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On-board Machine Learning Fault Detection and Diagnosis for Automatic Beacon Structure Customization

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Abstract

Spacecrafts are susceptive to various faults once they are in orbit. However, these faults can occur before the contact time with their designated ground stations. Therefore, it will be default for the operation engineer to identify the root cause of these faults as the spacecraft lost the contact with the ground segment. Moreover, this causes a major loss in cost and time to operators trying to detect the cause of the fault and mitigate it to ensure the spacecraft will operate normally. Satellite beacons can be a useful source of information about satellite faults that can be received from any ground station worldwide. They are vital in informing operators of the spacecraft's critical signs and status. Accordingly, using beacons as a valuable source of early detection and error identification will result in reducing the cost and time for the satellite operators greatly. Thus, selecting data to be included in the beacon is important in detecting and mitigating any faults and aids in mitigating abnormalities in the satellite. The use of Fault Detection Isolation and Recovery (FDIR) in the beacon structure will aid in efficiently identifying and detecting anomalies in the spacecraft and preserve its safety. This research proposes on-board automatic beacon structure customization based on fault detection and diagnosis using machine learning techniques. The proposed system indicates and reports the abnormalities during the orbit with a selective set of data based on the telemetry parameters to facilitate a faster knowledge of the fault. The customized beacon structure is based on the FDIR flag(s) with a priority level preassigned to each case. The initial outcomes of this study show that this system is feasible to be implemented in space missions.
Keywords: AI-based algorithm, SVM, Deep Learning, beacon, FDIR

Acronyms/Abbreviations

1U	1 Unit
ADCS	Attitude Determination and Control
COMM	Communication Subsystem
COTS	Commercial off-the-shelf
ELM	Extreme Learning Machine
EPS	Electrical Power Subsystem
FDIR	Fault Detection Isolation and Recovery
GWO	Grey Wolf Optimization
HK	House Keeping
MES	Mechanical Subsystem
ML	Machine Learning
OBC	On Board Computer
SVM	Support Vector Machine
FTA	Fault Tree Analysis

1. Introduction

Space missions have increased tremendously in the last decade for various factors, namely the availability of Commercial off-the-shelf (COTS) components and lower launch cost. CubeSats are a type of nanosatellite in the shape of a cube where one unit (1U) has the dimensions of 10x10x10 cm with a weight of around 1.3 kg [1]. They can be made from 1U, 1.5U, 2U, 3U, 6U, up to 16U. CubeSats are typically used by universities, non-space-faring countries as their first satellite or for technology demonstration. Moreover, they can be used for educational purposes or testing new technologies before developing them on larger satellites. CubeSats have 6 subsystems, namely the Mechanical Subsystem (MES), the Electrical and Power Subsystem (EPS), the Communication Subsystem (COMM), the On-board Computer (OBC), the Attitude Determination and Control Subsystem (ADCS), and the payload subsystem.

The MES holds the various components of satellites in a modular structure that has the needed strength and stiffness to ensure the mission's success. The EPS generates, distributes, stores, and manages the power within satellites. The

COMM establishes the communication link between satellites and ground stations to transmit and receive data and commands. The OBC is the spacecraft's 'brain' that manages and controls the various subsystems. The ADCS manages and controls the position and direction of the spacecrafts. The payload is the 'heart' of the mission and is the main purpose of sending CubeSats to space. Moreover, the payload subsystem can be categorized into remote sensings such as earth observation, technology demonstration like testing a newly developed propulsion system, and scientific research such as monitoring space particles or space radiation. Each satellite subsystem has different operating modes that change from one mode to another over time depending on the satellite's condition [2]. Ground operators monitor and control the satellite through its communication during the access time or by monitoring the beacon data obtained from the satellite. Beacons are transmitted data that contain various predetermined parameters for all the subsystems in the satellite that pertain to the health status of the spacecraft. CubeSats have limited bandwidth, with high data volume collection and a vital need to have a precise decision ability when faults are detected [3].

Though many advancements have happened in the field of space, spacecraft are still susceptive to various faults once they are in orbit, as they are considered highly complex systems due to all the interconnections between the various components of spacecrafts. These faults may lead to the loss of spacecraft and, ultimately, the failure of space missions. The detection of these faults is critical in mitigating and reducing this risk. However, these faults can occur before contact time with their designated ground stations. Therefore, it will be the operation engineer's responsibility to identify the root cause of these faults that led to the loss of communication with the spacecraft. These faults cause major losses in money, time, and effort when trying to detect and identify the cause of the fault traditionally. Hence, reliability and safety are the two main factors determining the mission's success, and precise monitoring, fault detection, and diagnostic process reduce time and cost.

Satellite beacons are used as a source of the spacecraft's health status and vital signs. Educational mission's beacons are typically open for any ground station around the world willing to receive them, as they indicate the spacecraft's presence in space. It can be a useful source of information about the satellite and its possible faults, and they are vital in informing operators of the spacecraft's critical signs and status. Accordingly, using beacons as a valuable source of early detection and error identification will greatly reduce the cost and time for satellite operators. Thus, the selection of data to be included in the beacon is important in detecting and mitigating any faults and aids in mitigating abnormalities in the satellite.

Fault Detection Isolation and Recovery (FDIR) is a strategy used in many systems, especially satellites, to ensure that the spacecraft is robust. It is usually implemented in the software of the OBC to facilitate real-time performance and autonomous decision-making for the defined parameters in the system. FDIR enables the handling of errors and faults in the spacecraft autonomously to ensure the safety of the mission until the next contact with the ground station. The use of FDIR in the beacon structure will aid in efficiently identifying and detecting anomalies in the spacecraft and preserve its safety at all times, as any occurrence of any unanticipated errors that lead to endangering the spacecraft's integrity or any errors that FDIR did not recover correctly from will let the spacecraft enter safe mode. It will also aid in reducing service interruption occurrences and ground operations, improving the system's reactivity and the early discovery of anomalies [4].

This research proposes an on-board automatic beacon structure customization based on fault detection and diagnosis using the Support Vector Machine (SVM) algorithm and Fault Tree Analysis (FTA) to be utilized for educational CubeSats that are typically used by universities. The proposed system indicates and reports the abnormalities during the orbit with a selective set of data based on the telemetry parameters to facilitate a faster knowledge of the fault.

2. Related work

The use of fault detection in beacons has been studied vigorously in recent times. The diagnosis of satellite health using beacons has been of utmost importance and the focal of fault detection in space research, as beacons have been the main source of health monitoring for spacecraft during their lifetime. The large data collected and retrieved throughout the lifetime of a mission enables further analysis of the overall mission. Several methods have been studied for detecting, predicting, and recovering faults using beacons for space missions, especially, using data mining [5], [6], [7]. In recent years, machine learning and deep learning have been utilized to enhance the methods used in fault detection and diagnosis [3], [4], [8], [9]. Abdelghafar et al. [9] developed an optimized predictive model for anomaly detection using Grey Wolf Optimization (GWO) algorithm and Extreme Learning Machine (ELM) named GWO-ELM. This approach finds faults by comparing actual observed parameters with predicted intervals of beacon data; however, it was developed to be used by ground operators on ground stations and did not address its usability on-board a spacecraft such as a CubeSat. Similarly, Kannan and Devi [7] have presented that the Rule Mining Algorithm is the most suitable to be used for fault detection in satellite applications and beacon datasets obtained. Additionally, Ibrahim et al. [4] studied the plausibility of using machine learning methods to diagnose satellite anomalies using the parameters obtained from beacons. This study used Egyptsat-1 as its case study to demonstrate the validity of using machine learning techniques for anomaly diagnosis. There are also numerous studies that have applied different machine learning approaches for aerospace systems fault diagnosis [10], [11], [12], [13], [14]. These studies have predominantly focused on using machine learning and data mining for analyzing satellite beacons after receiving the beacons on ground.

The use of FDIR has been primarily applied to spacecraft flight software which needs to be reliable and resilient in the face of the harsh environment. Thus, various methods and approaches have been studied to ensure the longevity and flexibility of the software on-board spacecrafts. Latachi et al. [15] proposed a framework for designing a reusable and reliable flight software architecture for educational CubeSat missions. The proposed solution follows a layered service-oriented architectural pattern that executes the mission functionalities in a deterministic manner. Moreover, it includes hierarchical fault tolerance architecture using reliability blocks and functional failure mode, effect, and criticality analysis to handle the faults occurring within the spacecraft autonomously to guarantee the safety of the mission until the next ground contact. This proposed flight software design process integrates FDIR in the hierarchical fault tolerance architecture to enable efficient failure diagnosis within the flight software. Implementing FDIR in the flight software of space missions is typically used, however, implementing FDIR in beacons has not been addressed yet. Likewise, Olive et al. [16] have proposed a mixed diagnosis technique for autonomous satellite FDIR by integrating numerous FDIR techniques corresponding with each satellite subsystem that is combined in one centralized automated system with a decisional architecture based on the defined FDIR strategy. This proposed system aims to introduce a new FDIR concept to be implemented in the spacecraft's flight software by improving the satellite's autonomy and fault detection process to reduce the reaction time and on-board decision using advanced autonomy approaches. These studies have aimed to enhance the autonomy of the spacecraft in handling occurring faults, however, the ground operator's ability to recognize the faults detected and autonomously dealt with by the satellite through its mission was not fully addressed.

Various studies have been done utilizing different methods to optimize the use of beacons for fault detection. Park et al. [3] have proposed a new approach to detect and diagnose faults within satellites using a beacon-based exception analysis named BEAM for multi-missions. The proposed approach uses beacons to detect and characterize faults on-board satellites in real-time by providing a signal-level system analysis capability that can be applied on-board space systems and on ground. This proposed approach defines a process for beacon monitoring that can be used as a way to enhance machine self-awareness.

However, this study proposes another approach for detecting and diagnosing faults using on-board automatic beacon structure customization based on fault detection and diagnosis using the SVM and FTA techniques. This study will add to the current literature on spacecraft reliability and autonomous space systems research. The proposed system indicates and reports the abnormalities during the orbit with a selective set of data based on the telemetry parameters to facilitate a faster knowledge of the fault. The customized beacon structure is based on the FDIR flag(s) with a priority level preassigned to each case.

3. Proposed system framework

The proposed system of this study detects and diagnoses the faults based on the telemetry data. Early fault detection through beacons will aid in faster decision making to prevent the permanent loss of satellites. This system focuses on the most critical subsystems that have a higher probability of permanent satellite failure, namely OBC, EPS, and COMM. In this study, the working framework consists of various stages, as shown in Figure 1.

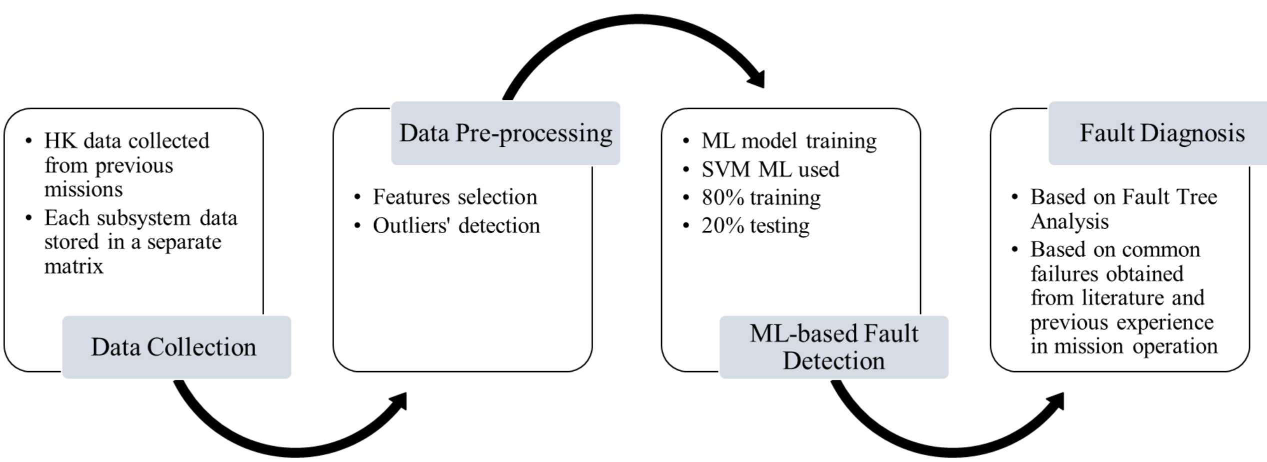

Fig. 1. Stages of the proposed framework

3.1 Data collection

The collected data will be used to train, test, and analyse the ML algorithm. These data were taken from previous educational CubeSat missions. Moreover, the raw House Keeping (HK) data include the in-orbit operation data for every subsystem individually. In addition, each subsystem data was stored individually in a matrix and organized in a time series manner. Furthermore, they were collected every 10s and stored on-board the CubeSats to be downlinked to the ground during access times. The raw HK data of the educational CubeSat missions had faults, and they were identified after a complicated and long process that took several weeks.

3.2 Data pre-processing

The data pre-processing starts by filtering the data from incomplete and missing data packets. Then, the features selection was done based on the data's parameters correlations. After that, the data outliers were detected and removed as they differ significantly from the other observations. In other words, Data outliers are points in a dataset that are not distributed normally. If left untreated, outliers can seriously impair statistical analysis. Moreover, they might result from malfunctioning sensors or noise.

3.3 ML-based fault detection

The objective of the SVM method is to find the optimum decision boundary or line that can divide an n-dimensional space into sets that facilitate the classification of fresh data points. The limits of this area are specified by hyperplanes [17]. The greatest margin hyperplane separating several data classes is found using SVM for a given dataset x with a specific number i of training data, as shown in Equation 1 [18].

$$x = (x_i, y_i), x_i \in R^p, y_i \in \{-1, 1\}, \forall \ i = 1, 2, \dots, N \qquad (1)$$

To obtain the best classification hyperplane, classification issues look for suitable (w, b) to divide up two different sorts of data. Furthermore, m-dimensional vectors (w) and constant (b) are present, as shown in Equation 2 [19].

$$\begin{cases} (w.x_i) + b > 0, y_i = 1 \\ (w.x_i) + b > 0, y_i = -1 \end{cases} \qquad (2)$$

The closest sample points referred to as Support Vectors, determine the best classification hyperplane, which has no connection to other samples. Equation 3 shows the hyperplane normalization [19].

$$y_i\big((w.x_i) + b\big) - 1 \geq 0, i = 1 \dots \dots n \qquad (3)$$

The best classification hyperplane is the one that satisfies the criteria in Equation 2 and reduces the classification interval. Equation 4 illustrates how to derive the ideal classification function by incorporating the Lagrange function and ensuring that the hyperplanes satisfy the Karush-Kuhn-Tucker theorem.

$$f(x) = sgn\,\{\textstyle\sum_{SV} \alpha_i^* y_i (x_i.x_i) + b^*\} \qquad (4)$$

The SVM ML algorithm used in this study was trained and tested for fault detection. Moreover, 80% of the pre-processed and collected data were used for training the SVM algorithm, and 20% were used for testing. The SVM algorithm was trained to detect 10 fault classes where they represent the most critical FDIRs, as shown in Table 1. The accuracy of the trained algorithm to detect the fault classes is 99.4%.

Table 1. SVM fault detection classes

Fault class number	Description
Class 0	Normal data
Class 1	High temperature in any critical subsystem
Class 2	Antenna deployment failure
Class 3	Very high angular rate
Class 4	Communication transceiver failure
Class 5	Low EPS temperature

Class 6	Defective solar cells
Class 7	High reset counter in any critical subsystem
Class 8	Software stuck in a specific operation mode
Class 9	FRAM storing data failure

3.4 Fault diagnosis

The fault diagnosis implementation uses FTA. FTA is an inquiry into the root causes of a chosen "top" fault (e.g., abnormal state) or failure event [20]. Moreover, the FTA was done based on previous satellite missions, literature review, and the experience of experts. In addition, the FTA includes a set of FDIRs where each one of them has a unique code. The FDIRs in the FTA were selected based on their level of risk and criticality, firstly high-risk level for critical faults can cause harm to satellites and cause mission failures. Furthermore, moderate-risk level FDIRs in the FTA may harm satellites and cause mission failures if the risk mitigation was done late. Figure 2 shows the subtree of the FTA where three main high severity failures are shown, namely command and data handling, power system, and loss of communication. The proposed system considered 29 FDIRs. Therefore, 29 different flags are needed to correspond to each FDIR code.

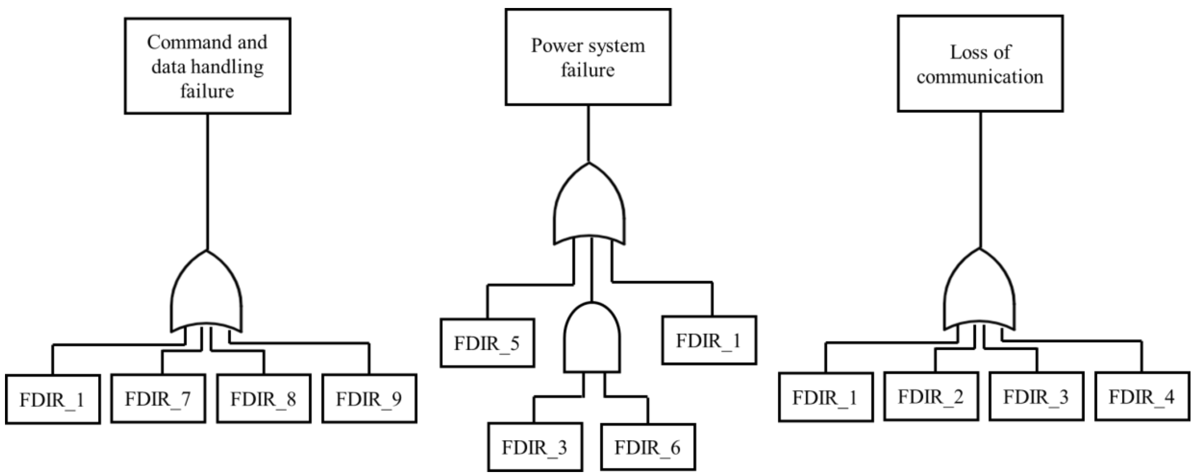

Fig. 2. Sub tree of the proposed system's FTA

4. Proposed system architecture

The proposed system uses three different customized beacon structures based on the detected faults during the in-orbit operation. The system is implemented as an OBC function that reads the received subsystem's HK data. Then, the generated ML model using SVM detects different fault classes for the most 9 critical FDIRs. If no faults were detected, the normal beacon structure will be transmitted. The fault diagnosis process will be enabled if faults from classes 1 to 9 were detected. Furthermore, there are two different customized beacon structure to be selected in case of faulty data. The selection between the two beacon structures is based on the failure's level of priority and severity. Figure 3 shows the flowchart of the proposed system, where Table 2 shows the description of the parameters used in the flowchart.

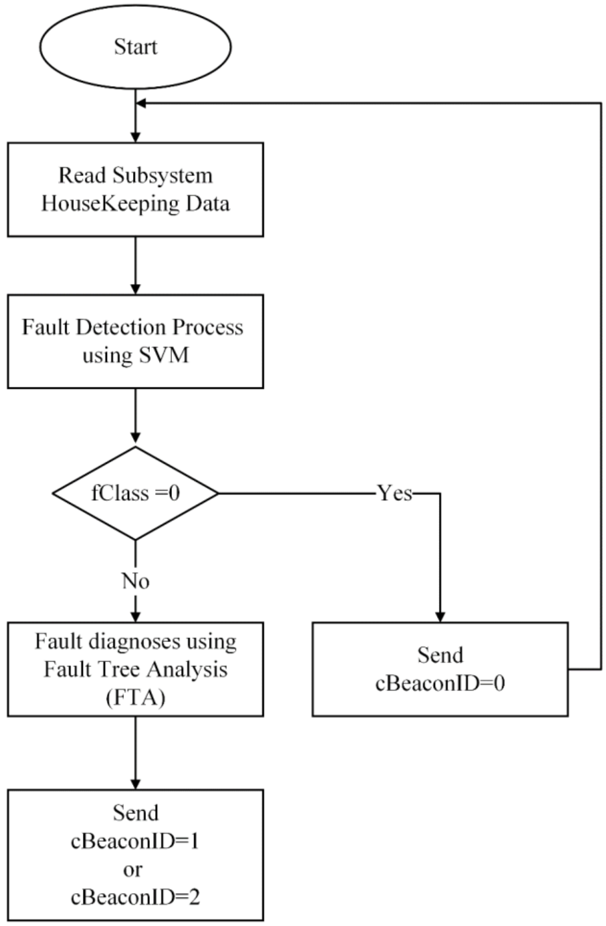

Fig. 3. Proposed system flowchart

Table 2. Flowchart parameters description

Parameter	Description
fClass	The FDIR code from 0 to 9
cBeaconID	Customized beacon structure ID: 0: Normal beacon structure 1: Moderate-risk level faults beacon structure 2: High-risk level faults beacon structure

4.1 Proposed beacon architecture

The beacon contains various parameters of the numerous subsystems within the CubeSat. The total number of bytes in the proposed system is 217 bytes. The first 145 bytes is the normal beacon structure that will be sent frequently regardless of any faults. Moreover, the second 72 bytes of the beacon will carry the dynamic structure based on the number of faults, priority, and severity. Figure 4 shows the normal beacon structure.

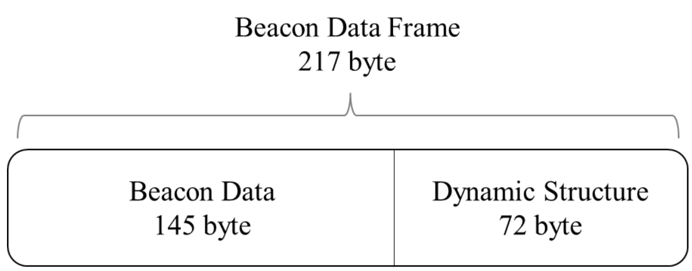

Fig. 4. Normal Beacon Structure

4.1.1 Moderate severity fault's structure

This structure will be used if moderate faults were detected and diagnosed. The dynamic structure consists of a header and the data portion. The header is structured as follows, the first byte is dedicated to the fault diagnoses code, the following 4 bytes are utilized for the time that the fault occurred, and finally, the last 67 bytes are for the HK data regarding the fault-related HK. Figure 5 shows the beacon structure for moderate severity faults.

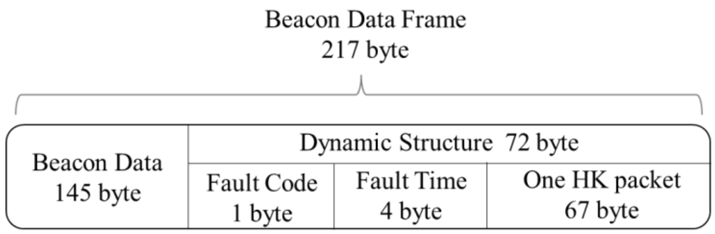

Fig. 5. Moderate severity fault's structure

4.1.2 High severity fault's structure

This structure will be used if more than one fault is diagnosed, whether moderate or high-severity faults. Furthermore, it will be used if high-severity faults are detected. The dynamic structure can carry up to 7 fault codes with their time occurrence. In addition, it includes 70 bytes from the HK data of the critical subsystems. Figure 6 shows the structure of the beacon for high-severity faults.

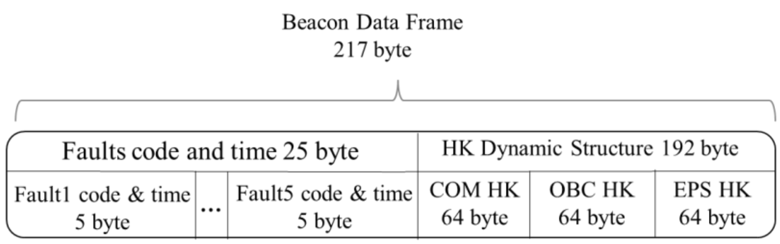

Fig. 6. High severity fault's structure

5. Preliminary Results and Discussion

The proposed system was tested using an engineering model for 1U CubeSat. The functionality test was done using historical data to test the system's ability to detect and diagnose different faults. Table 3 shows the functionality test results where 436 faults were in the historical HK data. Thus, this system is feasible to be implemented on-board CubeSats.

Table 3. Results of the functionality test

Percentage	Results (%)
Percentage of false detection	2
Percentage of faults not detected	0.5
Percentage of correct detection	97.5

6. Conclusions

Spacecrafts are prone to suffer from errors and faults in orbit. Thus, it is crucial to have robust fault detection and diagnosis to ensure that the faults suffered by the spacecraft do not lead to the mission's failure and spacecraft loss. Spacecraft's beacon can be used as a more efficient tool to aid in detecting and mitigating faults, as they are the main source of the satellite's health status and vital information. Hence, using the beacon with the FDIR strategy in its structure will efficiently aid in the preservation of the safety of the spacecraft at all times. This paper proposed an on-board automatic beacon structure customization based on fault detection and diagnosis using ML SVM algorithm and FTA. The implementation of the proposed system was based on the FDIR flag(s) with a priority level preassigned to each case. Furthermore, the proposed system indicates and reports the anomalies during the orbit with a selective set of data based on the telemetry parameters to facilitate faster knowledge and transfer of the fault. The preliminary results showed that the overall system achieved an accuracy of 97.5%. Hence, the results of this study showed that this system is feasible to implement in space missions, especially educational ones. As for future work, the proposed system can be implemented in a space mission for validation and technology demonstration.

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