

ENHANCING ISRO'S MISSION PLANNING WITH AI-DRIVEN SATELLITE LIFETIME PREDICTION MODELS

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ABSTRACT

Since its inception in 1969, the Indian Space Research Organisation (ISRO) has been at the forefront of space exploration, contributing significantly through a wide range of satellite missions in areas such as communication, Earth observation, and navigation. Traditionally, the prediction of satellite lifetimes has relied on empirical models, component testing, and expert judgment. While effective to a certain extent, these conventional approaches often struggle with analyzing large volumes of data and are limited in predictive accuracy. To address these challenges, this research proposes the application of machine learning techniques to model and predict the expected lifetime of ISRO satellites. By leveraging historical mission data and advanced analytical methods, the aim is to enhance the precision of lifetime estimations, ultimately supporting better mission planning, resource management, and operational decision-making. The methodology involves collecting comprehensive datasets from past satellite missions, including operational parameters, environmental influences, and component performance records. This data will undergo preprocessing to identify significant patterns and correlations. Using this processed information, a suite of machine learning models will be developed to estimate satellite lifespans based on variables such as launch conditions, operational anomalies, and degradation behaviors. Additionally, visualization tools will be incorporated to provide actionable insights in an intuitive format, enabling more informed planning by mission teams.

Keywords: ISRO Space Missions, Satellite Lifetime Prediction, Time Series Forecasting, LSTM Regressor, Artificial Intelligence.

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1. INTRODUCTION

The Indian Space Research Organisation (ISRO) has established itself as a major player in global space exploration. Since its founding in 1969, ISRO has launched numerous satellite missions that have revolutionized fields such as communications, earth observation, meteorology, navigation, and scientific research. Some of ISRO's most significant missions include the Mars Orbiter Mission (Mangalyaan), Chandrayaan lunar missions, and the launch of the Polar Satellite Launch Vehicle (PSLV). With over 300 satellites launched and partnerships with multiple countries, ISRO has built a reputation for cost-effective and efficient space exploration. Predicting the lifespan of satellites has

traditionally relied on expert judgment and empirical data. However, as satellite technology advances, the need for more precise predictions is growing.



Fig.1: ISRO's Mission Planning with AI-Driven.

Machine learning offers an opportunity to enhance these predictions by analyzing large datasets to model and predict satellite lifetimes with greater accuracy. Applications of such a model include mission planning, risk management, and optimization of satellite resources to ensure maximum operational efficiency. Before the integration of machine learning techniques, predicting the lifetime of satellites involved using traditional methods, such as empirical models based on historical performance data and expert evaluations. These methods, while useful, often struggled with scalability and lacked precision. For instance, failure models depended heavily on physical testing of components and extrapolating results based on small sample sizes. In addition, expert assessments, while valuable, were subjective and often limited by human bias and the availability of historical data. These methods were time-consuming, error-prone, and often unable to capture complex relationships between operational data and satellite degradation patterns. The inability to analyze large datasets efficiently led to inaccuracies in lifetime predictions, which could, in turn, affect resource allocation, mission planning, and satellite operations.

2. LITERATURE SURVEY

Williams and Bell [1] analyzed the Chang'e 5 mission, discussing its objectives, lunar sampling techniques, and technological innovations. They examined the spacecraft's performance and mission outcomes in the context of China's lunar exploration program. Dunbar [2] presented an overview of NASA's Artemis program, focusing on its objectives, planned lunar missions, and technological advancements. The study highlighted Artemis' role in future lunar exploration and its significance in human spaceflight. Dobrijevic [3] provided a comprehensive guide to NASA's DART mission, explaining its purpose, execution, and impact on planetary defense strategies. The study discussed how the mission tested kinetic impact technology for asteroid deflection.

Williams and Bell [4] described Chandrayaan 3, outlining its scientific objectives, technological advancements, and expected contributions to lunar exploration. The mission aimed to improve India's lunar research capabilities. Williams and Bell [5] examined the Luna 25 mission, detailing its goals, spacecraft design, and expected contributions to Russia's lunar exploration efforts. The study explored its significance in the country's space ambitions. Ebeling [6] introduced fundamental concepts of reliability and maintainability engineering, discussing various analytical techniques for assessing system performance and longevity. The book emphasized the importance of reliability in engineering design. Huangpeng et al. [7] proposed a methodology for determining the optimal sample size for launch vehicle reliability analysis. They utilized Sequential Probability Ratio Test (SPOT) and Bayesian recursive estimation to improve the accuracy of reliability predictions. Their study aimed to enhance launch vehicle assessment through statistical modeling.

Krevor and Wilhite [8] introduced a framework for estimating the cost of improving launch vehicle reliability. They analyzed cost trade-offs associated with enhancing reliability and presented a model

to optimize investment in failure prevention measures. Their findings contributed to cost-effective launch vehicle development strategies. Guarro [9] conducted an in-depth assessment of space launch vehicle reliability, evaluating various statistical methods for estimating failure probabilities. His study highlighted the challenges in predicting launch success and emphasized the importance of historical data analysis in improving launch outcomes. Guikema and Paté-Cornell [10] applied Bayesian analysis to assess launch vehicle success rates, integrating historical data with probabilistic models. Their research demonstrated how Bayesian updating can improve predictions of launch reliability and reduce uncertainty in failure assessments. Guikema and Paté-Cornell [11] investigated the probability of infancy-related failures in space launch vehicles, emphasizing the role of early-life performance in determining overall reliability. They found that launch vehicles often exhibit higher failure rates in initial flights before stabilizing in performance. Castet and Saleh [12] analyzed satellite reliability using statistical methods, comparing various reliability estimation techniques. Their study provided insights into the failure rates of different satellite classes and contributed to the understanding of satellite longevity in space missions.

3. PROPOSED SYSTEM

The complete workflow of an AI-based system designed to predict the expected lifetime of satellites for ISRO's space missions. The process begins with uploading the satellite dataset, which is then subjected to data preprocessing to clean and prepare it for analysis. After preprocessing, the dataset is split into training and testing subsets. The training data is used to develop three models: a Ridge Regression model, a Linear Regression model, and the proposed LSTM Regressor model. The Ridge and Linear models are evaluated based on their performance using metrics such as MAE, MSE, RMSE, and R^2 . Separately, test data is also preprocessed to match the format used during training. This preprocessed test data is then passed through the proposed LSTM Regressor model to generate predictions of satellite lifetime. The workflow highlights a comparative analysis between traditional regression models and the LSTM-based deep learning model, with the latter serving as the core innovation for achieving higher prediction accuracy.

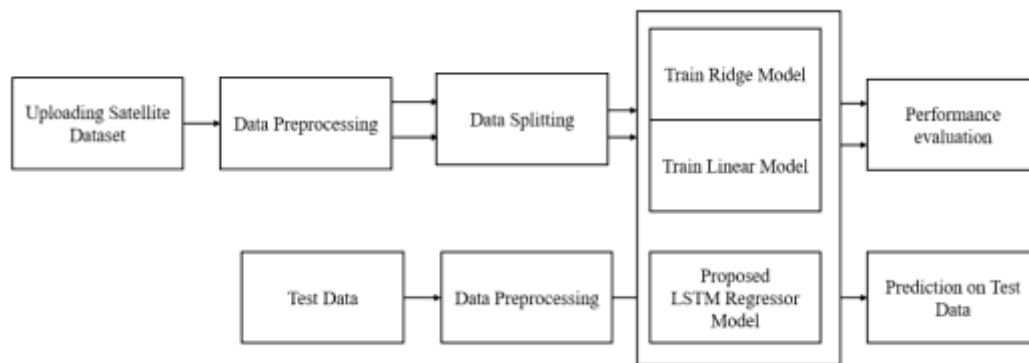


Fig. 2: Architectural Block Diagram of Proposed System.

What is LSTM Regressor? Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) that is well-suited for learning from sequences of data, such as time series or sequential data. Unlike regular RNNs, LSTMs are capable of capturing long-range dependencies due to their unique architecture, which helps in solving the vanishing gradient problem faced by standard RNNs.

An LSTM Regressor is a regression model that leverages the LSTM architecture to predict a continuous target variable. This is particularly useful when the target variable depends on sequential data, such as time series data, where the future values are influenced by past observations.

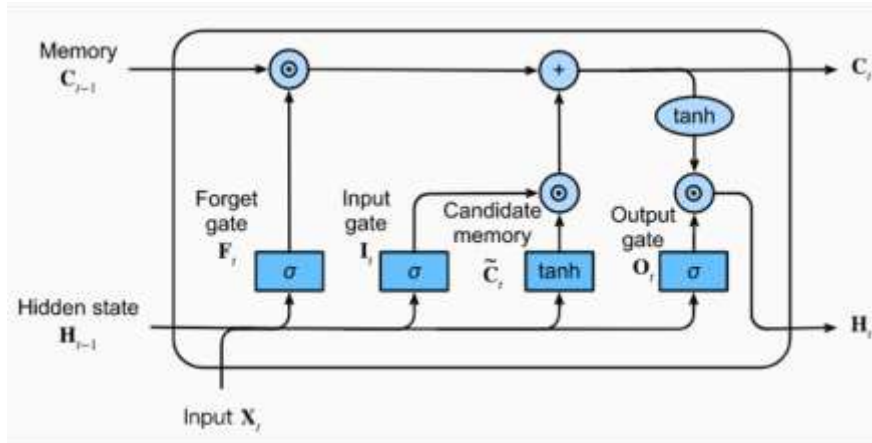


Fig. 3: Internal workflow of LSTM.

How it Works:

Long Short-Term Memory (LSTM) networks use a set of gates—input, forget, and output gates—to regulate the flow of information through the network. These gates enable LSTMs to retain relevant information over extended periods, making them highly effective for learning time-dependent patterns. The architecture of an LSTM cell is specifically designed to maintain memory over time, allowing the model to focus on important data while filtering out irrelevant inputs. A typical LSTM regressor includes several key components: an input layer that receives the sequence data, one or more LSTM layers that capture temporal dependencies, a dense layer that processes the learned features, and an output layer that produces the final regression prediction.

Architecture:

In an LSTM-based regression model, sequential data such as time series is first fed into the network as input. The core of the model consists of LSTM layers, which contain memory cells designed to retain important information and pass relevant data across time steps. These layers can be stacked to capture more complex temporal patterns in the data. Following the LSTM layers, a dense layer is employed to transform the learned features into a format suitable for prediction. Finally, the output layer generates a continuous value, representing the regression prediction.

Advantages:

LSTM models are particularly well-suited for time-series and sequential data as they effectively capture long-term temporal dependencies. Unlike traditional models such as linear regression or ridge regression, LSTMs are capable of learning from more complex data patterns, making them ideal for handling intricate sequences. Additionally, LSTM networks are designed to overcome the vanishing gradient problem, a common issue in traditional recurrent neural networks (RNNs) that hampers the learning of long-range dependencies.

4. RESULT AND DISCUSSION

The figure 4, the exploratory data analysis (EDA) plots are showcased, highlighting the relationship between the various features in the satellite dataset. These plots include visualizations such as histograms, scatter plots, and box plots that give an initial overview of the dataset's distribution, correlations, and potential outliers. The goal of EDA is to understand the characteristics of the dataset and to identify patterns or anomalies that could influence the model-building process, helping guide data preprocessing decisions.



Fig. 4: EDA Plots of the Project

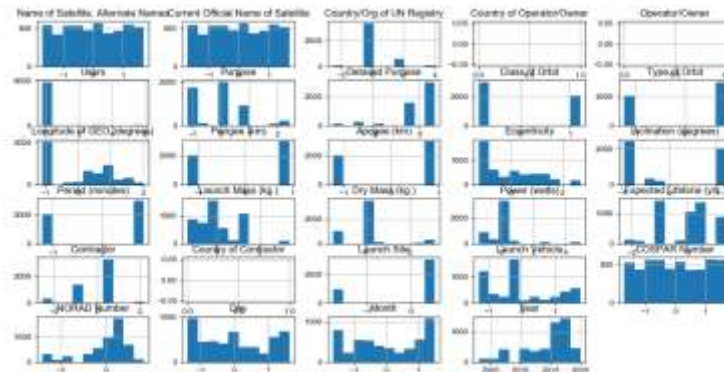


Fig. 5: Data Preprocessing in the GUI

The figure 5 presents the data preprocessing phase within the GUI interface. It visualizes the steps where the raw dataset is cleaned, missing values are handled, categorical data is encoded, and the dataset is transformed into a format suitable for machine learning models. It also highlights how feature scaling, such as normalization or standardization, is applied to prepare the data for better model performance. The preprocessing steps are displayed interactively within the interface, ensuring that users can track and manage each stage of data transformation.

Performance Metrics of Ridge Regressor

The performance of the Ridge Regressor model is evaluated using several key metrics. The Mean Absolute Error (MAE) is 1.259, indicating that, on average, the model's predictions deviate from the actual satellite lifetimes by approximately 1.26 years. The Mean Squared Error (MSE) is 2.356, reflecting the average of the squared differences between predicted and actual values, which provides a measure of overall prediction accuracy. The Root Mean Squared Error (RMSE), calculated as the square root of MSE, is 1.535, offering an error measure in the same units as the target variable satellite lifetime in years. Lastly, the R-squared (R^2) value is 0.847, meaning that the model explains 84.7% of the variance in satellite lifetime, indicating a strong fit to the data.

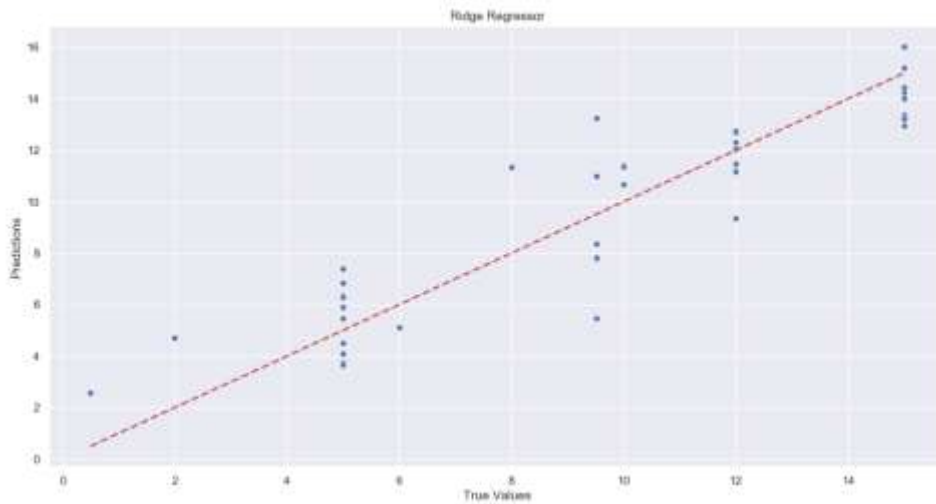


Fig. 6: Performance Metrics and Regression Scatter Plot of the Ridge Regressor Model

The figure 6 presents the performance metrics along with a regression scatter plot for the Ridge Regressor model. The plot visually compares the predicted values against the actual satellite lifetimes. The closeness of the points to the diagonal line indicates the accuracy of the predictions. The performance metrics provided further quantify the model's prediction accuracy, giving a clear picture of how well the Ridge Regressor performs.

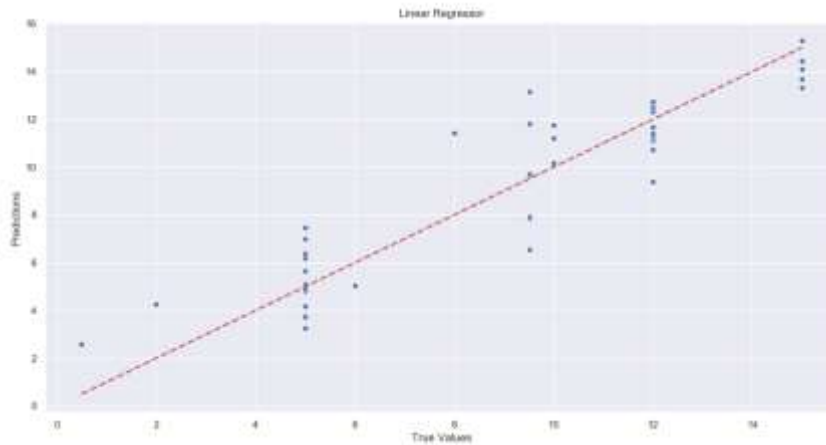


Fig. 7: Performance Metrics and Regression Scatter Plot of the Linear Regressor Model

Similar to Fig. 5, this figure 7 shows the performance metrics and regression scatter plot for the Linear Regressor model. The scatter plot highlights how the model's predicted satellite lifetimes compare to the actual values. The performance metrics indicate that the Linear Regressor model outperforms the Ridge Regressor, as seen in the lower error metrics and higher R^2 value.

Performance Metrics of Linear Regressor

The performance metrics for the Linear Regressor model indicate slightly better results compared to the Ridge Regressor. The Mean Absolute Error (MAE) is 1.197, suggesting that the model's predictions deviate from the actual satellite lifetimes by an average of about 1.2 years. The Mean Squared Error (MSE) stands at 2.174, showing a slightly lower average squared prediction error than the Ridge model. The Root Mean Squared Error (RMSE) is 1.475, which is also lower than that of the Ridge Regressor, indicating improved prediction accuracy. Furthermore, the R-squared (R^2) value is 0.859, meaning the model explains 85.9% of the variance in satellite lifetime, reflecting a marginally better fit than the Ridge Regressor.

Performance Metrics of LSTM Model

The performance metrics for the LSTM Regressor model demonstrate its exceptional predictive accuracy. The Mean Absolute Error (MAE) is just 0.072, indicating a very low average deviation between the predicted and actual satellite lifetimes, and highlighting the model's high precision. The Mean Squared Error (MSE) is 0.008, suggesting that the predictions are extremely close to the true values. Similarly, the Root Mean Squared Error (RMSE) stands at only 0.089, further confirming the model's ability to deliver accurate predictions. Most impressively, the R-squared (R^2) value is 0.999, meaning the LSTM model explains 99.9% of the variance in the satellite lifetime data, reflecting an outstanding fit and near-perfect predictive performance.

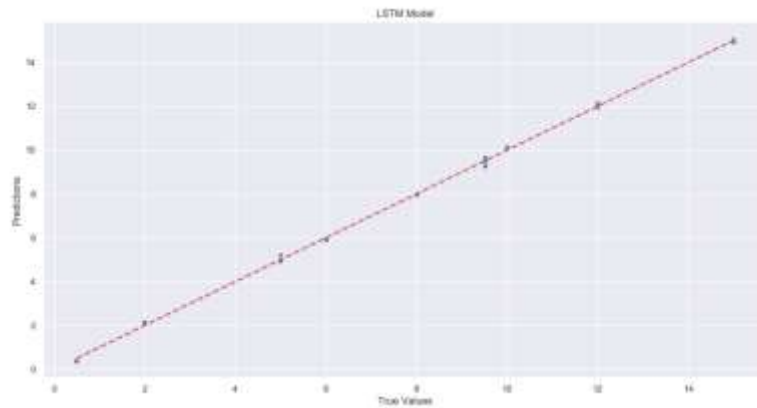


Fig. 8: Performance Metrics and Regression Scatter Plot of the LSTM Regressor Model

This figure 8 shows the performance metrics and regression scatter plot for the LSTM Regressor model. The regression plot illustrates how closely the model's predictions align with the actual satellite lifetimes, showcasing the superior performance of the LSTM model. Given the very low error metrics and the high R^2 score, this plot emphasizes the strong predictive power of the LSTM model.

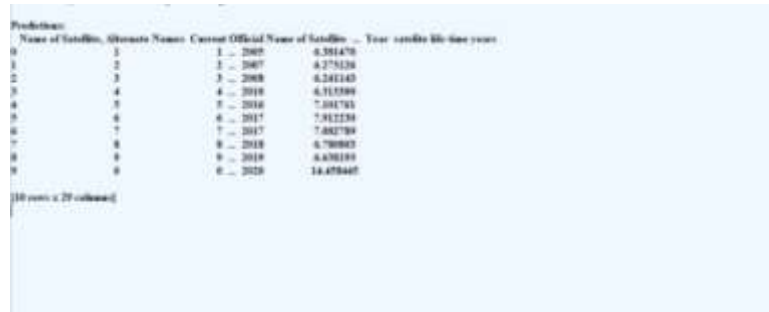


Fig. 9: Model Prediction on the Test Case.

This figure 9 shows the model's predictions applied to the test dataset. It visually represents the predicted satellite lifetimes versus the actual lifetimes, demonstrating how accurately the model performs on unseen data. The test data results are essential for validating the model's ability to generalize and make accurate predictions beyond the training set.

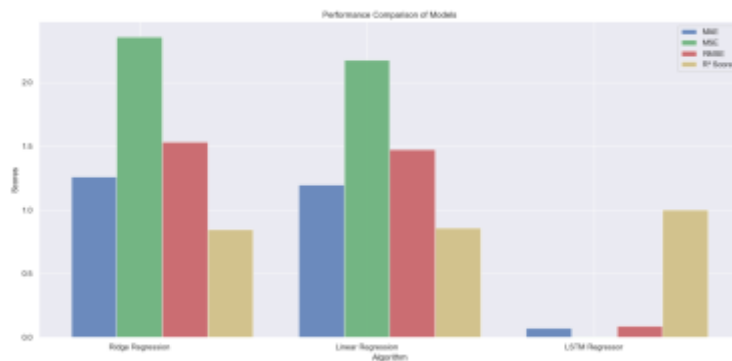


Fig. 10: Performance Comparison Graph of All Models

This figure 10 presents a comparative graph of the performance metrics for all three models: Ridge Regressor, Linear Regressor, and LSTM Regressor. The graph shows how the models perform relative to each other in terms of MAE, MSE, RMSE, and R^2 . It clearly illustrates that the LSTM model outperforms both Ridge and Linear Regression models, confirming its superior ability to predict satellite lifetimes accurately.

5. CONCLUSION

The research on predicting the expected lifetime of satellites using machine learning models aims to leverage satellite-related data for more accurate forecasting and analysis. By using a variety of features such as satellite mass, power, orbit parameters, and launch details, the research provides valuable insights into satellite longevity. The use of both traditional machine learning algorithms like Linear Regression and Ridge Regression, along with more advanced models such as LSTM Regressors, demonstrates the ability to handle complex data patterns and temporal dependencies in predicting satellite lifetimes. The successful application of these models can significantly improve satellite management and space mission planning, offering benefits such as more efficient resource allocation, reduced costs, and optimized satellite usage for various purposes.

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