ECGR 4105 - Spring 2025 Final Project
Dodging Space Waste

GitHub repository URL: https://github.com/smendes801/ECGR4105.git

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Abstract - Space debris poses a significant threat to operational satellites and future space missions. This paper presents a machine learning approach to classify and analyze space debris using orbital parameters from multiple catalog sources. We propose a comprehensive framework that ingests satellite and debris data, extracts meaningful features, and trains classification models to distinguish between active satellites and debris fragments. Our Random Forest classifier achieved 93.93% accuracy and 99.06% recall, demonstrating strong performance in identifying debris objects. The results reveal distinct orbital patterns of debris clusters at specific altitudes and inclinations, particularly in sun-synchronous orbits where 1,859 debris objects were identified. This analysis provides valuable insights for targeted space debris monitoring and cleanup strategies, offering a data-driven approach to mitigate collision risks in increasingly congested orbital environments.

Keywords — machine learning, space debris, orbital analysis, Random Forest, classification, collision avoidance, feature importance, Sun-Synchronous Orbit (SSO)

I. Introduction

Space debris, consisting of defunct satellites, spent rocket stages, and collision fragments, has become a critical issue for space operations. With over 34,000 trackable objects larger than 10cm in Earth orbit and millions of smaller fragments, the risk of collision with operational satellites increases annually [1]. The 2009 collision between active Iridium-33 and defunct Cosmos-2251 satellites demonstrated the cascading effect of such events, generating thousands of new debris fragments [2].

Traditional debris tracking relies on radar and optical observations to catalog objects, but classification of these objects often requires significant expert analysis. This manual assessment becomes increasingly challenging as the number of objects grows exponentially.

Moreover, while cataloging provides positional data, it often lacks efficient categorization of debris versus active satellites based on orbital behavior patterns.

This research addresses these challenges by developing a machine learning approach to classify and analyze space debris using publicly available orbital element datasets. The objectives were to develop an automated classification system to distinguish between active satellites and debris fragments based on orbital parameters, identify key orbital characteristics that differentiate debris from operational satellites, analyze debris concentration in critical orbital regions, particularly sun-synchronous orbits (SSO), create a model capable of informing targeted debris monitoring and cleanup strategies.

By achieving these objectives, our research contributes to addressing the growing space debris problem through data-driven classification and analysis, potentially enabling more effective debris mitigation efforts and enhancing space sustainability.

II. Related work

A. Space debris detection and classification

Space debris detection and classification has traditionally relied on ground-based radar and optical telescopes. Johnson et al. [3] reviewed these methods, highlighting their limitations in classifying smaller objects and determining whether objects are active satellites or debris. More recently, Frueh et al. [4]

demonstrated using light curve analysis for satellite classification, but this approach requires extensive observation campaigns.

B. Machine Learning Applications in Space Object Classification

Machine learning applications in space domain awareness have grown in recent years. Linares and Furfaro [5] applied supervised learning to classify space objects using light curve features, achieving promising results but requiring specialized photometric data. Sharma et al. [6] used convolutional neural networks for radar signal classification of space objects, focusing on differentiating satellites from debris based on radar returns rather than orbital parameters.

C. Comparison with Our Approach

While previous research has applied machine learning to space object classification using specialized sensor data, our approach differs by:

- Utilizing publicly available two-line element (TLE) datasets rather than specialized sensor data
- Incorporating derived features from orbital mechanics (e.g., altitude from mean motion)
- Focusing specifically on distinguishing debris from active satellites using orbital behavior patterns
- Analyzing debris concentration in commercially valuable orbital regions
- Comparing multiple classification algorithms to identify the most effective approach

This approach makes our system more accessible and practical for organizations without specialized sensors while providing valuable insights into debris distribution patterns.

III. Methodology

A. Data

We utilized publicly available data from Celestrak [9], specifically targeting the following datasets:

- Active satellites: Analyst satellite catalog
- Debris fragments: Four distinct debris catalogs: Cosmos-1408 debris (Russian ASAT test), Fengyun-1C debris (Chinese ASAT test), Iridium-33 debris (Collision with Cosmos-2251), Cosmos-2251 debris (Collision with Iridium-33)
- Impending reentry objects: Objects predicted to re enter Earth's atmosphere

The raw data was provided in two formats: CSV for regular catalogs and TLE (Two-Line Element) format for impending reentry objects. The TLE data required additional parsing using the SGP4 propagator library to extract orbital elements.

B. Features

The dataset contained 11 primary features derived from orbital elements. These features were cleaned, standardized, and prepared for model training:

- Handling missing values through removal of incomplete entries
- Feature scaling to ensure all parameters contributed equally to the classification
- Creation of a binary target variable (1 for debris, 0 for active satellites)

We calculated additional features to enhance model performance: altitude (derived from mean motion) and SSO Flag (binary indicator for Sun-Synchronous Orbit, defined as orbits with inclination between 96° and 102°).

We analyzed feature importance and correlation with the target variable to identify the most relevant parameters for classification.

C. Training and Model Developments

We implemented a comprehensive model training pipeline by splitting data into training (80%) and testing (20%) sets, standardizing features to ensure consistent scaling, Training multiple model types for comparison and evaluating performance using accuracy, precision, recall, and F1-score. Then, compared six different classification algorithms to identify the most effective approach:

1. Random Forest
2. Logistic Regression
3. Support Vector Machine (SVM)
4. Naive Bayes
5. K-Nearest Neighbors (KNN)
6. Decision Tree

Each model was evaluated using five-fold cross-validation to ensure robust performance assessment.

We implemented specialized analysis functions to extract insights about orbital patterns distinguishing debris from active satellites. This analysis focused on identifying altitude and inclination ranges with high debris concentration, detecting distinctive orbital patterns that characterize debris fragments and quantifying debris presence in critical orbital regions, including sun-synchronous orbits.

D. Orbital Data Analysis

We implemented specialized analysis functions to extract insights about orbital patterns distinguishing debris from active satellites. This focused on:

- Identifying altitude and inclination ranges with high debris concentration
- Detecting distinctive orbital patterns that characterize debris fragments
- Quantifying debris presence in critical orbital regions, including SSO

IV. Results and analysis

A. Dataset

The final processed dataset contained:

- Total objects: 3,209
- Debris objects: 2,652 (82.6%)
- Active satellites: 557 (17.4%)

B. Model Performance

The Random Forest classifier achieved the best overall performance:

- Accuracy: 93.93%
- Precision: 93.93%
- Recall: 99.06%
- F1 Score: 96.43%

This high recall rate (99.06%) indicates the model's strength in identifying debris objects, with very few false negatives—critical for space safety applications where missing debris classification could lead to collision risks.

1) Model Comparison Results

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Logistic Regression	90.03%	91.18%	97.36%	94.17%
Random Forest	93.61%	93.59%	99.06%	96.25%
SVM	92.06%	91.52%	99.62%	95.40%
Naive Bayes	89.10%	91.83%	95.29%	93.53%
KNN	91.43%	91.61%	98.68%	95.01%
Decision Tree	93.61%	95.20%	97.18%	96.18%

While the Decision Tree showed the highest precision (95.20%), the Random Forest provided the best balance of metrics with superior recall and cross-validation scores, indicating better generalization to unseen data.

2) Feature Importance

Feature importance analysis from the Random Forest model revealed the most predictive parameters:

- MEAN_MOTION (highest importance): Directly related to orbital altitude and period
- INCLINATION: Angle between orbital plane and Earth's equator
- ARG_OF_PERICENTER: Argument of perigee
- MEAN_MOTION_DOT: Rate of change in mean motion, related to orbital decay
- RA_OF_ASC_NODE: Right ascension of ascending node

These importance rankings align with orbital mechanics principles, as mean motion (and thus altitude) and inclination are fundamental parameters differentiating orbital regimes.

C. Orbital Pattern Analysis

1) Altitude Distribution

The analysis revealed distinct altitude distributions:

- Debris objects: 235.1 - 1,988.0 km range
- Active satellites: 374.7 - 526,392.6 km range

This wide discrepancy reflects the concentration of debris in Low Earth Orbit (LEO), while active satellites span from LEO to Geostationary and beyond.

2) Sun-Synchronous Orbit Analysis

The Sun-Synchronous Orbit (SSO) analysis showed:

- 1,866 debris objects in SSO (70.4% of all debris)
- 164 active satellites in SSO (29.4% of all satellites)

This high concentration of debris in commercially valuable sun-synchronous orbits highlights a significant concern for Earth observation and remote sensing missions that commonly utilize these orbits.

3) Orbital Clustering

The orbital pattern visualization revealed clear clustering of debris at specific inclinations (particularly near 98° for SSO), higher debris density in the 700-900 km altitude range and distinct orbital behavior patterns resulting from specific fragmentation events.

These patterns demonstrate that debris from different sources (ASAT tests, collisions) maintain identifiable orbital characteristics, allowing for potential source attribution of newly detected debris.

V. Conclusion

This research successfully developed a machine learning approach for space debris classification with several notable outcomes.

- **High Classification Performance**: Random Forest model achieved 93.93% accuracy and 99.06% recall in distinguishing debris from active satellites, demonstrating strong predictive capability using orbital parameters alone.
- **Critical Orbital Regions Identified**: The analysis revealed concerning debris concentrations in sun-synchronous orbits, with 1,866 debris objects occupying these commercially valuable orbital regions.
- **Distinctive Pattern Recognition**: Clear debris clustering patterns emerged at specific altitude and inclination combinations, potentially enabling attribution of debris to source events.
- **Feature Significance:** Mean motion (related to altitude) and inclination proved to be the most predictive features, aligning with orbital mechanics principles and providing physical interpretability to the model.

References

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