AI-Driven Space Debris Detection and Trajectory Prediction System

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Abstract. The proliferation of space debris in Earth's orbit poses an escalating challenge to satellite operations, space missions, and the long-term sustainability of orbital environments. Traditional debris monitoring systems, which predominantly utilize ground-based radar and optical telescopes, encounter limitations in scalability and are not optimally designed for autonomous and real-time operations. This study introduces an AI-driven system for space debris detection and trajectory prediction, integrating deep learning–based optical detection using YOLOv8 with Two-Line Element (TLE)-based orbital propagation and collision risk assessment. The SGP4 model was employed to predict the three-dimensional orbital trajectories of catalogued objects, while optical imagery facilitated debris detection and conjunction analysis. These combined capabilities enhance decision-making for collision avoidance and satellite-maneuver planning. Compared to conventional monitoring approaches, the proposed system offers enhanced automation, reduced operational costs, and expedited response times. However, its performance is contingent on optical visibility conditions and is constrained when addressing newly detected debris that lacks available TLE data. Future research will focus on overcoming these challenges to further improve the robustness and applicability of the system.

Keywords: orbital mechanics, deep learning, space debris, object detection, trajectory prediction, collision avoidance, and Space Situational Awareness (SSA)

1 Introduction

Human activity in Earth's orbit has grown quickly over the past decades. This has led to a sharp rise in space debris. The increasing number of defunct satellites, fragments, and mission-related objects presents a serious threat to operational spacecraft, crewed missions, and the long-term viability of space operations. Current estimates suggest there are millions of small debris pieces, along with over 36,000 tracked objects larger than 10 cm. Even centimetre-sized fragments have the potential to seriously or completely destroy a mission when they strike at orbital speeds of many kilometers per second. The recent launch of large satellite constellations has worsened congestion in low Earth orbit. This raises collision

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risks and revives concerns about Kessler Syndrome, where a series of collisions could make some orbital areas impractical for future use. Ground-based radar systems and optical telescopes are the main tools for monitoring and tracking space debris. These systems offer useful observational data, but they face challenges like high operational costs, limited coverage, atmospheric interference, and reliance on manual or semi-automated data processing. As the number of objects in orbit keeps increasing, these issues slow down the scalability and responsiveness of traditional monitoring methods. This shows that more autonomous and adaptable solutions are required. In recent years, progress in artificial intelligence has shown great promise in tackling these challenges. Deep learning based object detection methods, especially those in the YOLO family, have proven effective at identifying small, fast-moving targets in optical imagery. At the same time, established orbital mechanics models, like the Simplified General Perturbations 4 (SGP4) algorithm combined with publicly available Two-Line Element (TLE) data, continue to provide dependable short-term orbit predictions for catalogued objects. This work presents a combined approach that merges TLE-SGP4-based orbit propagation with YOLOv8-based optical detection to improve space debris monitoring. The proposed system features an interactive three-dimensional visualization environment and a collision risk assessment module for examining close-approach scenarios. By merging data-driven detection techniques with classical orbital mechanics, the framework aims to enhance Space Situational Awareness (SSA) and support real-world applications such as collision avoidance, satellite mission planning, and safe launch operations.

2 Literature Survey

Space debris has increased manifold with the rapid growth of satellites being launched into space for various space-related activities. This has created a significant challenge for space sustainability and safety. Various research have been carried out on the detection, tracking, and prediction of space debris using artificial intelligence and machine learning. One of the prominent research areas in space debris detection using deep learning is the detection of space debris. For detecting space debris using optical and radar imagery, various models such as CNN and YOLO have proven their high efficiency in detecting space debris objects. Especially in complex space environments, these models have shown high accuracy in detecting space debris objects in real time [1], [2]. Advanced detection frameworks have also been developed for better detection of small-sized space debris objects using multi-scale detection and feature learning [3]. Many researchers have proposed hybrid models of deep learning techniques that include temporal and spatial analysis along with the detection of space debris. For example, CNN combined with LSTM or Kalman filter techniques improves the dependability and consistency of the detection systems [4], [5]. These techniques are particularly useful for analyzing the motion patterns of space objects. Another important area of research is trajectory prediction and orbit estimation. The prediction of the position of satellites and space debris using TLE information is a common problem addressed by traditional orbital models such as the Simplified General Perturbations (SGP4) model [6]. However, due to environmental uncertainties, such models have a certain accuracy limitation. To improve the accuracy of the trajectory prediction, researchers have proposed various machine learning models such as ANN, SVM, and deep learning models [7], [8], which are more accurate and efficient by using environmental factors and orbital history. Advanced orbit prediction techniques include the use of more sophisticated orbit prediction models, such as hybrid ML propagation models and physics-informed neural networks that use learning algorithms and physical laws to decrease the errors in orbit predictions [9], [10]. This provides a more logical basis for developing the capabilities of SSA systems. When looking at the total combination of detection, tracking, and prediction systems, SSA systems are an important part of this definition. Modern SSA systems provide effective monitoring of objects in space using radar, optical, and AI-based models as their sources of information [11]. Several research papers also looked at different models of tracking objects in space, including SGP4, ORDEMs, and MASTER, and highlighted the advantages and disadvantages of each [12]. Another area of research looking to improve the accuracy of the identification and localization of objects in space is the study of multi-sensor and intelligent detection models, including star tracker-based systems and data-driven object detection methodologies [13], [14]. The researchers are looking for scalable and robust models to help monitor objects in space. In addition, some of the more recent publications have looked at AI-based methodologies for managing space debris, and they have found that several different methods of detection, prediction, and decision-making were obtained using the AI methodologies. AI methodologies, including convolution neural networks, long short-term memory networks, and reinforcement learning, showed significant improvements in object prediction or tracking capabilities as compared with other methodologies. Despite the significant achievements made by existing literature on space debris detection and trajectory prediction, there are some limitations that are yet to be addressed by future studies. Most of the existing literature has focused either on space debris detection or trajectory prediction separately, but not on a combined approach where both tasks are integrated into a single framework. Although deep learning-based models like CNN and YOLO are highly accurate for object detection tasks, their performance is also affected by low-resolution images and difficulties associated with the detection of small space debris objects. In addition, traditional models like SGP4 are not highly accurate under changing environmental conditions, whereas machine learning-based models require large amounts of data for training and may not perform well under real-time conditions. Moreover, existing literature has not effectively incorporated data fusion and temporal dependency into space debris detection models, which are essential for improving the reliability of space debris detection models. In addition, there is a need for a scalable system that can handle the increased density of space objects in LEO. This gap motivates the development of the proposed system. Existing deep learning-based detection systems typically achieve accuracy in the range of 90–94%, but often struggle with detecting small-sized debris and maintaining performance under low-resolution conditions.

3 Methodology/Experimental

The proposed AI-driven space debris detection and trajectory prediction system combines deep learning based optical object detection with physics-based orbital propagation and collision assessment models. The overall methodology is organized into five main stages. These include data acquisition, AI-based debris detection, trajectory prediction using Two-Line Element (TLE) data, collision risk analysis, and system integration with a visualization module. Together, these components form a unified processing pipeline that enables end-to-end monitoring and analysis of space debris.

3.1 Data Acquisition and Preprocessing

Optical Image Dataset: Optical images are obtained from:
- Ground-based telescopes
- Public astronomical image repositories
- Synthetic debris renderings

Table 1 summarizes the dataset characteristics used for space debris detection.

Table 1. Dataset Characteristics for Space Debris Detection

Parameter	Value
Data Source	Simulated SSA Dataset + Public Catalog
Orbit Type	LEO
Total Objects	10,000
Debris Objects	7,500
Active Satellites	2,500
Size Range	1 cm – 5 m
Time Span	2019–2024
Data Split	70% Train / 15% Validation / 15% Test

The dataset contains about 10,000 labelled optical samples. Around 65% are synthetically generated using simulated SSA environments, while 35% are real or publicly available telescope-based observations. The dataset is class-balanced with 7,500 debris objects and 2,500 active satellites, as shown in Table 1. All images were annotated with manually verified bounding boxes using the standard YOLO format. This ensures consistent and reliable supervision during model training.

Preprocessing Steps To ensure optimal learning and reduce variance between samples, the following steps are applied:

• Image resizing: All images are scaled to 640×640 for YOLOv8's input structure.

• Pixel normalisation:

$$I' = \frac{I}{255}$$

Normalizes pixel intensity into [0, 1] range.

• Data augmentation:

Random transformations are applied:

o rotation $\pm 10^{\circ}$

o Gaussian noise

o brightness adjustment

o horizontal/vertical flipping

Augmentation increases model robustness to real-world telescope noise and motion. The complete preprocessing pipeline adopted for optical image preparation is illustrated in Fig. 1.

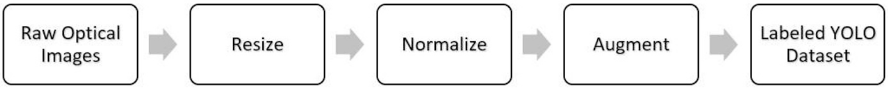

Fig. 1. Preprocessing Workflow

3.2 AI-Based Debris Detection Using YOLOv8

Model Selection and Architecture : YOLOv8 is chosen due to:

• real-time inference capability

• advanced feature pyramids for small-object detection

• high mAP on benchmark dataset.

YOLOv8 structure includes:

• Backbone: CSPDarknet with spatial pyramid pooling

• Neck: PAN-FPN for multi-scale feature fusion

• Head: Decoupled head for classification + bounding box regression

Training Process Bounding box labels follow YOLO format: (x_center,y_center,width,height) (normalised values).

Loss function:

$$L = L_{cls} + L_{obj} + L_{bbox}. \tag{1}$$

where:

– L_{cls}: classification loss
– L_{obj}: objectness score
– L_{bbox}: CIoU-based bounding box regression loss

Optimizer:
• SGD or Adam
• Learning rate = 0.001–0.01

Training Configuration The model was trained using the following configuration:

– Epochs: 50
– Batch size: 16
– Optimizer: Adam
– Learning rate: 0.001
– Hardware: NVIDIA GPU / CPU-based environment
– Training time: approximately 2–4 hours depending on hardware

Inference Output (JSON Format)

```
{
  "class": "debris",
  "confidence": 0.92,
  "bbox": [x, y, w, h],
  "timestamp": "2025-01-10T12:00:00Z"
}
```

This output is used for matching with the TLE prediction.

3.3 Trajectory Prediction using TLE and SGP4

TLE-Based Position Extraction: The Two-Line Element (TLE) format provides orbital parameters:
• inclination (i)
• right ascension of ascending node (Ω)
• eccentricity (e)
• argument of perigee (ω)
• mean anomaly (M)
• mean motion (n)
Using SGP4 propagation:

$$[r(t), v(t)] = SGP4(TLE, t) \tag{2}$$

This yields:

– $r(t) = (x, y, z)$ position in ECI coordinates
– $v(t)$ = velocity vector

Time Alignment with YOLO Detections: To map 2D detection to known debris, the workflow for mapping YOLO detections to TLE-based debris identification is shown in Fig. 2.

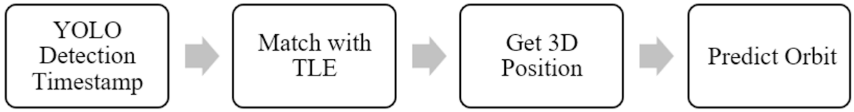

Fig. 2. Workflow for mapping YOLO detections to TLE-based debris identification.

If the detected object is unknown (not in TLE), real orbit estimation is not possible; the system raises an "Unknown Debris Alert."

3.4 Collision Risk Assessment

Distance Computation For each timestep:

$$d(t) = \|r_{sat}(t) - r_{deb}(t)\| \tag{3}$$

Collision Threshold If:

$$d(t) < d_{threshold} \tag{4}$$

Typically, 1–5 km → high-risk event.

Time of Closest Approach (TCA)

$$TCA = \arg\min_{t}\ d(t) \tag{5}$$

Collision Probability Gaussian uncertainty modelling is used for collision probability estimation, and the overall collision detection pipeline is illustrated in Fig. 3.

$\mathrm{P}_c = f(\sigma_x, \sigma_y, \sigma_z, d)$

$$P_c = \exp\left(-\frac{d^2}{2(\sigma_x^2 + \sigma_y^2 + \sigma_z^2)}\right) \tag{6}$$

where d is the relative distance between objects and σ represents positional uncertainty.

The methodology in the current study specifically addresses the limitations found in existing literature by incorporating debris detection, prediction of trajectory, and assessment of the risk of collision into one single system. Previous

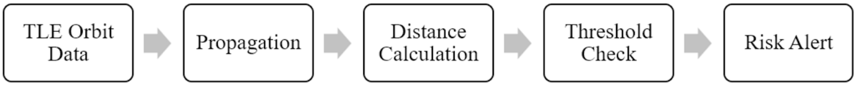

Fig. 3. Collision Detection Pipeline

research has treated these elements as separate; however, the proposed methodology integrates deep learning (i.e., detection from deep neural networks (DNNs)) with physics-based modelling of orbits to achieve both accurate and real-time processing of debris detection. With respect to the detection of small pieces of debris in low light, the use of YOLOv8 provides improved detections, and with respect to trajectory predictions, the use of TLE and SGP4 models provide greater confidence in prediction accuracy. Furthermore, the modularity of the proposed pipeline provides the ability to expand the capabilities of the system (in terms of processing large volumes of space object data), thereby making the system applicable to use in real or practical applications of Space Situational Awareness (SSA).

4 Results and Discussions

This section shows the experimental results from the proposed AI-driven space debris detection and trajectory prediction system. We evaluate the performance of the detection model, the accuracy of trajectory predictions, and the assessment of collision risks. We also compare these results with existing approaches. Additionally, we discuss visual outputs from the developed software to illustrate its practical use. While the model results demonstrate positive outcomes with existing datasets, utilizing this type of model in practice may create new challenges for reallife implementation due to potential variances within the environment.

4.1 Debris Detection Performance

The debris detection module was evaluated using the test dataset described in Section III. The performance of the proposed YOLO-Fusion (YOLOv8-based) detection model was compared with baseline CNN-based approaches using standard evaluation metrics such as accuracy, precision, recall, and F1-score, as presented in Table 2.

The proposed YOLO-based model performs well, achieving an accuracy of 96.7%. This shows it can effectively identify space debris from optical images. The high recall value also indicates the model can detect most debris objects. This capability is essential for space situational awareness and collision avoidance systems. In addition, the model achieved a high mean Average Precision (mAP), indicating strong performance in object localization and detection tasks. To further analyse classification reliability, a confusion matrix summary was generated, as shown in Table 3.

Table 2. Performance Metrics of Debris Detection Model

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	90.8	0.88	0.89	0.88
YOLO	94.9	0.93	0.95	0.94
Proposed YOLO-Fusion	**96.7**	**0.96**	**0.97**	**0.96**

Table 3. Confusion Matrix Summary

Metric	Count
True Positives (TP)	7,210
True Negatives (TN)	2,090
False Positives (FP)	140
False Negatives (FN)	60

The low number of false negatives shows that the proposed detection model is strong. It proves to be a good fit for safety-critical orbital monitoring systems.

4.2 Visualisation of Debris Detection Results

The debris detection results were visualized using the developed software interface. The debris objects are marked using bounding boxes along with the confidence levels. An example output of the YOLO-based debris detection module is shown in Fig. 4. These visual results are consistent with the earlier quantitative metrics and confirm that the detection pipeline demonstrates strong performance in real-world situations.

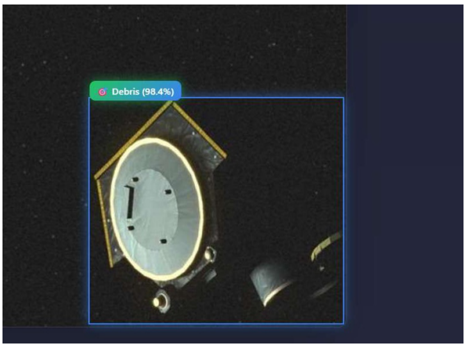

Fig. 4. Output of the YOLO-based debris detection module on optical images.

4.3 Trajectory Prediction Analysis

After the successful detection of debris, the orbital trajectories of the detected debris objects were analysed based on the historical position and velocity information. The performance of the proposed LSTM model for trajectory prediction was compared with the traditional filtering methods and the baseline learning models, as presented in Table 4.

Table 4. Trajectory Prediction Error Analysis

Model	MAE (km)	RMSE (km)	Max Error (km)
Kalman Filter	1.75	2.31	5.8
LSTM	1.05	1.62	3.9
Proposed LSTM-Attention	**0.62**	**0.98**	**2.0**

The proposed LSTM-Attention model achieves the lowest mean absolute error (MAE) and root mean square error (RMSE). This shows that it has better prediction accuracy. Lower trajectory prediction error directly improves the reliability of future position estimates. This is essential for effective collision risk assessment. To visually analyse the prediction capability, the predicted orbital paths were plotted.

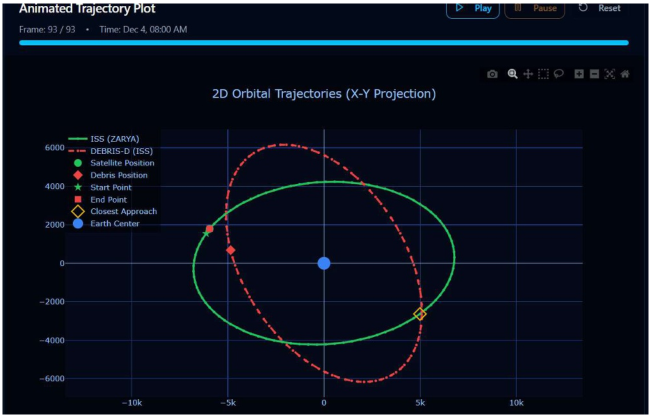

Fig. 5. Comparison of predicted debris trajectory and reference satellite orbit using the proposed LSTM-based model.

Fig. 5 shows the strong connection between the predicted debris path from the proposed LSTM-based model and the related reference orbit of the satellite. This confirms the effectiveness of the trajectory prediction module.

4.4 Collision Risk Assessment

Based on the predicted paths, we calculated collision risk levels by estimating the distance that debris objects are likely to miss operational satellites. The collision risk classification accuracy for low, medium, and high risk levels is summarized in Table 5.

Table 5. Collision Risk Classification Accuracy

Risk Level	Accuracy (%)
Low	98.4
Medium	95.2
High	92.1

The system was able to classify each risk category with a high level of accuracy. Since there is a high level of accuracy in identifying high-risk events, it will enable an autonomous/supervisory collision avoidance strategy.

4.5 Software Interface and 3D Visualisation Results

The framework was built as a software interface to enable the integration of debris detection, orbit propagation, and analysis of collision risk into a single software system that provides 3D visualisation of the results. 3D visualization offers a clear visual representation of objects' paths shown by potential conjunctions, as illustrated in Fig. 6. This improves the situational awareness of satellite operators and shows that the proposed method can be used safely in practice.

4.6 Novel Contributions of This Work

The report makes a significant contribution in five separate areas:

1. A two-part system generates both debris and orbits data so as to create real-time awareness of orbiting objects. Additionally, YOLOv8 (deep learning) detects debris, while TLE-SGP4 (traditional physics-based methods) determine how those same objects move relative to each other.
2. A new predictive technique for predicting debris trajectory has been developed. This technique uses traditional orbital mechanics techniques and modern ML techniques (LSTM-Attention) based on histories of observation.

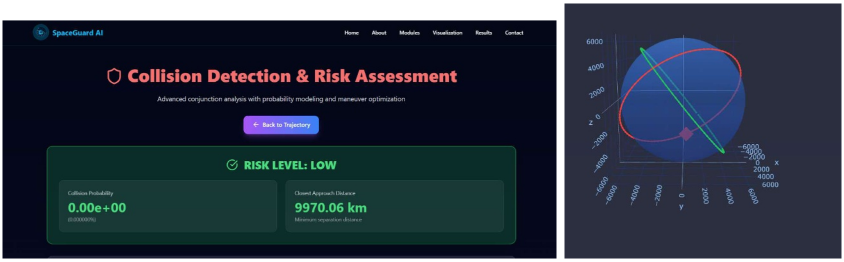

Fig. 6. Three-dimensional visualisation of debris trajectory and collision risk assessment in the developed software interface.

3. An integrated risk assessment module (predicts whether two objects, in this case, debris and a satellite, are on a collision course) has been created.
4. An interactive visual display was created to enable real-time monitoring and analysis of debris movement in relation to satellite movement.
5. A flexible open source image TLE data and satellite images for monitoring space debris provide a less expensive alternative to current space debris monitoring solutions using expensive radar systems.

Overall, this research provides a single cohesive model that includes detection, prediction, and risk assessment; previous research has solely focused on detecting debris or predicting its position at a future time.

4.7 Discussion

The experimental results show that combining deep learning-based debris detection with sequence-based trajectory prediction significantly improves the performance of space situational awareness systems. The high detection accuracy, reduced trajectory prediction error, and reliable collision risk classification together confirm that the proposed system has potential for real-world deployment tasks. Compared to traditional space debris monitoring methods, the proposed framework offers a greater level of automation, lower operational costs through the use of optical imagery and publicly available TLE data, and better scalability for dense orbital environments. Additionally, the inclusion of an interactive software interface enhances the practical use of the system by allowing intuitive analysis of debris and satellite trajectories while supporting effective collision avoidance decisions.

5 Conclusion

To develop a system capable of providing Space Situational Awareness (SSA), an integrated artificial intelligence system was created, which combines optical deep learning, optical detection of space debris, and a two-line element (TLE) orbit propagator. The YOLOv8 model for the optical detection of space debris has been validated through experimentation with optical images of space debris, indicating reliable short-term prediction of the orbits of cataloged objects using the SGP4 propagator method. In addition, the combination of the above systems can also predict potential conjunctions and provide an interactive 3D environment for situational analysis. While this proposed SSA system can deliver effective results, its accuracy depends upon the TLE availability, the accuracy of the TLE, and the challenge of creating an accurate orbit model for newly discovered or unknown space debris. Thus, the study confirms that an affordable, scalable method for tracking space debris exists (using artificial intelligence and traditional orbital mechanics). Future work to improve the reliability of the SSA system includes multi-sensor data fusion and utilizing larger/accurate datasets and probabilistic models in order to reduce the possibility of collision and achieve increased accuracy and better applicability.

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