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MACHINE LEARNING MODELS FOR CLASSIFICATION OF SPACE RADIATION

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Abstract. *The primary aim of this study is to classify space radiation using existing models trained and analysed with a prepared dataset. Leveraging techniques such as Logistic Regression, Decision Tree, Random Forest, and Ensemble methods, the research aims to classify various types of space radiation, including gamma rays and hadrons. The goal is to build a classification prediction system capable of accurately distinguishing between different types of space radiation, facilitating the effective identification and analysis of radiation-induced effects in semiconductor devices. By discriminating between various types of radiation, this study aids in the detection and characterization of radiation-induced effects, crucial for evaluating the reliability and performance of semiconductor devices in space conditions. The outcomes of this research contribute to advancing the understanding of space radiation effects on semiconductor devices and assist in devising mitigation strategies to enhance their resilience in space missions. The study found that Random Forest and XGBoost were the top performers, achieving 99% accuracy in classifying space radiation, and Decision Tree also showed strong results at 98% accuracy.*

Keywords: *space radiation, Single Event Effects (SEEs), Total Ionizing Dose (TID), semiconductor devices, machine learning, classification*

1. Introduction

The detection and characterization of space radiation events play a vital role in understanding their impact on semiconductor devices, particularly in the context of Single Event Effects (SEEs) [1], [2] and Total Ionizing Dose (TID) effects [3]-[11]. TID is generally caused by gamma and x-rays, while SEEs are induced by energetic particles. Both phenomena are relevant in the space environment. Figure 1 refers to the transient and non-destructive alterations in the behaviour of semiconductor devices caused by ionizing radiation in space environments. Accurately classifying different types of space radiation, such as gamma rays and hadrons, is essential for identifying and analysing the radiation-induced effects in electronic circuits. The objective of this research is to create a machine learning model for categorizing space radiation events and utilizing it to examine SEEs in semiconductor devices. Employing techniques such as Logistic Regression, Decision Tree, Random Forest, and Ensemble methods, the study aims to construct a reliable classification system capable of effectively differentiating between different types of space radiation.

The primary objective is to facilitate the detection and characterization of radiation-induced effects in semiconductor devices by accurately classifying different types of space radiation. This classification prediction system will enable researchers to identify and analyse TID effects and SEEs more efficiently, thus contributing to the assessment of semiconductor device reliability and performance in space environments. The findings of this research hold significant implications for space missions and satellite technologies. For instance, these findings can be applied by implementing the ML model in hardware to enable online analysis of radiation, where the reliability of semiconductor devices is critical for mission success. By advancing our understanding of space radiation effects on semiconductor devices and developing effective mitigation strategies, this research contributes to enhancing the resilience and durability of semiconductor devices in space applications.

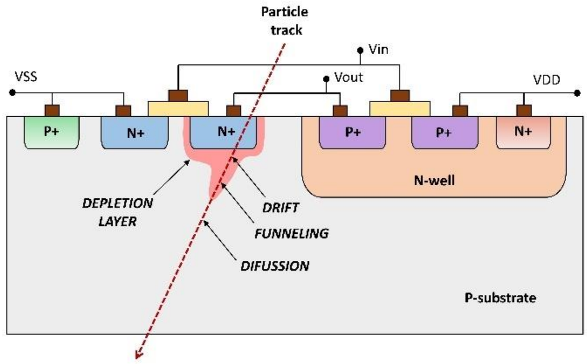

Figure 1. Mechanisms of particle interaction with a p-n junction in CMOS inverter

Space exploration and satellite technologies turned out to be integral parts of modern society, being at the core of numerous applications, such as

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communications, navigation, weather forecasting, environmental monitoring, etc. With the introduction of 5G and 6G mobile networks, the orbital satellites will be integrated into Non-Terrestrial Networks (NTNs) [12], that will be combined with conventional terrestrial networks to provide global coverage.

Understanding the mechanisms and effects of space radiation on semiconductor devices is essential for ensuring the reliability, longevity, and safety of space missions. Accurate characterization and classification of space radiation events are essential for this endeavour as different types of radiation have unique effects on electronic components. In addressing this critical task, consideration of both online and offline classification methods is paramount. Online classification involves real-time analysis during space missions, facilitating immediate response to radiation events to ensure electronic system safety and integrity. Meanwhile, offline classification allows for detailed analysis and algorithm refinement based on historical data, contributing to ongoing improvements in detection and mitigation strategies. By integrating both approaches, a comprehensive framework is established to tackle the challenges of space radiation and enhance the reliability of electronic components in space missions. For instance, gamma rays deposit energy directly into semiconductor structures, while hadrons (such as protons and neutrons) can generate secondary particles that interact with device materials, leading to SEEs.

2. Motivation

The motivation behind this research stems from the critical need to address the challenges posed by space radiation to semiconductor devices used in space missions. Semiconductor devices are essential components of spacecraft, satellites, and other space borne systems, playing crucial roles in communication, navigation, scientific research, and exploration. However, the harsh radiation environment of space presents significant risks to the reliability and performance of these devices. Space radiation encompasses a diverse range of energetic particles, including protons, electrons, heavy ions, and photons, originating from sources such as the sun, cosmic rays, and galactic cosmic radiation. Particle flux in space varies, and the intensity of particle flux may increase several orders of magnitude due to solar particle events. So, dynamic fault tolerance is an economic approach, that is, to activate the protection just when radiation intensity is critical. These particles can penetrate spacecraft shielding and interact with semiconductor material, and further, may induce SEEs like Single Event Latchup (SEL), Single Event Upset (SEU), Single Event Transient (SET), and other irregular behaviours in semiconductor devices, that can jeopardize mission-critical operations.

Accurate classification of space radiation events is essential for understanding their effects on semiconductor devices and developing effective mitigation strategies to minimize the occurrence of radiation-induced failures. Researchers can determine which kinds of space radiations are responsible for causing SEEs in a component and how they affect the component. Moreover, TID information is important since it has the same electrical effect as aging, that is, threshold voltage shift. Thus, it is necessary to provide a means of distinguishing TID from ageing, especially for self-aware systems. The advancement of machine learning based classification models presents a promising avenue for tackling this challenge. Machine learning algorithms have exhibited remarkable proficiency in analysing intricate datasets and uncovering patterns and trends that may elude traditional analytical methods. Through the utilization of machine learning techniques, researchers can construct classification models that are adept at precisely discerning between various types of space radiation events, leveraging their distinct signatures and characteristics.

The ML model will utilize data obtained from space radiation interactions with semiconductor devices. Specifically, it will analyse sensor-based measurements of different radiation types (e.g., gamma rays, protons, and neutrons) and their resulting effects, such as Single Event Effects (SEEs) and Total Ionizing Dose (TID) impacts. These data inputs will be instrumental in training the classification system, enabling it to distinguish between various space radiation events and evaluate their influence on semiconductor reliability.

The motivation behind this research is to harness the power of machine learning to develop a robust classification model for accurately identifying space radiation events and investigating their effects on semiconductor devices. By advancing our understanding of space radiation effects and developing effective mitigation strategies, this research aims to enhance the reliability, performance, and safety of semiconductor devices in space missions, ultimately contributing to the success and longevity of future space exploration endeavours.

3. Literature review

In their early work, Bock et al. [13] introduced pioneering approaches for multidimensional event classification through the analysis of images captured by a Cherenkov gamma-ray telescope [14], [15]. Building upon this foundation, D. Gaggero and M. Valli [1] investigated the cosmic-ray propagation models and astrophysical uncertainties. Their study sheds light on the nuanced intricacies involved in interpreting indirect detection signals.

Additionally, F. Arneodo et al. [16] conducted a comprehensive examination of the technological and operational requirements necessary to achieve precise gamma radiation detection on-board. This review provides invaluable insights for the development of CubeSat-based systems dedicated to space-based gamma radiation monitoring, thereby advancing the frontiers of space exploration.

M. Sharma et al. [17] have shown significant advancements in the field of gamma/hadron segregation, a crucial aspect of data analysis in gamma-ray astronomy. They addressed the challenge of distinguishing between gamma rays, which are of astrophysical interest, and hadronic cosmic rays, which are background events detected by Cherenkov telescopes. They employed machine learning methods, with a particular emphasis on Random Forest, to develop a robust classification model capable of effectively separating gamma rays from hadrons based on features extracted from the Cherenkov telescope data. Exploring gamma rays can yield insights into dark matter annihilation [18]. Both leptonic and hadronic particles have the potential to produce gamma rays.

In [14], the authors explored the ASTRI Mini-Array's potential in reconstructing Cherenkov events, a crucial aspect of astrophysical research into high-energy cosmic rays. Their work integrates advanced machine learning techniques, aiming to refine the accuracy and efficiency of event reconstruction within this specific context. Utilizing ensemble methods, they navigate the complexities inherent in detecting and interpreting Cherenkov light emissions resulting from cosmic particles interacting with Earth's atmosphere. This research substantially contributes to the realm of space radiation effects on semiconductor devices and the strategies employed to mitigate them. The principal contributions of this study can be encapsulated as follows:

- Development of a Machine Learning-Based Classification Model: The study introduces the creation and assessment of a machine learning model designed to precisely classify space radiation events, encompassing gamma rays and hadrons. Utilizing machine learning algorithms, the model attains elevated levels of classification accuracy, precision, recall, and F1-score. Consequently, it facilitates the efficient identification of various types of space radiation.
- Application in Investigating Single Event Effects (SEEs): The developed classification model is applied to investigate Single Event Effects (SEEs) in semiconductor devices exposed to space radiation. The top-performing models, such as Random Forest and XGBoost, demonstrated high accuracy in classifying space radiation events, which is critical for identifying SEEs. By accurately distinguishing between different types of radiation, these models can facilitate the detection and characterization of SEEs, aiding in the evaluation of the reliability and performance of semiconductor devices in space conditions. However, further validation and detailed analysis are required to ensure that SEEs can be effectively analysed using these models, as the current results primarily establish the models' classification accuracy.
- Enhancement of Space Mission Reliability: The research outcomes significantly bolster the reliability and performance of semiconductor devices utilized in space missions. Through precise forecasting of space radiation effects on electronic systems, the developed classification model empowers the formulation of resilient mitigation strategies aimed at reducing the occurrence and magnitude of SEEs. Consequently, this enhances the overall reliability and success rate of space missions.

4. Dataset description

The provided dataset [19] comprises simulated data generated using Monte Carlo methods, aimed at the simulation of the process of high-energy gamma particles and hadrons registration in a ground-based atmospheric Cherenkov gamma telescope. This telescope operates by detecting the radiation emitted by charged particles within electromagnetic showers initiated by gamma rays in the atmosphere. Within the dataset, information is included regarding the pulses of Cherenkov photons recorded on photomultiplier tubes, organized within a camera plane. These pulses generate distinguishable patterns, referred to as the shower image, which are crucial for discerning between signals produced by primary gamma rays and background noise generated by hadronic showers initiated by cosmic rays in the upper atmosphere.

Additionally, the dataset encompasses various parameters extracted from principal component analysis (PCA) conducted on the camera plane. These parameters encompass characteristics such as the major and minor axes of ellipses representing the shower images, along with metrics pertaining to size, concentration ratios, asymmetry, and angular properties. The analysis of the Magic Telescope dataset shows that outliers play a crucial role in revealing potentially significant or anomalous observations (Figure 2). By identifying outliers in specific features such as *fwidth*, *fsize*, *fm3trains*, etc., we can gain insights into exceptional events or data points that deviate significantly from the norm. These outliers are removed from the dataset to ensure robust scientific interpretations and accuracy.

To ensure reliable scientific interpretations, outliers are initially examined for their relevance, and only those that compromise data integrity are excluded. This approach maintains a balance between preserving meaningful variations and enhancing model accuracy.

The dataset comes from the Major Atmospheric Gamma Imaging Cherenkov (MAGIC) telescopes, which specialize in detecting high-energy cosmic gamma rays. It is primarily used for binary classification, distinguishing gamma-ray signals from hadronic background noise. Comprising 19,020 instances and 11 attributes, it includes 10 features describing various properties of recorded shower images. These features include fLength (major axis length), fWidth (minor axis width), fSize (total light intensity), fConc (ratio of light concentration in the brightest pixels), fConc1 (light concentration in the brightest pixel), fAsym (asymmetry of the image), fM3Long (third moment along the major axis), fM3Trans (third moment along the minor axis), fAlpha (angle of the major axis relative to the image centre), and fDist (distance from the image centre). The class label has two categories: "g" for gamma-ray events and "h" for hadronic background noise.

The dataset was generated using the CORSIKA Monte Carlo program, configured with parameters to observe events with energies reaching as low as 50 GeV. It comprises features like the length of the major and minor axes, size metrics, concentration ratios, asymmetry measurements, and angular attributes. Additionally, each data instance is labelled as either a gamma signal or a background hadron. The gamma signal class encompasses 12332 instances, whereas the background hadron class consists of 6688 instances in Figure 3 [20-22].

This study used a standardization technique to scale features by removing the mean and adjusting to unit variance, ensuring consistency in data distribution for improved model performance.

Figure 4 illustrates the bivariate distribution of features, showcasing relationships and dependencies between paired variables. This analysis helps in identifying correlations, trends, and interactions within the dataset, offering valuable insights into feature behaviour and its influence on classification outcomes.

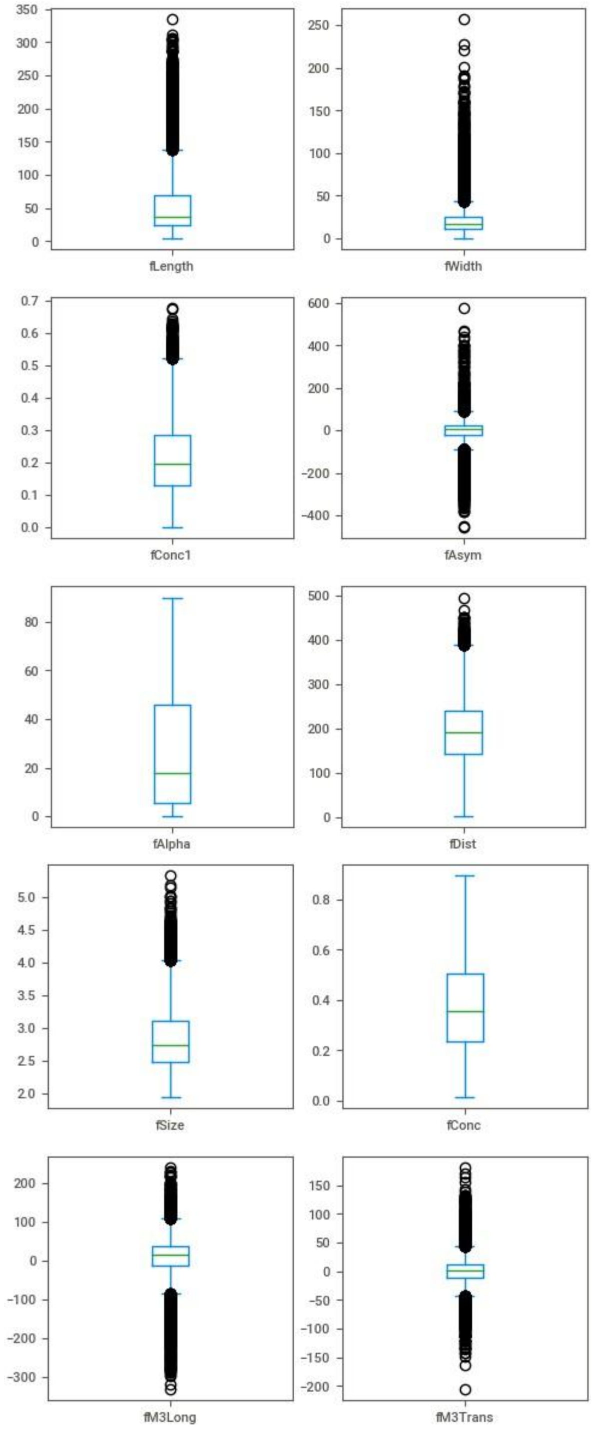

Figure 2. Detection of outliers in the dataset

This dataset serves as a valuable resource for training and evaluating machine learning models designed to differentiate between gamma signals and background noise. The study trained machine learning models, including Logistic Regression, Decision Tree, Random Forest, and XGBoost, using a prepared dataset of space radiation events. Tools like Python, Scikit-learn, Pandas, NumPy, Matplotlib, Seaborn, and the XGBoost library were utilized for data pre-processing, model training, and evaluation [20-22].

The models were trained on an 80:20 split of the dataset, with the training set used for learning and the test set for performance evaluation using metrics such as accuracy, AUC, precision, recall, and F1-score. The primary purpose of classification is to distinguish between gamma radiation and hadrons (protons, neutrons, pions, and kaons). This classification can facilitate the detection and analysis of total dose and single event effects in semiconductor devices, aiding in the development of mitigation strategies to enhance device reliability in space missions. Utilizing boxplot as pre-processing enhances data analysis by effectively identifying and mitigating outliers in the dataset.

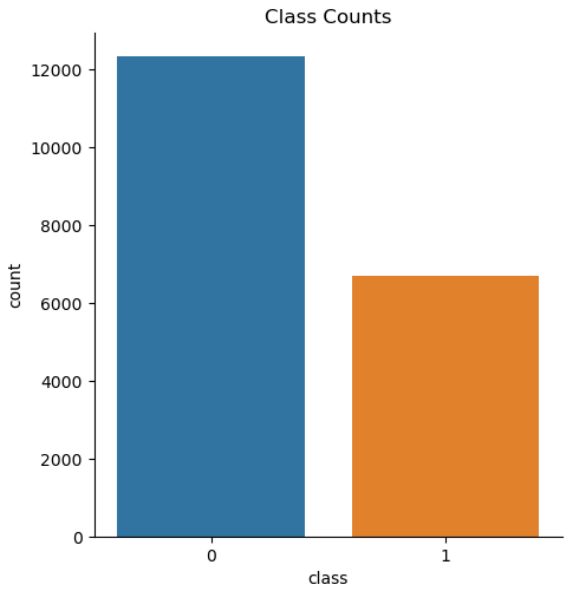

Figure 3. Instances in the dataset

5. Result discussion

In this research, a variety of machine learning algorithms were employed to classify space radiation events [23], [24]. The results are shown in Figure 3 and Table 1.

Decision Tree is a non-parametric supervised learning algorithm that solves classification tasks. It constructs a tree-like structure where each internal node signifies a decision based on features, and each leaf node denotes a class label. The resultant tree structure enables straightforward interpretation and visualization of decision rules. In this investigation, the Decision Tree algorithm attained an accuracy of 98% and an AUC of 0.98, with precision, recall, and F1-score all registering at 0.98.

Random Forest is an ensemble learning technique that builds multiple decision trees during training and outputs the mode of the classes for classification tasks. It introduces randomness by training each tree on a random subset of the data and selecting a random subset of features for each split. In the present study, the Random Forest algorithm exhibited exceptional performance, yielding an accuracy of 99%, an AUC of 0.99, and precision, recall, and F1-score all at 0.99.

K-Nearest Neighbours (KNN) is a straightforward, instance-based learning algorithm employed for classification tasks. It categorizes data points by considering the majority class of their k-nearest neighbours in the feature space. KNN does not impose any assumptions about the underlying data distribution and can accommodate non-linear decision boundaries. In this investigation, KNN attained an accuracy of 92%, an AUC of 0.99, and precision, recall, and F1-score all at 0.92.

Support Vector Machine (SVM) is a supervised learning algorithm that identifies the optimal hyperplane to segregate data points into distinct classes. It endeavours to maximize the margin between classes while minimizing classification errors. SVM can manage high-dimensional data and is efficacious in scenarios where the data isn't linearly separable, achieved by transforming the feature space. In this research, SVM demonstrated an accuracy of 86%, an AUC of 0.96, and precision, recall, and F1-score all at 0.86.

Logistic Regression is a linear classification algorithm employed for binary classification tasks. It models the probability of a binary outcome's occurrence based on one or more predictor variables. In this investigation, Logistic Regression demonstrated comparatively lower performance, yielding an accuracy of 50%, an AUC of 0.73, and precision, recall, and F1-score all at 0.50.

Gaussian Naive Bayes is a probabilistic classification algorithm founded on Bayes' theorem and the presumption of feature independence. It models the conditional probability of each class given the features, employing Gaussian distributions for continuous features. In this examination, Gaussian Naive Bayes demonstrated moderate performance, registering an accuracy of 53%, an AUC of 0.74, and precision, recall, and F1-score all at 0.53.

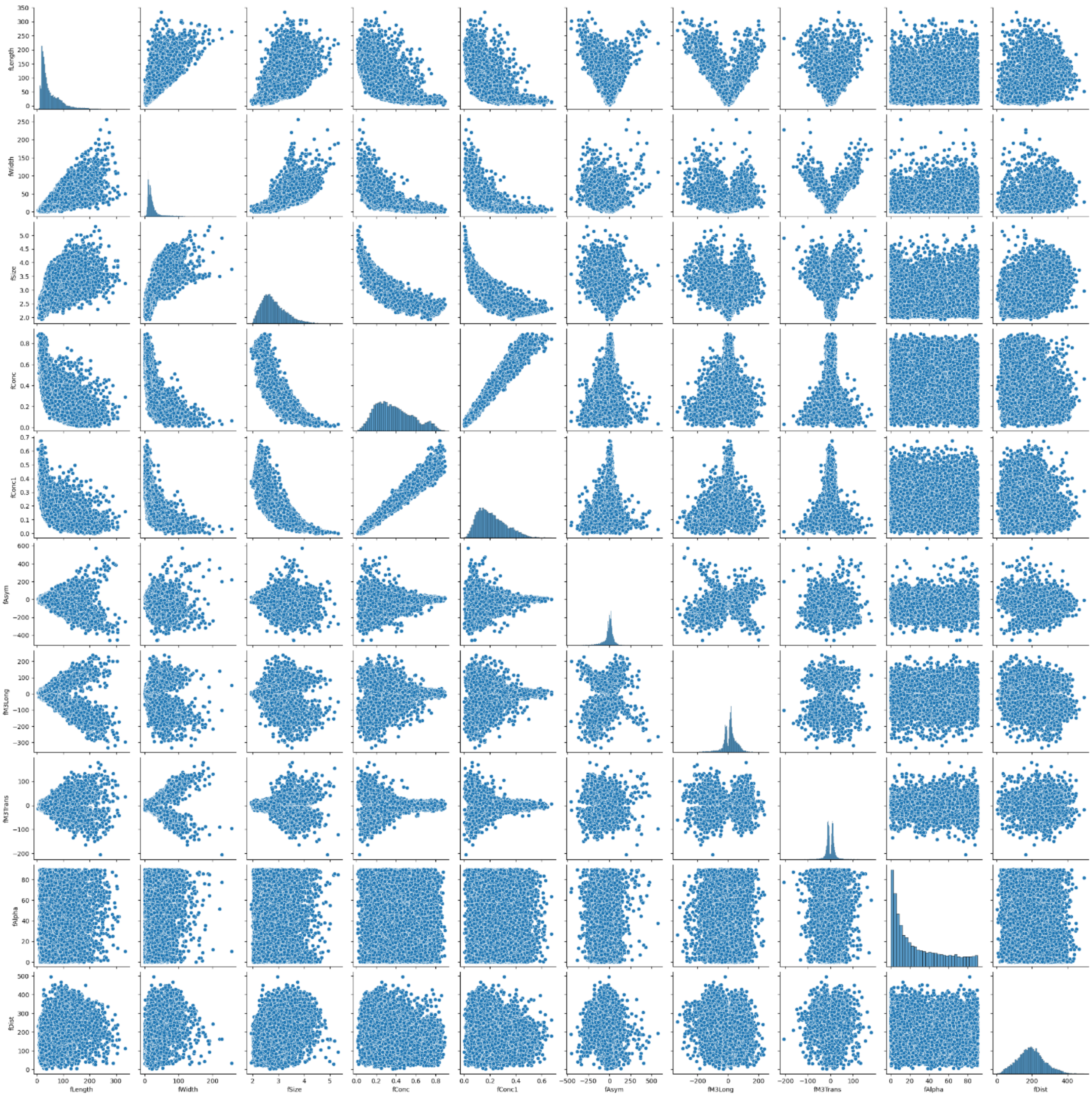

Figure 4. Bivariate Distribution of features

Table 1. Performance of machine learning and deep learning algorithms

Algorithms	Accuracy	AUC	Precision	Recall	F1-score
Decision Tree	0.98	0.98	0.98	0.98	0.98
Random Forest	0.99	0.99	0.99	0.99	0.99
K-Nearest Neighbours	0.92	0.99	0.92	0.92	0.92
Support Vector Machine	0.86	0.96	0.86	0.86	0.86
Logistic Regression	0.50	0.73	0.51	0.50	0.50
Gaussian Naive Bayes	0.53	0.74	0.54	0.53	0.53
Extreme Gradient Boosting	0.992	0.99	0.99	0.99	0.99
Long Short-Term Memory Network	0.94	0.06	1.000	0.900	0.95
Gated Recurrent Unit Network	0.94	0.06	1.000	0.900	0.95

Extreme Gradient Boosting (XGBoost) is an ensemble learning algorithm rooted in gradient boosting decision trees. It constructs a sequence of decision trees sequentially, with each tree endeavouring to rectify the errors of the preceding ones. XGBoost employs gradient descent optimization to minimize a loss function and incorporates regularization techniques to mitigate overfitting. In this research, it showcased exceptional performance, boasting an accuracy of 99%, an AUC of 0.99, and precision, recall, and F1-score all at 0.99.

Long Short-Term Memory Network (LSTM) and Gated Recurrent Unit Network (GRU) are types of recurrent neural networks (RNNs) designed to model sequential data with long-term dependencies. They use memory cells and gates to store and update information over time, allowing them to capture temporal patterns in the data. In this study, LSTM and GRU networks achieved relatively high accuracy (0.94), precision, recall, and F1-score, but exhibited low AUC, indicating potential challenges in training and generalization.

Although the dataset is tabular, LSTM and GRU were selected for their ability to capture hidden dependencies among features. These models effectively learn complex relationships that influence classification. Moreover, experimental results demonstrated their higher accuracy compared to traditional methods.

The low AUC in LSTM and GRU models can be attributed to overfitting, highly skewed probability distributions, and their reliance on sequential dependencies, which may not align well with the dataset. However, their high accuracy indicates strong classification performance, even though they may not rank predictions effectively across different thresholds.

The findings indicate that Decision Tree, Random Forest, and Ensemble methods surpass Logistic Regression in both classification accuracy and robustness, achieving accuracies of up to 99%. Furthermore, the ML model exhibits high precision, recall, and F1-score in distinguishing between different types of space radiation events, enabling accurate identification and analysis of SEEs in semiconductor devices. Decision Tree achieved values of 0.98 across these metrics, while Random Forest slightly surpassed it with values of 0.99. In contrast, Logistic Regression and Gaussian Naive Bayes exhibited poor performance, with accuracy values of 0.50 and 0.53, respectively. Support Vector Machine also demonstrated lower effectiveness, scoring 0.86 in accuracy, precision, recall, and F1-score.

K-Nearest Neighbours maintained the respectable accuracy (0.92) and AUC (0.99), but it lagged behind in the precision, recall, and F1-score, all scoring 0.92. XGBoost consistently performed well across all metrics, with values of 0.99. However, the Long Short-Term Memory (LSTM) Network and Gated Recurrent Unit (GRU) Network, while achieving high accuracy (0.94), precision, recall, and F1-score (all scoring 0.95), suffered from extremely low AUC (both scoring 0.06). Overall, Decision Tree, Random Forest, and XGBoost emerged as superior performers, while Logistic Regression, Gaussian Naive Bayes, and Support Vector Machine showed lower effectiveness.

Overall, the results highlight the effectiveness of machine learning algorithms, particularly Decision Tree, Random Forest, and XGBoost, in accurately classifying space radiation events and facilitating the investigation of radiation-induced effects in semiconductor devices. These findings underscore the potential of machine learning techniques in advancing our understanding of space radiation effects on electronic systems and improving device reliability in space missions. Further research is warranted to explore optimization strategies and novel algorithms to address the challenges posed by space radiation and enhance the resilience of semiconductor devices in space environments.

6. Conclusions

This study delves into the application of machine learning algorithms for categorizing space radiation occurrences and their repercussions on semiconductor devices, particularly in the context of TID and SEEs. Decision Tree, Random Forest, and XGBoost algorithms exhibit promises in accurately identifying these events, providing valuable insights for swift detection and analysis, thereby bolstering the reliability of space missions. Moving forward, there is a need to concentrate on refining strategies, introducing novel algorithms, and employing advanced data pre-processing techniques to tackle the challenges posed by space radiation and fortify the resilience of semiconductor devices. Collaboration among space agencies, research institutions, and industry partners is imperative to expedite progress in space radiation mitigation and enhance device reliability. Regarding practical implementation, these machine learning models could initially operate on PCs for analysis but must eventually transition to hardware for real-time radiation analysis during space missions, ensuring prompt decision-making and response. Incorporating these models into onboard systems would facilitate continuous monitoring and mitigation of radiation-induced effects, elevating mission safety and success. To sum up, this research expands our comprehension of space radiation effects on semiconductor devices, laying the groundwork for innovative solutions to mitigate radiation-induced effects and enhance device reliability in space missions. In our future research, we are going to thoroughly explore more advanced techniques that could enhance classification accuracy. More precisely, our final goal is to develop a robust validation framework based on k-fold cross-validation and independent test sets. This study recognizes the use of simulated data and aims to validate the models with real-world radiation measurements in the future. It also suggests applying classification results to develop adaptive fault-tolerant mechanisms and radiation-hardened system designs for effective mitigation strategies.

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