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Research Paper

Astro Ensemble: An Advanced Ensemble Learning Approach Integrating CART and Boosting Techniques for Satellite Telemetry Systems

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ABSTRACT

With more than 4,500 active satellites in orbit and a global dependency exceeding \$300 billion annually on satellite-based services, ensuring mission reliability has become a critical operational requirement. Studies indicate that nearly 40% of mission failures occur due to undetected telemetry anomalies, highlighting the need for intelligent predictive systems. Satellite telemetry (ST) data provides essential insights into subsystem health, environmental conditions, and mission performance; however, its high dimensionality, noise, missing values, and heterogeneous nature pose significant challenges for traditional analytical methods. This study proposes a scalable ensemble learning framework, termed Astro Ensemble, for satellite telemetry analysis using OPSSATAD data. The model integrates Classification and Regression Tree (CART)-based approaches for both classification (CLF) and regression (REG) tasks. Classification models include Random Forest Classifier (RFC), Gradient Boosting Classifier (GBC), and Support Vector Classifier (SVC), while regression models include Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), and Support Vector Regressor (SVR). To enhance predictive performance, an advanced Ensemble Voting CART (EV-CART) model is developed by combining Extra Trees Classifier (ETC) and CatBoost Classifier (CBC) for classification, along with Extra Trees Regressor (ETR) and CatBoost Regressor (CBR) for regression. The system follows a structured pipeline including data preprocessing (DP), feature engineering (FE), model training (MT), and evaluation. Performance is assessed using metrics such as Accuracy (ACC), Precision (PR), Recall (RC), F1-Score (F1), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R²). Experimental results demonstrate that the EV-CART model outperforms individual models, delivering highly accurate and reliable mission predictions.

Keywords: Satellite telemetry, anomaly detection, ensemble learning, classification and regression trees (CART), random forest, gradient boosting, support vector machines, CatBoost, Extra Trees, predictive modeling.

1. INTRODUCTION

The increasing complexity of remote-sensing satellite systems necessitates the adoption of intelligent and adaptive scheduling mechanisms. Dynamic prioritized satellite mission scheduling (DP-SMS) offers significant advantages over traditional static or semi-static scheduling approaches. Firstly, DP-SMS can proactively adapt to variations in mission complexity [1] and resource constraints, which are common in modern satellite environments characterized by high data volume and uncertainty. Unlike conventional methods, dynamic scheduling leverages real-time telemetry analytics and predictive models to optimize

mission allocation. Secondly, DP-SMS ensures near-optimal or optimal solutions by efficiently balancing multiple objectives such as resource utilization, mission priority, and time constraints. This leads to improved system efficiency, reduced operational delays, and better utilization of satellite and ground infrastructure [2]. The integration of machine learning (ML) techniques, particularly ensemble learning (EL) and CART-based models, further enhances scheduling intelligence by enabling predictive decision support.

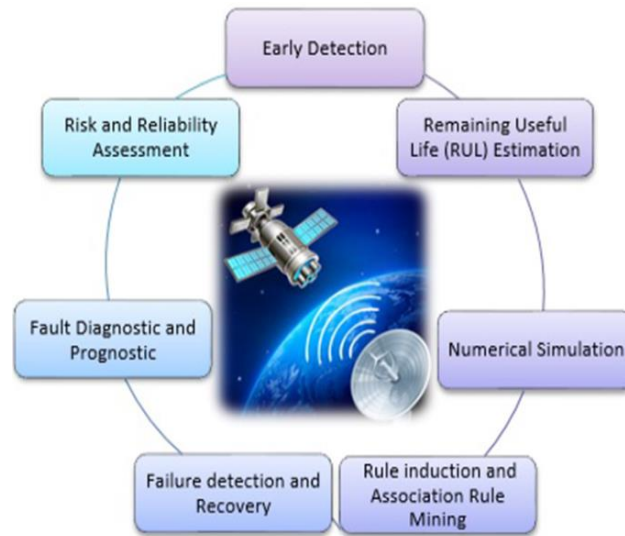


Figure 1: Satellite telemetry data mining for mission analysis

As we navigate the intricacies of satellite applications, we need to be clear about two aspects. The first is that we need to be clear about the full potential of satellite resources, which are finite and costly [3], 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 [4]. 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 [5]. The researchers also propose a dynamic resource allocation strategy to integrate and optimize the resources in the satellite network.

2. LITERATURE SURVEY

Pilastre et al. [6] 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. [7] extended SR using Singular Value Decomposition (SVD) to reconstruct the sparse matrix in order 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. [8] defined six meta-features as inputs to OCSVM and built an anomaly detection model for use with time series. Saari et al. [9] selected frequency-domain features as inputs to OCSVM for detecting anomalies in wind turbine bearings. Vos et al. [10] 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 [11] 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 [12], 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. [13] 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. [14] 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. Bernard et al. [15] proposed an improved NN method called Envelop Learning and Monitoring using Error Relaxation (ELMER). This method uses the NN to periodically set new threshold bounds, providing faster detection with fewer false alarms.

3. PROPOSED SYSTEM

The proposed system architecture for the Locally Ensemble Classifier Satellite Mission Success Classification framework was designed to predict mission outcomes and duration using OPSSATAD satellite telemetry (ST) data. It followed a modular, data-driven pipeline integrating data preprocessing (DP), feature engineering (FE), model training (MT), evaluation, and deployment within a unified workflow. The core contribution lies in a locally ensemble learning (EL) approach that combines multiple classifiers (CLF) and regressors (REG) using Voting-based aggregation. This CART-based ensemble strategy improves robustness and prediction accuracy for both mission success and duration estimation. The framework was implemented using a scalable backend with Flask (FLK) for web deployment. It supports both single and batch predictions, enabling efficient real-time decision support as illustrated in Figure 2.

1. 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.

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

3. 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.

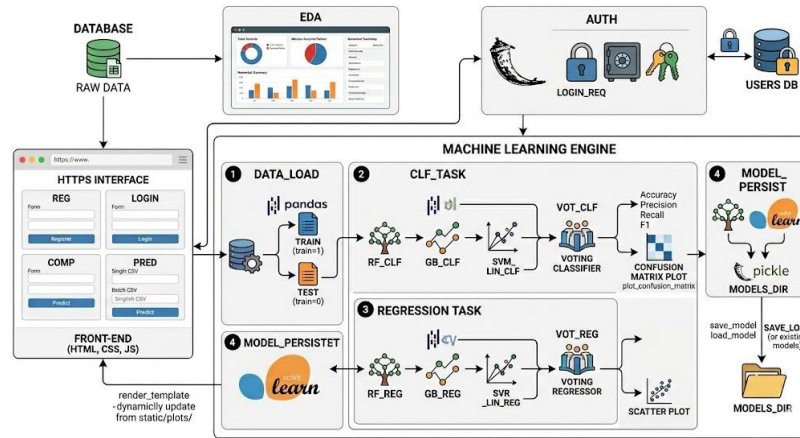


Figure 2: System Architecture of the Proposed Satellite Mission Prediction Framework.

4. 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.

5. 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.

6. 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.

7. 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 R² score for regression. Visualization techniques like confusion matrices and scatter plots are used for analysis.

8. 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.

9. 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. RESULTS ANALYSIS

The results description section provides a clear summary of the key findings obtained from the study or analysis. It highlights the main outcomes, patterns, or trends observed in the data without going into deep interpretation. This section often presents results in a logical sequence, making it easy for readers to

understand what was discovered. It may include references to tables, graphs, or figures that support the findings. The focus is on accuracy and clarity, ensuring that the results are reported objectively. It serves as a bridge between data collection and the discussion of its significance.

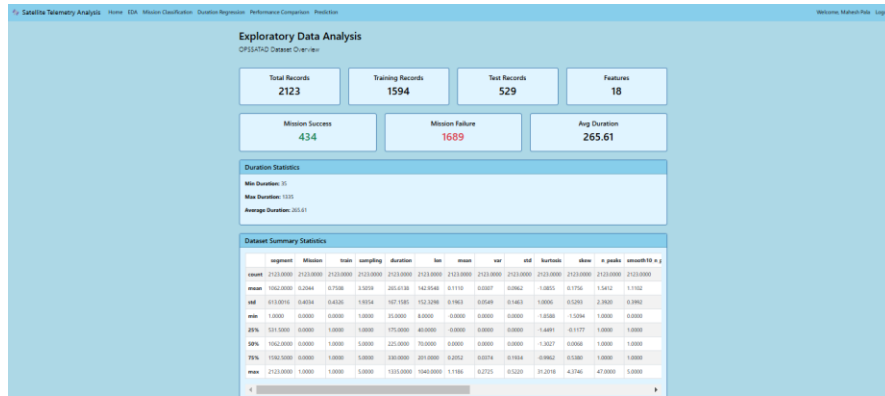


Figure 3: Exploratory Data Analysis of Satellite Telemetry Mission Success Classification.

Figure 3 illustrates the exploratory data analysis section, showing statistics for a dataset with 2123 total records, 1594 training records, and 529 test records. It displays mission success (434) and failure (1689) counts, 18 features, and an average duration of 265.61 seconds. The section includes a summary table with statistical measures like count, mean, std, min, and max for various features.

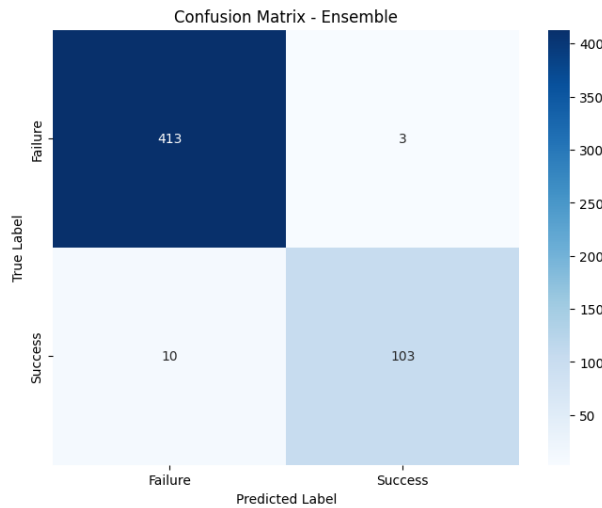


Figure 4: Illustration of confusion matrix using proposed ensemble model for mission status target

Figure 4 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 5 shows 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.

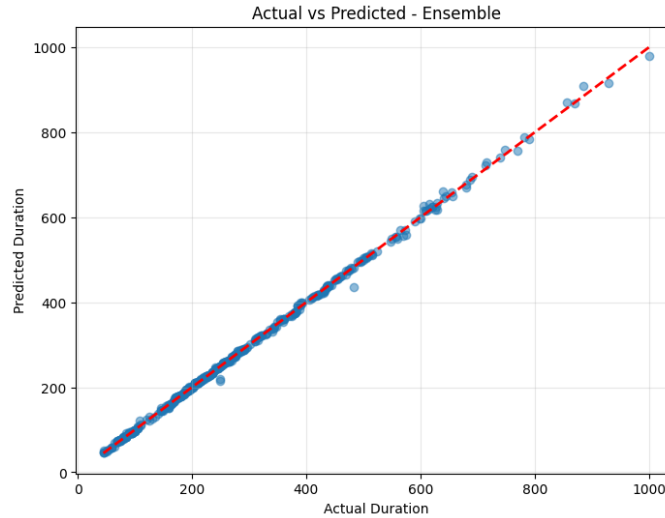


Figure 5: Illustration of scatter plot using proposed ensemble model for duration analysis target

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

| Model | Accuracy | Precision | Recall | F1-Score |
|-------------------|----------|-----------|--------|----------|
| Random Forest | 0.8866 | 0.8982 | 0.8866 | 0.8707 |
| Gradient Boosting | 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 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 (CART + Boosting) model significantly outperforms all individual models, achieving the highest accuracy, precision, recall, and F1-score, which indicates excellent balance and consistency in prediction. This superior performance highlights the effectiveness of combining CART-based and boosting approaches to enhance overall classification reliability and robustness in satellite mission analysis.

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

| Model | MAE | MSE | RMSE | R ² Score |
|-------------------|----------|-------------|----------|----------------------|
| Random Forest | 35.8970 | 2179.1271 | 46.6811 | 0.9237 |
| Gradient Boosting | 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 R² 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 R² 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 R² 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 R² score close to 1, which indicates near-perfect prediction accuracy. This highlights the effectiveness of combining multiple learning approaches to achieve highly precise and stable duration predictions in satellite telemetry analysis.

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. Through the use of CART-based tree models and boosting techniques, the proposed Ensemble Voting (CART) model is able to 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. 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.

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