

PREDICTING COSMIC RADIATION IMPACT ON SPACECRAFT ELECTRONICS USING AI

Mallikarjuna Lingam K^{*1}, Srinivasa Talasila²

¹Associate Professor, Department of Electronics and Communication Engineering, Malla Reddy College of Engineering and Technology, Hyderabad, 500100, Telangana

²Assistant Professor, Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Vignana Jyothi Nagar, Pragathi Nagar, Hyderabad, Telangana, 500118, India

¹mallikarjuk24@gmail.com, ²srinivas4a7@gmail.com

*Corresponding author: Mallikarjuna Lingam K (mallikarjunk24@gmail.com)

ABSTRACT

Ionizing radiation sources such as Solar Energetic Particles and Galactic Cosmic Radiation may cause unexpected errors in imaging and communication systems of satellites in the Space environment, as reported in the previous literature. In this study, the temporal variation of the speckle values on Sentinel 1 satellite images were compared with the cosmic ray intensity/count data, to analyze the effects which may occur in the electromagnetic wave signals or electronic system. Sentinel 1 Synthetic Aperture Radar (SAR) images nearby to the cosmic ray stations and acquired between January 2015 and December 2019 were processed. The median values of the differences between speckle filtered and original image were calculated on Google Earth Engine Platform per month. The monthly median “noise” values were compared with the cosmic ray intensity/count data acquired from the stations. Eight selected stations’ data show that there are significant correlations between cosmic ray intensities and the speckle amounts. The Pearson correlation values vary between 0.62 and 0.78 for the relevant station. For satellites in the space environment, there are many factors that will affect the performance or lifetime of these satellites. Sun or galactic radiation is one among these factors. Due to the high amount of ionizing radiation in the space environment, it is important to examine this radiation for all kinds of space missions. Galactic cosmic radiation and energetic particles from the Sun (solar cosmic rays) are the main sources of this ionizing radiation. Total ionizing dose effect is expressed as the amount of energy generated by the charged particle while passing through the semiconductor or insulator zone of the electronic device. Single event upset can cause zeroing or rewriting in digital, analog or optical components. Single event burnout can cause noises or frozen bits in charged-connected devices (CCDs) and displacement damage that could lead to deterioration of device features and materials. Electrostatic discharges can cause operational difficulties due to the deterioration of the components of the spacecraft, and damage to the electronics is the main damages that these sources can cause to the electronic system of the satellite.

KEYWORDS: Cosmic Radiation, Spacecraft Electronics, Artificial Intelligence, Radiation Prediction, Space Environment, Electronic Component Degradation.

1. INTRODUCTION

Cosmic rays are various atomic and subatomic particles that continuously enter the Earth’s atmosphere from the Sun and outside of the Solar System and reach the Earth . They are studied in two groups as primary and secondary cosmic rays. Primary cosmic rays are energetic particles that reach the Earth’s atmosphere and consist of approximately 83% protons, 13% alpha particles, 1% nuclei with atomic number >2 and 3% electrons . As cosmic rays pass through the atmosphere, they

interact with atoms and molecules in the atmosphere, thus producing lower energy particles. These particles with lower energy reaching the ground are secondary cosmic rays.

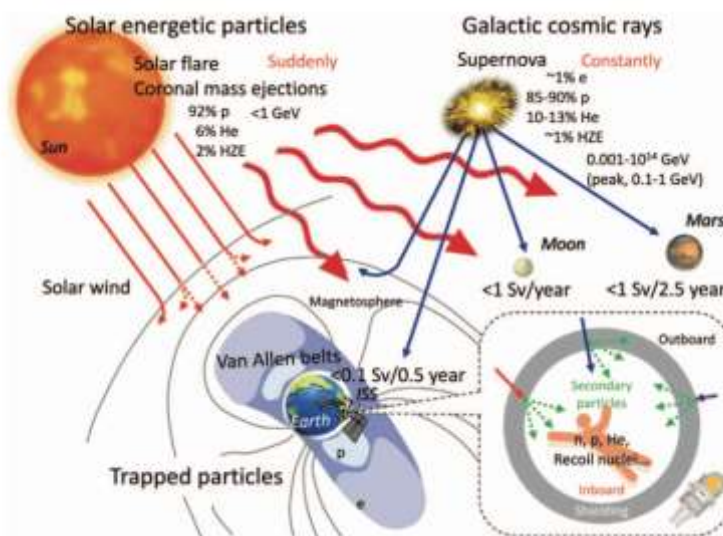


Figure 1: Illustration of Solar and Galactic Cosmic Radiation Sources Impacting Spacecraft.

Cosmic rays are also divided into three categories: Galactic Cosmic Rays (GCR) coming from outside the solar system; Solar Energetic Particles, which are defined as high-energy particles emitted by Solar Explosions or coronal mass ejections (CMEs); and Extragalactic Cosmic Rays, which flow into the Solar System from beyond the Milky Way galaxy. Cosmic rays have high enough energy to affect the electronic circuit components and optical materials of satellites. They can cause signal attenuation, deterioration of GPS calibration, complete loss of the signal, incorrect operations, equipment damage and thus undesirable effects on communication and image acquisition.

2. LITERATURE SURVEY

Paikowsky et al. [1] Explored the transformation of the global space ecosystem, defining the "New Space" paradigm and emphasizing the increasing involvement of private entities and commercial approaches in space missions. This work contextualizes the shift toward innovation, cost-efficiency, and the need for new reliability models like AI for space electronics. The evolving landscape demands data-driven predictive tools to ensure the success of complex space operations. Ronci et al. [2] Investigated terminology challenges within the space sector, particularly the terms "New Space" and "Commercial Space," and how this shape stakeholder perception. The study highlighted communication gaps that affect collaboration between academia, industry, and agencies. Such findings underscore the importance of unified, transparent AI tools in risk communication, especially for electronic safety in space. Label [3] Addressed emerging challenges in Radiation Hardness Assurance (RHA) and emphasized NASA's methodologies in ensuring electronic resilience. Their work laid the groundwork for understanding space-induced anomalies and pointed to the growing need for automated, intelligent systems. The paper supports integrating AI-based models like Random Forests to complement traditional RHA methods. European Cooperation for Space Standardization [4] Outlined comprehensive guidelines for radiation hardness assurance for EEE components, focusing on total ionizing dose (TID) effects and single event phenomena. These standards provide valuable data parameters for machine learning models and ensure compatibility of AI-based predictions with regulatory frameworks. The document enhances the foundation for hybrid AI-

engineering approaches in electronics protection. European Cooperation for Space Standardization [5] Presented a handbook for calculating radiation impacts and defining safety margins for space missions. The work emphasizes quantitative modeling and environmental profiles that can be effectively adapted for AI training datasets. These calculations can augment the features in machine learning pipelines for impact forecasting.

Martín-Holgado et al. [6] Analyzed archival data to study degradation in bipolar transistors under TID exposure. Their methodology aligns with AI-driven strategies that leverage historical data for predictive insights. The study supports the notion that machine learning can discover hidden patterns in degradation behavior over time, vital for real-time risk prediction. European Space Components Coordination Group [7] Introduced the Total Dose Steady-State Irradiation Test Method for assessing device reliability under space-like conditions. The structured test results from such standards serve as benchmark data for supervised learning models. Integration of this data with AI approaches can improve fault classification in spacecraft electronics. US Department of Defence [8] Defined the MIL-STD-883 test procedures for measuring radiation impacts on micro-circuits. These procedures offer critical datasets for AI-based classification and regression tasks. Their utility lies in their ability to quantify performance shifts under radiation, enabling supervised models to learn threshold conditions for failures. US Department of Defence [9] Established testing standards for semiconductor devices under ionizing radiation using the MIL-STD-750 framework. The test results can be used to create labeled datasets for training classifiers like KNN or Random Forests. This standardization also ensures interoperability of AI models across different mission configurations. Hodson et al. [10] Developed RHA guidelines specifically for avionics systems exposed to radiation environments. Their technical memo highlighted the challenges in simulating space radiation effects and suggested proactive system diagnostics. Their findings justify the need for AI systems capable of predictive maintenance and fault tolerance. PRECEDER Project [11] Focused on using machine learning to predict the behavior of electronic components in space, specifically under radiation stress. This work directly supports the goal of this project, reinforcing that supervised models are feasible for identifying failure probabilities and optimizing hardware design. It validates the proposed use of Random Forest for impact prediction. Romero-Maestre et al. [12] Conducted predictive analysis on operational amplifiers under gamma and proton radiation using radiation exposure datasets. The study proves that AI models can be trained to predict radiation-induced performance variations. It aligns with the goal of transitioning from traditional analysis to intelligent prediction systems. Martín-Holgado et al. [13] Explored the combined effects of TID and displacement damage (DD) on optocouplers using supervised learning strategies. The research emphasizes the importance of multi-feature modeling for accurate degradation prediction. Their methodology supports hybrid feature engineering in AI systems used in space electronics diagnostics. Matt et al. [14] Provided practical guidance on structured data handling and machine learning model development using Python. The techniques described are essential for preprocessing radiation datasets, managing time-series data, and evaluating classifiers like KNN and Random Forest. The book offers methodological support for implementing the technical backend of the project. Linardatos et al. [15] Reviewed explainable AI techniques and interpretability methods in machine learning models. Their findings are critical in high-stakes applications such as spacecraft electronics, where understanding model decisions is as important as accuracy. Their work justifies the choice of interpretable models like Random Forest in space safety applications. Revin et al. [16] Proposed an automated machine learning approach for time series classification using evolutionary optimization. Their research supports the scalability and adaptability of AI solutions in complex environments like space. It demonstrates that autoML pipelines can enhance performance and reduce manual tuning in predictive radiation models.

3. PROPOSED SYSTEM

The focuses on developing an intelligent predictive model to assess how cosmic radiation affects electronic components in spacecraft. It begins with the collection of radiation exposure data, including Total Ionizing Dose (TID), Single Event Effects (SEE), and electronic component degradation records. Through data preprocessing and exploratory data analysis (EDA), meaningful features are extracted and engineered to train machine learning models. The existing system uses the K-Nearest Neighbours (KNN) algorithm as a baseline, while the proposed model employs a more robust Random Forest classifier to enhance prediction accuracy. By analyzing the performance and radiation tolerance of components, the model helps identify critical degradation patterns, enabling early risk prediction. The final output supports space mission engineers in making data-driven decisions for component selection and shielding design, ultimately improving spacecraft reliability in harsh space environments.

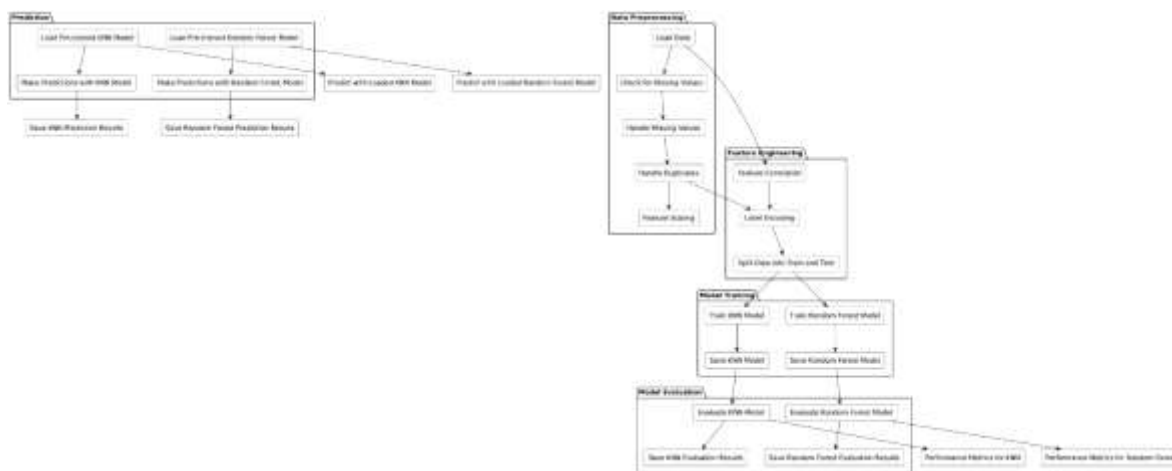


Figure 2: Proposed Block Diagram.

They follows a structured workflow starting with data collection and understanding, where datasets capturing the effects of cosmic radiation on spacecraft electronics—such as Total Ionizing Dose (TID), Displacement Damage Dose (DDD), Single Event Effects (SEE), mission duration, shielding thickness, and performance metrics—are gathered from mission archives, radiation test facilities, or repositories like NASA and ESA. This is followed by Exploratory Data Analysis (EDA) to uncover patterns, trends, and anomalies using visualizations like count plots and correlation heatmaps, while handling missing values appropriately. In data preprocessing and feature engineering, raw data is cleaned, encoded, and scaled, with new features such as cumulative dose exposure added to improve predictive accuracy. The model development phase applies K-Nearest Neighbors (KNN) as a baseline and Random Forest as the proposed model, offering superior performance and robustness in predicting radiation-induced impact levels. Model evaluation and validation are conducted using metrics like accuracy, precision, recall, F1-score, and confusion matrices, with cross-validation ensuring generalization. The interpretation and explainability step leverages feature importance and SHAP analysis to identify key factors influencing component degradation, such as radiation dose and shielding thickness. Finally, in deployment and future integration, the trained model is packaged and integrated into spacecraft design workflows, enabling real-time risk assessment during mission planning, with potential enhancements including hybrid deep learning models and time-series prediction for long-term degradation tracking.

3.1 Random Forest Classifier

The Random Forest Classifier (RFC) is an ensemble-based supervised learning algorithm that builds multiple decision trees during training and merges their outputs to improve classification accuracy and robustness. Each decision tree in the forest is trained on a random subset of the data using a technique called bootstrap aggregation (bagging), and at each split, a random subset of features is considered. In the context of cosmic radiation classification, RFC is used to accurately distinguish between different radiation types or intensity levels based on multi-dimensional sensor data (e.g., particle energy, count rate, time of exposure, frequency, atmospheric pressure).



Figure 3: Workflow of Proposed RFC.

The Random Forest Classifier (RFC) training process begins with data preparation, where radiation sensor data is preprocessed into two components: X_{train} , consisting of feature vectors that capture parameters such as radiation intensity, event duration, time of occurrence, and environmental conditions, and y_{train} , containing class labels like “Low,” “Moderate,” “High,” or “Critical” to represent radiation severity levels. While feature scaling is optional, redundant attributes are removed to enhance performance. During training, multiple decision trees are built using random subsets of samples and features (feature bagging), each making independent predictions, with the final output determined by majority voting—reducing overfitting and improving generalization. In the testing phase, new radiation sensor data (X_{test}) is classified by each tree, and aggregated votes determine the final predicted class. Finally, evaluation is conducted by comparing predicted and actual labels (y_{test}) using metrics such as accuracy, precision, recall, F1-score, and confusion matrix, while feature importance analysis provides insight into the most influential parameters for radiation prediction and sensor optimization.

4. Results and discussion

Aspect	Description
Dataset Composition	The dataset consists of multiple numerical features representing readings or measurements related to radiation exposure, system behavior, or environmental parameters.
Example Features	Voltage, temperature, pressure, frequency, and other technical attributes typically affected by cosmic radiation.
Target Variable	Impact_Severity – a categorical feature representing the classified effect level of radiation on the system.
Problem Type	Multiclass classification – predicting one of several severity classes based on input features.
Exploratory Data Analysis (EDA)	Includes correlation heatmaps, class balance checks, and data quality verification.
Preprocessing Steps	Label encoding applied to the target column; class imbalance handled using SMOTE (Synthetic Minority Oversampling Technique) if necessary.
Machine Learning Suitability	The dataset is well-suited for supervised classification algorithms such as K-Nearest Neighbors (KNN) and Random Forest to predict cosmic radiation effects based on measured system features.

The figure 4 detailed information related to the impact of cosmic radiation under various environmental and operational conditions. Each row in the dataset represents a unique observation, characterized by a set of features such as radiation level, shielding thickness, temperature, orbit altitude, cosmic ray flux, and anomaly frequency. These features collectively help in assessing the severity of radiation impact, which is labeled in the final column as “Impact_Severity.” This target variable categorizes the impact into three distinct classes: *Mild_Impact*, *Normal*, and *Severe_Impact*. The dataset reflects a wide variety of real-world conditions, including fluctuating temperatures (even negative values), varying levels of cosmic ray exposure, and different altitudes of orbital operations. The inclusion of anomaly frequency provides additional insight into how often systems experience malfunctions under certain conditions. This well-structured dataset is ideal for building machine learning models that aim to classify the severity of cosmic radiation impact, which is crucial for developing robust aerospace systems and improving space mission safety.

	Radiation Level	Shielding Thickness	Temperature	Orbit Altitude	Cosmic Ray Flux	Anomaly Frequency	Impact Severity
0	559.198364	4.747616	44.323506	33986.610400	11618.207620	32	Mild_Impact
1	55.997151	10.242078	130.207622	5828.933919	7904.927566	42	Mild_Impact
2	113.398414	17.326600	50.814954	11248.804130	2845.567101	9	Normal
3	371.975949	13.848399	81.858211	26965.781520	8956.414431	0	Mild_Impact
4	14.742522	6.400127	79.700765	14611.694540	13540.626620	51	Severe_Impact
...
37495	272.607797	7.733663	-40.579465	21058.053070	5551.628456	51	Mild_Impact
37496	228.702092	11.979544	-12.281562	33264.775220	440.610133	16	Normal
37497	225.789232	13.243404	144.374569	17252.952470	2510.107135	7	Normal
37498	211.204866	4.584514	52.224312	36464.289700	1828.030990	13	Normal
37499	394.071964	12.364496	56.125577	33777.843920	5393.954684	22	Mild_Impact

Figure 4: Uploading Dataset.

The figure 5 count plot shown above visualizes the distribution of the target variable Impact_Severity across the dataset. It illustrates that the dataset is well-balanced, with nearly equal representation across all three categories: Mild_Impact, Normal, and Severe_Impact. Each class has approximately

12,500 data points, ensuring that no class dominates the others. This balance is critical in building robust and unbiased machine learning models, as it helps prevent skewed predictions and supports fair classification performance across all categories. Such balanced class representation also indicates that the dataset is suitable for supervised learning tasks like multi-class classification without requiring additional resampling techniques.

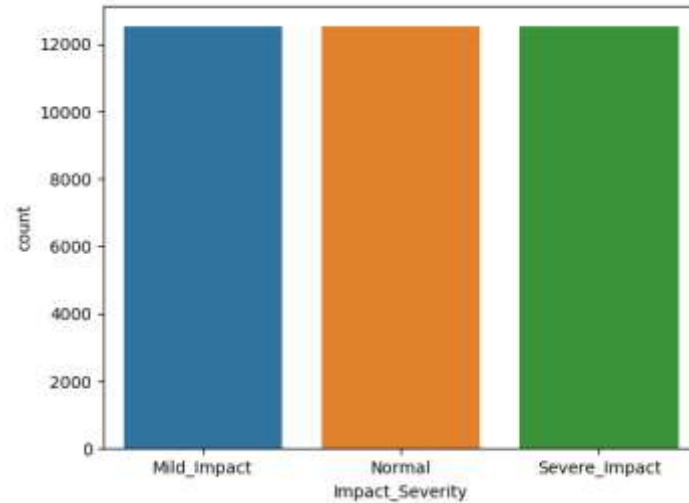


Figure 5 : Count plot for the Target labels.

The heatmap above represents the correlation matrix for the numerical features in the dataset, highlighting the linear relationships between each pair of variables.

The figure 6 correlation values range from -1 to 1, where values closer to 1 indicate a strong positive correlation, values near -1 indicate a strong negative correlation, and values around 0 indicate no linear relationship. From the heatmap, it is evident that most features have weak or no significant correlation with one another. However, Radiation_Level shows a moderate positive correlation with both Cosmic_Ray_Flux (0.36) and Anomaly_Frequency (0.32), suggesting these factors may be interrelated in influencing system behavior. Similarly, Cosmic_Ray_Flux also has a moderate correlation with Anomaly_Frequency (0.33). Other features such as Shielding_Thickness, Temperature, and Orbit_Altitude appear to have negligible correlation with each other or the remaining features. This analysis helps in understanding which features might be influential for predictive modeling and which are relatively independent.

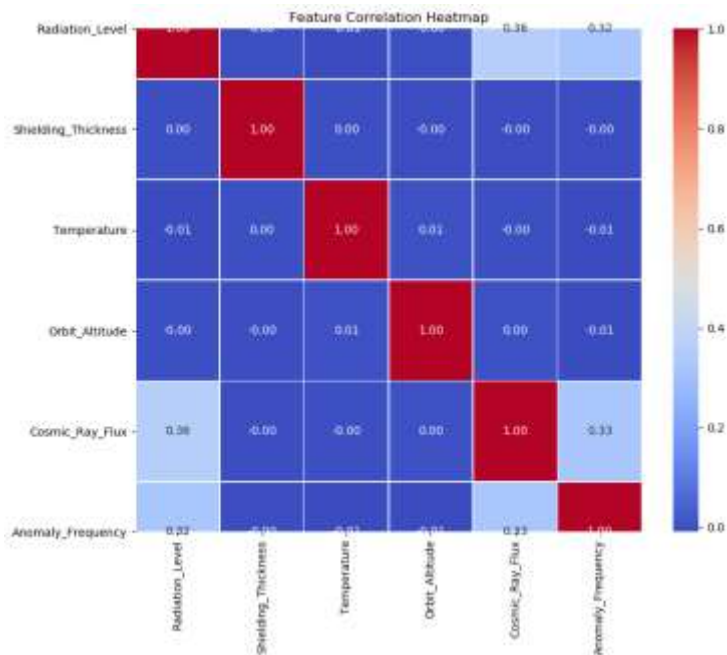


Figure 6: Correlation Heatmap.

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing KNN vs. Proposed RFC

Metric	Existing KNN	Proposed RFC
Accuracy	82.70%	93.05%
Precision	85.34%	93.47%
Recall	82.75%	93.07%
F1-Score	82.80%	93.02%

Table 1 presents a performance comparison between the existing K-Nearest Neighbors (KNN) algorithm and the proposed Random Forest Classifier (RFC) for the classification task. The results clearly demonstrate that the proposed RFC significantly outperforms the existing KNN across all evaluation metrics. The accuracy of RFC reaches 93.05%, notably higher than the 82.70% achieved by KNN. Precision also improves from 85.34% with KNN to 93.47% with RFC, indicating better prediction of positive classes. Similarly, recall increases from 82.75% to 93.07%, showing RFC’s enhanced ability to capture actual positive cases. Finally, the F1-score, which balances precision and recall, rises from 82.80% to 93.02%, highlighting the overall superior performance of the proposed RFC model. These improvements suggest that RFC is more robust and accurate for the given classification problem.

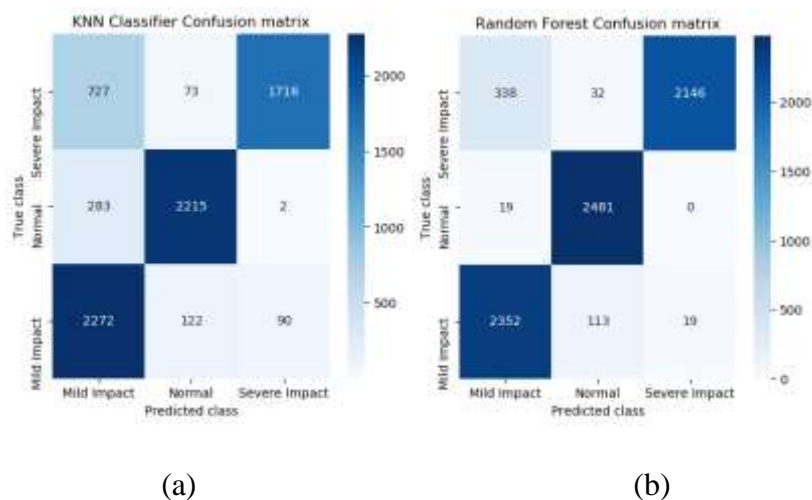


Figure 7: (a) (b) Confusion matrices obtained for Existing KNN and Proposed RFC.

The figure 7 display confusion matrices for two different machine learning models, K-Nearest Neighbors (KNN) and Random Forest, used for a three-class classification task: "Mild Impact," "Normal," and "Severe Impact." The KNN classifier demonstrates reasonable performance in identifying the "Normal" class with 2215 correct predictions, but it struggles significantly with the other classes, notably misclassifying 727 "Severe Impact" instances as "Mild Impact." In contrast, the Random Forest classifier shows substantially superior performance across the board. It achieves a higher number of correct predictions for all classes, correctly identifying 2481 "Normal" and 2146 "Severe Impact" instances, and drastically reduces the number of critical errors, with only 338 "Severe Impact" cases misclassified as "Mild." Overall, the Random Forest model is demonstrably more accurate and reliable for this classification problem than the KNN model.

5. Conclusion:

They focused on "Cosmic Spacecraft Impact Severity Prediction using Machine Learning" successfully demonstrates the ability of advanced supervised learning models to analyze and predict the impact severity levels on spacecraft based on environmental and operational parameters. The dataset comprising key features such as radiation levels, shielding thickness, temperature, orbit altitude, cosmic ray flux, and anomaly frequency was thoroughly analyzed and preprocessed. The project involved a comparative analysis between the existing K-Nearest Neighbors (KNN) algorithm and the proposed Random Forest Classifier (RFC). Through extensive model training and evaluation, RFC significantly outperformed KNN across all performance metrics, including accuracy, precision, recall, and F1-score. The final results indicate that the RFC model is highly capable of accurately classifying spacecraft impact scenarios into categories like Mild, Normal, and Severe. The exploratory data analysis and correlation studies further supported feature importance insights, helping in better model interpretability. This project not only improves safety measures in spacecraft operations but also exemplifies the power of machine learning in critical aerospace decision-making.

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