Astro Ensemble: A CART-Boosted Learning Model for Satellite Telemetry-Based Decision Systems

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Abstract

With more than 4,500 active satellites currently orbiting Earth and a global dependency valued at over $300 billion annually on satellite-based services, ensuring mission reliability has become a critical operational priority. Real-world reports indicate that nearly 40% of unexpected mission losses arise from undetected telemetry anomalies, highlighting the urgent need for predictive intelligence capable of interpreting complex spacecraft data. Satellite telemetry captures vital information regarding subsystem health, environmental conditions, and mission progress, but its high dimensionality, noisy signals, missing values, and heterogeneous behavior pose substantial challenges for conventional analytics. The research presents a robust and scalable solution for satellite telemetry analysis by developing a locally deployed ensemble learning system for mission success classification and duration prediction using OPSSATAD data. The system integrates multiple machine learning algorithms by combining classification and regression, referred to as classification and regression tree (CART), including Random Forest Classifier (RFC), Gradient Boosting Classifier (GBC), and Support Vector Classifier (SVC) for classification, along with Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), and Support Vector Regressor (SVR) for regression tasks. Additionally, the proposed framework introduces an advanced ensemble model that combines Extra Trees Classifier (ETC) and CatBoost Classifier (CBC) for classification, and Extra Trees Regressor (ETR) and CatBoost Regressor (CBR) for regression using a voting-based aggregation method, referred to as the proposed Ensemble Voting (CART) model. The ET-CART models effectively capture hierarchical decision patterns, while CatBoost-CART improves performance through boosting and handling complex feature interactions.

Key words: CatBoost (CBC/CBR), Extra Trees (ETC/ETR), Gradient Boosting, Random Forest, Support Vector Machines (SVM).

1. Introduction

The application fields of remote-sensing satellites are constantly evolving and changing. The scale of the satellite observation network constituted by different sensor satellites and star cluster networks will grow. Satellite ground stations will receive satellite telemetry data and transmit satellite control commands at the same time. Satellite mission scheduling technology is the unified and orderly scheduling management of multiple missions from multiple ground stations for numerous satellites. The remote-sensing satellite systems field is experiencing an unprecedented surge in complexity, which drives the need for dynamic and intelligent satellite mission scheduling. Dynamic prioritized satellite mission scheduling has two advantages over traditional static or semi-static scheduling frameworks. Firstly, dynamically prioritized satellite mission scheduling can preemptively adapt to fluctuations in mission complexity [1,2,3] and resource constraints [4,5,6,7] in modern satellite networks compared to obsolete static or semi-static scheduling frameworks. Secondly, dynamic mission prioritized satellite mission scheduling can always find the optimal solutions to improve efficiency and save time. That improves efficiency and saves a lot of time. This can open many new opportunities and applications. Certainly, satellite mission scheduling has undoubtedly faced significant challenges in recent years as technological breakthroughs in remote-sensing satellite applications and growing demands in the era of globalization continue to drive conventional systems forward. As we navigate the intricacies of satellite applications, we need to be clear about two aspects.

Figure. 1: Satellite telemetry data mining for mission analysis

The first is that we need to be clear about the full potential of satellite resources, which are finite and costly, and adapt to the fluidity of mission priorities in real time. Inflexible mission scheduling mechanisms may lead to suboptimal allocation of resources, which may result in a significant decrease in efficiency. Second, we need to ensure that tasks located on the priority ladder are executed with unparalleled accuracy as shown in figure. 1 and scheduling capabilities to achieve optimal results and time to complete satellite task execution. Finally, realizing these two paths is full of challenges, navigating the constant changes in task priorities, specifying the optimal time within tight resource constraints, and ensuring the algorithms are robust.

To cope with and overcome these challenges, researchers have proposed a dynamic mission scheduling framework in the remote-sensing satellite application domain [2,8,9]. The dynamic mission scheduling framework can be effectively applied to the time-varying nature of satellite networks and the timeliness of remote-sensing satellite mission scheduling in the face of the dynamic mobility of satellite resources in remote-sensing satellite networks and the complexity of the environment. The researchers also propose a dynamic resource allocation strategy to integrate and optimize the resources in the satellite network [10,11].

2. Literature Survey

Pilastre et al. [12] decomposed telemetry signals into a dictionary using SR and analysed the residuals resulting from this sparse decomposition to detect potential anomalies, however, this method cannot deal with correlation anomalies between continuous parameters. Takeishi et al. [13] extended SR using Singular Value Decomposition (SVD) to reconstruct the sparse matrix to detect correlation anomalies in multivariate time series by analysing the reconstruction residuals. However, it is difficult to select the number of the retained singular values, which seriously affects detection performance.

Hu et al. [14] defined six meta-features as inputs to OCSVM and built an anomaly detection model for use with time series. Saari et al. [15] selected frequency-domain features as inputs to OCSVM for detecting anomalies in wind turbine bearings. Vos et al. [16] combined LSTM and OCSVM for gearbox anomaly detection, using the LSTM prediction error as a feature and OCSVM to perform the detection task. One-class classifiers can solve the anomaly detection problem well, although because of the high dimensionality of telemetry data feature extraction and selection need to be carried out before building the one-class classifier.

Heras and Donati [17] have applied thresholding models in many ESA (European Space Agency) missions by integrating a new automatic telemetry monitoring prototype. The novel detection monitoring approach has been managed to analyze the behavior of 2000 parameters during the XMM (X-ray Multi-Mirror Mission) Newton orbit mission. In [18], another anomaly detection method, based on parametric causality and Double-Criteria Drift Streaming Peaks Over Threshold (DCDSPOT), was proposed to solve the problem of high rates of false negatives. The performance of the DCDSPOT method was assessed using four anonymous telemetry parameters generated by a military communications satellite. Compared to other baseline methods, the proposed method obtained the highest recall (91%) and precision (85%).

Gao et al. [19] developed a normal behavior clustering anomaly detection approach. They performed this method to detect anomalies of six parameters related to the power subsystem of an actual in-orbit satellite. Jin et al. [20] adopted an extended dominant sets clustering algorithm to distinguish between 00normal and abnormal samples of synthetic and real telemetry datasets generated by the Tianping-2B satellite.

3. Proposed Methodology

The proposed system architecture for the Locally Ensemble Classifier Satellite Mission Success Classification framework is designed to predict satellite mission outcomes and mission duration from OPSSATAD satellite telemetry data. The architecture follows a modular, data-driven workflow that integrates preprocessing, feature engineering, model training, evaluation, and deployment within a unified pipeline. The core contribution lies in a locally ensemble learning approach that leverages the strengths of multiple classifiers and regressors through Voting-based aggregation strategies. This ensures robust and accurate mission success prediction and mission duration estimation. The entire framework is implemented with a scalable backend using Flask for web-based deployment, allowing both single and batch predictions as shown in figure. 2.

Data Collection and Input Handling: The system begins by collecting satellite telemetry data from the OPSSATAD dataset, which contains various operational parameters related to mission performance. This data is stored in a structured CSV format and serves as the primary input for both classification and regression tasks.

Feature Extraction and Selection: Relevant features are selected from the telemetry data to represent satellite behaviour effectively. These features are used as inputs for machine learning models, ensuring that only significant attributes contribute to prediction performance.

Implementation of Classification Models (Including CART): The system applies multiple classification algorithms such as Random Forest, Gradient Boosting, and Support Vector Machine (SVM). Tree-based models like Random Forest and Gradient Boosting are based on CART, which helps in learning decision rules for mission success classification.

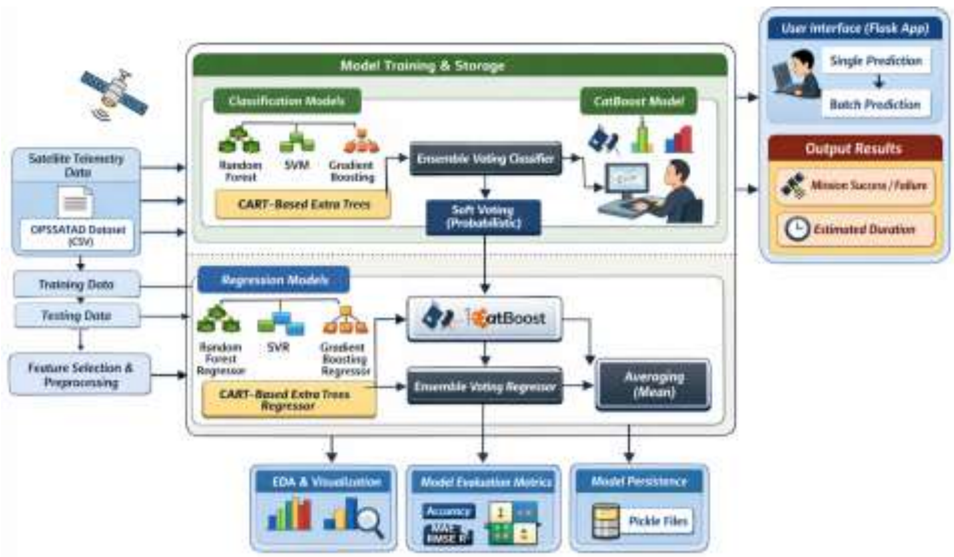

Figure. 2: System architecture of the satellite mission prediction framework.

Implementation of Regression Models (Including CART): For predicting mission duration, regression models such as Random Forest Regressor, Gradient Boosting Regressor, and Support Vector Regressor (SVR) are used. CART-based regression techniques are utilized in tree-based models to capture nonlinear relationships in telemetry data.

Proposed Ensemble Model Construction: In addition to individual models, a proposed ensemble model is developed using Extra Trees and CatBoost algorithms. These models are combined using a Voting mechanism to enhance prediction accuracy and reduce variance compared to single models.

Model Training and Storage: All classification and regression models, including CART-based and ensemble models, are trained using the training dataset. The trained models are then saved using serialization techniques to enable reuse without retraining.

Model Evaluation and Performance Analysis: The system evaluates model performance using metrics such as accuracy, precision, recall, and F1-score for classification, and MAE, MSE, RMSE, and R^2 score for regression. Visualization techniques like confusion matrices and scatter plots are used for analysis.

Prediction Module (Single and Batch Processing): The system provides prediction functionality where users can input individual telemetry values or upload batch CSV files. The trained models generate outputs for mission success classification and mission duration prediction.

Web-Based Deployment and User Interaction: The complete system is deployed using a Flask web application that includes user authentication, data visualization, model comparison, and prediction interfaces. This ensures easy accessibility and interaction for users.

4. Dataset Description

The dataset provided is a sample of satellite telemetry data, stored in a CSV format, and used by the Flask-based web application for analysis, classification, and regression tasks.

- **segment**: Integer identifier for each telemetry segment (1 to 15 in the sample).
- **Mission**: Binary target variable for classification (1 = success, 0 = failure).
- **train**: Binary indicator for train/test split (1 = training set, 0 = test set).
- **channel**: String identifier for the communication channel (all values are "CADC0872" in the sample).
- **sampling**: Integer indicating the sampling rate (all values are 1 in the sample).
- **duration**: Integer representing the duration of the telemetry segment (in seconds or another time unit).
- **len**: Integer representing the length of the signal (slightly higher than duration, possibly due to additional metadata or samples).
- **mean**: Float representing the mean of the signal values.
- **var**: Float representing the variance of the signal values.
- **std**: Float representing the standard deviation of the signal values.
- **kurtosis**: Float measuring the "tailedness" of the signal distribution.
- **skew**: Float measuring the asymmetry of the signal distribution.
- **n_peaks**: Integer counting the number of peaks in the signal.
- **smooth10_n_peaks**: Integer counting peaks after applying a smoothing filter (window size 10).
- **smooth20_n_peaks**: Integer counting peaks after applying a smoothing filter (window size 20).
- **diff_peaks**: Integer representing the number of peaks in the first derivative of the signal.
- **diff2_peaks**: Integer representing the number of peaks in the second derivative of the signal.
- **diff_var**: Float representing the variance of the first derivative of the signal.
- **diff2_var**: Float representing the variance of the second derivative of the signal.
- **gaps_squared**: Integer representing the sum of squared gaps in the signal.
- **len_weighted**: Integer, likely a weighted version of len.
- **var_div_duration**: Float, variance divided by duration.
- **var_div_len**: Float, variance divided by length.

4. Results and Description

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications.

Figure. 3 depicts the confusion matrix of the Ensemble (CART) model shows highly balanced and improved performance, correctly classifying 413 failure cases with only 3 misclassified as success, and accurately identifying 103 success cases with just 10 misclassified as failure. This demonstrates a significant improvement over individual models, especially in capturing mission success patterns while maintaining strong failure detection. The combination of CART-based tree learning and boosting effectively reduces bias and variance, resulting in more reliable and generalized predictions for satellite mission outcomes.

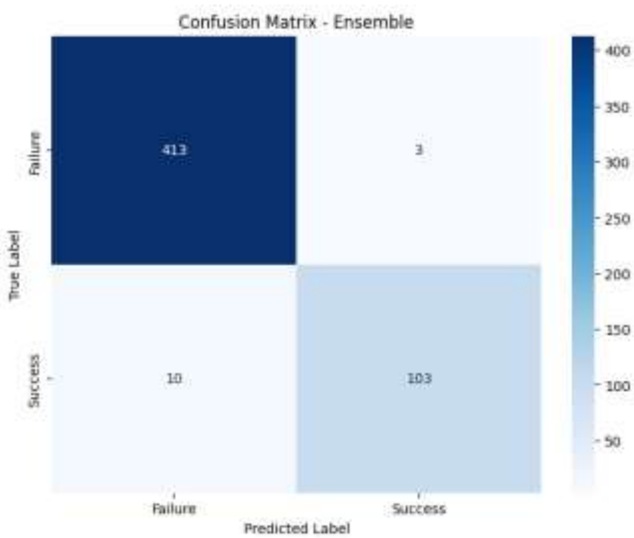

Figure. 3: Illustration of confusion matrix using proposed ensemble model for mission status target

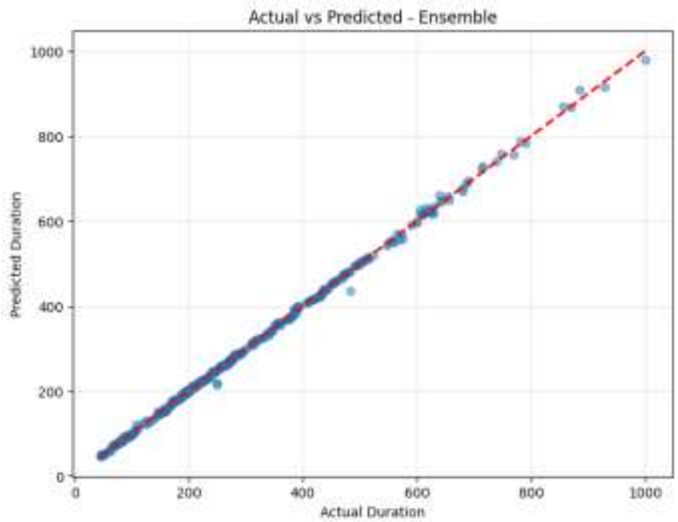

Figure. 4: Illustration of scatter plot using proposed ensemble model for duration analysis target

Figure. 4 presents scatter plot of the Ensemble (CART) model for duration prediction shows an almost perfect alignment of data points along the diagonal reference line, indicating very high prediction accuracy. The predicted values closely match the actual durations across the entire range, demonstrating the model's strong ability to capture both linear and nonlinear relationships in the telemetry data. Unlike individual models, there is minimal deviation and very few outliers, reflecting improved stability and consistency. The ensemble model provides highly precise and reliable duration predictions by effectively combining multiple learning approaches.

Table 1 presents the performance comparison of different classification models for mission status prediction, highlighting clear differences in their effectiveness. The RF (CART) model achieves strong performance with high accuracy and precision, indicating its ability to correctly identify mission outcomes, though its F1-score suggests slight limitations in balancing both classes. The GB (CART) model shows comparatively lower performance, with reduced precision and F1-score, reflecting its bias toward the dominant class and weaker capability in distinguishing successful missions. The SVM (CART) model demonstrates balanced and improved results, achieving higher accuracy and better F1-score than the previous models, indicating more reliable classification across both classes. However, the Ensemble model significantly outperforms all individual models, achieving the highest accuracy, precision, recall, and F1-score, which indicates excellent balance and consistency in prediction.

Table. 1: Performance comparison of all the classification models for mission status target

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
RF	0.8866	0.8982	0.8866	0.8707
GB	0.7864	0.6184	0.7864	0.6924
SVM	0.8922	0.8970	0.8922	0.8803
Ensemble	0.9754	0.9754	0.9754	0.9751

Table. 2: Performance comparison of all the regression models for duration analysis target

Model	MAE (%)	MSE (%)	RMSE (%)	R^2 Score (%)
RF	35.8970	2179.1271	46.6811	0.9237
GB	118.7667	25034.0234	158.2214	0.1232
SVR	324.9601	105979.5512	325.5450	-2.7117
Ensemble	2.7594	24.4241	4.9421	0.9991

Table 2 presents the performance comparison of different regression models for duration prediction, clearly showing variations in prediction accuracy and error levels. The RF (CART) model demonstrates strong performance with relatively low error values and a high R^2 score, indicating that it can effectively capture the relationship between telemetry features and mission duration. In contrast, the GB (CART) model shows significantly higher error values and a very low R^2 score, reflecting poor learning capability and inability to model the data accurately. The SVR (CART) model performs the worst among all, with extremely high error metrics and a negative R^2 score, indicating that its predictions are highly unreliable and worse than a simple baseline model. However, the Ensemble (CART) model outperforms all other models by a large margin, achieving extremely low error values and an R^2 score close to 1, which indicates near-perfect prediction accuracy.

5. Conclusion

The research successfully demonstrates an efficient and intelligent approach for satellite mission analysis by leveraging a locally deployed ensemble learning framework on OPSSATAD telemetry data. The system effectively integrates both classification and regression tasks to predict mission success and estimate mission duration, providing a comprehensive analytical solution within a unified platform. Using CART-based tree models and boosting techniques, the proposed Ensemble Voting (CART) model can capture complex nonlinear relationships, hierarchical decision patterns, and feature interactions present in satellite telemetry data. Experimental results clearly show that while individual models such as RF (CART), GB (CART), and SVM (CART) exhibit varying levels of performance with certain limitations like class imbalance bias or poor generalization, the proposed Ensemble Voting (CART) model significantly outperforms them in all evaluation metrics. It achieves highly balanced classification results with superior accuracy, precision, recall, and F1-score, along with near-perfect regression performance indicated by extremely low error values and a very high R^2 score. The integration of model persistence using pickle further enhances system efficiency by enabling faster predictions without retraining, making it suitable for real-time applications. Additionally, the Flask-based deployment provides an interactive interface supporting both single and batch predictions, along with visualization and comparative analysis features. The research proves that combining CART-based learning with boosting in an ensemble framework leads to robust, reliable, and highly accurate prediction systems, making it highly suitable for advanced satellite telemetry analysis and decision support in space mission operations.

References

[1] Santthosh Saai Reddy Purmani. (2026). Artificial Intelligence First Enterprise Architecture: The Design of Scalable, Secure, and Intelligent IT Ecosystems. American Journal of AI Cyber Computing Management, 6(1(2)), 1–8. https://doi.org/10.64751/ajaccm.2026.v6.n1(2).pp1-8

[2] Patel, S., & Patyrykin, K. (2025). Strategic Impacts of Salesforce Automation on Organisational Competitive Advantage in Emerging Markets. Journal of Posthumanism, 5(12), 357–372. https://doi.org/10.63332/joph.v5i12.3782

[3] Vasagam, M., Kumar, A., & Garg, A. (2026). Learning Execution Plan Embeddings for Multi-Dimensional Query Resource Prediction. IEEE Access.

[4] He, Y.; Xing, L.; Chen, Y.; Pedrycz, W.; Wang, L.; Wu, G. A generic Markov decision process model and reinforcement learning method for scheduling agile earth observation satellites. IEEE Trans. Syst. Man Cybern. Syst. 2020, 52, 1463–1474.

[5] Kalae, U. K. (2021). Enhancing data analytics and reporting efficiency using Power BI and SQL in cloud computing environments. Journal of Computational Analysis and Applications, 29(6), 2021. https://doi.org/10.48047/jocaaa.2021.29.06.48

[6] Poojari, R. Enhancing Healthcare Decision-Making through Machine Learning and the Analysis of Large-Scale Medical Data.

[7] Reddy, S. K. R. Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms.

[8] Prodduturi, S. M. K. To Secure Your Paper as Per UGC Guidelines We Are Providing A ElectronicBar code.

[9] Gaddam, S. From Fixed Specifications to Self-Adapting Systems: A Machine Learning Perspective on Software Engineering.

[10] Explainable AI Framework for Policy-Compliant Anomaly Detection in Data Pipelines. (2025). Inaternational Journal of Communication Networks and Information Security, 16(4). https://doi.org/10.48047/ijcnis.16.4.2111

[11] Huang, J.; Su, Y.; Huang, L.; Liu, W.; Wang, F. An optimized snapshot division strategy for satellite network in GNSS. IEEE Commun. Lett. 2016, 20, 2406–2409.

[12] Pilastre, B.; Boussouf, L.; d'Escrivan, S.; Tourneret, J.-Y. Anomaly detection in mixed telemetry data using a sparse representation and dictionary learning. Signal Process. 2020,168, 107320.

[13] Takeishi, N.; Yairi, T. Anomaly Detection from Multivariate Time-Series with Sparse Representation. In Proceedings of the2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC), San Diego, CA, USA, 5–8 October 2014; IEEE:Piscataway, NJ, USA, 2014; pp. 2651–2656.

[14] Hu, M.; Ji, Z.; Yan, K.; Guo, Y.; Feng, X.; Gong, J.; Zhao, X.; Dong, L. Detecting anomalies in time series data via a meta-featurebased approach. IEEE Access 2018,6, 27760–27776.

[15] Saari, J.; Strömbergsson, D.; Lundberg, J.; Thomson, A. Detection and identification of windmill bearing faults using a one-class support vector machine (SVM). Measurement 2019,137, 287–301.

[16] Vos, K.; Peng, Z.; Jenkins, C.; Shahriar, M.R.; Borghesani, P.; Wang, W. Vibration-based anomaly detection using LSTM/SVMapproaches. Mech. Syst. Signal Process. 2022,169, 108752.

[17] Martínez-Heras, J.; Donati, A. Enhanced Telemetry Monitoring with Novelty Detection. AI Mag. 2014, 35, 37–46

[18] Zeng, Z.; Jin, G.; Xu, C.; Chen, S.; Zhang, L. Spacecraft Telemetry Anomaly Detection Based on Parametric Causality and Double-Criteria Drift Streaming Peaks over Threshold. Appl. Sci. 2022, 12, 1803.

[19] Gao, Y.; Yang, T.; Xu, M.; Xing, N. An Unsupervised Anomaly Detection Approach for Spacecraft Based on Normal Behavior Clustering. In Proceedings of the 2012 Fifth International Conference on Intelligent Computation Technology and Automation, Zhangjiajie, China, 12–14 January 2012; pp. 478–481.

[20] Jin, X.; Wang, H.; Jin, Z. Anomaly detection of satellite telemetry data based on extended dominant sets clustering. J. Phys. Conf. Ser. 2023, 2489, 012036.