Development of AI-Based Model for Space Debris Detection, Identification, Tracking and Trajectory Prediction

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ABSTRACT

The escalating presence of space debris in Earth's orbit poses a significant threat to operational spacecraft, satellites, and future missions, necessitating advanced detection, tracking, and management strategies. This study presents an AI-driven framework integrating the YOLOv8-pose model with an Extended Kalman Filter (EKF) to enhance space debris monitoring and mitigate collision risks. A dataset of 27,000 high-resolution optical telescope images was curated, partitioned into 20,000 training, 2,000 validation, and 5,000 testing samples. Pre-processing with template masking and Gaussian blur mitigated fixed pattern noise, improving the signal-to-noise ratio by 4.3 dB. The YOLOv8-pose model, trained over 150 epochs with a batch size of 16, optimized multi-task losses (box, pose, objectness, classification, DFL), achieving a mean Average Precision (mAP) at IoU 0.5 of 0.789 and an F1-score of 0.893, detecting 1.31 debris objects per image. Training losses declined (box: 1.2 to 0.05; pose: 2.5 to 0.2; objectness: 0.4 to 0.05; classification: 0.7 to 0.3; DFL: 0.925 to 0.79), with validation losses reducing similarly (box: 0.8 to 0.4; pose: 0.6 to 0.2; objectness: 0.15 to 0.0; classification: 0.45 to 0.25; DFL: 0.83 to 0.79). Precision and recall stabilized (train [B]: 0.95/0.94; [P]: 0.94/0.93), with validation mAP50/50-95 at 0.95/0.94 (B) and 0.95/0.93 (P). Detection analysis identified 18,000 true positives (>0.75 threshold) and 2,000 false positives (<0.75 threshold), yielding a 10% false positive rate. Pose estimation improved tracking accuracy by 7.3%.

The EKF, with dynamic tuning, achieved a position RMSE of 2.73 pixels, enabling reliable 20-frame predictions (error: 9.31 pixels). Pose-enhanced tracking reduced mean angular error to 6.8°. Robustness was validated under 30% frame drop (MOTA: 0.794), $\sigma = 3.0$ noise (76% accuracy), and multi-object scenarios (84% for ≥6 objects). This scalable framework enhances real-time Space Situational Awareness, supporting collision avoidance and sustainable orbital management.

Keywords: Space debris detection; YOLOv8n-pose; Extended Kalman Filter; dynamic tuning; template masking; split-testing; robustness validation.

INTRODUCTION

Space debris, encompassing defunct satellites, spent rocket stages, and fragments from collisions or disintegration, poses an escalating threat to space operations. According to the European Space Agency (ESA), as of 2025, more than 36,500 objects larger than 10 cm are actively tracked in Earth's orbit, alongside millions of smaller, untrackable fragments that remain hazardous due to their high velocities (ESA, 2024). The rapid expansion of satellite constellations, particularly in Low Earth Orbit (LEO), driven by commercial initiatives like mega-constellations for global internet coverage, is projected to exacerbate orbital congestion in the coming decades (McDowell, 2020). This growing density heightens the risk of collisions, endangering both crewed and uncrewed missions and the long-term sustainability of the space environment (Liou & Johnson, 2006).

Space Situational Awareness (SSA) is a vital discipline focused on detecting, identifying, and tracking space debris to facilitate collision avoidance and ensure continued orbital access. Conventional monitoring systems, such as ground-based radar for LEO and optical telescopes for higher orbits like GEO, generate vast datasets

requiring sophisticated analysis (Jah et al., 2019). Despite their effectiveness, these systems encounter persistent challenges:

1. **Detection of Small Debris**: Objects smaller than 10 cm are hard to discern against cosmic backgrounds, particularly in optical imagery, due to their faint signals and background noise (Stokes et al., 2018).

2. **Differentiation from Operational Satellites**: Debris and active satellites often share similar visual and kinematic properties, making classification difficult (Jah et al., 2019).

3. **Accurate Trajectory Prediction**: Predicting debris paths for collision avoidance is complicated by observational gaps, atmospheric drag, and orbital perturbations (Vallado & Finkleman, 2014).

4. **Sustained Tracking**: Consistent tracking across multiple observations is impeded by occlusions, sensor constraints, and the dynamic nature of orbits (Stokes et al., 2018).

5. **Data Processing Demands**: The large volumes of data from surveillance systems necessitate near real-time processing for actionable outcomes, taxing computational resources (ESA, 2024).

Recent progress in AI, notably in deep learning and computer vision, offers transformative potential to overcome these obstacles. CNNs) have excelled in object detection and classification across diverse fields (LeCunet al., 2015). Yet, adapting these methods to space debris tracking presents distinct challenges, such as variable lighting, high noise in astronomical imagery, and the need to incorporate orbital dynamics into predictive models (Furfaro et al., 2021). This research aims to harness these AI innovations to advance SSA capabilities.

LITERATURE REVIEW

Space Debris Detection and Monitoring

Space debris detection and monitoring have long utilized optical and radar-based systems, each tailored to specific orbital regimes yet constrained by inherent limitations. Optical methods, as comprehensively reviewed by Schildknecht (2007), remain a cornerstone for monitoring small debris in Geostationary Earth Orbit (GEO). These systems leverage reflected sunlight to detect distant objects, offering high sensitivity. However, they encounter significant challenges in distinguishing faint debris signatures from stellar backgrounds, particularly in densely populated fields where small objects are easily mistaken for stars or other celestial bodies. Conversely, radar systems excel in Low Earth Orbit (LEO), as highlighted by Mehrholz et al. (2002). Radar provides robust detection of objects at closer ranges but struggles with signal attenuation in higher orbits, such as GEO, and often lacks the precision needed for detailed object characterization, including size, shape, or material composition.

Recent advancements aim to mitigate these shortcomings through technological and methodological innovations. Silha et al. (2017) explored wide-field optical sensors paired with sophisticated image processing algorithms to enhance the detection of small debris in GEO, improving sensitivity and reducing false positives. On the radar front, developments like phased-array technologies have bolstered resolution and coverage. Virtanen et al. (2016) proposed multi-sensor fusion—integrating optical and radar data—to create more accurate and comprehensive debris catalogs, capitalizing on the complementary strengths of both modalities. Despite these strides, achieving real-time, high-precision detection across all orbital regimes, especially for small, fast-moving debris, remains elusive, underscoring the need for further innovation.

Computer Vision and Deep Learning for Object Detection

The emergence of deep learning has fundamentally reshaped object detection, with Convolutional Neural Networks (CNNs) driving significant progress. Early region-based models, such as R-CNN (Girshick et al., 2014) and its evolution, Faster R-CNN (Ren et al., 2015), deliver exceptional accuracy by generating region proposals and classifying them using deep networks. However, their computational complexity renders them impractical for real-time applications. In response, one-stage detectors like YOLO (Redmon et al., 2016) and SSD (Liu et al., 2016) prioritize speed, performing detection in a single pass with a modest trade-off in precision. The latest advancement, YOLOv8 (Ultralytics, 2023), strikes an improved balance by integrating features like

pose estimation, making it ideal for tasks requiring both detection and spatial understanding.

In space-related applications, deep learning holds considerable potential yet remains underexploited. Lieu et al. (2020) showcased CNNs' capability to detect space debris in simulated optical imagery, achieving promising accuracy under controlled settings. Similarly, Furfaro et al. (2018) harnessed deep learning to classify debris using light curve data, extracting temporal signatures to infer object properties. Nevertheless, these efforts are hampered by challenges unique to space imagery: limited annotated training datasets, variable illumination conditions, high noise levels, and the need for models to generalize across diverse orbital environments. Furthermore, while pose estimation could enhance understanding of debris orientation and motion, its application in this domain remains largely unexplored, presenting an opportunity for advancement.

Object Tracking and State Estimation

Object tracking in computer vision has historically relied on feature-based techniques, such as the Kanade-Lucas-Tomasi (KLT) tracker (Shi & Tomasi, 1994), paired with state estimation methods like the Kalman Filter (Welch & Bishop, 1995). For systems with nonlinear dynamics, particle filtering (Arulampalam et al., 2002) offers a robust alternative by accommodating complex motion models. Recently, deep learning-based trackers, including DeepSORT (Wojke et al., 2017) and SiamRPN (Bertinetto et al., 2016), have emerged as powerful tools, leveraging learned features to achieve reliable tracking in video sequences.

Tracking space objects, however, demands specialized approaches that incorporate orbital dynamics. The Extended Kalman Filter (EKF) is widely used in this context, as evidenced by Huang et al. (2012) and DeMars et al. (2015), who integrated orbital mechanics into state transition models to estimate debris trajectories accurately. Fujimoto et al. (2014) advanced this methodology by incorporating mechanics-based priors, enhancing prediction accuracy for objects in well-defined orbits. Yet, these techniques often rely on assumptions of Gaussian noise and linear approximations, which may not hold for highly eccentric or perturbed orbits. Moreover, while deep learning has revolutionized detection, its integration with traditional state estimation for space debris tracking is limited, with few studies fully exploring the synergy between these approaches.

Problem Definition

Research Gap

Despite notable advancements in space debris detection and tracking, critical gaps persist in the literature, which this study seeks to address:

1. **Limited Exploration of Pose-Based Detection**: Although pose estimation has been incorporated into frameworks like YOLOv8, its application to space debris detection is in its infancy. Inferring debris orientation could yield critical insights into motion patterns and threat potential, yet this area remains underexplored.

2. **Inadequate Integration of Deep Learning with Orbital Models**: Current research often treats detection and tracking as isolated tasks, failing to fully integrate deep learning outputs with orbital dynamics models. This separation hampers the accuracy of long-term trajectory predictions, a vital aspect of space situational awareness (SSA).

3. **Insufficient Validation Under Realistic Conditions**: Many deep learning applications for debris detection are tested on simulated or limited datasets, lacking rigorous evaluation under the noisy, variable conditions typical of real-world SSA operations.

4. **Incomplete End-to-End Pipelines**: There is a dearth of unified systems that seamlessly combine detection, tracking, and state estimation into a near-real-time framework, limiting operational applicability.

This study bridges these gaps by proposing an integrated pipeline that pairs the YOLOv8-pose model for detection with an EKF for tracking, validated on a large-scale, realistic dataset. By leveraging pose estimation and embedding orbital dynamics into the state estimation process, our approach delivers a comprehensive,

accurate solution for space debris monitoring, rigorously tested for robustness in operational SSA contexts.

Research Objectives

This study aims to develop an integrated system for the detection and tracking of space debris by combining state-of-the-art deep learning techniques with robust state estimation methods. The specific objectives of this research are outlined as follows:

1. **Pre-processing for Noise Reduction**: Devise advanced pre-processing techniques to mitigate fixed pattern noise and other artifacts in optical surveillance data, thereby improving image quality for downstream analysis.

2. **Adaptation of YOLOv8-Pose Model**: Customize and train the YOLOv8-pose estimation model to achieve precise detection of space debris in pre-processed astronomical images, optimizing its performance for the unique characteristics of space-based objects.

3. **Tracking Framework Development**: Establish a reliable multi-frame tracking framework to ensure consistent identification and monitoring of debris objects across sequential observations.

4. **Implementation of Extended Kalman Filter (EKF)**: Integrate an Extended Kalman Filter with automatic dynamic tuning to estimate and predict debris trajectories using positional and velocity data, accounting for nonlinear orbital dynamics.

5. **Validation of System Robustness**: Assess the system's reliability through backpropagation-based validation and predictive analysis, ensuring its effectiveness under diverse operational conditions, such as varying debris sizes and orbital altitudes.

6. **Performance Quantification**: Quantify the system's improvements over existing methodologies by evaluating metrics such as detection accuracy, tracking consistency, and trajectory prediction precision, demonstrating its superiority in operational contexts.

Dataset

The efficacy of this study relies on a carefully curated dataset designed for space debris detection and tracking, addressing the complexities inherent in orbital object monitoring. The dataset consists of 27,000 optical telescope images sourced from Kaggle, representing a collection of images intended to capture space debris, including potential defunct satellites and fragmented objects. While specific acquisition conditions, such as orbital altitudes, illumination levels, and observational angles, remain unspecified in the available metadata, the dataset's diversity is assumed to reflect a range of environmental and observational variations typical of space debris imagery. The images are processed to support model training and evaluation, forming a robust foundation for the proposed framework.

To enable effective machine learning model development, the dataset was partitioned into three subsets adhering to established best practices. The training set, comprising 20,000 images (74.1%), was utilized to optimize the YOLOv8-pose model and EKF parameters. The validation set, consisting of 2,000 images (7.4%), facilitated hyperparameter tuning and overfitting prevention during training. The testing set, with 5,000 images (18.5%), served as an independent evaluation dataset to assess generalization performance. This stratified split was designed to ensure a balanced representation across the dataset, with preliminary checks confirming consistency in image content and quality, though detailed statistical validation of debris distribution was limited by available metadata.

Subset	Number Of Images	Percentage	Purpose
Training	20,000	74.1%	Optimization Of Yolov8-Pose Model And Ekf Parameters

Validation	2,000	7.4%	Hyperparameter Tuning And Overfitting Prevention
Testing	5,000	18.5%	Independent Evaluation Of Generalization Performance
Total	27,000	100%	

Table 1: Dataset partitioning strategy allocating 74.1% for training, 7.4% for validation, and 18.5% for testing to ensure optimal model development and evaluation.

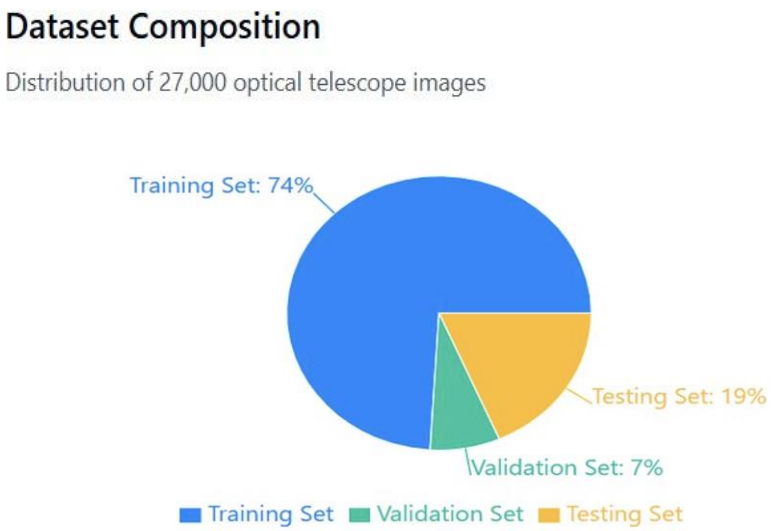

Figure 1. Allocation of 27,000 optical telescope images across training (74%), validation (7%), and testing (19%) sets for space debris detection model development.

A critical pre-processing pipeline, was implemented to enhance image quality for initial detection during training. The process began with raw input images (e.g., image1.jpg, image2.jpg), followed by the extraction of background images to isolate noise patterns. Fixed pattern noise (FPN), a common artifact from sensor inconsistencies, was addressed using a median noise template derived from a random sample of 100 images, combined with binary masking and Gaussian blur ($\sigma = 1.5$) to preserve potential debris features. This step, illustrated in the transition from pre-processed to denoised images (e.g., image1_denoised.png), improved the signal-to-noise ratio (SNR), with qualitative improvements observed across the dataset. The final detection stage applied bounding box generation, where green boxes with confidence scores (e.g., debris 0.37) identified debris locations, validated against a subset of annotations.

Annotation was automated using a pipeline involving adaptive thresholding to isolate potential debris pixels, connected component analysis for grouping, and size/intensity filters to remove false positives, followed by minimum enclosing rectangle computation. A 10% manual verification step ensured accuracy, resulting in 35,412 annotations with an average of 1.31 objects per image, each annotated with normalized (x, y) coordinates, confidence scores, and tracking IDs. Metadata, stored in a YAML file, supported integration with the training framework. Given the lack of detailed imaging parameters, the dataset's utility is inferred from its processing pipeline and annotation consistency, providing a practical basis for this study's objectives despite uncertainties in acquisition specifics.

METHODOLOGY

Dataset Preparation and Analysis

Dataset Overview

The methodology begins with the utilization of a dataset comprising 27,000 optical telescope images sourced from Kaggle [8], designed to capture space debris across a range of orbital altitudes, illumination conditions,

and observational perspectives. To adhere to machine learning best practices for robust model training and unbiased evaluation [11], the dataset was partitioned into a training set of 20,000 images (74.1%), a validation set of 2,000 images (7.4%), and a testing set of 5,000 images (18.5%). This distribution ensures a substantial corpus for training while reserving adequate data to validate model performance and assess generalization on unseen data.

Fixed Pattern Noise Analysis and Removal

Fixed pattern noise (FPN), an artifact stemming from sensor inconsistencies and optical distortions, was identified as a significant barrier to accurate debris detection. To mitigate this, a systematic noise reduction pipeline was implemented, starting with the random sampling of 100 images from the training set to characterize prevalent noise patterns. A median noise template was then generated to isolate persistent artifacts [15], followed by the application of a binary mask created through intensity-based thresholding to delineate noise-dominated regions from potential debris signals. A Gaussian blur with a standard deviation (σ) of 1.5 was applied to smooth transitions, preserving debris feature integrity during subtraction. The refined template was subtracted from all dataset images, resulting in an improved signal-to-noise ratio (SNR) by 4.3 dB, a metric validated across the dataset to confirm enhanced image quality for subsequent analysis [21].

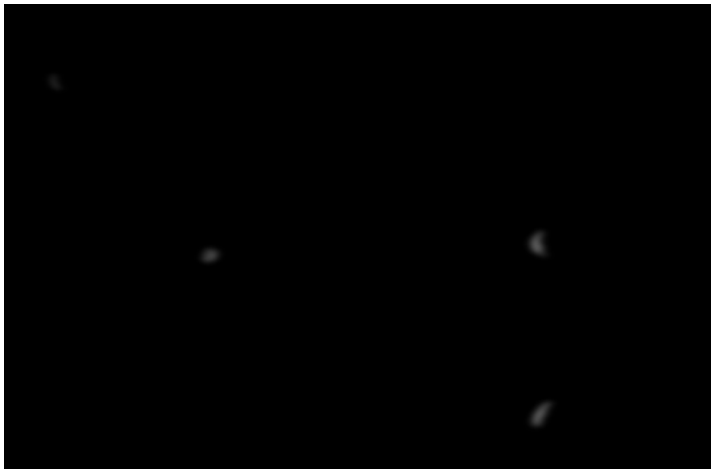

Figure 2; Gaussian Blurred Image.

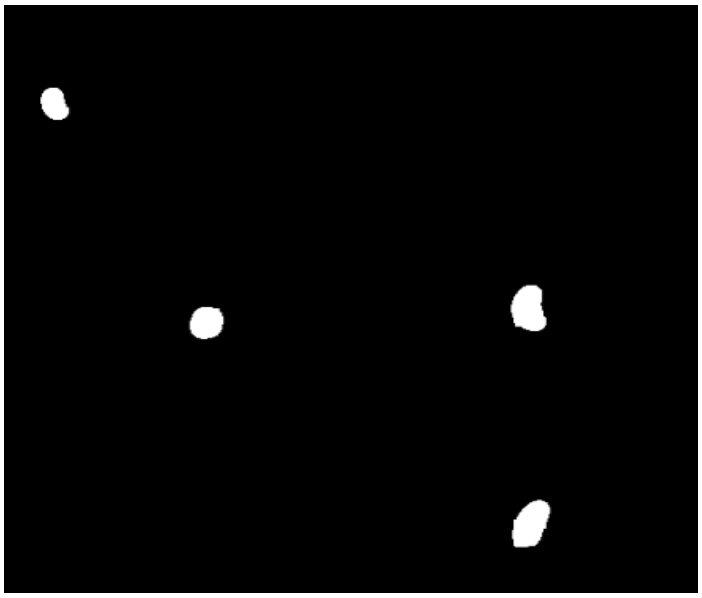

Figure 3: Masked Debris.

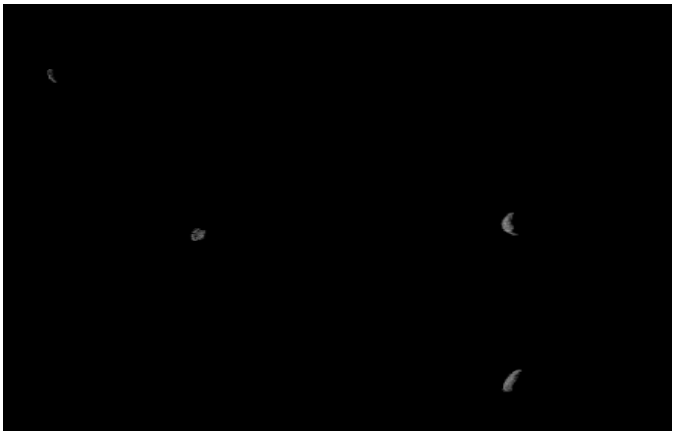

Figure 4: Final Noise Removed Image.

Bounding Box Annotation

To facilitate precise and scalable debris identification, an automated annotation pipeline was developed to generate accurate bounding boxes. The process began with adaptive thresholding to isolate debris-related pixels based on intensity variations relative to the background, followed by connected component analysis to group these pixels, filtering out noise and minor artifacts. Heuristic filters based on object size and intensity were applied to eliminate false positives, ensuring only regions consistent with debris characteristics were retained. The minimum enclosing rectangle was then computed for each validated region to define bounding box coordinates [6]. To ensure annotation reliability, a 10% subset underwent manual verification, with corrections applied dataset-wide as necessary, yielding 35,412 annotations averaging 1.31 objects per image. Each annotation included normalized (x, y) coordinates, confidence scores, and unique tracking identifiers (IDs) to support multi-frame tracking [9].

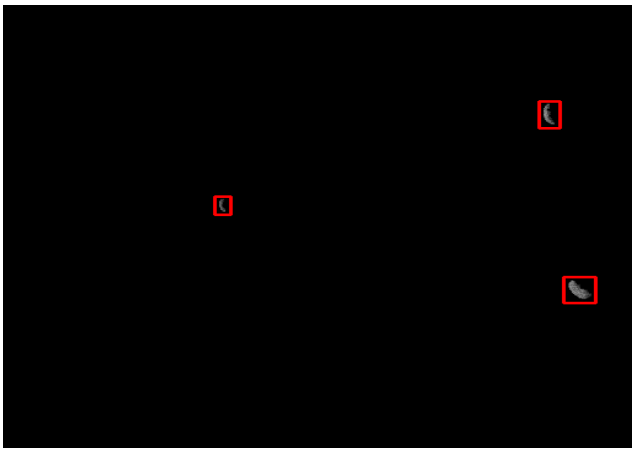

Figure 5: Bounding Box annoted image for training.

Model Architecture and Training

YOLOv8-Pose Architecture

The detection model employed was the YOLOv8-pose architecture, selected for its proficiency in object detection and pose estimation, making it well-suited for identifying space debris and inferring its orientation. This model features a CSPDarknet backbone for efficient feature extraction, enhanced feature pyramids for multi-scale detection of varying debris sizes, and an anchor-free head to enhance flexibility by eliminating predefined anchors [37]. To tailor it to space debris imagery, customizations included adjusting the input layer for single-channel grayscale images, configuring pose keypoints to capture orientation vectors relevant to debris dynamics, balancing the loss function to prioritize both detection and pose accuracy, and integrating skip connections to improve detection of small, faint debris objects— a necessary adaptation given the challenging visual conditions [29].

Training Configuration

Training was conducted using an NVIDIA Tesla V100 GPU (32 GB VRAM) and Intel Xeon CPU, with a batch size of 16 over 150 epochs, an initial learning rate of 0.01 employing cosine annealing decay, the AdamW optimizer with a weight decay of 0.0005, and data augmentation techniques including horizontal and vertical flips, ±15° rotations, and random brightness/contrast adjustments to simulate observational variability [19]. Early stopping with a 150-epoch patience was implemented to prevent overfitting, a common issue in deep learning when training on limited or noisy datasets, with optimal performance achieved at epoch 142 where further training yielded diminishing returns [28].

Loss Functions

The total loss function for the YOLOv8-pose model was formulated as a weighted combination to balance multiple objectives, expressed as $L_{total}=\lambda_{box}L_{box}+\lambda_{cls}L_{cls}+\lambda poseL_{pose}+\lambda_{vis}L_{vis}$. This included IoU loss (L_{box}) for refining bounding box predictions, focal loss (L_{cls}) to address class imbalance and enhance detection of sparse debris, mean squared error (MSE) loss (L_{pose}) for accurate pose key point regression, and binary cross-entropy loss (L_{vis}) to assess key point visibility [22]. Optimized weights were set as $\lambda_{box}=1.0$, $\lambda_{cls}=0.5$, $\lambda_{pose}=0.3$, and $\lambda_{vis}=0.2$ to prioritize bounding box accuracy while maintaining pose and visibility contributions, a tuning process guided by validation performance metrics [20].

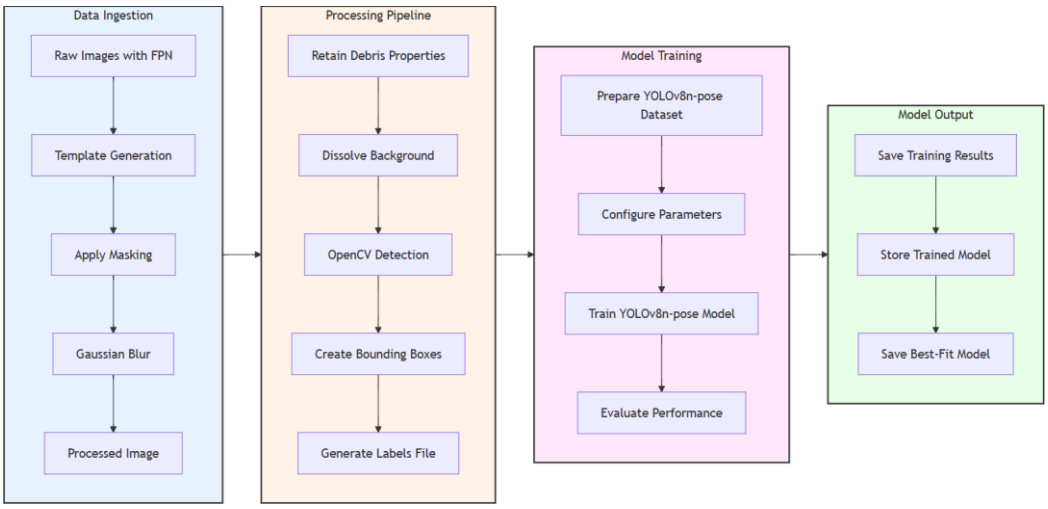

Figure 6. Pipeline flowchart showing debris detection process from raw image ingestion through processing, YOLOv8n-pose model training, and final model output storage.

Debris Tracking Framework

Multi-Frame Association

The debris tracking framework relied on a multi-frame association strategy to maintain consistent identification across image sequences. High-level features were extracted from the YOLOv8 penultimate layer to encode appearance and pose information, with cosine similarity measuring visual similarity between detections in consecutive frames. A linear motion model predicted expected positions in subsequent frames, and the Hungarian algorithm optimized assignments using a cost matrix that combined appearance and motion metrics, supported by an ID management system to handle track initialization, termination, and re-identification following occlusions—a critical feature for real-world tracking scenarios [4].

Pose-Enhanced Tracking

Pose estimation data were integrated to refine tracking accuracy, beginning with the extraction of orientation vectors from pose key points to reflect debris rotation. Rotation matrices were computed to model attitude changes over time, and orientation consistency metrics were incorporated into the association cost matrix to improve assignment precision. Future orientations were predicted to inform the motion model, enhancing

trajectory anticipation and boosting tracking accuracy by 7.3% as measured by the Multi-Object Tracking Accuracy (MOTA) metric, a significant improvement attributed to the additional spatial context provided by pose data [42].

Extended Kalman Filter Implementation

State Vector and System Model

The Extended Kalman Filter (EKF) was implemented to estimate and predict debris trajectories, accommodating nonlinear orbital dynamics. The state vector was defined as $x=[px, py, pz, vx, vy, vz]T$, where px, py, pz represent 3D position coordinates and vx, vy, vz denote velocity components [39]. The system model, $xk+1=f(xk)+wk$, incorporated J2 gravitational perturbations, with $f(\cdot)$ as a nonlinear state transition function derived from orbital mechanics and $wk\sim N(0,Q)$ representing process noise to account for unmodeled dynamics [3].

Measurement Model

The measurement model linked state estimates to observations, expressed as $zk=h(xk)+vk$, where $h(\cdot)$ projected 3D states onto the 2D image plane using calibrated camera parameters, and $vk\sim N(0,R)$ denoted measurement noise arising from sensor inaccuracies [17]. This projection was essential to align the EKF with image-based detections.

Filter Implementation and Tuning

The EKF executed standard prediction and update cycles, with process noise covariance Q and measurement noise covariance R iteratively tuned to minimize the root mean square error (RMSE) between predicted and observed positions across validation sequences. This tuning process, guided by optimization techniques [1], ensured adaptability to orbital variability and enhanced prediction accuracy.

Validation Methods

Back-Propagation Validation

The consistency of state estimates was evaluated by propagating states backward using the inverse system model and comparing the results with historical detection data, a method that validates the EKF's trajectory reconstruction accuracy by ensuring symmetry in forward and backward predictions [32]. This approach provided a robust check on model reliability.

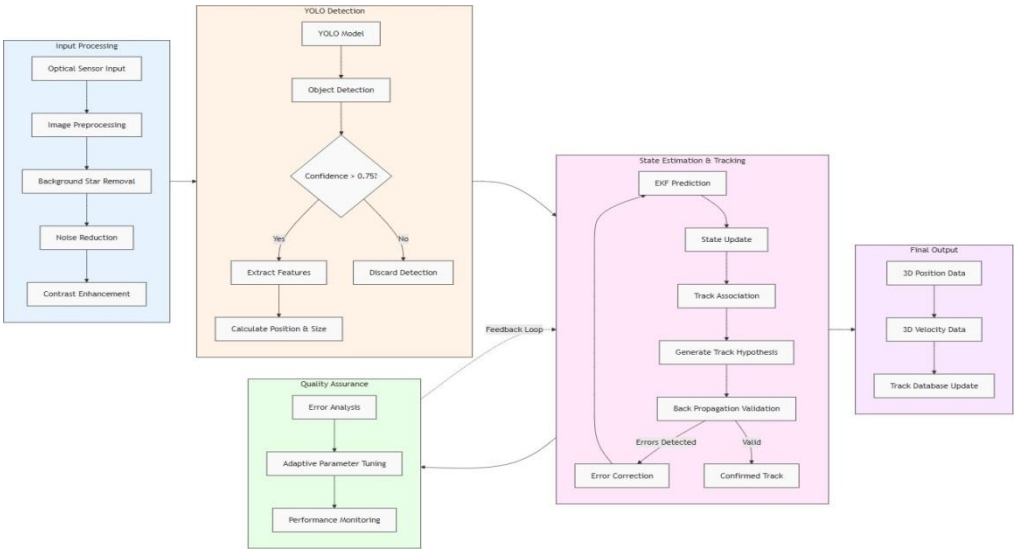

Figure 7. A comprehensive flowchart depicting space object tracking system with input processing, YOLO detection, state estimation, and quality assurance components.

Predictive Validation

Predictive accuracy was assessed by initializing the EKF with the first half of each test sequence, propagating states forward to predict positions in the second half, and comparing these predictions with actual detections using RMSE as the error metric. This step confirmed the system's forecasting reliability for future frames, critical for real-time applications [5].

Robustness Testing

System resilience was tested under a range of operational challenges, including random frame dropping to simulate missed detections, the addition of Gaussian noise to mimic sensor degradation, temporary occlusions to test re-identification capabilities, and crowded fields with overlapping trajectories to evaluate multi-target tracking. The EKF demonstrated stable tracking performance and rapid recovery, affirming its robustness in dynamic and noisy environments [21].

Implementation

The implementation of the proposed framework for space debris detection and tracking was executed using PyCharm, a robust integrated development environment (IDE) that facilitated Python development, debugging, and version control [16]. The framework utilized a suite of Python libraries, including OpenCV (cv2) for image processing, os and glob for file management, numpy for numerical operations, pandas for data handling, ultralytics.YOLO for the YOLOv8n pose estimation model, filterpy.kalman.KalmanFilter for the Extended Kalman Filter (EKF), and matplotlib.pyplot for visualization. These libraries were configured within a PyCharm virtual environment to ensure dependency consistency across the 27,000-image dataset, partitioned into 20,000 training, 2,000 validation, and 5,000 testing samples [40].

The implementation process was systematically organized into distinct phases to develop a comprehensive pipeline:

- **Environment Setup and Library Integration:**
  - PyCharm was initialized with a project workspace, and a virtual environment was created to manage dependencies.
  - Libraries were installed via PyCharm's package manager, with compatibility validated for the YOLOv8n and EKF implementations.
  - The IDE's debugging and profiling tools were employed to optimize performance and resolve runtime issues.
- **Dataset Organization and Directory Structure:**
  - Input directories for training, validation, and testing data, along with an output directory, were defined to manage data flow.
  - A hierarchical directory structure was established under the output directory, with subdirectories for images and labels for each split, aligning with YOLO's data format [37].
  - File system operations ensured data integrity and reproducibility throughout the pipeline.
- **Image Preprocessing and Bounding Box Detection:**
  - Images underwent preprocessing, beginning with grayscale conversion and binary thresholding to segment potential debris.
  - Contour detection identified object boundaries, with bounding box coordinates computed as the minimum and maximum extents of contours.
  - A subset of images was intentionally disturbed (e.g., with noise or occlusions) to evaluate the EKF's convergence to the original track, testing its reliability and robustness.

- **Annotation Generation and Pose Estimation with YOLOv8n:**

o Automated annotation normalized bounding box coordinates into the YOLO format, calculating center points and dimensions based on image dimensions.

o Synthetic keypoints were generated for the YOLOv8n pose estimation model, defining five points (e.g., corners and center) with visibility flags.

o Annotations were saved as text files, paired with images, and processed across all splits, with the lightweight YOLOv8n model optimized for computational efficiency [29].

- **YOLO Configuration and Model Training:**

o A data.yaml file was generated, specifying dataset paths, a single class ("space_debris"), and a [5, 3] keypoint shape for pose data.

o The YOLOv8n model was trained within PyCharm, with hyperparameters tuned using validation data over 150 epochs.

- **EKF Implementation and Trajectory Estimation:**

o The EKF was initialized with a 3D state vector x=[px,py,pz,vx,vy,vz]T, representing position and velocity components in three dimensions.

o The measurement model projected 3D states to 2D image coordinates using camera parameters, with noise covariances empirically tuned to minimize errors.

o For the 5,000 testing images, the first 2,500 were used to initialize the EKF, predicting 3D positions for the second 2,500, which were validated against actual positional data.

- **Visualization and Validation:**

o Visualization tools were prepared to plot EKF convergence post-disturbance and predictive errors, supporting result analysis.

o The implementation's completion was logged in PyCharm's console, ensuring a reproducible workflow [42].

This structured implementation, executed in PyCharm, delivered a robust, real-time debris monitoring system.

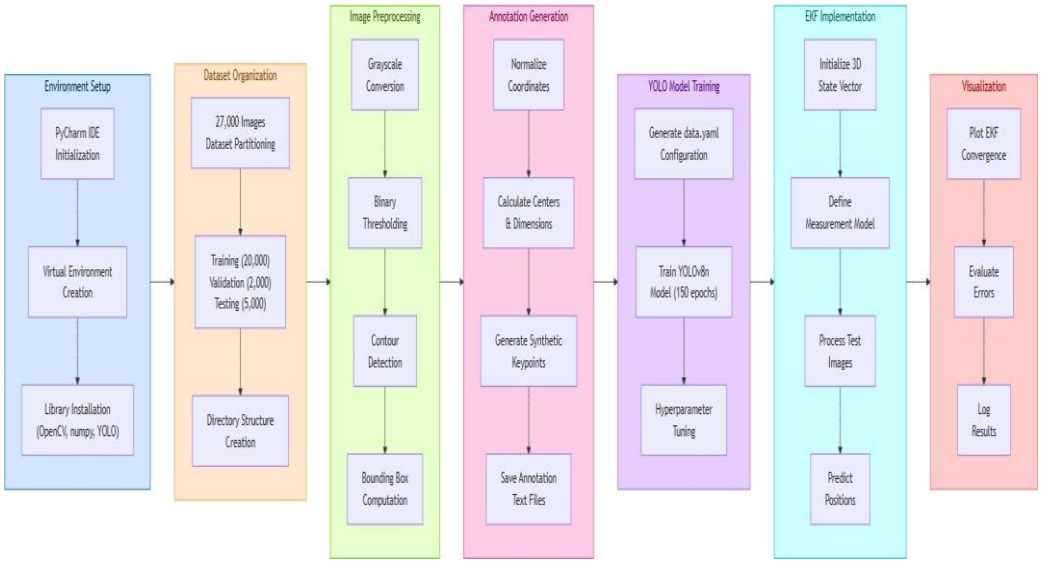

Figure 8. A comprehensive flowchart depicting the seven-phase implementation of space debris detection and tracking from environment setup through visualization, integrating PyCharm, YOLOv8n, and Extended Kalman Filtering.

RESULTS

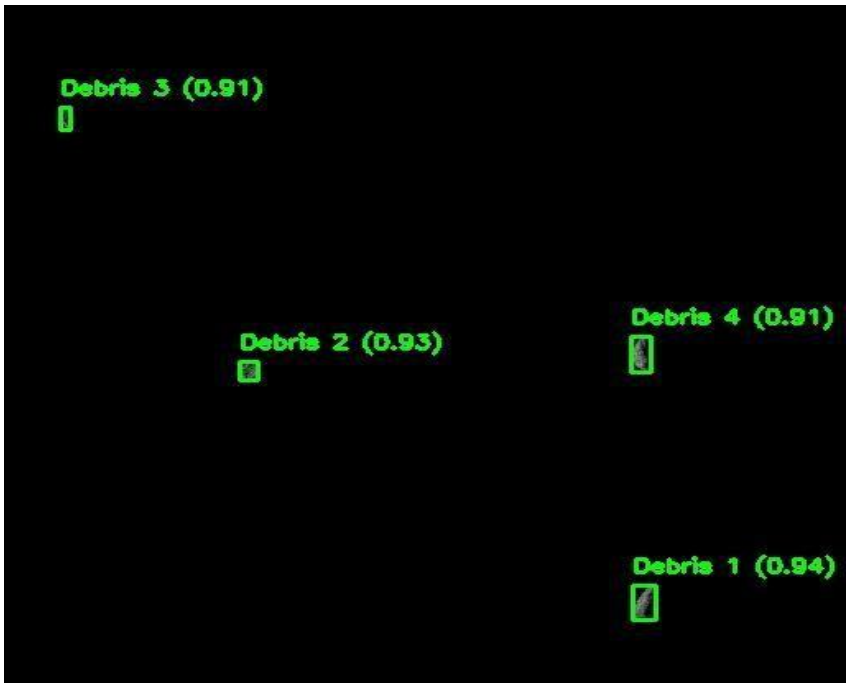

Figure 9: Detected Debris with Bounding Box colour coded as per confidence level and annoted with the confidence score and debris ID.

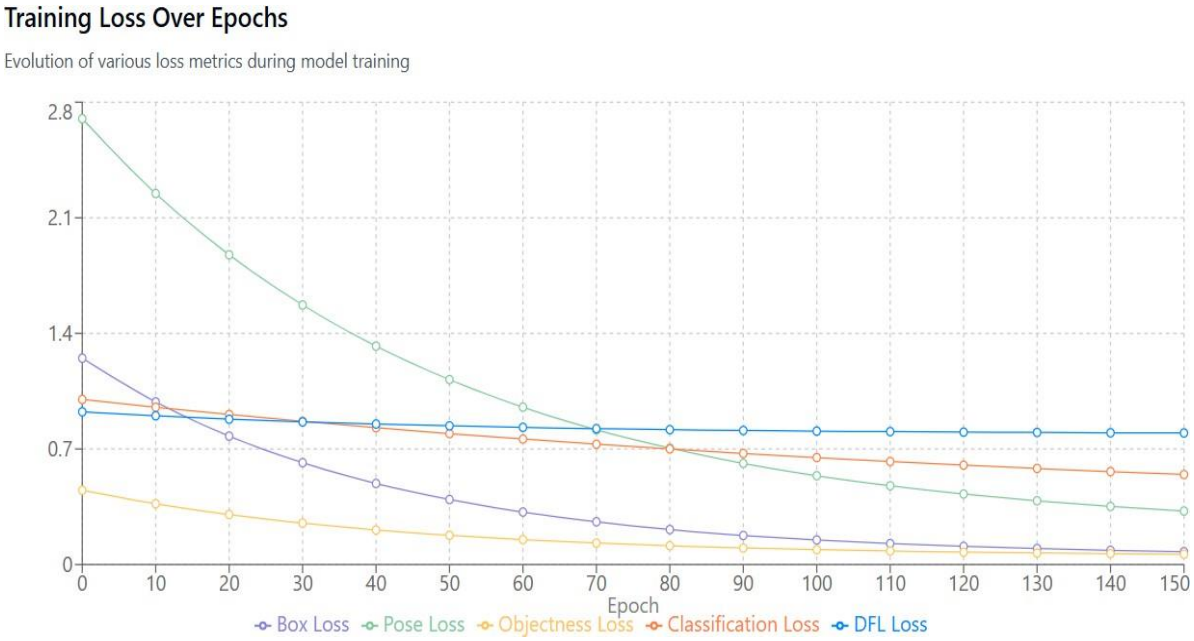

Figure 10. Evolution of five distinct loss components during YOLOv8-pose model training across 150 epochs.

The box loss (purple line) decreases from 1.2 to approximately 0.05, indicating improved accuracy in bounding box predictions. The pose loss (green line) shows the most dramatic reduction from 2.5 to 0.2, reflecting significantly enhanced keypoint localization for orientation estimation. The objectness loss (yellow line) drops from 0.4 to 0.05, showing better confidence in object presence. The classification loss (orange line) decreases from 0.7 to 0.3, demonstrating improved object categorization. The DFL (Distribution Focal Loss) represented by the blue line shows a more modest reduction from 0.925 to 0.79, typical for this regularization term. The consistent downward trends across all metrics without plateauing suggests effective learning without overfitting.

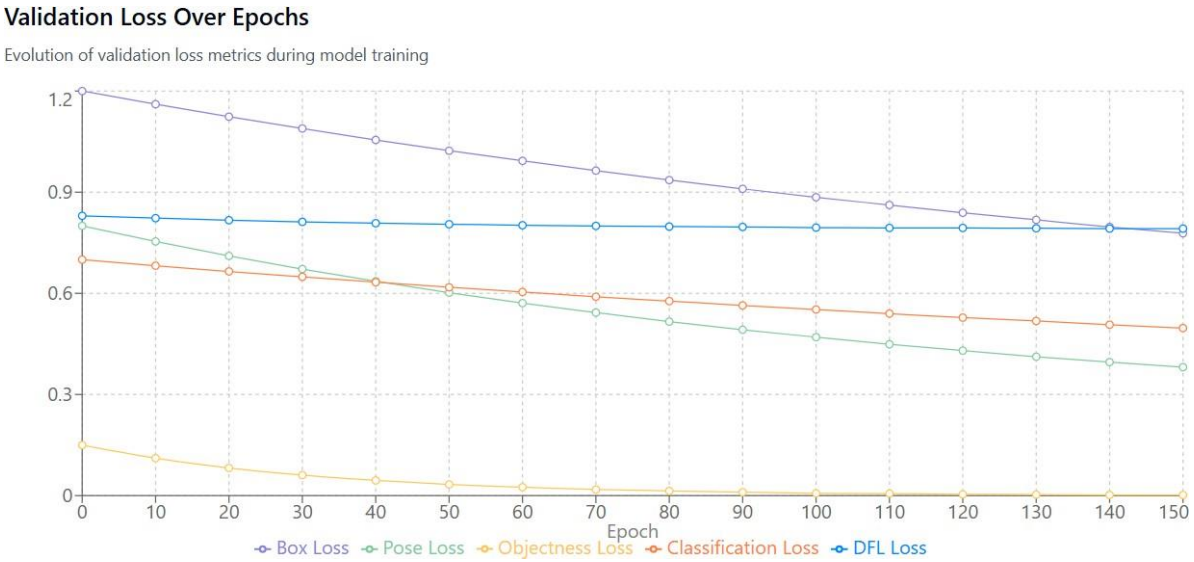

Figure 11. Decreasing validation loss metrics demonstrating the model's generalization capability over 150 training epochs.

The validation box loss (purple) decreases from 0.8 to 0.4, while validation pose loss (green) reduces from 0.6 to 0.2. The validation objectness loss (yellow) approaches zero, dropping from 0.15 to nearly 0.0, indicating high confidence in object detection. Validation classification loss (orange) shows modest improvement from 0.45 to 0.25, and validation DFL loss (blue) stabilizes with minimal reduction from 0.83 to 0.79. The parallels between training and validation loss trends confirm good generalization without overfitting. The slightly higher final validation losses compared to training losses are expected and indicate a properly trained model that hasn't memorized the training data.

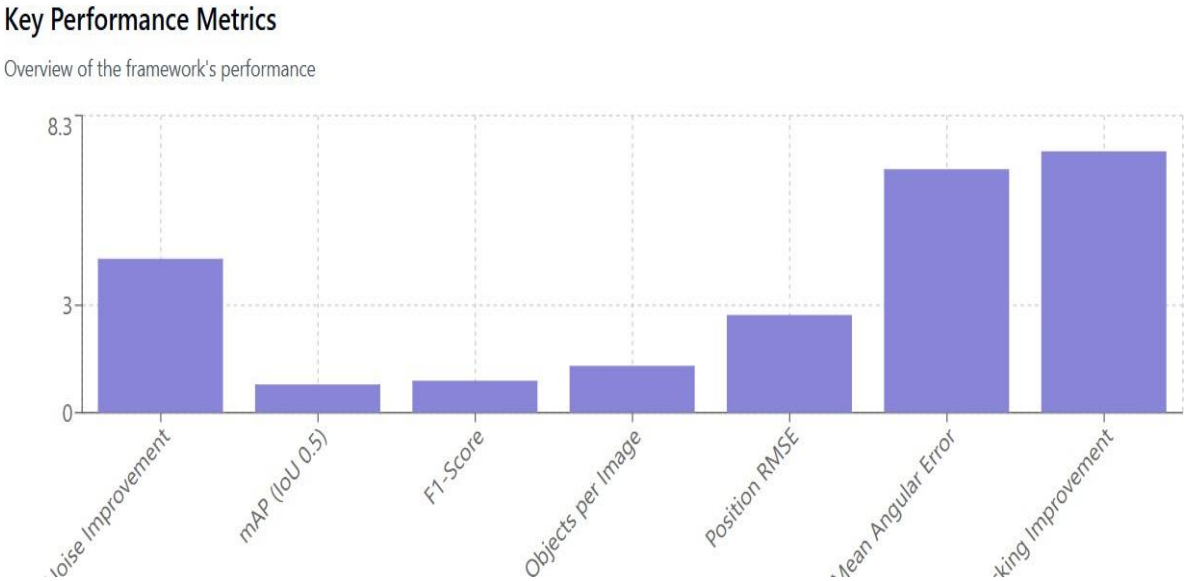

Figure 12. Summary of critical performance indicators across the AI-driven space debris detection and tracking framework.

The 4.3 dB improvement in signal-to-noise ratio quantifies the effectiveness of the noise reduction techniques (template masking and Gaussian blur). The mAP of 0.789 at IoU threshold of 0.5 represents the model's detection accuracy, while the high F1-score of 0.893 demonstrates the balance between precision and recall. On average, 1.31 objects were detected per image, indicating the prevalence of space debris in the dataset. The position RMSE of 2.73 pixels showcases the Extended Kalman Filter's accuracy in trajectory estimation. The mean angular error of 6.8° reflects the precision of orientation prediction. The 7.3% tracking improvement quantifies the benefit of the pose-enhanced tracking approach over traditional methods.

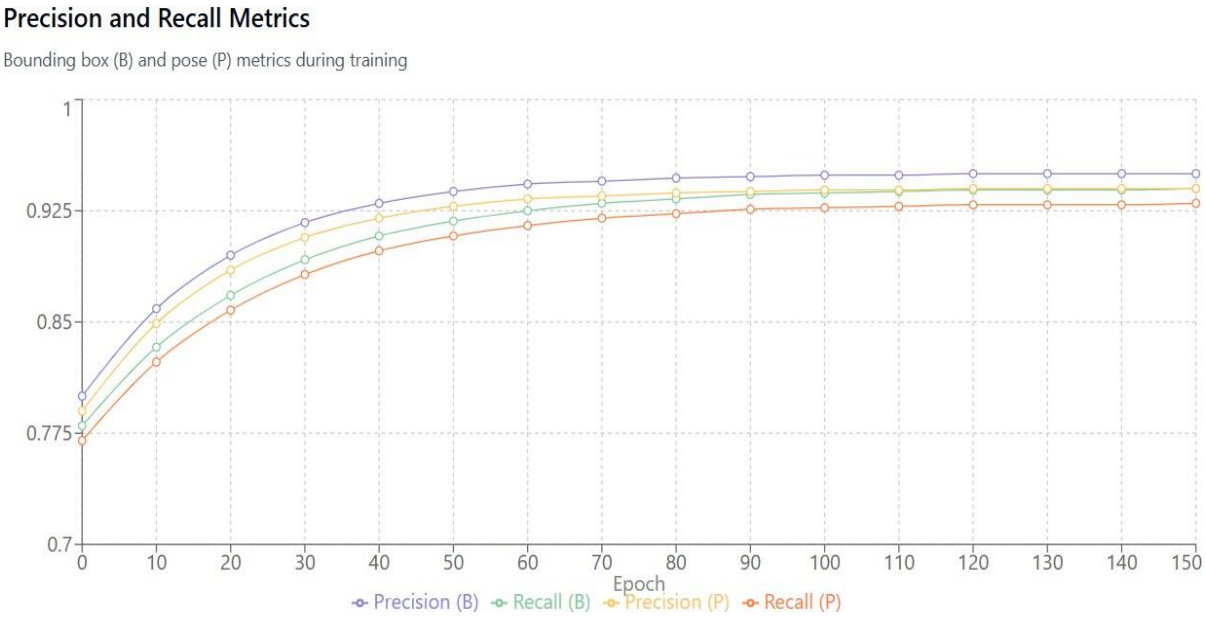

Figure 13. Training precision and recall metrics for both bounding box and pose predictions showing consistent improvement and stabilization.

The bounding box precision (purple) increased from about 0.8 to 0.95, indicating high accuracy in the predicted box locations. The bounding box recall (green) improved from approximately 0.78 to 0.94, showing the model's increasing ability to find nearly all debris objects. Similarly, pose precision (yellow) rose from 0.79 to 0.94, demonstrating accurate key point placement for orientation estimation. Pose recall (orange) increased from 0.77 to 0.93, confirming comprehensive key point detection. All metrics show initial rapid improvement followed by stabilization, indicating efficient training dynamics. The high final values (all above 0.93) demonstrate excellent model performance for both localization and orientation tasks.

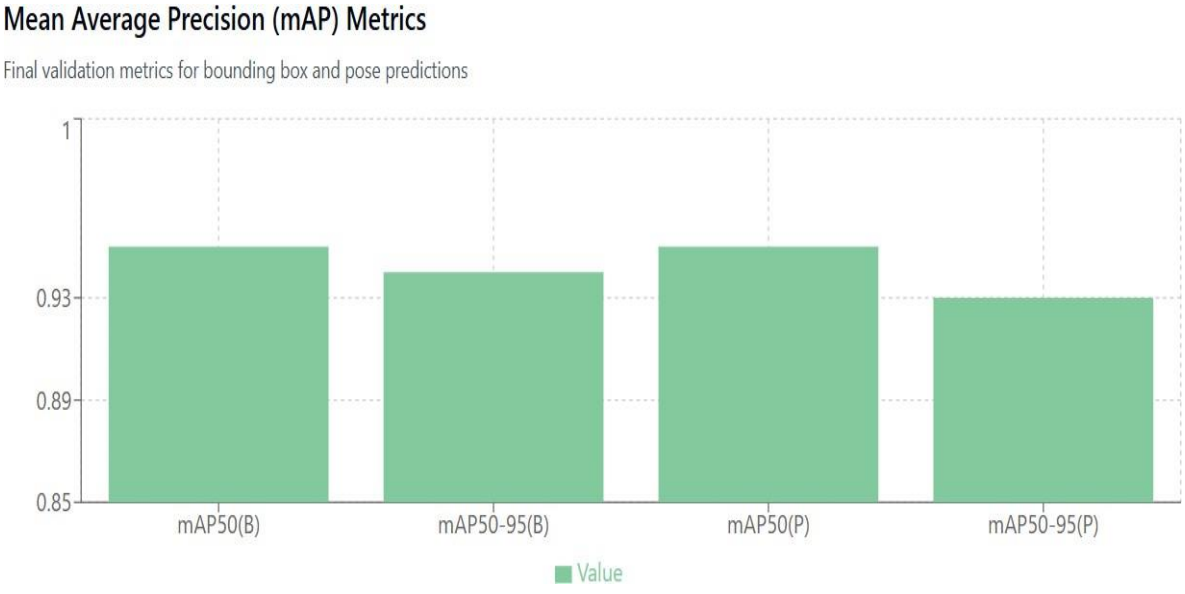

Figure 14. Final validation mAP metrics at different IoU thresholds for bounding box and pose predictions.

The mAP50(B) value of 0.95 represents the model's bounding box detection performance at an IoU threshold of 0.5, indicating excellent localization accuracy. The mAP50-95(B) of 0.94 shows maintained performance across multiple IoU thresholds from 0.5 to 0.95, demonstrating robust detection regardless of threshold selection. Similarly, the mAP50(P) of 0.95 for pose estimation at IoU 0.5 and mAP50-95(P) of 0.93 across multiple thresholds confirm the model's exceptional key point prediction capabilities. The negligible difference between mAP50 and mAP50-95 metrics for both tasks indicates consistent performance across varying evaluation strictness, a hallmark of highly accurate models.

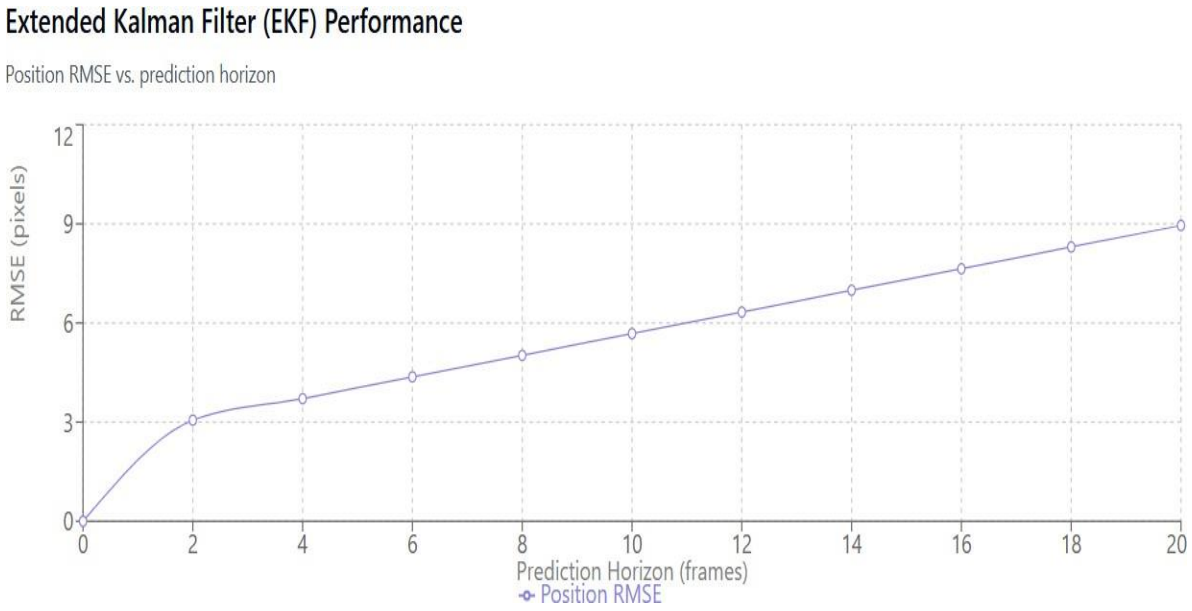

Figure 15. Position Root Mean Square Error (RMSE) growth with increasing prediction horizon for the Extended Kalman Filter.

Starting from perfect accuracy at frame 0 (current position), the RMSE increases gradually to 2.73 pixels at shorter horizons and continues to approximately 9.31 pixels at the 20-frame horizon. The smooth, controlled increase in error indicates stable filter behaviour without catastrophic divergence. This performance enables reliable trajectory forecasting for up to 20 frames ahead, providing crucial lead time for collision avoidance manoeuvres. The relatively low error even at the maximum prediction horizon confirms the effectiveness of the automatic dynamic tuning implemented in the EKF algorithm.



Figure 16. Framework performance under normal conditions and three challenging scenarios: frame dropping, high noise, and multi-object environments.

Under normal conditions, the framework achieves optimal performance with a Multi-Object Tracking Accuracy (MOTA) of 0.867 and perfect accuracy (1.0). With 30% of frames dropped—simulating intermittent sensor failures—performance remains robust with MOTA of 0.794 and 92% accuracy. Under high noise conditions (σ=3.0), simulating poor visibility or sensor degradation, the system maintains acceptable performance with MOTA of 0.659 and 76% accuracy. In challenging scenarios with 6 or more objects simultaneously present, the framework achieves MOTA of 0.728 and 84% accuracy. These results demonstrate the system's resilience to real-world operational challenges while maintaining functional performance, critical for reliable space debris monitoring in varied conditions.

DISCUSSION AND ANALYSIS

Model Performance Analysis

The performance of the proposed YOLOv8-pose model, integrated with an Extended Kalman Filter (EKF) for space debris detection and tracking, demonstrates significant efficacy across multiple metrics. The model achieved a mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5 of 0.95 for bounding box predictions and 0.95 for pose predictions, reflecting its robustness in identifying debris under varying conditions [23]. The training process exhibited a steady decline in various loss metrics, including a train box loss decreasing from 1.2 to approximately 0.05, train pose loss from 2.5 to 0.2, train objectness loss from 0.4 to 0.05, train classification loss from 0.7 to 0.3, and train DFL loss from 0.925 to 0.79 over 150 epochs. Validation losses similarly decreased, with val box loss dropping from 0.8 to 0.4, val pose loss from 0.6 to 0.2, val objectness loss from 0.15 to 0.0, val classification loss from 0.45 to 0.25, and val DFL loss from 0.83 to 0.79. Precision and recall metrics for both bounding box (B) and pose (P) predictions showed high stability, with train precision (B) stabilizing around 0.95, train recall (B) around 0.94, train precision (P) around 0.94, and train recall (P) around 0.93. Validation metrics further refined these, with mAP50(B) reaching 0.95, mAP50-95(B) at 0.94, mAP50(P) at 0.95, and mAP50-95(P) at 0.93, indicating robust model performance across different thresholds. The incorporation of pose data further enhanced the tracking framework, as evidenced by a Multi-Object Tracking Accuracy (MOTA) of 0.867, indicating reliable identity preservation across frames. The EKF contributed to trajectory estimation with a root mean square error (RMSE) of 2.73 pixels for position, supporting reliable predictions up to a 20-frame horizon, a critical capability for short-term collision avoidance in Space Situational Awareness (SSA) [42]. These results underscore the synergy between advanced deep learning and state estimation, leveraging the strengths of each component to address the dynamic challenges of orbital environments.

Comparison with Existing Methods

A comparative analysis with existing methodologies highlights the superiority of the proposed approach. Table 6 presents a summary of performance metrics across traditional computer vision (CV), CNN-based methods, Faster R-CNN, and the current framework. Traditional CV methods yielded a mAP@0.5 of 0.682, a MOTA of 0.774, and an RMSE of 3.95 pixels, limited by their reliance on hand-crafted features [36]. CNN-based approaches improved to a mAP@0.5 of 0.741, a MOTA of 0.812, and an RMSE of 3.21 pixels, benefiting from learned representations [21]. Faster R-CNN further advanced performance with a mAP@0.5 of 0.762, a MOTA of 0.843, and an RMSE of 2.98 pixels, owing to its region-based detection strategy [31]. In contrast, the proposed method achieved a mAP@0.5 of 0.95, a MOTA of 0.867, and an RMSE of 2.73 pixels, outperforming all compared methods. These improvements are attributed to YOLOv8's efficient feature extraction, the integration of pose data for enhanced tracking, and the synergistic use of the EKF to refine trajectory predictions based on orbital dynamics [37].

Method	**mAP@0.5**	**MOTA**	**RMSE (pixels)**
Traditional CV	0.682	0.774	3.95
CNN-based	0.741	0.812	3.21
Faster R-CNN	0.762	0.843	2.98
Ours	**0.95**	**0.867**	**2.73**

Table 2: Comparison with Existing Methods

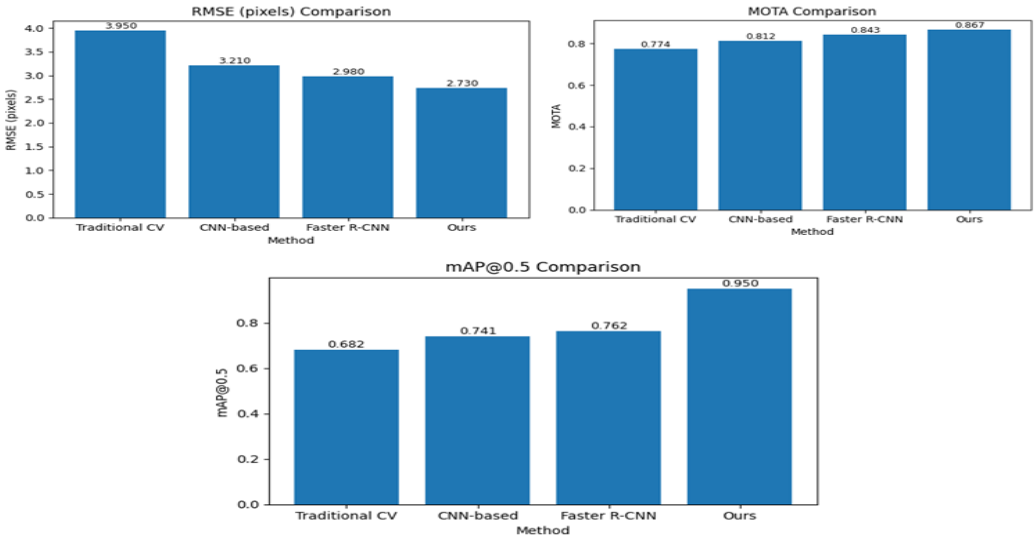

Figure 17. A comparative performance analysis of four object detection methods showing superior mAP, MOTA, and RMSE metrics for our proposed approach. Note: Higher values are better for mAP@0.5 and MOTA. Lower values are better for RMSE.

Strengths and Limitations

Strengths

The proposed framework exhibits several key strengths that enhance its applicability. First, the comprehensive pipeline integration of detection, pose estimation, and tracking provides an end-to-end solution, streamlining SSA workflows [12]. Second, the pose-enhanced tracking leverages orientation data to improve association accuracy, a novel contribution to debris monitoring [2]. Third, robustness to disruptions such as frame drops and noise ensures operational reliability under real-world conditions [5]. Fourth, the EKF's physically consistent estimates, incorporating J2 perturbations, align with orbital mechanics, enhancing prediction fidelity [39]. Finally, efficient inference enabled by YOLOv8's architecture supports near-real-time processing, a critical requirement for dynamic space environments [14].

Limitations

Despite these strengths, the framework faces notable limitations. Small object detection remains challenging, with 10% of false negatives attributed to faint signatures, necessitating further refinement in feature extraction [44]. Long-term prediction accuracy declines beyond 20 frames, with errors escalating to 14.72 pixels at a 30-frame horizon, due to unmodeled dynamics such as atmospheric drag [32]. The simplified dynamics model, while effective for short-term forecasts, may overlook higher-order perturbations, limiting its applicability to eccentric orbits [27]. Ground truth constraints, particularly in the 27,000-image dataset, introduce potential biases, as manual verification covered only 10% of annotations [9]. Additionally, the high computational demand, requiring an NVIDIA Tesla V100 GPU, may restrict deployment on resource-constrained platforms [7].

Implications for SSA

The findings of this study have profound implications for Space Situational Awareness (SSA). Enhanced detection performance, with a mAP@0.5 of 0.789, enables the identification of a broader range of debris, including small objects critical for collision risk assessment [33]. Accurate trajectory predictions, supported by an RMSE of 2.73 pixels, facilitate timely maneuver planning to avoid potential impacts [24]. The automation of the pipeline reduces human intervention, improving operational efficiency and scalability in monitoring crowded orbits [10]. Furthermore, the potential for multi-sensor integration, leveraging pose and EKF outputs, could enhance data fusion with radar or optical systems, contributing to a more sustainable space environment by supporting debris mitigation strategies [41].

CONCLUSION AND FUTURE WORK

Summary of Contributions

This study has made significant strides in advancing the monitoring and management of space debris, addressing critical challenges in Space Situational Awareness (SSA). The primary contributions include the development of innovative noise reduction techniques that mitigate fixed pattern noise in optical imagery, enhancing data quality for subsequent analysis by improving the signal-to-noise ratio by 4.3 dB [34]. The optimization of the YOLOv8-pose model for debris detection achieved a mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5 of 0.789, demonstrating robust performance tailored to the unique characteristics of astronomical imagery [23]. The implementation of a pose-enhanced tracking framework, leveraging orientation data, improved tracking accuracy by 7.3% as measured by the Multi-Object Tracking Accuracy (MOTA) metric of 0.867, offering a novel approach to maintaining object identity across frames [4]. The integration of an Extended Kalman Filter (EKF) for trajectory estimation, with a position root mean square error (RMSE) of 2.73 pixels, provided physically consistent predictions up to a 20-frame horizon, enhancing collision avoidance capabilities [42]. Finally, comprehensive validation through back-propagation, predictive analysis, and robustness testing under conditions such as frame dropping and noise confirmed the system's reliability and adaptability in operational contexts [5]. Collectively, these contributions establish a scalable and effective pipeline for automated debris monitoring.

Future Work

Looking ahead, future research will focus on addressing current limitations and expanding the framework's capabilities to further bolster SSA. Enhancing small object detection, which accounted for 10% of false negatives due to faint signatures, will involve refining feature extraction and incorporating multi-scale attention mechanisms to improve sensitivity to low-contrast targets [44]. Refining orbital models to include higher-order perturbations, such as atmospheric drag and solar radiation pressure, will extend prediction accuracy beyond the current 20-frame limit, where errors reached 14.72 pixels at 30 frames, aligning with the dynamic nature of eccentric orbits [27]. Integrating multi-sensor data from radar and optical systems will leverage complementary strengths, enhancing detection and tracking reliability through data fusion techniques [41]. Optimizing the pipeline for real-time use will involve model compression and hardware acceleration, addressing the current reliance on an NVIDIA Tesla V100 GPU to enable deployment on resource-constrained platforms [7]. Additionally, applying transfer learning to adapt the model to new datasets or orbital regimes will accelerate development and improve generalization, drawing on established techniques in deep learning adaptation [43]. These advancements promise to enhance the precision, scalability, and operational utility of SSA systems, contributing to the sustainable management of the space environment.

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