AI-Driven Space Debris Detection, Tracking and Removal System

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***Abstract*—The growing number of inactive satellites, spent launch components and collision fragments presents a continuing hazard to operational spacecraft. Detecting an object is only one part of the problem: its movement must also be followed, possible conjunctions assessed, and a response made available to an operator or removal mechanism. This paper describes an integrated academic prototype for space-debris monitoring that combines computer-vision detection, state estimation, proximity sensing, a small robotic capture mechanism and a browser-based visualisation. The software workflow uses YOLOv8 to identify debris-related objects in image frames and combines detections with tracking and orbital information to estimate motion and assess risk. An ESP32-based hardware layer coordinates sensing and actuation, while a tabletop moving platform and servo-driven arm demonstrate capture of physical debris analogues. The project report records 94.2% detection precision, 0.91 mAP@0.5, 0.9 km position RMSE for the YOLOv8–Unscented Kalman Filter (UKF) tracking pipeline, and 55 successful captures in 60 trials. These values describe the reported test setup and should not be interpreted as flight-system performance: the physical platform emulates selected behaviours at laboratory scale. The contribution is an end-to-end demonstrator that links perception, tracking, risk indication and a tangible removal action in a relatively low-cost educational environment.**

***Index Terms*—space debris, YOLOv8, computer vision, Unscented Kalman Filter, SGP4, ESP32, collision risk, robotic arm, 3D visualisation.**

I. INTRODUCTION

Satellites support communication, navigation, weather observation and scientific missions, but the orbital environment is increasingly shared with objects that no longer serve a useful purpose. Defunct spacecraft, discarded launch stages and fragments from break-ups can remain in orbit for long periods. Because relative orbital velocities are high, even a small fragment can damage a functioning satellite. A collision may also create further fragments, increasing the hazard for later missions.

Space Situational Awareness systems commonly combine radar or optical observations with orbit catalogues and mathematical propagation. These capabilities are important, but the full process remains challenging when observations are sparse, objects are faint or small, and detections must be converted into actionable warnings.
Tracking and removal are also often treated as separate engineering problems. For an academic team, access to operational sensors and flight-qualified removal equipment is impractical.

This work therefore develops a laboratory-scale system that demonstrates the main stages of a debris-management workflow: image-based object detection, movement tracking, collision-risk indication, sensor-supported response and robotic capture of a physical analogue. The platform is intended for experimentation and learning; it does not claim to detect or remove debris directly in orbit.

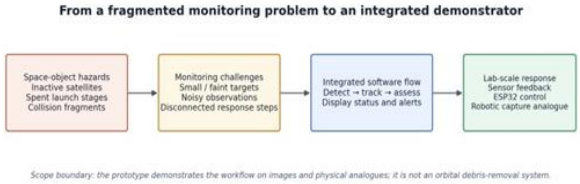


Fig. 1. Motivation and scope of the integrated debris-management demonstrator.

II. PROBLEM DEFINITION AND OBJECTIVES

The central problem is to connect object perception with a usable response while keeping the prototype affordable and reproducible. A detection-only application can mark an object in an image, but does not by itself preserve an object's identity across frames, estimate its evolving state, or demonstrate what happens after a risk is identified. Conversely, a capture mechanism operating without reliable perception may fail to locate or grasp the target.

The project has four objectives: (1) detect debris-like objects and related space-object classes from camera imagery; (2) track detections and estimate motion using a filter-based approach supported by orbital information where available; (3) communicate risk and system status through a visual interface; and (4) demonstrate a physical response using an ESP32-controlled platform and servo-actuated arm. A further objective is to document the software and hardware in a form suitable for undergraduate research.

III. RELATED WORK

Recent space-object research covers optical detection, orbit estimation, conjunction assessment and active debris removal. Deep-learning detectors such as the YOLO family provide a practical way to localise objects in images, while tracking filters help combine noisy observations over time. Orbital propagators such as SGP4 provide a physics-based estimate of an object's future state from Two-Line Element (TLE) data. These methods address complementary parts of the monitoring problem rather than replacing one another.

The project report's literature review highlights three recurring limitations: some detection and tracking approaches are validated mainly on synthetic imagery; many monitoring studies stop at an alert rather than connecting perception to a removal demonstration; and flight-scale active debris removal is too costly for routine undergraduate experimentation. The design presented here responds to these gaps through mixed image sources, a hybrid detection-and-tracking workflow, and a tabletop robotic capture demonstration. Detailed comparisons should be supported by verified bibliographic records for each cited study before submission.

IV. PROPOSED SYSTEM ARCHITECTURE

The prototype is organised into five connected layers. The sensing layer collects camera frames and short-range distance measurements. The perception layer applies image preprocessing and YOLOv8 inference to locate and classify visible objects. The tracking and risk layer associates' detections over time and uses state estimates and orbital information, where available, to support movement analysis. The actuation layer receives a capture or response command and controls the moving platform and arm. Finally, the visualisation layer presents detections, system status and risk indications to the user.

The ESP32 serves as the hardware control and communication unit. The project report specifies an HC-SR04 ultrasonic sensor for short-range distance estimation, an OV2640 camera module for video input, a DC motor with a driver for platform movement, and servo motors for arm motion. Computationally heavier visual inference is handled by an edge computer rather than assumed to run entirely on the microcontroller. This division separates timing-sensitive sensor and actuator control from image-model processing.

The browser dashboard is intended to show a 3D representation of Earth and orbital paths alongside detections and risk states. The physical model uses small objects as debris analogues. It is a controlled demonstration of the detect–decide–actuate sequence, not a physical reproduction of orbital mechanics or microgravity.

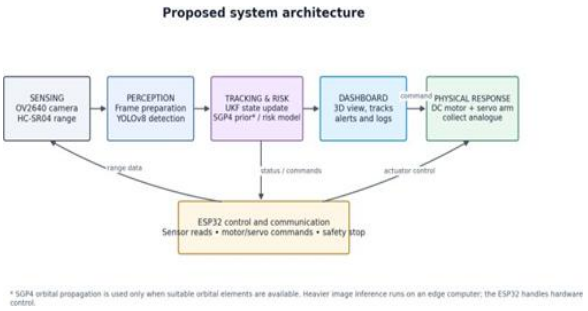


Fig. 2. Proposed architecture linking image processing,

V. METHODOLOGY

A. Image Preparation and Object Detection

Image frames are collected from the sources described in the project report, including public or rendered

imagery and laboratory captures. The reported dataset contains 5,000 annotated images across three classes: debris, satellite and rocket body. Labels are represented in YOLO format. Preprocessing and augmentation are used to expose the detector to variations in colour, orientation, scale and background. YOLOv8 is then trained and evaluated on a held-out test subset. Detection output consists of a class label, bounding box and confidence score.

B. Tracking and State Estimation

Detections from successive frames must be associated so that the system can estimate a continuous movement history rather than treating each frame independently. The reported approach combines an Unscented Kalman Filter with SGP4-based propagation. The filter updates an estimated state using incoming observations while accounting for uncertainty. SGP4 provides an orbital prior when suitable TLE data are available. This hybrid design is intended to retain a physics-based reference while allowing observations to correct the evolving estimate.

C. Collision-Risk Indication

Risk assessment considers the relative state of a debris object and a protected satellite. The report describes a gradient-boosting/XGBoost-based classifier using conjunction-related features, including miss distance, relative velocity, uncertainty and time to closest approach.

The dashboard communicates the assessed state through visual risk categories and warning indications. Risk thresholds and training-data provenance must be clearly documented in any publication; a tabletop sensor reading alone cannot establish an actual orbital collision probability.

D. Hardware Response and Capture

For the physical demonstration, the ultrasonic sensor measures the distance to a nearby target, the DC motor moves the model platform, and servo motors position the robotic arm to pick up a debris analogue and place it in a designated collection area. The ESP32 coordinates sensor readings and actuator commands. A stop/failsafe response is important if communication is interrupted or an actuator does not behave as expected. The physical capture test evaluates the integrated prototype under controlled laboratory conditions only.

E. Visualisation and Logging

The dashboard provides a unified view of the perception output, tracking status, risk indication and hardware state. Event records can include timestamps, sensor range, detector confidence and capture outcome. Separating these modules allows each part to be tested individually and makes failures easier to diagnose during integration.

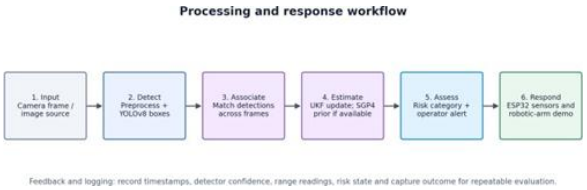


Fig. 3. Processing sequence from input imagery to the laboratory response and event logging.

VI. EXPERIMENTAL SETUP AND REPORTED RESULTS

The project report describes evaluation of the detector on a 500-image test split containing 1,010 labelled instances, testing of ultrasonic ranging at multiple distances, and 60 autonomous capture trials. The following values are reproduced from the report and should be retained only if the team can provide the corresponding logs, plots or test records.

Table I. Dataset and test quantities stated in the project.

Evaluation component	Reported setup	Use in evaluation
Annotated image dataset	5,000 images; 3 classes	Training and detector development; confirm split details
Detector test subset	500 images; 1,010 labelled instances	Image-level detection evaluation
Physical capture test	60 trials; 55 successful captures reported	Laboratory analogue capture success
Short-range ranging	HC-SR04; 97.5% accuracy reported at 1 m	Local distance sensing, not orbital measurement

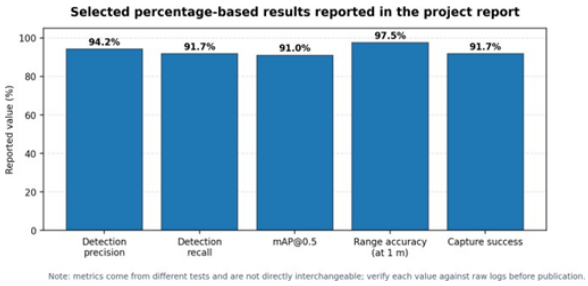


Fig. 4. Percentage-based results as stated in the project report; the underlying tests differ by metric.

Table II. Summary of the performance values reported in the project.

Evaluation item	Reported result	Interpretation
YOLOv8 detection	94.2% precision; 0.91 mAP@0.5	Image-based object localisation on the reported dataset
Detection recall	91.7%	Fraction of labelled instances recovered in the reported evaluation
Tracking	0.9 km position RMSE	Reported result for the YOLOv8–UKF/SGP4 workflow
Inference speed	38 FPS on RTX 3060	Hardware- specific throughput; not a universal speed figure
Ultrasonic ranging	97.5% accuracy at 1 m	Short-range laboratory measurement under the stated test conditions
Robotic capture	55/60 trials; 91.7% success	Laboratory capture success for physical analogues
Sense-to-capture latency	Mean 2.1 s; under 2.3 s reported	End-to-end response time in the tested prototype
Estimated hardware cost	Approximately ₹6,350	Report estimates; prices and final bill of materials should be checked

The report also records a comparison in which the combined YOLOv8–UKF approach has lower position RMSE than the SGP4-only baseline. These results suggest that combining visual observations with filtering can improve the consistency of the prototype's state estimate. The capture trials indicate that the software and hardware can be linked in a repeatable laboratory sequence. However, results from a tabletop model cannot establish performance against real orbital debris, where range, lighting, tumbling, dynamics and sensing conditions differ substantially.

For a final conference submission, include the dataset split protocol, model version and configuration, computing platform, definition of each metric, number of repetitions, and any failed trials. Do not report a metric unless its calculation can be reproduced from the team's evaluation artefacts.

VII. DISCUSSION

The main value of the proposed system is the integration of several functions in one demonstrator. The detector provides image-level localisation; the tracking module introduces temporal consistency; the risk component converts state information into a warning; and the robotic arm makes the response visible as a physical action. The modular arrangement also allows future work to replace the detector, refine tracking or improve the actuator without redesigning the entire application.

Several limitations remain. The laboratory sensor measures nearby objects rather than objects at orbital distances. The platform does not reproduce microgravity, full three-dimensional tumbling or true orbital dynamics. Detector performance depends on the diversity and quality of the training data, while orbit estimates depend on observation quality and the validity of orbital inputs. The physical arm is a demonstration mechanism, not flight-qualified capture equipment. These boundaries should be explicit so that the educational contribution is not confused with operational space capability.

VIII. CONCLUSION AND FUTURE WORK

This paper presents a low-cost, laboratory-scale framework for demonstrating space-debris detection, tracking, risk indication and physical capture in a connected workflow. The design combines YOLOv8-based visual detection, filter-supported tracking, ESP32-based sensor and actuator control, and dashboard visualisation. According to the project report, the prototype achieved 94.2% detection precision, 0.9 km tracking RMSE and a 91.7% success rate across 60 physical capture trials. These figures

require traceable test evidence and apply only to the reported evaluation conditions.

Future development can improve the diversity of the image dataset, evaluate performance under additional lighting and motion conditions, strengthen multi-sensor fusion, quantify uncertainty in risk estimates, and improve the robustness of the capture mechanism. More rigorous comparisons with established baselines and reproducible release of configurations and test logs would strengthen the research contribution. Any extension toward operational use would require independent validation with appropriate space-surveillance data and substantially different hardware.

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