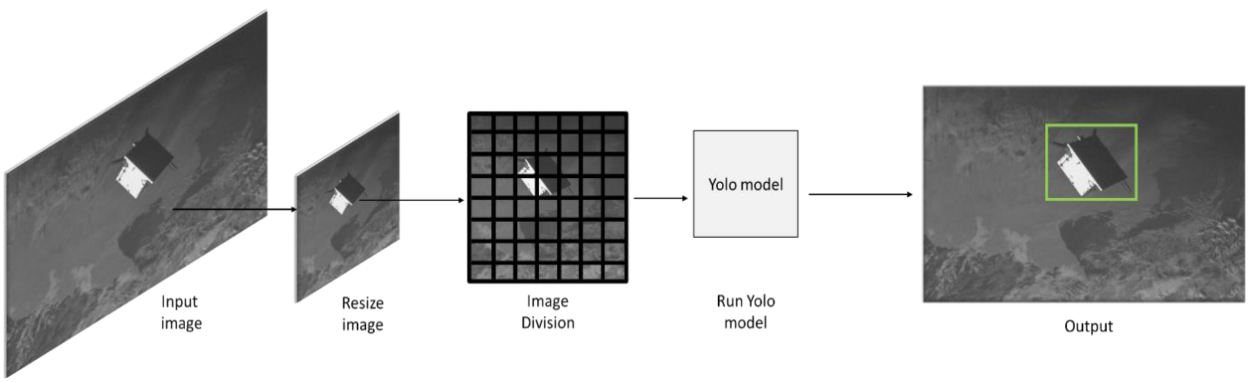

Fig. 3. The results of the YOLO algorithm in detecting space debris

$$Recall = \frac{TP}{(TP + FN)} \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \quad (3)$$

Where TP refers to the true positive, TN refers to the true negative, FN indicates the false negative, and FP represents the false positive. The model uses a confusion matrix to find the different outcomes of the actual results against the predicted results obtained. The purpose of doing the confusion matrix is to get the performance of the model for the dataset used. The confusion matrix shows the results of the actual and predicted values of the classifier to get the performance errors of the model. The results show that the precision value of the trained model is 92%, while the recall value is 97.7%. Figure 4 shows the confusion matrix of the results.

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP= 3323	FP=288
	Negative	FN=77	TN=1112

Fig. 4. The confusion matrix of the results

The algorithm's accuracy was found for both the training and testing, as seen in figure 5 below. The overall performing accuracy of the model is 92.4%.

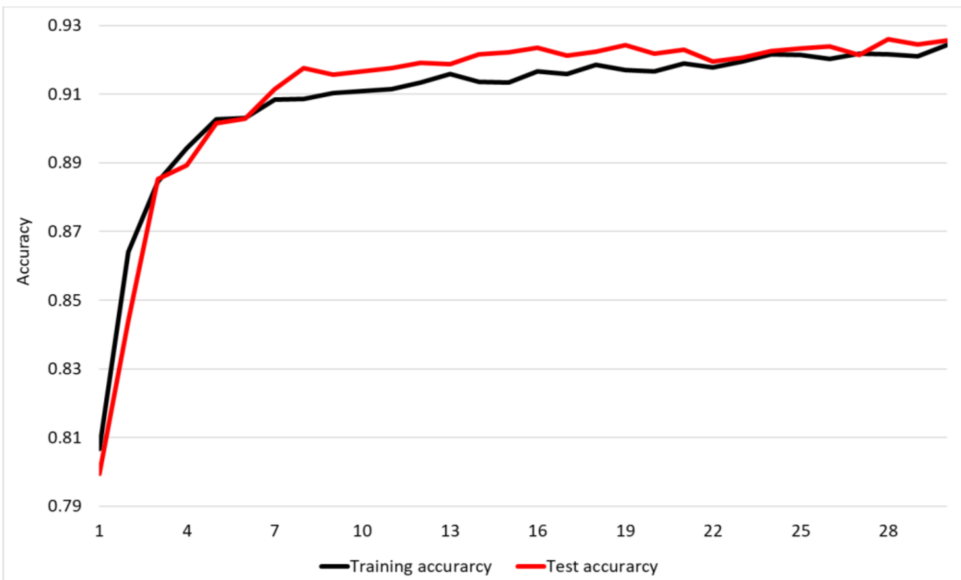

Fig. 5. The accuracy of the training and testing results for the YOLO algorithm

6. Conclusions

The accessibility to space and its sustainability is vital. Hence space debris is a key concern to all spaceflight entities, as it will hinder the sustainability of space for future missions and generations. The detection and monitoring of space debris have always been limited to large debris of 10 cm sizes and above. The detection of small debris is still considered in the research and development phase. Previous work has shown that for 1 cm and below debris sizes, the developed systems' performance accuracy are low, and enhanced systems have not been addressed as of yet. This paper showed that the proposed system analyzed captured images for space debris detection using YOLO, where the output can be downloaded with the analyzed results obtained to be used for tracking and monitoring the debris. The system has shown a performance accuracy of about 92.4%. This has also shown that the proposed system has a promising contribution to the world's effort in tracking space debris and collision avoidance. The proposed system can be implemented as a payload onboard a small satellite for future work to further validate the system in orbit.

References

[1] C. Luke, "What is space junk and how does it affect the environment?", 06-Sep-2021. [Online]. Available: https://earth.org/space-junk-what-is-it-what-can-we-do-about-it/.

[2] J. Xi, Y. Xiang, O. K. Ersoy, M. Cong, X. Wei and J. Gu, "Space Debris Detection Using Feature Learning of Candidate Regions in Optical Image Sequences," in IEEE Access, vol. 8, pp. 150864-150877, 2020, doi: 10.1109/ACCESS.2020.3016761.

[3] Y. Barniv, "Dynamic programming solution for detecting dim moving targets", IEEE Trans. Aerosp. Electron. Syst., vol. AES-21, no. 1, pp. 144-156, Jan. 1985.

[4] I. S. Reed, R. M. Gagliardi and H. M. Shao, "Application of three-dimensional filtering to moving target detection", IEEE Trans. Aerosp. Electron. Syst., vol. AES-19, no. 6, pp. 898-905, Nov. 1983.

[5] S. Kong, J. Zhou and W. Ma, "Effect analysis of optical masking algorithm for GEO space debris detection", Int. J. Opt., vol. 2019, pp. 1-8, Mar. 2019.

[6] J. Xi, D. Wen, Z. Song, W. Gao, M. Kang, J. Mou, H. Lu, and P. Pang, "A frame correlation and Kalman filtering algorithm for space debris detection," Journal of Information and Computational Science, vol. 11, no. 15, pp. 5317–5325, 2014.

[7] K. M. Brumbaugh, H. C. Kjellberg, E. G. Lightsey, A. Wolf, and R. Laufer, "AAS 12-001 in-situ sub-millimeter space debris detection using CUBESATS," Research Gate, Feb-2012. [Online]. Available: https://www.researchgate.net/profile/Katharine-Gamble-2/publication/260798433_In-Situ_Sub-Millimeter_Space_Debris_Detection_Using_CubeSats/links/5696e63908ae34f3cf1de7fb/In-Situ-Sub-Millimeter-Space-Debris-Detection-Using-CubeSats.pdf.

[8] A. Anttonen, M. Kiviranta, and M. Höyhtyä, "Space debris detection over intersatellite communication signals," Acta Astronautica, vol. 187, pp. 156–166, 2021.

[9] Zhao H., Fu X., Gao M., Ding S. Research on the visibility of low-orbit debris using space-borne radar IET Commun., 9 (1) (2015), pp. 31-37.

[10] Felicetti L., Emami M. A multi-spacecraft formation approach to space debris surveillance Acta Astronaut., 127 (2016), pp. 491-504.

[11] D. Cerutti-Maori, et al. Preliminary concept of a space-based radar for detecting MM-size space debris, in: Proc. 7th European Conf. Space Debris, Darmstadt, Germany, 2017, pp. 1–12.

[12] S. P. Simakov and I. V. Belokonov, "CubeSat onboard algorithm for space debris motion determination by processing stereo images," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XLIII-B1-2021, pp. 229–234, 2021.

[13] F. Sultana, A. Sufian, and P. Dutta, "A review of object detection models based on Convolutional Neural Network," Advances in Intelligent Systems and Computing, pp. 1–16, 2020.

[14] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A review of Yolo algorithm developments," Procedia Computer Science, vol. 199, pp. 1066–1073, 2022.

[15] J. Du, "Understanding of object detection based on CNN family and Yolo," Journal of Physics: Conference Series, vol. 1004, p. 012029, 2018.

[16] Lin, M., Chen, Q., & Yan, S. (2013). Network in network. arXiv preprint arXiv:1312.4400.

[17] T. H. Park, M. Martens, G. Lecuyer, D. Izzo, and S. D'Amico, "Speed+: Next-generation dataset for spacecraft pose estimation across domain gap," 2022 IEEE Aerospace Conference (AERO), 2022.

[18] M. Logothetis, "AI for Space Debris Detection and Orbit Determination," thesis, 2020.