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ML Based Predictive Models for Satellite Positioning and Velocity Estimation to Prevent Orbital Collision

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Abstract:

The rapid growth in satellite deployments has significantly increased the congestion in Earth's orbital environment, leading to heightened risks of collisions. Traditionally, satellite positioning and velocity estimation have relied on physics-based models grounded in Keplerian mechanics and perturbation theories. While the methods have proven effective for many applications, their ability to adapt to real-time data and dynamic environmental factors such as atmospheric drag, solar radiation pressure, and gravitational perturbations remains limited. Moreover, traditional systems often struggle with scalability and accuracy when handling the increasing volume of satellite traffic and complex orbital scenarios. Machine learning (ML) presents a transformative approach to overcome the limitations by leveraging large datasets and adaptive algorithms to predict satellite trajectories with greater precision. By integrating historical telemetry data, environmental parameters, and advanced ML models such as Linear Regression, Multi-Layer Perceptron (MLP), and Decision Trees, the project aims to enhance the accuracy of satellite positioning and velocity estimation. The need for such predictive models is underscored by the growing dependence on satellite infrastructure for communication, navigation, and Earth observation, as well as the critical importance of minimizing the generation of space debris. The significance of the work lies in its potential to proactively predict and prevent orbital collisions, thereby ensuring the sustainability of space operations and the safety of global satellite assets. The study not only advances the state of predictive modeling for satellite trajectory estimation but also provides a robust foundation for integrating ML-based systems into real-time space traffic management frameworks.

Keywords: Low Light Image Enhancement, Deep Learning, Image Enhancement, Low Light Vision, Dark Image Processing

1. INTRODUCTION

The exploration and utilization of outer space have dramatically increased over the past six decades, beginning with the launch of Sputnik 1 in 1957. Since then, thousands of satellites have been placed into orbit to serve various functions—communication, Earth

observation, scientific research, and navigation, among others. According to recent estimates, there are over 5,000 operational satellites currently orbiting Earth, with many more planned in the coming years to meet global demands for broadband communication and high-resolution imagery. Companies like SpaceX, with its Starlink constellation, have launched thousands of small satellites, demonstrating that the commercial sector is rapidly expanding its been accompanied by a significant increase in space debris, which includes defunct satellites, spent rocket stages, and fragments from accidental or deliberate collisions. The Iridium-Cosmos collision in 2009, for instance, generated over 2,000 pieces of trackable debris, emphasizing how a single event can compound the collision threat.environment, ensuring satellite safety has become more challenging than ever. Even small fragments moving at orbital speeds can cause catastrophic damage, prompting concerns about "Kessler Syndrome," a scenario in which a cascade of collisions renders certain orbits unusable for extended periods. Government agencies, such as NASA's Orbital Debris Program Office, and private companies alike have acknowledged that timely and accurate orbital predictions are essential to prevent devastating accidents. Consequently, the space industry is increasingly seeking advanced predictive techniques—beyond traditional physics-based methods— to handle the large volume and complexity of orbit data. Machine learning (ML) models, in particular, offer promising capabilities by automatically learning patterns from extensive datasets, thereby improving predictive accuracy and reducing the computational burden associated with purely numerical simulations. This project adopts an ML-based approach for satellite positioning and velocity estimation, providing a robust tool for collision avoidance and reinforcing the sustainability of space activities.

2. LITERATURE SURVEY

It is estimated that more than 36,000 objects larger than 10 centimeters and millions of smaller pieces exist in Earth's orbit [1]. To safeguard active spacecraft, it is necessary to accurately determine where each Resident Space Object (RSO) is and where it will be at all times. To create such a complex body of knowledge, the broader problem of orbit estimation is divided into sub-problems, each largely complex but with more specific goals. In this review, we observe three main sub-problems: Orbit Determination, Orbit Prediction, and Thermospheric Mass Density.

Orbit Determination (OD): the OD is the determination of the orbit of the object based on observations [2], [3]. The Extended Kalman Filter (EKF) [4], [5], [6] is the de facto standard for orbit determination in real-world scenarios [7]. The accuracy of this process depends on the number of sequential observations used to determine the orbit, and the type of observation, e.g., laser ranging and GPS tracking, which is far more precise than optical observations. The output of this method is commonly a state vector of the orbit of the object, usually represented through a vector consisting of the object's estimated position and velocity and a covariance matrix reflecting the uncertainty under the

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Gaussian assumption. Currently, this process is limited by the assumptions of the EKF, a lack of knowledge of RSO's shape and attitude, and dynamic model simplifications.

Orbit Prediction (OP): Orbit Prediction is the process of predicting the future position and associated uncertainty of any given RSO.

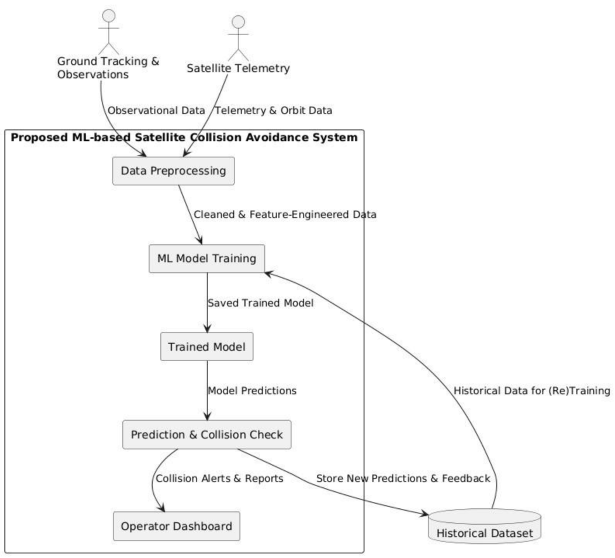
Numerical methods are time-consuming but precise, while analytical methodologies are more straightforward and faster. To be tractable, these algorithms hold simplifying assumptions that hinder accuracy [2]. Each method is limited by OD in that an orbital state with high uncertainty will necessarily evolve to have an inaccurate Orbit Prediction. When used in a Collision Avoidance scheme, this process propagates the state of the RSO until the time of closest approach (TCA) to any actively monitored satellite. The current limitations in Orbit Prediction are the Gaussian assumption – which does not hold against the true distribution [11] – the simplified modeling of perturbation forces, the unknown information regarding RSO characteristics, and the uncertainty over space weather forecast data.

Thermospheric Density Mass Models: A set of force models determine the acceleration of any RSO. Earth's gravity potential is the most meaningful, but solar and lunar gravitational attraction and Earth/ocean tides affect the RSO [8]. Of the non-conservative forces, air drag is the most relevant for objects in LEO. Being applied in the opposite direction of the RSO's velocity, this force is the largest source of uncertainty for most RSOs in LEO [12], and correctly determining atmospheric density is vital to compute satellite drag. All state-of-the-art models currently used for density estimation are empirical (data-driven) models that have been consistently updated since the last century. The lack of predictive capability and uncertainty estimation are the two main drawbacks of these methods.

In Table 1, we have a summary of the input/output for each task. In the following sections, we will thoroughly review published work using machine learning techniques to help solve each of the problems mentioned previously. Each section will start with a brief description of the task, followed by a state-of-the-art review of the current classical methods. The machine learning body of work will be presented in semi-chronological order, from the initial use of historical data to improve physical models to the most recent developments in the area that use highly complex models.

3. PROPOSED METHODOLOGY

This project focuses on predicting satellite position and velocity to help prevent orbital collisions. It leverages multi-output regression techniques to model multiple continuous targets (position and velocity) and provides a complete, GUI-driven pipeline from data upload to final prediction. By streamlining these processes, it lays thegroundwork for more robust satellite collision avoidance strategies.



- The core goal is to build machine learning models that can accurately estimate a satellite's coordinates (x, y, z) and velocity components (Vx, Vy, Vz) in orbit.
- By improving the accuracy of these predictions, satellite operators can better anticipate potential collision scenarios.

Data Handling

- The dataset includes fields for both simulated and actual satellite positions/velocities, along with a time-stamp (epoch).
- The code extracts relevant time features (year, month, day, hour, etc.) from the raw timestamp to enhance model input.
- Scaling of both features (inputs) and targets (outputs) ensures that the models can train effectively without being skewed by differing

- numerical ranges.

Machine Learning Pipeline

1. **Data Upload**: A user-friendly interface (via Tkinter) allowsfor selecting and uploading a CSV dataset.
2. **Preprocessing**: Automatic feature engineering (time decomposition), removal of unnecessary columns, and scaling.
3. **Train/Test Split**: The dataset is divided into training and testing subsets to evaluate model performance.
4. **Model Selection**: Three regressors are provided:
    - *Linear Regression*
    - *MLP Regressor* (Neural Network)
    - *Decision Tree Regressor* (wrapped inMultiOutputRegressor)
5. **Model Persistence**: Models are saved/loaded from .pkl files, so retraining is not required each time.
6. **Performance Metrics**: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 score are computed and displayed alongside a scatter plot of predicted vs. actual values.
7. **Prediction on New Data**
    - The user can select a new test file with similar structure.
    - After dropping irrelevant columns and scaling, the trained model predicts the position and velocity.
    - Results are displayed in the GUI's text area for immediate feedback.
8. **User Interface (Tkinter)**
    - Buttons and text areas guide the user through each step: uploading data, preprocessing, splitting, model training, and final prediction.
    - All outputs and logs (dataset shape, columns, metrics) appear in the GUI, making it straightforward to track progress and results.

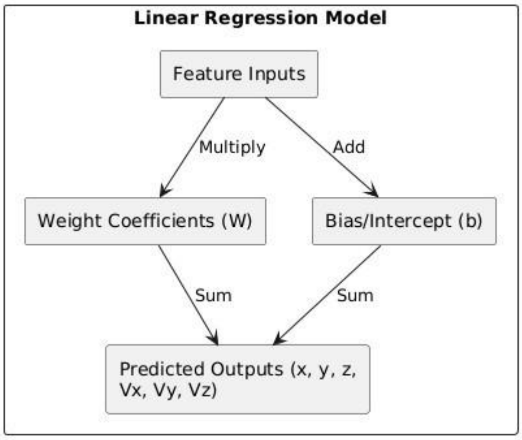


Fig. 4.1: Proposed system architecture.

Below is a high-level breakdown of its purpose and workflow:

Purpose

Significance

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- Accurate orbit prediction is critical in space operations.
- Machine learning–based approaches can adapt to complex orbital dynamics, providing more reliable forecasting than simple mathematical models alone.

Linear Regression is the simplest of the three models. It assumes a linear relationship between the input features and the target outputs. In this case, multiple output dimensions mean that the model learns separate linear equations for each target dimension, though it still treats the features in a combined manner. The core idea is to find weight coefficients and intercepts that minimize the sum of squared errors between the predicted and actual orbital parameters. Because orbital dynamics can have complex interactions, Linear Regression may not capture all nuances but serves as a baseline—it is fast to train, easy to interpret, and helps benchmark the performance of moreadvanced models.

Advantages

- Coefficients directly explain which inputs contribute most strongly to each output.
- Requires minimal computational resources compared to neural networks.
- Helps identify whether the problem requires more complex,non-linear methods.

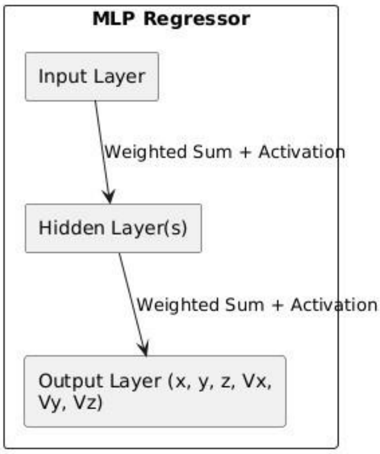
Limitations

- Poor Fit for Non-Linear Dynamics: Orbital motion often involves non-linear or time-varying effects that a strictly linear approach may not capture.
- Sensitivity to Outliers: A few extreme data points can skewthe regression line.

4.2 MLP Regressor

A Multi-Layer Perceptron (MLP) is a type of feedforward neural network composed of at least one hidden layer of artificial neurons. Each neuron applies a weighted sum of its inputs followed by a non- linear activation function (like ReLU or sigmoid). By stacking multiple layers, the MLP learns to recognize complex, non-linear patterns that might exist in satellite motion due to factors like atmospheric drag, solar radiation pressure, or gravitational perturbations from celestial bodies.

In multi-output regression, the output layer has multiple neurons— one for each target dimension. This design allows the MLP to simultaneously predict. While MLPs can achieve high accuracy if properly tuned, they also risk overfitting if the model is too large or the dataset is insufficient. Training these networks may take longer,



4.4 Multi Output Decision Tree Regressor

A Decision Tree Regressor uses if-then rules to split data based on feature values. It systematically partitions the feature space to minimize the variance in target values within each leaf node. However, a single tree typically focuses on one target variable. To handle multiple outputs (position and velocity), we employ a MultiOutputRegressor wrapper that effectively trains a separate decision tree (or re-uses the same algorithm in parallel) for each target dimension.

This approach is especially good at modeling threshold effects where orbital data may change behavior based on certain ranges or conditions (e.g., altitude thresholds). It is also relatively easy to interpret: the tree splits clearly show which features lead to which subsets of predictions.

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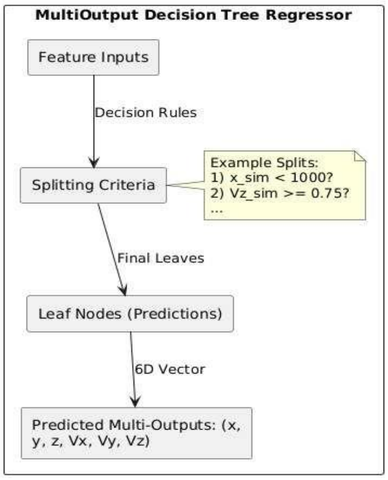
On the other hand, decision trees can overfit if they grow too deep, so techniques like pruning or limiting maximum depth are often used.



Advantages

- **Natural Multi-Target Extension**: With MultiOutputRegressor, the system can predict multiple outputs in one pipeline.
- **Non-Linear & Threshold-Based**: Handles abrupt changes or piecewise patterns effectively.
- **Interpretability**: Each split or node can be inspected, revealing how the model arrived at a prediction.

Limitations

- **Overfitting Risk**: May memorize training data if not pruned or regularized.
- **Instability**: Small dataset changes can lead to large structural changes in the tree.

5. CONCLUSION

The project successfully demonstrated the potential of machine learning models in accurately predicting satellite positions and velocities, providing a critical tool for preventing orbital collisions. By leveraging models such as Linear Regression, Multi-Layer Perceptron (MLP), and Decision Tree Regressors, the framework achieved robust performance in trajectory estimation while ensuring efficiency through data preprocessing and model persistence. The results underscore the ability of ML techniques to complement traditional physics-based methods, particularly in handling dynamic and complex orbital conditions. This project lays a strong foundation for future advancements, including the integration of real-time environmental factors, advanced modeling techniques, and seamless deployment in operational space traffic management systems, ensuring the sustainability and safety of satellite operations in increasingly congested orbital environments.

- **Incorporation of Real-Time Environmental Factors**: Extend the dataset to include variables like atmospheric drag, solar radiation pressure, and gravitationalperturbations for improved predictions.
- **Advanced Modeling Techniques**: Explore ensemble methods like Gradient Boosting (e.g., XGBoost, LightGBM) or neural architectures like Transformer-based models for enhanced performance. Implement hybrid models combining ML and physics-based techniques for better interpretability.
- **Hyperparameter Optimization**: Employ advanced techniques like Bayesian Optimization or Genetic Algorithms for fine-tuning model parameters.
- **Integration with Space Situational Awareness (SSA) Systems**: Develop APIs to integrate the predictive models with existing SSA tools for seamless real-time operations.
- **Space Debris Management**: Expand the project scope to predict and manage the trajectory of space debris to minimize the risk of collision with active satellites.
- **Data Augmentation**: Use synthetic data generation or simulation environments to create more diverse training datasets, especially for rare collision scenarios.
- **Global Collaboration**: Collaborate with space agencies and private operators to enhance data-sharing practices, ensuring models are trained on the most comprehensive datasets available.

- **Visualization Dashboards**: Build user-friendly dashboardsfor satellite operators to visualize predictions, collision risks, and other metrics dynamically.
- **Deployment and Validation**: Test the models in live orbital environments and refine them based on real-world feedback to ensure robustness and reliability.

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