Artificial Intelligence Techniques for Spacecraft Health Monitoring System - A Survey

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Abstract
Artificial intelligence, including Machine learning, Deep learning, and Reinforcement learning, has shown successful results in various applications in the fields of science and engineering, such as electrical engineering, computer engineering, bioengineering, financial engineering, medicine, aerospace engineering, and more. From this point of view, researchers have turned to AI techniques to solve various challenges in their respective fields and have designed successful applications to overcome various challenges in the aerospace industry. The main concern of any space mission operation is to ensure the health and safety of the spacecraft. The worst case in this circumstance is probably the loss of a mission but the more common interruption of spacecraft functionality can result in compromised mission objectives. As spacecraft complexity rises, many present methods of system health monitoring are challenging to employ. Also, the possibilities to observe and interact with any given spacecraft are naturally limited compared to ground-based systems due to several factors. These include but are not limited to the availability and bandwidth of their connection to ground, the availability of staff, communication latencies, and power budgets. That's the reason why every space-crafts need a minimum level of autonomy during their missions. The goal of this survey is to provide an overview of the world of artificial intelligence and its different methods, then talk about anomaly detection, Fault Detection Isolation and Recovery (FDIR), and a verity of methods of health monitoring systems and explain why it's essential for every space missions.

Keywords: *Health monitoring system - Artificial Intelligence - Anomaly detection – Autonomy - fault detection.*

1. Introduction
The possibility of observing and interacting with satellites in space is usually limited due to several factors compared to terrestrial systems. Past experiments and missions have shown that the use of more complex mechanisms with autonomous capability can greatly increase the efficiency of many missions in terms of reliability, output, and the number of attempts to make the desired mission operational. Also, this independence or autonomy can lead to a significant reduction in mission costs, otherwise, a large number of human resources are needed to carry out such activities. Artificial intelligence is a popular and widely used method for implementing autonomous capability space-crafts.[1]

This paper gives a general introduction to Artificial intelligence and its methods, and spacecraft autonomy provides an extensive survey of existing techniques and algorithms for anomaly detection and Fault Detection Isolation and Recovery (FDIR) and then brings some more detail about a useful application like health monitoring system using AI techniques.[2]

The paper is organized as: Section 2 gives a general introduction to the terminology of artificial intelligence and spacecraft autonomy, Anomaly Detection and Fault Detection, Isolation and Recovery. In section 3, the purpose of anomaly detection as a foundation for the self-awareness of systems as well as corresponding algorithms are described, and then describes FDIR concepts for spacecraft with an example and finally bring a survey of health monitoring system and different techniques. Subsequently, section 4 gives an overview of related work in the field of a health monitoring system based on AI techniques, and section 5 wraps up the paper.

2. Terminology
The following sections give an introduction to the terminology used in this paper. These are autonomy, artificial intelligence, anomaly detection, and Fault Detection Isolation and Recovery (FDIR).

2.1. Autonomy
Autonomy is the capability to make rational, informed, self-determined, and self-reliant decisions. For a system to be called autonomous, it needs to be able to sense, think and act in the world around it. It requires the capability to sense its surroundings and some

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consciousness about its capabilities and their effects on its environment and internal state. From this knowledge about the world and about itself, an autonomous system can draw conclusions and make decisions concerning its own goals and carry out actions to reach these goals.[2]

Furthermore, an autonomous system has to be able to respond to off-nominal situations by adjusting its sequence of actions to continue achieving its goal as well as maintain safety. Commanding of an autonomous system is done via sets of goals it shall achieve. Autonomy describes a set of system functions and capabilities instead of techniques by which they are implemented. Artificial intelligence is, thus, one of many possible approaches to reaching autonomy. A brief introduction to artificial intelligence (AI) is given in the following section.[2]

2.2. Artificial intelligence

Artificial intelligence (AI) is the study of intelligence as it exists in computer systems, as opposed to natural intelligence as it is seen in people and other living things. More generally, for a computer system to be called intelligent, it needs to be able to make rational decisions based on its observations of the world and a set of goals it shall achieve. Despite sounding like a cutting-edge strategy, artificial intelligence (AI) has roots in the 1950s and spans a number of paradigms and techniques. As shown in Figure 1, Machine learning, Deep learning, Reinforcement learning, and their intersections are all components of AI. Thus, a major part of AI follows the learning approach, although approaches without any learning aspects are also included. The overall goal of AI research is to enable directed learning or to make the machine smarter by following specific rules. Here, the term "smarter" refers to the capacity to carry out difficult cognitive activities that would typically need a person, such as classification, regression, clustering, detection, recognition, segmentation, planning, scheduling, or decision-making. Many people thought that these jobs could be accomplished in the early days of AI by teaching computers a vast array of rules that incorporate human knowledge. The implementation of sophisticated customized commands that computers might directly employ was thus given a lot of attention. Even though this symbolic AI has a wide range of applications, it has exhibited a number of limitations in terms of precision and accuracy for more difficult issues that have less structure, more complexity, and hidden features, such language processing and computer vision tasks. Researchers used a learning strategy called ML to overcome these constraints.[3]

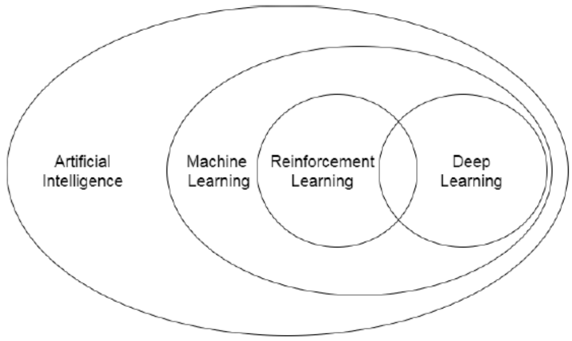

Figure 1 Artificial Intelligence, Machine Learning, Deep Learning and Reinforcement[4]

2.3. Machine Learning (ML)

A portion of AI is known as ML, which includes DL and RL. ML necessitates a learning strategy in contrast to symbolic AI, where the computer is given all the rules to tackle a specific problem. As demonstrated in Figure 2 and best explained by the father of AI, Alan Turing: “An important feature of a learning machine is that its teacher will often be very largely ignorant of quite what is going on inside, although he may still be able to some extent to predict his pupil’s behavior,” An ML system is trained rather than programmed with explicit rules. The learning process requires data to extract patterns and hidden structures; the focus is on finding optimal representations of the data to get closer to the expected result by searching within a predefined space of possibilities using guidance from a feedback signal, where representations of the data refer to different ways to look at or encode the data. Three things are need to accomplish that: input data, examples of the anticipated output, and a way to assess the algorithm's performance.[5]

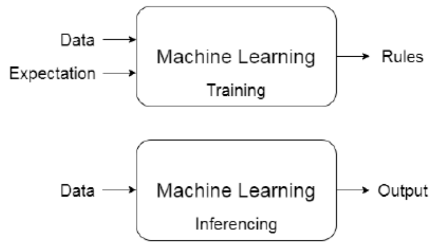

Figure 2 Machine Learning Approach[4]

Deep learning and non-deep learning are two prominent categories for machine learning algorithms. Although deep learning (DL) has received greater attention and popularity, some traditional non-deep ML techniques are more beneficial in some applications, particularly when data is scarce. As illustrated in Figure 3, ML algorithms can also be divided into supervised, semi-supervised, unsupervised, and RL classifications.[4]

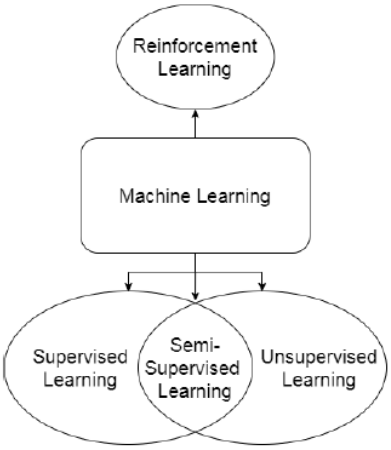

Figure 3 Machine Learning Sub-fields[4]

ML techniques such as supervised, unsupervised, and semi-supervised learning can all be used to address a wide range of issues. During supervised learning, all of training data is labeled with the correct answer. The algorithm is thus fully supervised, as it can check whether its predictions are right or wrong at any point in the training process. A supervised model may predict labels for unlabeled data during inference by learning patterns from training data. Supervised learning has been applied for classification and regression tasks. As labeling can be impossible due to a lack of information or infeasible due to high costs, unsupervised learning employs an unlabeled data set during training. The model can employ unlabeled data to uncover hidden patterns or structures that may help to explain a particular phenomenon or whose output may be used as an input for other models.[5]

Auto-encoders, association, grouping, and anomaly detection have all frequently used unsupervised learning (AEs).[5]

Semi-supervised learning enables a mix of unlabeled and labeled training data as a middle ground between supervised and unsupervised learning. Thus, when only a small portion of the data is labeled and/or the labeling process is either time-consuming or expensive, semi-supervised learning is a fantastic alternative. Pseudo-labeling is an illustration of this method that has been applied to enhance supervised models.[5]

2.4. Deep Learning (DL)

This area of machine learning needs a lot of computational resources, as opposed to shallow models. Recent developments in computing power and the automation of feature engineering have paved the way for deep learning (DL) algorithms to outperform traditional machine learning (ML) algorithms for handling challenging problems, especially perceptual ones like computer vision and natural language processing. Since shallow ML algorithms are relatively simple, they need human interaction and skill to extract useful features or to modify the data so that the model can learn more easily. Since these changes are carried out implicitly by deep networks, DL models minimize or eliminate these processes.[6]

2.5. Reinforcement Learning (RL)

Learning which actions to execute in order to maximize a reward signal is the focus of RL. As seen in Figure 4, the agent must try each action to determine which produces the greatest reward. Both current and future rewards may be impacted by these behaviors. Some RL methods call for the addition of DL; these methods are a subset of deep RL (DRL). An RL system has four sub-elements in addition to the agent and the environment: a policy, a reward signal, a value function, and occasionally an environment model. In this case, learning entails the agent figuring out the optimal way to link environmental states to the actions that should be conducted in those states the objective of the RL problem is to have the environment send the RL agent a reward signal after each action. A value function, as opposed to a reward, predicts the total amount of compensation that agent might hope to get over the course of time. Rewards result in an immediate appraisal of the action. Last but not least, an environment model imitates the behavior of the environment. These models can be useful for planning since they let the agent think about potential future events before they happen. Model-free approaches are those without models, whereas model-based methods are those for addressing RL issues that make use of models.[4]

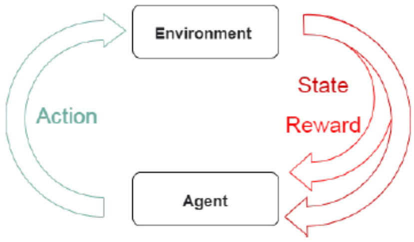

Figure 4 Reinforcement Learning[4]

2.6. Anomaly Detection

Finding patterns in some underlying group of data points and identifying deviations from those patterns are the goals of anomaly detection. This is crucial for spacecraft to detect off-nominal situations and react appropriately. Anomaly detection is done on multi-dimensional data, such as pictures, as well as time-series data, such as temperature readings over time, primarily to identify scientific opportunities or reduce the amount of data chosen for downlink.[2]

2.7. Fault Detection, Isolation and Recovery (FDIR)

A fault is when one or more system parameters deviate from the desired value. In addition to a flipped bit in the computer's memory brought on by a Single Event Effect, this could be a temperature value that is outside of acceptable limits. Failures are the outward signs of a functional flaw in a system. Correct fault handling that prevents failure is crucial for ensuring system availability, reliability, and performance. This is referred to as FDIR in spacecraft design. The ability of a system to recognize when a defect has occurred is known as fault detection. It is typically followed by fault isolation to pinpoint the exact site of the fault (subsystem, memory region, etc.). Ultimately, in the fault recovery step, the system tries to transfer to a safe state of execution in which the fault has been mitigated.[2]

3. Health Monitoring System

A cognitive system that can assess its environment and internal condition, form inferences based on its goals, and act accordingly without ground assistance is one of the goals of bringing autonomy to spacecraft. In this regard, it's critical to be able to detect patterns and anomalies in order to spot off-nominal circumstances when a mission is in operation. Point anomalies, contextual anomalies, and collective anomalies are all distinguished. A data point is an anomaly for point anomalies if it differs from all the other normal data points. A data point's surrounding data points must be analyzed in order to classify it as a contextual anomaly. For example, a high temperature that is nominal during daytime would be considered an anomaly when observed during nighttime Even though a single data point may occur nominally when viewed in isolation, an entire sequence of data points is considered anomalous for collective anomalies. It goes without saying that the detection of contextual anomalies, and particularly collective anomalies, is much more difficult than the detection of point anomalies.[2]

Anomaly detection can be divided into three basic categories: supervised, unsupervised, and semi-supervised. Both anomalous and nominal data sequences are accessible for training in the supervised instance, and each sequence is tagged as either one or the other. The disadvantage of this is that the system may miss first-time abnormalities during operations since it has never seen them before and categorizes them as normal behavior. The algorithm assumes that in the unsupervised scenario, anomalies occur far less frequently than expected behavior. As a result, it makes an effort to understand the overall structure of the training data and labels any deviations as anomalies. But if the same abnormalities are regularly seen, the system can mistakenly identify them as normal behavior. The training data in the semi-supervised instance only includes nominal data. Engineers may now be confident that they are not feeding anomalies to the system during training. The system learns to detect patterns in the underlying data once more.[2]

Calculating a set of statistical measures (minimum, maximum, average, and standard deviation) for a sequence in time of a given parameter and then computing the Euclidean distance to other time-sequences that have already been observed are two straightforward mathematical and computational approaches. Then, using local outlier probabilities, the probability of having detected an outlier or abnormality is calculated. The technique has successfully been used to perform ground-based analysis of the telemetry of the ESA X-ray space observatory XMM-Newton.[7]

Another effective method for anomaly detection is supported vector machines (SVMs). SVMs are a mathematical technique for classification and regression that raises the dimensions of the input data in the hopes that the data would eventually become linearly separable by a hyper-plane. Kernels are used as similarity functions for this. Linear, polynomial, or radial basis function (RBF) kernels are examples of typical kernels. Based on the few training instances that have been discovered to be necessary, this hyper-plane may turn into a non-linear separator during the backward transformation. In SVMs as opposed to other classifiers, the hyper-plane that minimizes the L2 norm and maximizes the lowest margin from any data point to the hyper-plane is chosen because there may be an endless number of hyper-plane. This produces a simple and robust hyper-plane. SVMs present a supervised mean of machine learning. For anomaly detection, this implies that labeled training data for both nominal and off-nominal situations has to be available. The problem of having only a limited number of anomalies, that are by definition rare compared to nominal behavior, by training an SVM in multiple steps with an increasing number of samples. Weighting input features according to their kernel-based distance before training speeds up training even more. The results have been verified using data from the Interferometry Program Flight Experiment II (IPEX II).[8]

Figure 5 depicts the schematic of a fault detection system that makes use of multiclass SVMs, binary PCA, and PCA.[2]

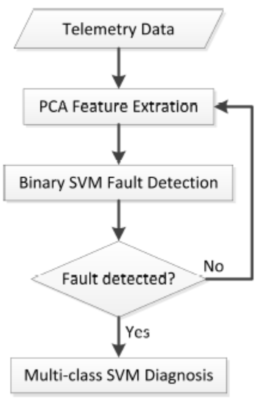

Figure 5 PCA- and SVM-based Fault Detection and Isolation[2]

In a first step, the telemetry data is mapped to a lower dimensional space by PCA. In the next step, the data point is classified by a binary SVM as representing a nominal or fault state. In case a fault is detected, the data point is passed to the fault classification performed by a multi-class SVM in a One-Against-All (OAA) fashion. Both SVMs are trained using telemetry data that has been manually labeled with its respective fault state.[2]

Let's talk more about the health monitoring system right now. A large group of people, including mission controllers and system engineers, monitor the health of a spacecraft to look for any irregularities in the down-linked data. Parameter limit checking, which creates a reference table of nominal sensor values for each sensor on a system, is one of the traditional methods of health monitoring. To determine whether the values fall within the ranges, this table is then contrasted against real-time telemetry. If not, there might be a problem with that sensor. This approach of health monitoring is particularly ineffective and time-consuming because it becomes increasingly difficult to generate this reference table as the number of components rises. It is challenging to accurately define what would be a healthy sensor value. Additionally, due to various component interactions, numerous reference tables would need to be created for each of the satellites' various operational modes. Such an approach also lacks the ability to describe complicated interactions that may involve multiple concurrent parameters in the operational context because it only takes individual parameter ranges into account when making its choice.[9]

To address the difficulties of tracking the increasingly complex component interactions of spacecraft, data-driven systems like the Inductive Monitoring System (IMS) were developed. IMS offers a more autonomous way of spotting anomalies inside a system. The amount of archival system telemetry that is available for numerous different spacecraft and applications has made these strategies possible. In order to provide system health monitoring, IMS leverages this archived data to construct nominal system behavior models that may be evaluated against real-time telemetry. The telemetry will fit one of the models if the system is operating normally. If not, then this can be a sign of a system fault or anomaly.[10]

IMS is a technique for detecting anomalies based on distance that clusters the relationships between a number of sensors in time-series data. It makes use of vectors as a data structure to store values for a set period of time for a number of connected system parameters. During the learning phase, it searches through the archived data, creates these vectors, and clusters vectors with comparable or consistent values. As a result, each cluster specifies a separate sensor range that represents a different characterization or notional state that the system may be in. The cluster defines a nominal operating region that is represented as an N-dimensional hyper-cube in the vector space where N is the number of parameters chosen. Each dimension of this hyper-cube specifies a minimum and maximum value for that parameter in the given cluster. This is beneficial because it allows us to model interactions between related parameters instead of looking at each one individually. The end result of the learning phase is a knowledge base of many clusters that define a model of the nominal states of the system. This knowledge base can then be queried with new input to see if it falls within a nominal operating region. It is important that the training data is free of any anomalies to ensure bad behavior isn’t incorporated into the system[10 ,1].

Once a knowledge base has been created from the learning phase, it can be used for real time monitoring or the analysis of archived events. This monitoring produces a deviation value that signifies how well the system is conforming to the model. Large deviation values may highlight a precursor to a malfunction or a malfunction itself. This monitoring phase does not explicitly pinpoint the exact problem with the system, rather it gives details as to which features are causing the issue and where it is occurring so that a mission controller can later do a closer inspection[10 ,1].

In order to begin IMS monitoring, real-time data from the system under observation is first formatted into the predetermined data vectors from the learning phase. This data vector has been standardized to ensure that the parameters are scaled similarly, and it can be further scaled by assigning weights to each parameter to give more important features a higher sensitivity. The knowledge base's clusters are then compared with the data vector to determine which cluster it belongs to or has the shortest distance to. This distance can be viewed as a deviation score, indicating how far the input vector deviates from a nominal cluster, if the vector does not lie within a cluster. The significance of the anomaly increases with the deviation value. Deviation scores that are small may indicate nominal behavior that was not captured in the training data. A threshold value is usually given as a parameter to the monitoring algorithm that accepts input vectors that have deviation scores that fall under the threshold. Along with the deviation score, the individual parameter contributions to the score can be saved to give the operator more details as to which sensors are causing the issues. An overview of the two phases can be seen in Figure 6.[1, 10]

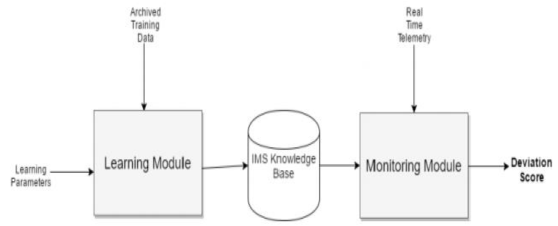

Figure 6 Overview of IMS[1]

Overall, IMS has strong and effective monitoring capabilities. It provides the capacity to quickly model the behavior of complicated systems using only nominally archived data. It is also particularly flexible for applications involving system monitoring. As more nominal telemetry is obtained, the knowledge base can be updated whenever necessary to create a more precise model of the system. It is also possible to alter the monitored features to remove or add new features that might produce better outcomes. IMS has achieved great success in a variety of system applications thanks to its strengths.[1]

4. Related Work

Over decades researchers have devoted considerable effort to develop various heath monitoring systems

(HMSs) for space operations. The methods used include machine learning/data mining techniques and multivariate statistical approaches. These methods can provide important tools for the field of intelligent monitoring which can learn, adapt, and support decision making concerning the system that flight experts are in charge of. Much of the previous work in fault detection for space operations has used unsupervised anomaly detection algorithms because they relied on historical data, and the historical data generally doesn't contain enough examples of faults to adequately train a supervised learning algorithm. One of the advantages of our design work described in this article is the database. It has training data with faulty cases that facilitate us to adequately train a supervised learning algorithm.[11]

A comparison of six unsupervised anomaly detection systems was published by Martin et al. Data from four space shuttle flights and two test stand firings were utilized for training the algorithms, and data from eight shuttle flights and four test stand firings were used for validation. They come to the conclusion that the algorithm with the best accuracy appeared to be either Orca or one-class support vector machines (OCSVM), but some reclassification is necessary in order to best represent the new anomalies discovered during analysis, even though they acknowledge that they don't have enough data to make statistically significant comparisons of the relative performance of the algorithms.[12]

Iverson used IMS to analyze data from four temperature sensors located inside the shuttle's wings following the STS-107 space shuttle Columbia incident. He tested it using data from STS-107 after training it with information from five earlier space shuttle flights. It indicated in hindsight that with the aid of IMS, flight controllers may have been able to identify the damage to the wing far sooner than they did by detecting an anomaly in data from the temperature sensors on the shuttle's left wing shortly after the foam impact. More recently, IMS has been deployed to the mission control center at NASA Johnson Space Center, where it is being used to monitor live data from the international space station (ISS).[13, 14]

One system failure and four additional anomalies of data from the SSME were provided by Schwabacher et al. They say that four unsupervised anomaly detection algorithms—Orca, GritBot, IMS, and OCSVMs—were used to identify anomalies. This allows SVMs to maintain the advantage of finding the globally optimal solution given the training data while still being "strongly effective using non-linear supervised models." The authors made it clear that some abnormalities were picked up by some algorithms while others weren't because different algorithms utilize varied definitions of what constitutes an anomaly. Orca, IMS, and GritBot are relatively straightforward algorithms that are simple to comprehend and offer some form of explanation for each anomaly in terms of the variables; as a result, they are more likely to be accepted by professionals than the more complex and challenging OCSVM method.[15]

Without utilizing cross-validation, Yairi et al. analyzed and compared a number of unsupervised and supervised dimensionality reduction techniques. According to the authors' perspective, using cross-validation may take too much time if there are a lot of classes or training sets.[16]

Verzola et al. made it clear that a reactive model is frequently the foundation for space operations. The complexity of this model is its biggest disadvantage. It is challenging to carry out preventive measures to avoid the anticipated faulty condition and to avert failures. Additionally, their paper discusses a study on a potential proactive failure model based on statistics, machine learning, and data mining approaches to determine future patterns of the object to predict the behavior of the system. However, the research work was not helpful for making real-time forecasts that could be compared to a set of predetermined thresholds for failure probabilities.[17]

MacGregor et al. established the potential of applying multivariate latent space methods in monitoring and fault diagnosis by comparing it with many other data-driven techniques. The authors stated that the class of regression methods/classifiers that does not allow for modeling the X-space includes black-box models like artificial neural networks (ANNs), hidden Markov models (HMMs), and SVMs. The capacity of these strategies to evaluate full rank data, handle missing data, and screen for outliers in fresh data is also limited, despite the fact that they acknowledge their potential utility in specific circumstances. [18]

A failure detection method for crucial satellite components dubbed the anomaly monitoring method (AMM) was presented by Peng et al. It consists of state estimate based on multivariate state estimation techniques (MSETs). The technique was used on satellite power supply subsystems, and lithium-ion battery failure analysis was done (LIBs). The authors did not conduct an in-depth analysis of LIBs failure or take into account more affecting aspects because they chose only two parameters as the essential parameters of AMM.[19]

An organized and thorough overview of the research on classification-based outlier detection was provided by Upadhyaya et al. The authors provided a list of numerous methods that can be used in this field of study, concentrating on the general strategy used by each method. Additionally, they have outlined the fundamental presumptions that the strategies rely on to distinguish between typical and exceptional behavior. Without relying on a common understanding of outliers, the study was done in an unstructured manner. Therefore, it is challenging to understand the outlier detection problem theoretically.[20]

Data-driven techniques were used by Schwabacher et al. to automatically identify and pinpoint flaws in the J-2X rocket engine. Since C4.5 decision tree algorithms tend to be simpler to understand than other data-driven approaches, it was decided to employ them. By doing a search over the space of potential decision trees to locate one that suits the training data, the decision tree algorithm automatically learns a decision tree. However, they didn't apply any other algorithms for compression or validation. ANNs have been utilized to represent the system in many of the current supervised learning methods for systems health monitoring. When used to solve a pump diagnosis problem, he and Shi discovered that SVMs performed more accurately than ANNs. One significant disadvantage of neural network approaches is that most humans are unable to understand or interpret the ANNs models and also SVMs models suffer from a similar lack of comprehensibility.[21]

5. Summary

This survey presents a starting point to understand the concept of artificial intelligence and machine learning, its potential, requirements, and limitations with a strong focus on the space domain.

We have given an introduction to the terminology of artificial intelligence and machine learning in the space domain. Building upon this terminology, we introduced important techniques suitable for the application on board and ground in the fields of anomaly detection and FDIR for health monitoring systems. Finally, we surveyed related work in the field of a health monitoring system based on AI techniques to show concepts of autonomous mission operations.

Future missions tend to rely more and more on autonomous systems to meet safety and cost requirements and be as reactive as possible. Techniques of artificial intelligence and machine learning show the potential to not only assist in mission operations, planning, and scheduling but also to enable new missions that require immediate action by the spacecraft without the possibility to shift important decisions to the ground and also keep missions safer and more reliable.

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