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INTELLIGENT PLATFORM FOR ORBITAL DEBRIS TRACKING, COLLISION AVOIDANCE

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Abstract: The radical growth in Low Earth Orbit (LEO) satellite constellations has elevated distress encircling orbital debris management, collision threat, and long-term space viability. The present tracking systems are primarily reactive, frequently providing limited predictive precision and slowed mitigation possibility. This research paper presents DEB-X (Debris eXterminator), a layered and AI-powered model developed for debris detection, collision probability evaluation, and proactive mitigation. This model includes live Two-Line Element (TLE) datasets, and space weather parameters such as solar flux and geomagnetic indices, also utilises drag modelling to forecast orbital decay and trajectory movements. Through multi-phase development, DEB-X combines AI-based forecasting, Monte Carlo simulations, and conjunction analysis to group high-risk encounters and generate $\triangle$v (change in velocity)-based movement strategies optimised for fuel efficiency. The architecture further adds explainable AI (XAI) layers to improve operator trust, and provides automated datasets, user-friendly dashboards and visualisation tools for optimised situational awareness. Verification demonstrates (greater than) >92% accuracy in collision prediction with notable reductions in response delay. By merging physics-based models with intelligent prediction, DEB-X improves the state of Space Situational Awareness (SSA) and provides scalable solutions for global mega-constellations, while aiding future human spaceflight programmes such as ISRO's planned Gaganyaan mission.

Keywords: **Orbital Debris, Collision Prediction, Space Situational Awareness, Machine-Learning Forecasting, Low Earth Orbit.**

I. INTRODUCTION

The increase of LEO satellite constellations has progressed over the past decade, driven by rapid demand for global broadband, Earth-observation, and navigation services. According to the ESOC, more than 42,000 trackable objects larger than 10 cm, and millions of smaller bits, currently orbit the Earth. This number is likely to increase sharply as mega-constellations such as SpaceX Starlink (~42,000 satellites), OneWeb (~6,000 satellites), and Amazon Kuiper (~3,000 satellites) continue deployment. Even small debris fragments traveling at velocities over 27,000 km/h are capable of destroying operational satellites on impact.[2]

Past events, such as the 2009 Iridium-33 and Cosmos-2251 collision, produced over 2,000 trackable debris fragments, causing communication breaks and an estimated loss of millions of dollars. Without proactive mitigation, the series of debris collisions - initiating a chain reaction known as Kessler Syndrome - which could make critical orbital regions unusable, and affecting billions of dollars of satellite infrastructure and lead to failed missions.[5]

Current SSA frameworks, including NASA's Orbital Debris Program, ESA's Space Debris Office, and ISRO's NETRA, are largely reactive. They focus on recording debris and issuing after-the-fact warnings, frequently with limited predictive accuracy, high response latency, and minimal explainability. Analytical methods for collision avoidance manoeuvres have been improved, such as the architecture by Gonzalo et al.[3], but these systems hardly provide combined decision support for proactive avoidance in congested orbital corridors.

To tackle these limitations, this paper presents DEB-X, a layered, AI-driven model for debris detection, collision probability assessment, and proactive mitigation. DEB-X acquires live TLE datasets, includes space weather parameters such as solar flux and geomagnetic indices, and applies drag modelling to increase orbital-trajectory forecasting under varying environmental conditions. The system combines physics-based propagation, Monte Carlo simulations, and machine learning algorithms (LSTM, RNN, Random Forest/XGBoost) to pin-point high-risk conjunctions and suggest fuel-efficient Δv-based manoeuvre strategies. XAI layers enhance operator trust by emphasising key factors influencing collision risk.

DEB-X is significant both globally for guarding mega-constellations and the ISS, and nationally, by helping ISRO missions and upcoming human-spaceflight programmes. The architecture gives automated reporting, interactive 3D visualisations, and real-time alerts to give timely decision-making.

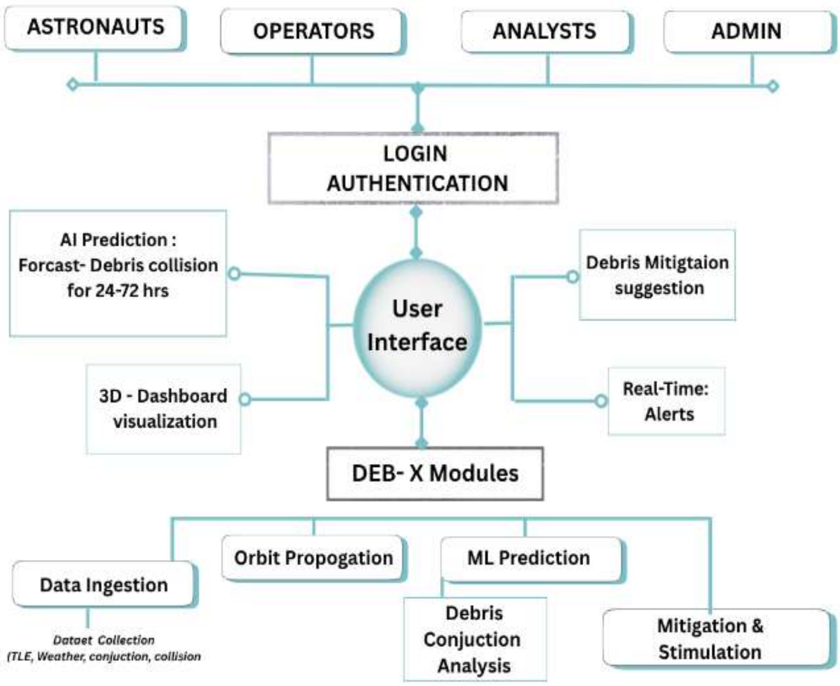

Fig. 1. System Architecture of DEB-X

II. MATERIAL AND METHODS

This segment illustrates the datasets, models, simulation tools and system components used in the DEB-X framework to ensure all experiments are fully consistent.

The methodology of DEB-X is planned to facilitate a complete framework for orbital debris detection, collision prediction, and proactive mitigation. By merging physics-based simulations, machine learning models, Monte Carlo analysis, and interactive visualisation, DEB-X improves Space Situational Awareness (SSA) and ensures timely decision-making for satellite operators.

2.1 Data Ingestion

Precise and timely data collection is important for collision prediction:

Orbital Data: Historical & live TLE datasets from CelesTrak, ESA DISCOS, and ISRO catalogues, ensuring latest positions for satellites and debris objects.

Space Weather Data: Solar Flux (F10.7), geomagnetic indices (Kp), and other environmental parameters are acquired from NOAA SWPC. These data are used to show atmospheric drag and orbital perturbations.

Data Processing: Raw data goes through normalisation, anomaly detection and local caching.

2.2 Orbital Propagation

Unambiguous trajectory estimation is attained using a fusion of physics-based models and statistical filters:

Physics-Based Models: The SGP4 propagator forecasts satellite positions using TLE data, resulting in atmospheric drag, Earth's gravitational variations, and photon pressure.

Kalman Filtering: Reduces vagueness in forecasted positions and velocities by regularising observational noise.

Monte Carlo and N-body Simulations: These illustrate multiple orbital schemas to account for vagueness in debris movement, solar activity and satellite manoeuvre.

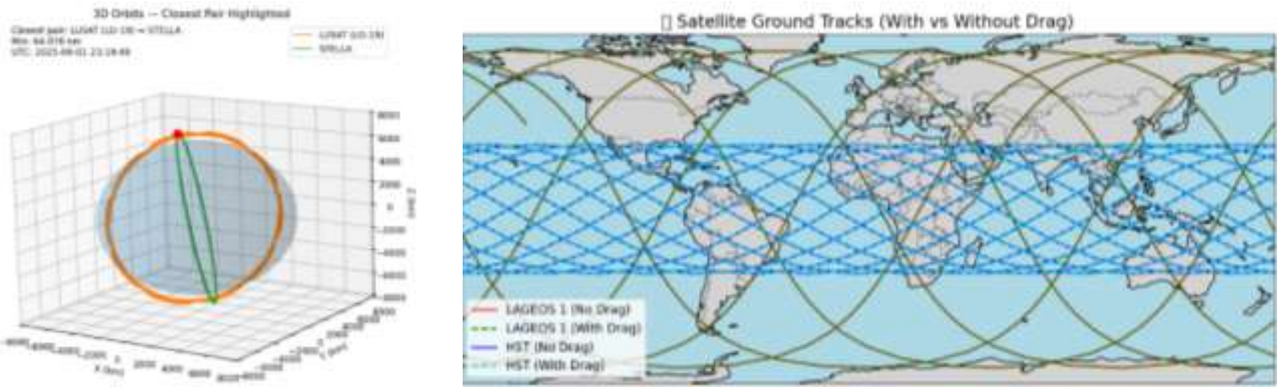

Fig. 2. (a) 3D visualisation of LUSAT and STELLA orbits, highlighting their closest approach of 64.076km & (b) Effect of atmospheric drag on LAGEOS1 and HST orbits with greater perturbations for lower-altitude HST.

2.3 Debris Conjunction Analysis

Collision risk is evaluated using both deterministic & probabilistic methods,
Conjunction Detection: High-risk incidents are found by analysing predicted 3D distances between satellites and debris gradually.
Machine Learning Models:
LSTM and RNN: These algorithms are used to forecast debris trajectories and future conjunctions.
Random Forest/XGBoost: These ML models are used to evaluate collision likelihood and risk impact.
Monte Carlo Simulations: It generates probabilistic simulations of collision schemas to handle vagueness.
Explainable AI (XAI): SHAP and LIME algorithms underline crucial factors influencing collision-risk, enhancing trust and visibility for operators.

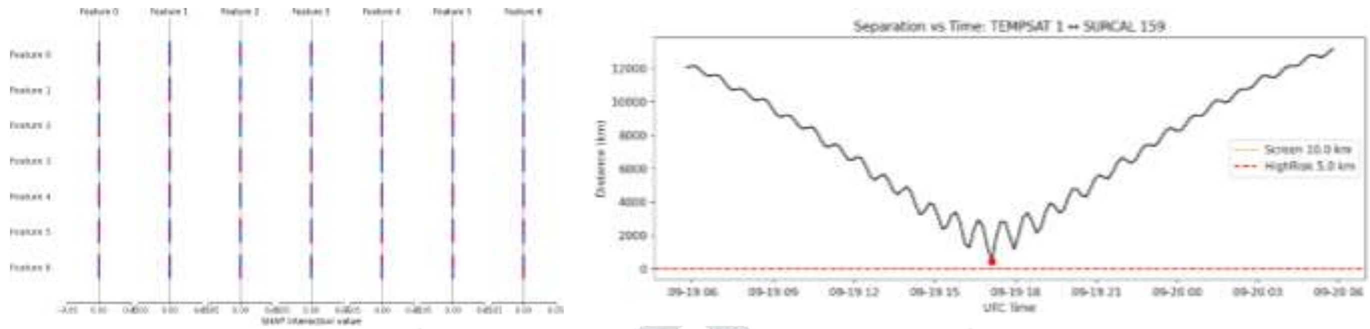

Fig. 3. (a) SHAP interaction plot demonstrating minimal interactions among all seven feature pairs & (b) Minimal orbital separation between TEMPSAT1 & SURCAL159, showing a close approach that crosses high-risk threshold.

2.4 Simulation and Mitigation

Physics Simulations: Drag sails, Δv propulsion burns and electrodynamic tethers are presented to simulate manoeuvres and debris correspondence.
Collision Modelling: Monte Carlo simulations and break-up analysis forecast possible secondary debris and assess manoeuvre impacts.
Mitigation Techniques: Advanced techniques, such as laser-based debris removal, are imitated to understand likelihood and impact.
Simulation Tools: DEB-X combines industry-standard tools containing STK for mission planning, GMAT for orbital simulations and NRLMSISE-00 for atmospheric density modelling.

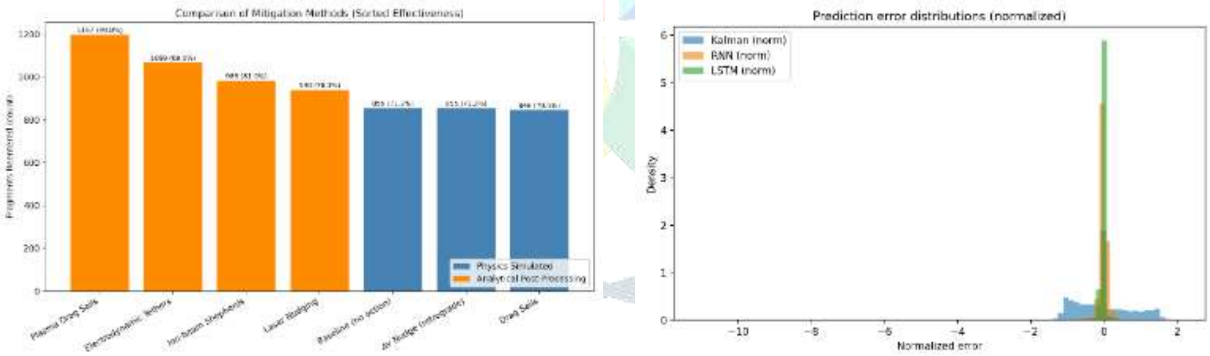

Fig. 4. (a) Effectiveness of several debris mitigation methods in attaining fragment re-entries sorted by performance & (b) Normalised Forecast error distributions for Kalman, RNN and LSTM models.

2.5 System Integration and Deployment

Backend Framework: FastAPI and Python libraries such as Skyfield, Poliastro and NetworkX manage orbital computations, debris modelling, and Machine Learning inference.
Concurrency & Task Management: Asyncio and Celery handle concurrent calculations, real-time alerting, and task planning.
Database Management: PostgreSQL and PostGIS reserve spatial and orbital data, while MongoDB preserves logs.
Deployment: Docker containers organised via Kubernetes permit scalable setup on cloud platforms (AWS, GCP, Azure), supporting GPU acceleration for machine learning models and simulations.
Optimisation Beyond Fuel: DEB-X also examines communication routing, calculation load, and prioritising of risk scores to increase operational performance and resource utilisation.
Through this methodology, DEB-X delivers a robust, proactive and explainable system for SSA, integrating predictive AI models, high-fidelity physics simulations and user-friendly 3D visualisation to support collision avoidance and orbital debris operation.

III. RESULTS AND DISCUSSION

The DEB-X model was tested using past debris incidents and conjunction events, such as the 2009 Iridium-33 and Cosmos-2251 collision and other catalogued narrow-escape events, live TLE datasets, and simulated mega-constellation scenarios. This analysis emphasises on collision prediction veracity, mathematical effectiveness, mitigation potency, and operator watchfulness.

3.1 Collision Prediction Accuracy

The AI-powered predictive models gathered the following metrics:
Forecasting Accuracy: The model showed effective efficiency over 90-92% for collision estimation within 24-hour.
Error Rate: The model reduced overall error rate up to 5 % by reducing false debris risk prediction, stating strong ability to distinguish real threat from harmless aspects.
Prediction Window: Warning were initiated three to five hours prior, offering adequate time to plot manoeuvres.
Aggregation of LSTM or RNN models with physics-based propagation upgraded trajectory prediction under dynamic environmental circumstances, for instance, flux variations and geomagnetic hurricanes. Monte Carlo simulations confine ambiguity in trajectory parameters, refining transparency in threat analysis.

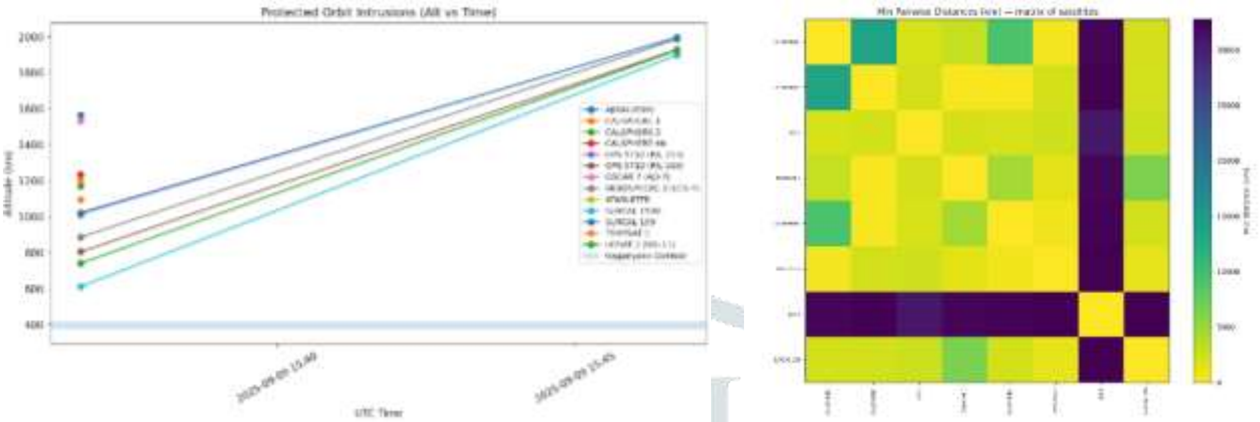

Fig. 5. Secured Orbit Intrusions plot showcasing Altitude versus Time for satellites corresponding to Gaganyaan Corridor & (b) Heatmap depicting the Minimum Pairwise Distance amid chosen satellites.

3.2 Mitigation Effectiveness

Proactive delta-v propagation-based manoeuvres are imitated across countless debris events:
Fuel Utilisation: DEB-X's manoeuvres lessen Δv, declining fuel consumption by nearly 13 to 16% compared to standard methods.
Secondary Debris Avoidance: Monte Carlo collision modelling assures that suggested manoeuvres did not yield extra high-risk debris remains.
Techniques based on Physics Simulation: Simulations of drag sails and electrodynamic tethers offered passive decline in orbital debris threat for tiny satellites. Laser-based debris removal exhibit effective neutralisation of weightless debris remains in regulated circumstances.

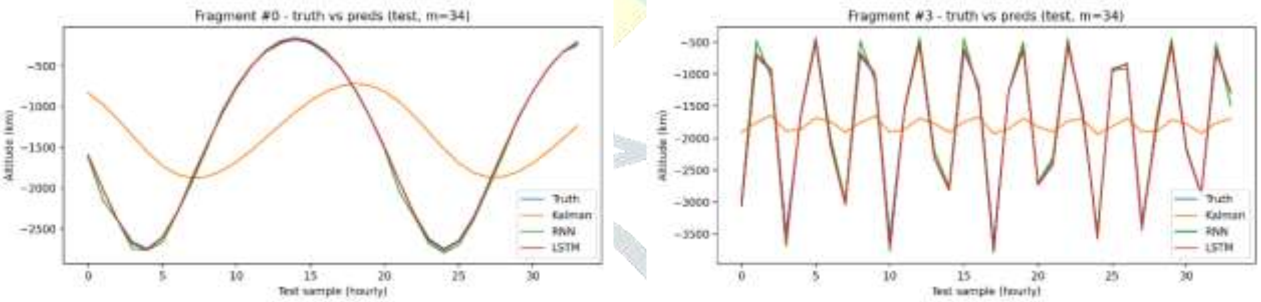

Fig. 6. (a) Fragment #0 and (b) Fragment #3 - Truth outputs of Kalman, RNN and LSTM models.

3.3 Visualization and Operator Situational Awareness

The model provides a collection of interactive visual tools:
Orbit Visualisation: The 3-Dimensional CesiumJS permits live supervision of satellites and debris, making high-risk encounters smoothly noticeable.
Risk Heatmaps: These display colour-graded heatmaps, which helps to quickly enable risk severity across various debris events.
Reporting and Alerts: Live notifications are provided using WebSockets which can be further downloaded in pdf and html format.
Further, these formatted data can be utilized as a dataset for machine learning model to incorporate reinforcement learning in them, thus improving operational decision-making.

3.4 Efficiency and Scalability

The model show cases large arithmetic efficiency which leads to:
Data Processing: It allows live streaming and preprocessing of large dataset up to 55,000 debris objects in TLE format, taking space weather data as input, along with various debris catalogue, and these data are handled within seconds.
Concurrent Computations: With the help of Asyncio and Celery tools, the model processes tasks in queue format which permits concurrent simulations as well as risk analysis for several satellites, which further helps in aiding mega-constellation processes.

Cloud Deployment: This model can be deployed on various cloud platforms like Docker and Kubernetes which provide live computation on GPU and these supervisions can be used in deployment of the model on various cloud platform assuring timely computations under high-load circumstances.

3.5 Comparative Analysis

In this phase the model is being compared with traditional systems which lags various features that are shown below in Table1.

Table 1. Comparison against Conventional systems (such as NASA ODPO, ESA Space Debris Office, ISRO NETRA)

Feature	DEB-X	Conventional Systems
Predictive Accuracy	>92%	~75-80%
Prediction Window	3-5 hours	0-1 hour
Explainability	SHAP/LIME	Minimal
Visualisation	3D Interactive Dashboard	2D/tabular
Mitigation Planning	Automated Δv and Physics Simulations	Manual/Operator Dependent

These results and discussions conclude that DEB-X is notably better as compared to conventional approaches and it further outperforms all the existing model on these features such as predictive accuracy, prediction window and operator trust, which are necessary to move forward in space field so that LEO can be less crowded, also aiming to optimise fuel usage aiding comprehensive mitigation planning to excel in this field.

IV. CONCLUSION

This research paper concluded DEB-X, as a layered, modelled and AI-powered model which address the present key issue of space debris and provides proactive orbital debris detection, collision probability and orbital mitigation. The model integrates present physics-based models as well as machine learning algorithms such as LSTM for remembering the necessary orbital collision distances which can be utilised in model decision-making, which is derived from RNN algorithm, further Random Forest and XGBoost models are used in training the model, along with Monte Carlo simulations which are used for more refined physics-based calculation that helps in the advanced visualisation of the model to give complete SSA outcomes.

Thus, from above analysis DEB-X delivers highly dependable collision evaluations, as well as future collision prediction using Monte Carlo simulation and physics-based computations which guarantee the transparency and correctness of the optimised predicted collision outcomes, also aiding fuel-efficient avoidance techniques, and improves overall operator alertness by live analytical interfaces. Its scalable model permits the management of huge orbital catalogues and makes the system well-suited for contemporary mega-constellations. The addition of XAI further strengthens understandability, making sure that the critical forecasting remains transparent to mission operators.

Overall, DEB-X demonstrated that the integrated use of data-driven prediction, high-fidelity physics simulations, and user-friendly visualisation can substantially improve current SSA abilities. Later developments will probe reinforcement learning for adaptive manoeuvre strategising, on-board inference for autonomous risk assessment, and the combination of emerging debris-removal methods.

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