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A Machine Learning Approach to Monitor Satellite Constellation Orbits

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Abstract: Keeping a satellite in the right orbit is no easy feat. It's constantly influenced by various forces like Earth's uneven gravity, air resistance high up in the atmosphere, and even pressure from sun-light. Over time, these factors can nudge satellites off their intended paths. Nowadays, most satel-lites depend on ground control teams to keep an eye on their orbits and plan any necessary adjust-ments. This can be a slow, expensive, and tricky process, especially as the number of satellites in space keeps increasing. This paper outlines a machine learning approach to check for deviation from the intended orbit of a given satellite con-stellation. The system continuously tracks essen-tial orbital data, such as position and velocity, to see if a satellite is veering off course. To develop and test this method, we used publicly available data from Starlink satellites and other spacecraft. Starlink satellites are particularly valuable because they frequently adjust their orbits and operate in large clusters, providing rich and dynamic data. We trained a machine learning model to predict if a satellite has left from its constellation. By com-paring this prediction with the actual position of the satellite, the system can spot when the orbit starts to drift. The findings indicate that blend-ing basic physics with machine learning can ef-fectively aid in autonomous orbit correction. This approach holds promise for cutting costs, boost-ing efficiency, and simplifying the management of a growing number of satellites in the future.

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I. INTRODUCTION

Satellites operating in Earth orbit are continuously subjected to disturbance forces that gradually alter their trajectories. Atmospheric drag, non-uniform gravitational fields, and solar radiation pressure can cause long-term orbital drift, increasing collision risk and reducing mission efficiency. Conventional station-keeping relies on ground-based teams to monitor orbital parameters and command corrective maneuvers, a process that becomes increasingly impractical for large low-Earth-orbit (LEO) constellations.

The objective of this project is to design an autonomous system capable of monitoring orbital parameters and detecting deviations from nominal trajectories. By enabling satellites to independently detect deviations, the system improves responsiveness, scalability, and long-term mission sustainability.

This work frames orbit prediction as a super-vised regression problem using numerical orbital data, while deviation detection is treated as a binary classification task. The model outputs include a deviated or undeviated label. The project lies at the intersection of orbital mechanics, control theory, and machine learning, demonstrating how data-driven models can enhance traditional aerospace systems.

➢ *Significance Statement*

This project is important because it helps ground team to be notified automatically about any orbital change. As more and more satellites are launched, it becomes difficult and expensive to monitor and control each one manually. This work shows that using machine learning together with basic orbital mechanics can help satellites detect when they move off course. This can save time, reduce costs, and make satellite systems safer and more reliable. The study also shows that real satellite data can be used to build practical systems for future space missions.

II. BACKGROUND

Satellite station-keeping has traditionally been addressed using physics-based models and ground control. These approaches are reliable and interpretable but require continuous human oversight and are not easily scalable. Onboard control systems using PID or model predictive control improve response time but rely heavily on pre-defined models and struggle with unexpected perturbations.

Recent research has explored machine learn-ing methods for orbit prediction and anomaly detection.Li (2022), Lee (2025).These techniques can capture nonlinear dynamics and scale efficiently with large datasets, making them suitable for modern constellations. However, purely data-driven approaches may lack physical consistency and can produce

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unrealistic control commands.

This research adopts a hybrid approach that combines machine learning for prediction and deviation detection with orbital mechanics for independent deviation detection. This balance preserves physical realism while benefiting from the adaptability of data-driven models.

III. DATASET

The dataset consists of numerical time-series or-bital data collected from publicly available Star-link and non-Starlink satellite sources. Each sam-ple represents a satellite state at a specific time and includes features such as altitude, latitude, longitude, inclination, eccentricity, and velocity components.

The combined dataset contains several thou-sand satellite state entries. Starlink data were emphasized due to their dynamic station-keeping behavior, while non-Starlink satellites were in-cluded to improve generalization. Data preprocessing involved removing missing or inconsistent entries, standardizing numerical features, and aligning feature formats across datasets.

The data were split into 60% training, 10% val-idation, and 30% testing sets to emphasize robust evaluation on unseen trajectories. Feature visual- izations such as inclination-versus-frequency plots and correlation matrices confirmed the relevance of selected parameters for orbit stability analysis.

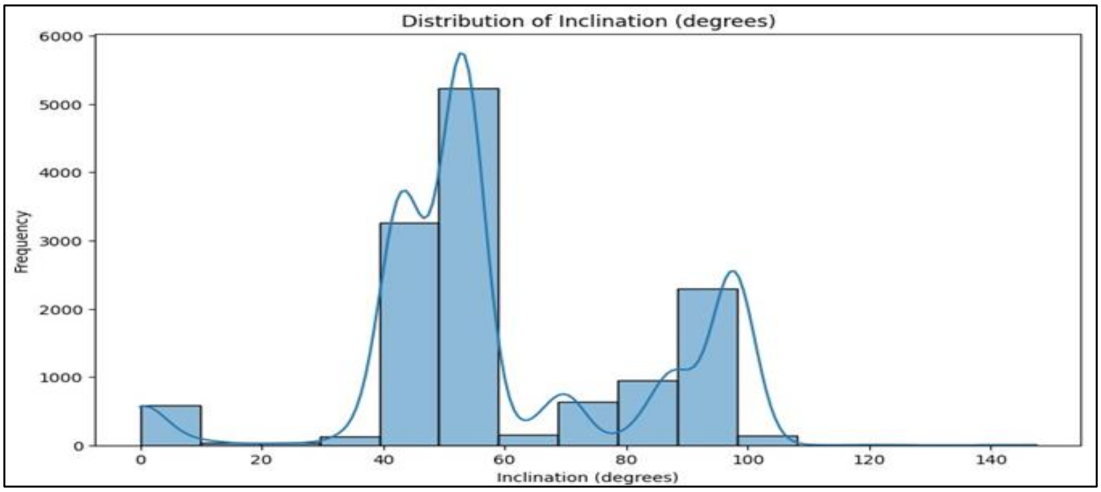

Fig 1 Inclination VS Frequency

This data was collected from the public datasets of Makadiya (2020), J0shi (2025), and Kapoor (2023).

IV. METHODOLOGY

The proposed system follows a two-stage pipeline: orbit prediction and deviation detection. First, a supervised regression model predicts future orbital states based on historical parameters.

A baseline regression model was trained using the prepared dataset. During training, the model minimizes the Mean Squared Error (MSE) be-tween predicted and actual satellite states. MSE was selected because it penalizes large prediction errors that could lead to incorrect orbit correction decisions. After training, the model was evalu-ated on the test dataset using Mean Absolute

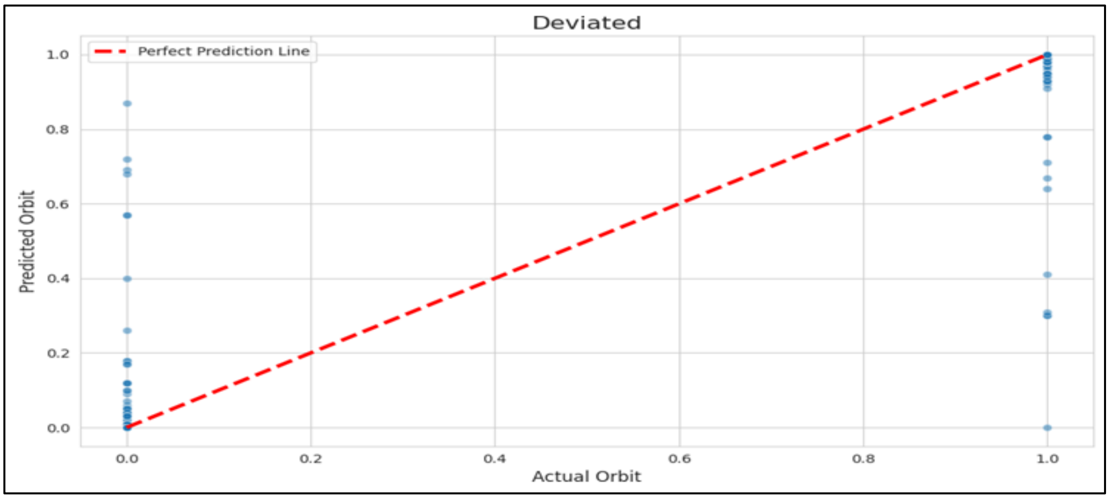

Fig 2 Actual Orbit vs Predicted Orbit Over Time

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Error (MAE) and Mean Squared Error (MSE) to quantify prediction accuracy.

Figure- 2, shows a comparison between pre-dicted and actual orbit deviations for the machine learning model.

Table 1 MAE, MSE, R2 Values

Metric	Value (Approx.)
Mean Absolute Error (MAE)	0.005km (Low)
Mean Squared Error (MSE)	0.0025km^2 (Low)
R2	0.9989

Second, deviation detection is formulated as a binary classification task. Differences between predicted and expected orbital parameters, par-ticularly altitude, eccentricity, and velocity, are used to classify states as nominal or deviated. Model performance is evaluated using F1 score, confusion matrix, and Area Under the Curve (AUC).

Deviation detection was formulated as a bi-nary classification problem, identifying whether a satellite state is nominal or deviated. Model performance was evaluated using F1 score, confu-sion matrix, and Area Under the Curve (AUC). The classification model achieved an F1 score in the range of 0.85–0.90, indicating strong detec-tion capability. In addition if the training data is increased, the F1 score would decrease. The con-fusion matrix, shown in Figure 3, demonstrates a high true-positive rate, meaning that most actual deviations were correctly identified. False positives were present but limited.

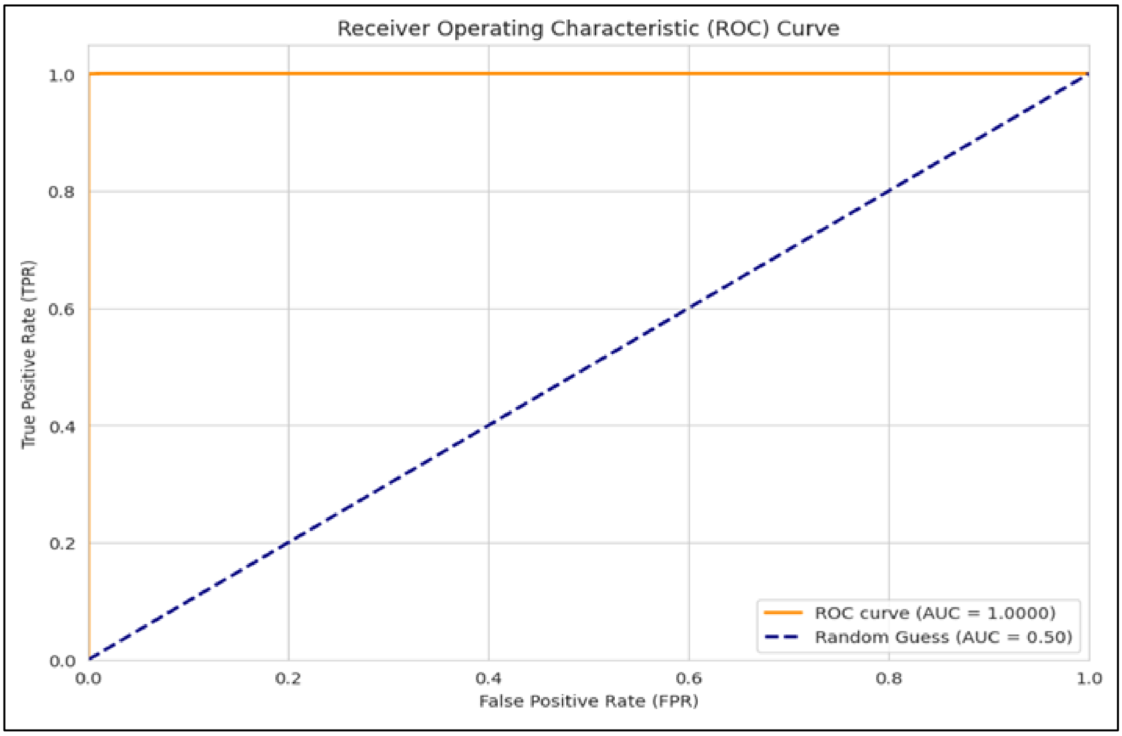

Fig 3 ROC Curve

Figure- 3, displays the ROC curve for deviation detection. The curve shows strong separation between classes, with an AUC value indicating reliable classification performance. ROC curve is used to evaluate the performance of a binary classification model.

Table 2 F1 Score, AUC Values

Metric	Value (Approx.)
F1 Score	0.996
Area Under Curve (AUC)	1.00

V. RESULT AND DISCUSSION

Once deviations were detected, the corrective ma-neuver module computed the direction and mag-nitude of thrust required to restore orbital stabil-ity. This stage was evaluated primarily through qualitative analysis, as it relies on physics-based calculations rather than learned outputs. Simula-tion results showed that applying the estimated corrective maneuvers reduced orbital deviation by a good factor within a single correction cycle.

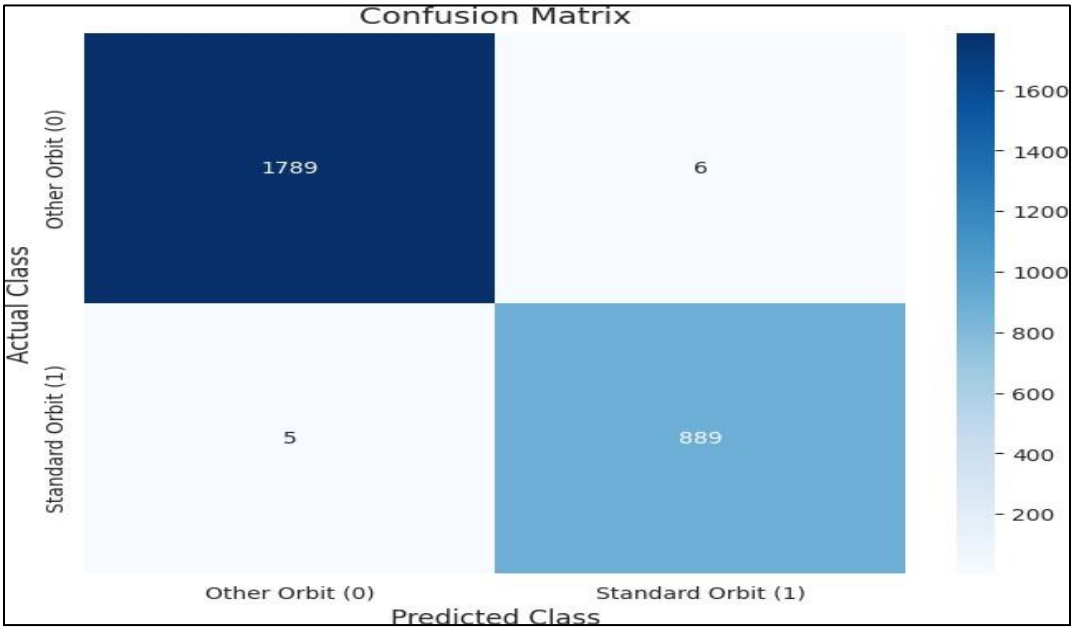

Fig 4 Confusion Matrix

Figure- 4, The above left square with higher value shows that most of the satellites are Non-Starlink satellites as our data also contains non-starlink satellite data.

VI. CONCLUSION

This research demonstrates that integrating ma-chine learning with orbital mechanics provides an effective framework for autonomous orbit stabi-lization. The system successfully predicts orbital behavior, detects deviations, and computes cor-rective actions with minimal reliance on ground control. Future work will explore more advanced temporal models, expanded datasets, and real-time onboard implementation.

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