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Telemetry Data Mining in Space Missions Using Machine Learning Algorithms: A Review and Open Issues from Deep Learning Perspective

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A B S T R A C T

The world has numerous satellite constellations in orbit collecting huge amounts of data, such as high-resolution multispectral imagery, as well as internal systems monitoring. These satellites are very expensive, highly complicated systems that operate in the most extreme environments. It is vital to monitor these satellite systems, as well as systems in other spacecraft, for abnormalities that function as precursors to system failure to avoid catastrophic damages and costs. Traditional spacecraft anomaly detection methods are limited in scope and rely on domain experts to correctly determine abnormal behavior. However, with thousands of distinct telemetry channels being transmitted, the amount of data is difficult to monitor manually. Deep learning models can be used to learn the normal behavior of the telemetry channels and flag or label any deviations. With the increased interest in machine learning, in particular deep learning, work has been done to show the effectiveness of an automated approach to anomaly detection. Therefore, this paper offers a review of telemetry data mining in space missions using data mining techniques. The research highlights open issues from a deep learning perspective.

Keywords: Machine Learning, Data Mining, Deep Learning, Space Craft, Anomaly Detection

1. Introduction

The world has numerous satellite constellations in orbit collecting huge amounts of data, such as high-resolution multispectral imagery, as well as internal systems monitoring (Dial, Bowen, Gerlach, Grodecki, & Oleszczuk, 2003). These satellites are very expensive, highly complicated systems that operate in the most extreme environment (Denis et al., 2017). It is vital to monitor these satellite systems, as well as systems in other spacecraft, for abnormalities that function as precursors to system failure to avoid catastrophic damages and costs (Baireddy et al., 2021). A few examples of anomalous behavior can be seen in Figure 1.

Due to the nature of these systems, there are usually thousands of telemetry channels that should be monitored to fully capture and describe any anomalous behavior or system failure (Hundman, Constantinou, Laporte, Colwell, & Soderstrom, 2018). Current system monitoring is performed in a limited scope by domain experts who observe each channel and manually flag sequences they believe to be anomalous (Hassanien, Darwish, & Abdelghafar, 2020). The limiting factor in this scenario is the number of available experts and the time-consuming nature of manual observation. With the increased interest in machine learning, in particular deep learning, work has been done to show the effectiveness of an automated approach to anomaly detection. The effectiveness of deep learning is usually dependent on the amount of data available for training. Though the limited domain expert knows a factor by making labeled anomalous data scarce, we can utilize deep learning in a semi-supervised manner (Baireddy et al., 2022). An efficient semi-supervised anomaly detection approach is to learn the normal and expected behavior of a telemetry channel, so any deviations from this behavior can be flagged in post-processing.

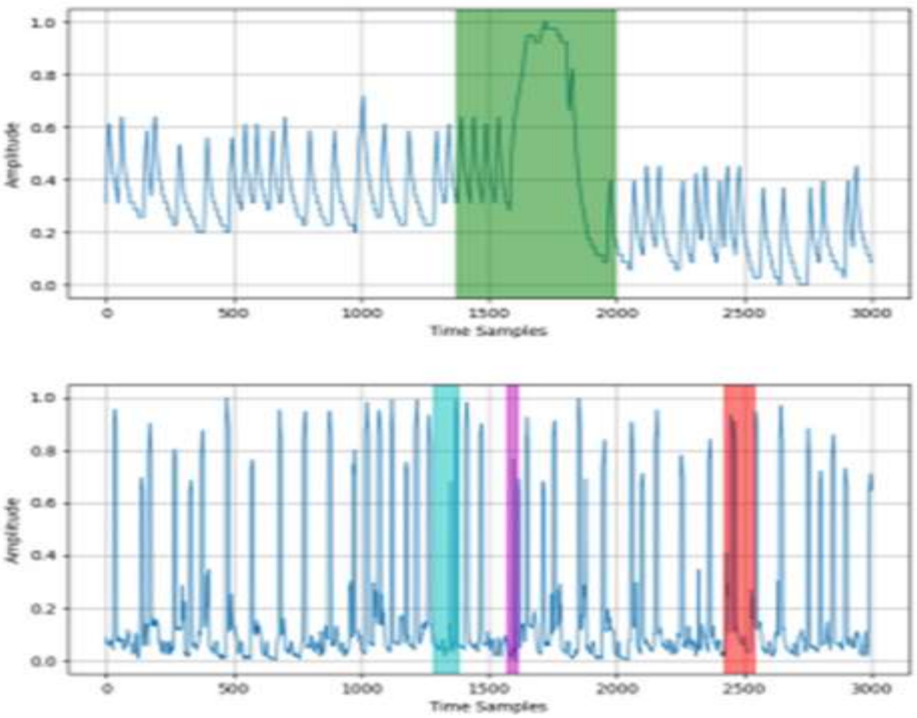

Figure 1: An example of normalized time-series anomalies identified by experts (highlighted in various colors) in two spacecraft telemetry channels

Source: (Baireddy et al., 2021)

This is done effectively by utilizing a recurrent neural network (RNN) as a predictor and a mathematical model of expected prediction errors [14, 20]. However, the large number of channels to monitor hamstrings this strategy for any realistic application; a unique RNN will need to be trained from scratch for every channel for this approach to work optimally. Anomaly detection in telemetry channels is a high priority for spacecraft, especially when considering the harsh environment of space and the magnitude of launch and operation costs. Traditional spacecraft anomaly detection methods are limited in scope and rely on domain experts to correctly determine abnormal behavior. However, with thousands of distinct telemetry channels being transmitted, the amount of data is difficult to monitor manually. Deep learning models can be used to learn the normal behavior of the telemetry channels and flag or label any deviations. The problem is that we have to train a unique model for each channel to ensure best performance. With the large number of channels to monitor, this may not always be possible. Upon preliminary investigation on transfer learning, which deals with adapting deep learning models for problems different from their initial task (Gao, Ruan, Fang, & Yin, 2020). The nature of the telemetry data recorded by the spacecraft means that there are undoubtedly similarities and correlations between various signal channels, both inter-, and intra-subsystem. One way to avoid training thousands of unique deep learning models from scratch would be to use a single anomaly detector for multiple channels, or an entire subsystem, with some finetuning for the predictor to tailor its performance for each channel. Therefore, this paper offers a review on telemetry data mining in space missions using data mining technique. The research highlights open issues from deep learning perspective. The reminder of the paper is organized as follows: section 2. Details theoretical background data mining techniques in space missions and related studies from the literature, section 3 discuss the challenges and proffer future opportunities. Finally, section concludes the study and proposed our future work.

2. Literature Review

M In this subsection, the researcher presents the detail literature and related researches done in the context of anomaly detection in space operations.

2.1 Anomaly Detection in Spacecraft Operations

Anomaly detection is a technique used to identify dataset which does not conform to an expected behavior or other items in a dataset. In general, these unexpected behaviors are defined as attacks. Whereas these situations can be unexpected behaviors which are previously not known, rather than an attack. The anomaly detection provides very significant and important information about the system. Also, anomaly detection helps prevent potential malfunctions and serious errors. This improves system security and reliability (Taburoğlu, 2019).

Anomaly detection is an important topic for space system, because so much money and time are spent. Also, satellites have become incredibly useful, especially for meteorology, communication, and navigation and military. These domains are costly and safety critical. Therefore, failures are not acceptable. The anomaly detection can help carry out fault diagnosis and prevent the occurrence of potential failures (Taburoğlu, 2019). There are many anomaly detection methods exist, in general following steps are done.

- Data Preprocessing and Feature extraction: A list of related parameters for components or subsystems of the spacecraft system are selected
- Model Generating: Model is generated on the normal or abnormal behavior of the spacecraft system.
- Detecting: Statistical based, knowledge based or machine learning and data mining algorithms are used.

Figure 2: Telemetry – Telecommand Communications (Taburoğlu, 2019)

Telemetry data include some sensor values, such as temperature, voltage, angular velocity and temperatures which have low and high limit value. That's why limit checking is one alternative for anomaly detection. But for some cases when limit values are normal, anomalies can exist, this means that some class of anomalies occur without violating the limits on the variables. In order to take measures before the situation occurs, these anomalies should be predicted. Also, domain experts or operators always should monitor and review out of limit values. If the limit values are inappropriate, anomaly will be detected, else false alarms will be generated and real anomalies may be missed.

Therefore, to overcome these problems machine learning methods (Ibrahim, Ahmed, Zeidan, & Ziedan, 2018) are used instead of limit checking. Also, have developed a new method for limit checking. They have combined limit checking and Sparse Bayesian Learning (or Relevance Vector Machine). RVM is used to learn a model of high and low limit values from old normal telemetry. The resulting models are then used in later operations to detect anomalies for target variables online. Data Mining Techniques (clustering and classification based) and hybrid approach are the most important methods. An important advantage of these approaches compared with the expert systems and model-based approach is that it does not require complete and accurate expert knowledge or models. There are a large number of surveys in the literature about the detection of anomaly but there is very limited number of in terms of space domain. In this review, the methods in the literature are shortly summarized for the industry (real world) which have just started to work on the anomalies in the spacecraft.

2.2 Computational Method Base on for Anomaly Detection in Spacecraft

There are two main approaches for anomaly detection: knowledge-driven approach and data-driven approach. In knowledge-driven approach, highly accurate results can be obtained, if knowledge is accurate. However, this method is costly because it requires expensive expert knowledge and manual checking. Data-driven approach includes machine learning methods (random Forest, K Neighrest Neighbour, Naïve Bayes, Decision Tree and Deep Learning) which can be categories into classification task or clustering task. This approach is better than knowledge-driven in terms of cost. Also, it is an automatic detection approach; however, most of the time highly accurate results are not available. However, the focus of this research is on improving the detection accuracy of machine learning approaches (Data-driven approaches). The following subsections presents an overview and basic fundamentals of some popular data mining algorithm used in classification task with focus on deep neural network.

2.2.1 Overview of Deep Learning Algorithms Used in Anomaly Detection

2.2.1.1 Neural Networks

Neural networks are biologically inspired and imitate human brain. Feed forward neural networks are a basic type of NN capable of approximating generic classes of functions. They are the most commonly used NN architectures. Multilayer Perceptron MLP is a famous class of FFNN which used Backpropagation training algorithm. In the neurons are organized in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this type of networks connections to the neurons in the same or previous layers are not permitted. Neurons in different layers are linked. These connection links have weights which need to be adjusted iteratively depending on the input signals till the desired output, MSE error value or epoch number is reached. NN are trained by examples, when unknown signal applied, it generalizes the past examples and produce an output (Eleyan, 2012).

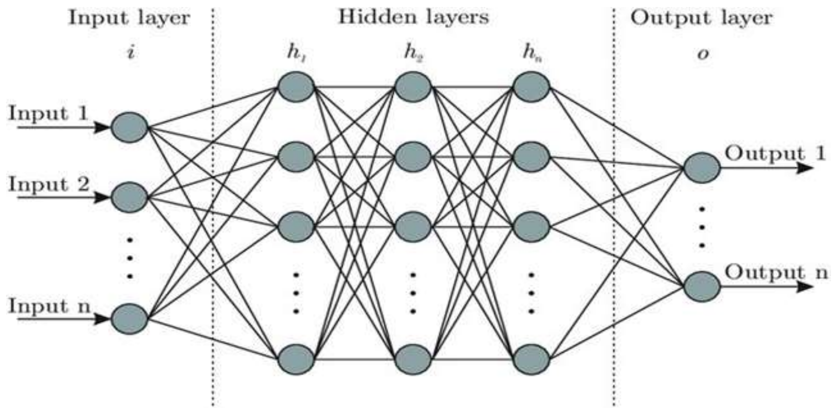

Figure 3. Structure of ANN(Bre, Gimenez, & Fachinotti, 2018)

2.2.1.2 Recurrent Neural Network (RNN)

RNNs is a basic deep learning model used for malicious file detection. RNNs are mainly employed to process sequential information, such as language translation. Figure 4 illustrates the structure of a typical RNN used to translate German sentences into English. However, RNNs have the disadvantage that the longer the input sentence, the smaller the influence of the preceding words. This is known as the vanishing gradient problem.

2.2.1.3 Deep Recurrent Neural Network (Long Short-Term Memory)

LSTM was proposed to solve the aforementioned vanishing gradient problem. LSTM has three gates, as shown in Figure 4. The gates are a way to optionally let information through. They are composed of a sigmoid neural net layer σ and a pointwise multiplication operation ×. The first is the forget gate f_t, which determines whether the state C_{t-1} of the previous cell is reflected as follows:

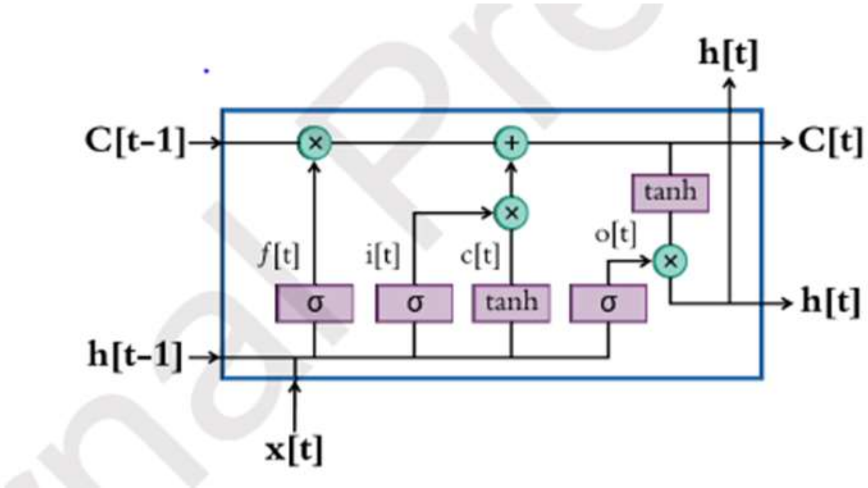

Figure 4. The Structure of a Long Short-term Memory Cell

The forget gate ($f(t)$) decides either to keep or discard the information from the cell state, shown in Figure 4. A logistical function generates either 0 or 1 as a value for $f(t)$ that represents either to abandon or keep the current cell state at time step t , respectively. Where w, h, x, and b are the weight, output, input, and bias, respectively. The activation function is represented by ¾. On the other hand, the input gate controls what input values can be stored in the cell state as shown in Eq. 4. Where $i(t)$ represents the signal (0 or 1) that controls the updating procedure, $g(t)$ is new candidate value and $c(t)$ is the new state of the cell. Moreover, the output gate ($o(t)$) is responsible for releasing the stored information to the next neurons making LSTM a powerful ML model to capture long-term dependency as well as the non-linear relationship in a complex dataset. In LSTM, the state C_{t-1} of the previous cell has the possibility to be changed less than in an RNN. Therefore, LSTM has the advantage that the initial state of a cell can be better reflected

2.2.2 Overview of Machine Learning Algorithms Used in Anomaly Detection

2.2.2.1 Support Vector Machines

The foundations of Support Vector Machines (SVM) have been developed by (Vapnik & Izmailov, 2017), and since then it gained popularity due to many attractive features, and promising empirical performance. Training SVM is a quadratic optimization problem. SVM construct the decision surface in the higher dimensional space mapping the input signals into that space using nonlinear mapping. For two-class problem, assuming optimal hyperplane in higher dimensional space is generated, the classification decision of an unknown signal X will be made based on kernel function. The kernel function forces the operations to be carried out in the input space rather than in the higher dimensional space. Choosing proper kernel function is dependent on the type of the problem and the given data. According to (Übeyli, 2007) optimal results for SVM were achieved using RBF kernel function (Eleyan, 2012).

2.2.2.2 k-Nearest Neighbors (KNN)

The KNN algorithm is used to predict the class or property of data. Given N training vector, suppose we have A and Z as training vectors in this bidimensional features space, we want to classify c which is feature vector. Classifying c depends on its k neighbors, and the majority vote, k is a positive integer, k is generally smaller than 5, if k=1 the class of c is the closest element from the two sets to c. We use the Euclidean distances to evaluate the distance of a sample with other points(Amrane, Oukid, Gagaoua, & Ensarİ, 2018). KNN considered one of the simplest and straightforward techniques in pattern recognition and it is based on a statistical data. The key advantages of KNN are that it can handle multi-class problems. Moreover, the decision is made according to the training items in the training phase. The decision rule of KNN method determines firstly the *K* nearest items in the feature space; afterwards, it assigns the unclassified item to the class of the majority vote of those *K* items(Saleh, Shehata, & Labeeb, 2019). The execution of KNN is based on two operators: the value of *K* that denotes to the count of neighbors to be considered and the utilized distance measure. The most common way for computing the distance between a new item and the training items is the Euclidean distance, which can be calculated by Eq. (1).

$$D(A, B) = \sqrt{\sum_{i=1}^{v} (A_i - B_i)} \tag{1}$$

Where *D*(*A*, *B*) represents the Euclidean distance between two items *A* and *B* of genes (1, 2,…, v), *Ai* symbolizes the genes of the new test item *A*, *Bi* symbolizes the genes of a specific training item *B*, and *v* represents the total number of genes. However, the drawback is that the solution relying on the value of K and the computational time for calculating the distance between a new test item and all class items(Ayyad, Saleh, & Labib, 2019).

2.2.2.3 Naïve Bayesian Classifier (NBC)

A Bayesian method is a basic result in probabilities and statistics, it can be defined as a framework to model decisions. In NBC, variables are conditionally independent; NBC can be used on data that directly influence each other to determine a model. From known training compounds, active (D) and inactive (H), Given representation B, the conditional probability distribution P(B/D) and P(B/H) are estimated, respectively. Bayesian classifiers are additionally well adapted for ranking of compound databases all with consideration to probability of activity.

Bayesian classifiers use Bayes theorem, which is:

$$p(h \mid d) = \frac{p(d \mid h)p(h)}{p(d)} \tag{2}$$

Where, P(h) is the priori probability that event h will occur. P(d) is the prior probability of the training data.

The conditional probability of d when p (d | h) is given. P(h | d) is the conditional probability of h when given d

training data. P (h | d) is the probability of generating instance d given class h. In the equation above Bayesian

decision theorem is used to determine whether a given xi belongs to Si where Si represents a class(Cruz & Wishart, 2006).

2.2.2.4 Random Forest

Random Forest is one of the most popular machine learning algorithms. It requires almost no data preparation and modelling but usually results in accurate results. Random Forests are based on the decision trees described in the previous section. More specifically, Random Forests are the collections of decision trees, producing a better prediction accuracy. That is why it is called a 'forest' – it is basically a set of decision trees. The basic idea is to grow multiple decision trees based on the independent subsets of the dataset. At each node, n variables out of the feature set are selected randomly, and the best split on these variables is found. In simple words, the algorithm can be described as follows (Chumachenko, 2017)

I. Multiple trees are built roughly on the two third of the training data (62.3%). Data is chosen randomly.

II. Several predictor variables are randomly selected out of all the predictor variables. Then, the best split on these selected variables is used to split the node. By default, the amount of the selected variables is the square root of the total number of all predictors for classification, and it is constant for all trees.

III. Using the rest of the data, the misclassification rate is calculated. The total error rate is calculated as the overall out-of-bag error rate.

IV. Each trained tree gives its own classification result, giving its own" vote". The class that received the most" votes" is chosen as the result. The scheme of the algorithm is seen in Figure 5.

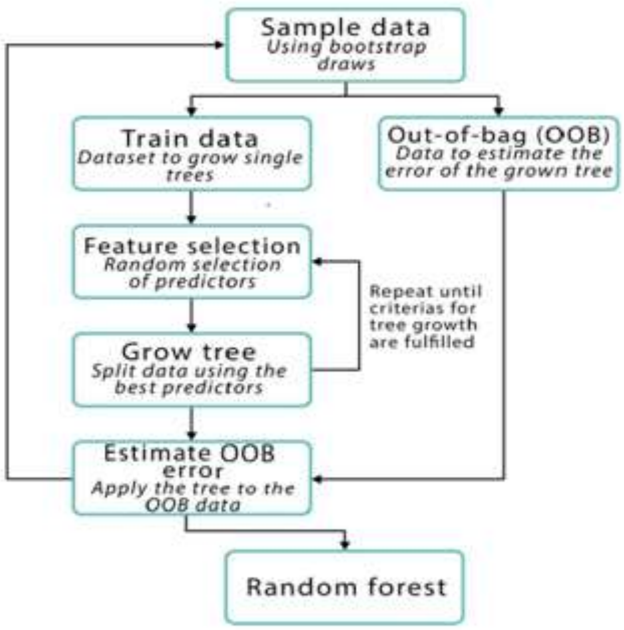

Figure 5. Random Forest Scheme(Chumachenko, 2017)

2.2.2.5 Genetic Algorithm (GA)

GA is metaheuristic and stochastic optimization algorithm inspired by the process of natural evolution. They are widely used to find near-optimal solutions to optimization problems with large search spaces. The process of GA includes operators that imitate natural genetic and evolutionary principles, such as crossover and mutation. The major feature of GA is the population of "chromosomes". Each chromosome acts as a potential solution to a target problem, and is usually expressed in the form of binary strings. These chromosomes are generated randomly, and the one that provides the better solution gets more chance to reproduce. The basic process involve in the processing of GA is depicted in figure 6.

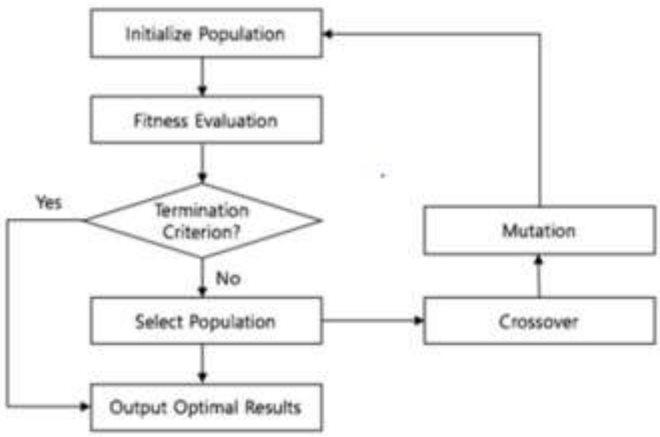

Figure 6: Basic process of a genetic algorithms(Chung & Shin, 2018)

2.3 Challenges of Anomaly Detection in Spacecraft

Anomaly detection in spacecraft is crucial for mission success and safety, but it faces several challenges, including limited training data due to high costs and few historical anomalies, which makes it difficult to develop accurate models. This is exacerbated by high-dimensional data from various sensors, requiring complex processing and dimensionality reduction to handle. Furthermore, the class imbalance between normal and anomalous data makes it challenging to detect rare anomalies effectively. Real-time processing is also essential to respond quickly to emerging issues, but this poses significant computational challenges. Additionally, anomaly detection models must be adaptable to changing environmental conditions, robust to noise and uncertainty in telemetry data, and provide human-interpretable results to aid decision-making. Scalability is also a concern due to increasing data volume, and models must be able to provide fault diagnosis and troubleshooting information. Privacy and security concerns for sensitive telemetry data must also be addressed, and models need to be adaptable to generalize across different missions. Finally, testing and validation of anomaly detection systems are difficult and costly due to environmental limitations, making comprehensive procedures essential to ensure reliability.

2.4 Literature Survey for Related Studies Proposed to Address the Aforementioned Challenges

With the increased interest in machine learning, in particular deep learning, work has been done to show the effectiveness of an automated approach to anomaly detection. The effectiveness of deep learning is usually dependent on the amount of data available for training. For example, (Fuertes et al., 2016) improves spacecraft health monitoring with automatic anomaly detection technique. The result shows adjustment of NOSTRADAMUS settings with the goal of reducing alarms. However, the classical spacecraft health monitoring systems sometimes failed to alert SOE teams.

Similarly, (Fernández, Yue, & Weber, 2017) telemetry anomaly detection system using machine learning to streamline mission operations. It was observed that MARTTE scores a false alarm rate of only 4%. However, there is limit checking or simple trend analysis.

Additionally, (OMeara, Schlag, & Wickler, 2018) Applied deep learning neural networks for satellite telemetry monitoring using big data and machine learning aid in space operations. The research ahieved promising results. However, it was difficult to inspect raw telemetry to determine whether it was false positive or if the system really learned something deeper.

Furthermore, (Ibrahim et al., 2018) proposed machine learning methods for spacecraft telemetry mining. The results show that LSTM and GRU algorithms give a high prediction accuracy. However, using Neural Network may be more efficient in long-term prediction as the case of communication satellites (15-20 years).

Moreso, (Tariq et al., 2019) detect anomalies in space using multivariate convolutional LSTM with mixtures of probabilistic PCA. The results show that the propose approach is 35.8% better in precision, and 18.2% better in F-1 score than the best baseline approach. However, the model was not deployed to actually apply real operation of KOMPSAT-2.

Similarly, (Shin et al., 2019) integrative tensor-based anomaly detection system for satellites. The result demonstrated that our proposed method can be applicable in variety of multivariate time series anomaly detection scenarios. However, there is high risk and cost detecting anomalies.

Furthermore, (Khan, Liew, Yairi, & McWilliam, 2019) unsupervised anomaly detection in unmanned aerial vehicles. The result shows that the solution can respond in timely manner to unexpected events. However, robustness in handling diagnostic problems is major weakness of the study.

Furthermore, (Taburoğlu, 2019) conduct a survey on anomaly detection and diagnosis problem in space system operation. It was obsevered that Naïve Bayes, Support Vector and k-Nearest Neighbour(KNN) classification are the most frequently used machine learning algorithms. However, there is limited unsupervised study but the number of papers is increasing fast.

Recently, (Stottler, Ramachandran, Belardi, & Mandayam, 2020) proposed an onboard autonomous hybrid spacecraft subsystem fault and anomaly detection diagnosis and recovery. The results show that hybrid MBR-ML fault detection and diagnosis system was validated in several experiment. However, autonomously handling faults requires a high of abstraction, closed-loop system replanning, and rescheduling; and adaptive execution.

Similalrly, (Meng, Zhang, Li, & Zhao, 2020) proposed spacecraft anomaly detection via transformer reconstruction error. The experiment result demonstrated our method saves about 80% time cost because of parallel computing compared with LSTM methods and achieves 0.78 F1 point-based score, moreover achieving a better score range based indicators. The experiment results verify our vision. However, there is problem of finding patterns in data that do not conform to expected behavior.

Additionally, (Song, Yu, Tang, Han, & Wang, 2020) telemetry data based spacecraft anomaly detection using generative adversarial networks. Results show that the proposed algorithm has a better performance in the finding the real anomalies while keeping a much lower false alarm. However, complicated structure of spacecraft and its working conditions, pose great challenge to the anomaly detection.

Also, (Baireddy et al., 2021) proposed spacecraft time series anomaly detection using transfer learning on NASA SMAP/MSL dataset . the result show that the model can achieve performance comparable to state-of-the-art anomaly detection methods. However, the study fails to explore the feasibility of the models in an online learning scenario

(Pesola & DC, 2021) Applies machine learning anomaly detection techniques to U.S Navy space system operations. The results show anomaly detection from NASA datasets is very promising. However, integrating other model approaches based on data driven methods still remain an open issue.

Similarly, (Vlontzos, Sutherland, Ganju, & Soboczenski, 2021) proposed a next-gen machine learning supported diagnostic system for spacecraft.The results show that POCUS algorithms constitute a complete diagnostic system. However, hierarchical approach to the problem would help keep complexity and computation low enough for spacecraft applications.

Furthermore, (Tennberg & Ekeroot, 2021) proposed anomaly detection on satellite time series. The results from the neural network indicate that CNN is best suited for further application. However, the anomaly detection aboard satellites leads to system malfunction.

Additionally, (Xiang & Lin, 2021) proposed a robust anomaly detection for multivariate data of spacecraft through recurrent neural networks and extreme value theory. The result shows that the proposed detection algorithm is superior to other state-of-arts anomaly detection approaches. However, there is need to improve the efficiency and robustness across multiply related spacecraft and machines by using transfer learning.

More recently, (Wang, Gong, Zhang, & Han, 2022) proposed deep learning anomaly detection framework for satellite telemetry with fake anomalies. The results have shown that the Deviation Divide Mean over Neighbours (DDMN) Method. However, there is nee to explored what condition could lead to false alarm.

Furthermore, (Lu, 2022) proposed semi-supervised deep learning for spacecraft anomaly detection. Dynamic thresholding clearly achieves higher F1 scores than fixed threshold. However, there is limited availability of anomaly labels in operational settings.

Additionally, (Rong, OuYang, & Sun, 2022) proposed anomaly detection in QAR data using VAE-LSTM with multithread self-attention mechanism. Experiments on real-world QAR data sets to prove the efficiency and accuracy of the proposed neural network model was done. The experimental results proved that the proposed model outperform state-of-the art models under different experimental settings. However, further investigation is needed in the application VAE-based MHSA-LSTM to the QAR dataset generated by real-world flights.

More recently in 2023, (Yu, Tao, Jianjiang, & Yajie, 2023) proposed anomaly detection method for spacecraft solar arrays based on the ILS-SVM model. The results show that the propose anomaly detection method for spacecraft solar arrays based on the integrated least squares support vector machine (ILS-SVM) model is better. However, there is damage on solar array power generation unable to fully meet the energy demand of a spacecraft. Table depict the comparison of various models used for telemetry data mining in spacecraft anomaly detection.

Table 1: comparison of various models used for telemetry data mining in spacecraft anomaly detection

Author	**Title of Paper**	**Proposed Model**	**Contribution**	**Research Findings**	**Limitation**
(Fuertes et al., 2016)	Improving spacecraft health monitoring with automatic anomaly detection technique.	Machine Learning	With earlier detection the operational teams will have more time to take appropriate actions before a definitive failure occurs.	The result shows adjustment of NOSTRADAMUS settings with the goal of reducing alarms.	There is high risk and cost detecting anomalies
(Fernández et al., 2017)	Telemetry anomaly detection system using machine learning to streamline mission operations.	Machine Learning	There is limit checking or simple trend analysis	MARTTE scores a false alarm rate of only 4%.	The approach requires little a prior knowledge of the system.
(OMeara et al., 2018)	Application of deep learning neural networks to satellite telemetry monitoring	Neural Network	Perform an investigation into potential applications of artificial neural networks to existing health monitoring system.	Big data and Machine learning aid in space operations.	It is difficult to inspect raw telemetry to determine whether it was false positive or if the system really learned something deeper.
(Ibrahim et al., 2018)	Machine learning methods for spacecraft telemetry mining.	Machine Learning	Efficient long-term prediction as the case of communication satellite.	The results show that LSTM and GRU algorithms give a high prediction accuracy.	Using Neural Network may be more efficient in long-term prediction as the case of communication satellites (15-20 years).
(Khan et al., 2019)	Unsupervised anomaly detection in unmanned aerial vehicles.	SVM	Detecting known and unknown anomalies instances.	The result shows that the solution can respond in timely manner to unexpected events.	Not Robust in handling diagnostic problems
(Taburoğlu, 2019)	A survey on anomaly detection and diagnosis problem in space system operation.	Machine Learning	Anomaly detection techniques have been investigated in this literature, but studies on space domain is quite	Naïve Bayes, Support Vector and k-Nearest Neighbour(KNN) classification are the most frequently used	There is limited unsupervised study but the number of papers is increasing fast.

			limited. It is considered to contribute to literature in terms of that.	machine learning algorithms.	
(Shin et al., 2019)	Integrative tensor-based anomaly detection system for satellites.	ITAD	The approach can analyze multiple telemetries simultaneously to detect anomalies	The result demonstrated that the proposed method can be applicable in variety of multivariate time series anomaly detection scenarios.	Classical spacecraft health monitoring systems sometimes failed to alert SOE teams.
(Song et al., 2020)	Telemetry data-based spacecraft anomaly detection using generative adversarial networks.	GAN	ST-GAN algorithms developed a model-based GAN structure to learn robust latent representation.	Results show that the proposed algorithm has a better performance in the finding the real anomalies while keeping a much lower false alarm.	Complicated structure of spacecraft and its working conditions, pose great challenge to the anomaly detection.
(Meng et al., 2020)	Spacecraft anomaly detection via transformer reconstruction error.	LSTM	The end-to-end algorithm was developed to better detect others outliers on range-based indicators.	The experiment result demonstrated the method saves about 80%-time cost because of parallel computing compared with LSTM methods and achieves 0.78 F1 point-based score, moreover achieving a better score range-based indicators. The experiment results verify our vision.	There is problem of finding patterns in data that do not conform to expected behavior.
(Stottler et al., 2020)	Onboard autonomous hybrid spacecraft subsystem fault and anomaly detection diagnosis and recovery.	Machine Learning	Inspired by ensemble learning.	The results show that hybrid MBR-ML fault detection and diagnosis system was validated in several experiment.	Autonomously handling faults requires a high of abstraction, closed-loop system replanning, and rescheduling; and adaptive execution.
(Tariq et al., 2019)	Detecting anomalies in space using multivariate convolutional LSTM with mixtures of probabilistic PCA.	LSTM	proposing a novel data driven anomaly.	The results show that our propose approach is 35.8% better in precision, and 18.2% better in F-1 score than the best baseline approach.	Fail to apply on real operation of KOMPSAT-2.
(Xiang & Lin, 2021)	Robust anomaly detection for multivariate data of spacecraft through recurrent neural	GRU	Spacecraft anomaly detection can help to discover and identify abnormal behaviors in advance and avoid	The result shows that the proposed detection algorithm is superior to other state-of-arts	Ignored how to improve the efficiency and robustness across multiply related spacecraft and

	networks and extreme value theory.		potential cascading downtime.	anomaly detection approaches.	machines by using transfer learning.
(Tennberg & Ekeroot, 2021)	Anomaly detection on satellite time series	CNN	The anomalies improve the performance of the networks and conduct accurate training validation and testing algorithms.	The results from the NNs indicate that CNN is best suited for further application.	The anomaly detection aboard satellites leads to system malfunction
(Vlontzos et al., 2021)	Next-Gen machine learning supported diagnostic system for spacecraft.	Machine Learning	The research highlighted the final frontier for ML applications space capable ML medal systems	The results show that POCUS algorithms constitute a complete diagnostic system.	Hierarchical approach to the problem would help keep complexity and computation low enough for spacecraft applications.
(Baireddy et al., 2021)	Spacecraft time-series anomaly detection using transfer learning	LSTM	Applied on real time NASA SMAP/MSL dataset	The anomaly detection performance of the finetuned models is comparable to that of similar models trained from scratch on the same data, as well as previous approaches to anomaly detection	Fail to establish a measure of dataset similarity for anomaly detection and prediction, as well as investigating attention and Transformers
(Baireddy et al., 2021)	Spacecraft time series anomaly detection using transfer learning.	LSTM	Explored the feasible to take knowledge learned from one spacecraft system and use it to quickly learn information about another system.	NASA SMAP/MSL dataset show that we can achieve performance comparable to state-of-the-art anomaly detection methods.	Could not explore the feasibility of models in an online learning scenario
(Rong et al., 2022)	Anomaly detection in QAR data using VAE-LSTM with multithread self-attention mechanism.	LSTM	Propose VAE-based MHSA-LSTM, an unsupervised deep learning-based method for anomaly detection in time series.	The experimental results proved that our proposed model can be outperform state-of-the art models under different experimental settings.	Further investigation is needed in the application VAE-based MHSA-LSTM to the QAR dataset generated by real-world flights.
(Lu, 2022)	Semi-supervised deep learning for spacecraft anomaly detection	Neural Network	Usefulness of such space craft anomaly data in supervised learning settings.	Dynamic thresholding clearly achieves higher F1 scores than fixed threshold.	There is limited availability of anomaly labels in operational settings.
(Wang et al., 2022)	A deep learning anomaly detection framework for satellite telemetry with fake anomalies.	LSTM	Superiority of DDMN compared with other unsupervised methods to take anomaly detection.	The results have shown that the Deviation Divide Mean over Neighbours (DDMN) Method.	There is need for an exploration of what condition that could lead to false alarm.

(Pesola & DC, 2021)	Applying machine learning anomaly detection techniques to U.S Navy space system operations.	Machine Learning	Integrated model approaches were further investigated	The results show anomaly detection from NASA is better compared with data-driven methods.	Integrated model approaches can further be investigated and compared with data driven methods.
(Yu et al., 2023)	An anomaly detection method for spacecraft solar arrays based on the ILS-SVM model.	ILS-SVM	The bagging model integration method adopted by the ILS-SVM model can effectively avoid the model over fitting situation.	The results show that the propose anomaly detection method for spacecraft solar arrays based on the integrated least squares support vector machine (ILS-SVM) model is better	There is damage on solar array power generation unable to fully meet the energy demand of a spacecraft

2.3 Discussion and Research Gap

Anomaly detection in telemetry channels is a high priority for spacecraft, especially when considering the harsh environment of space and the magnitude of launch and operation costs. Traditional spacecraft anomaly detection methods are limited in scope and rely on domain experts to correctly determine abnormal behavior. However, with thousands of distinct telemetry channels being transmitted, the amount of data is difficult to monitor manually. Deep learning models can be used to learn the normal behavior of the telemetry channels and flag or label any deviations. The problem is that we have to train a unique model for each channel to ensure best performance. With the large number of channels to monitor, this may not always be possible. One way to avoid training thousands of unique deep learning models from scratch would be to use a single anomaly detector for multiple channels, or an entire subsystem, with some finetuning for the predictor to tailor its performance for each channel. Anomaly detection in spacecraft is a critical area of research, but it still presents several research gaps and opportunities for further investigation as highlighted below.

Most anomaly detection methods require a significant amount of labeled data for training. Research is needed to develop anomaly detection techniques that can operate effectively in scenarios where labeled data is limited or unavailable, which is often the case in spacecraft missions. Also, spacecraft systems evolve over time, and new anomalies may emerge during the mission. There is a need for anomaly detection approaches that can adapt and learn incrementally, incorporating new data and anomalies as they occur without the need for retraining the entire model.

While supervised and semi-supervised methods are common, more research is needed in the area of unsupervised anomaly detection for spacecraft. Developing techniques that can identify anomalies without prior knowledge of normal behavior can be valuable. Moreso, spacecraft generate data from various sensors, including telemetry data, images, spectroscopy, and more. Integrating and jointly analyzing multi-modal data for anomaly detection is a complex challenge that requires novel approaches.

Additionally, space missions often involve human operators who need to understand the reasoning behind anomaly alerts. Developing anomaly detection methods that provide interpretable explanations for detected anomalies is essential for effective decision-making. Thus, creating anomaly detection models that can transfer knowledge and adapt across different spacecraft missions is a significant research gap. Such models would reduce the need for extensive retraining for each new mission. Also, creating standardized benchmark datasets for spacecraft anomaly detection can facilitate the comparison of different algorithms and approaches. These datasets should include a variety of anomalies encountered in real missions.Spacecraft often have limited computational resources, especially for real-time processing. Developing lightweight anomaly detection algorithms suitable for edge computing in space environments is crucial.

1. Ensuring that anomaly detection systems are resilient to intentional adversarial attacks is a growing concern, especially in the context of space missions where cybersecurity is paramount.
2. Investigating how human operators can effectively collaborate with automated anomaly detection systems is an important research area. This includes designing user interfaces and decision support tools that enhance human understanding and decision-making.
3. Ensuring that telemetry data privacy is maintained while performing anomaly detection is a research challenge, particularly when sharing data with international partners or ground stations.
4. Developing methods for predicting anomalies before they occur, rather than just detecting them in real-time, can be valuable for proactive spacecraft maintenance and mission planning.

Addressing these research gaps will advance the field of anomaly detection in spacecraft, making space missions safer, more efficient, and better equipped to handle the complexities of the space environment. Researchers and practitioners in the field of aerospace engineering, machine learning, and data science can contribute to filling these gaps. From the review, we noticed that, existing studies uses spacecraft time-series anomaly detection using transfer learning method. The anomaly detection performance of the finetuned models is comparable to that of similar models trained from scratch on the same data, as well as previous approaches to anomaly detection (Baireddy et al., 2021). Researchers have shown that it is feasible to take the knowledge learned from one spacecraft system and use it to quickly learn information about another system. However, establishing a measure of dataset similarity for anomaly detection and prediction, as well as investigate attention and transformers as an option to further highlight patterns in time-series data is still very challenging task (Baireddy et al., 2021). Also, from the review table, it was observed that most of the existing detection framework uses raw time series as input, and all input feature sequences are treated equivalently. However, paying more attention to the specific crucial prediction input feature sequence to extract the key feature sequences effectively and eliminate the influence of the redundant feature sequences due to attention weight has theoretically proven to be a better prediction approach with better accuracy (Zhang et al., 2019). Addressing these challenges requires a combination of domain expertise, advanced machine learning techniques, and robust engineering practices. As space missions continue to advance and become more ambitious, the development of effective anomaly detection systems remains a critical focus.

3. Conclusion

With thousands of distinct telemetry channels being transmitted, the amount of data is difficult to monitor manually. Deep learning models can be used to learn the normal behavior of the telemetry channels and flag or label any deviations. The problem is that we have to train a unique model for each channel to ensure best performance. With the large number of channels to monitor, this may not always be possible. Upon preliminary investigation on transfer learning, which deals with adapting deep learning models for problems different from their initial task (Gao et al., 2020). The nature of the telemetry data recorded by the spacecraft means that there are undoubtedly similarities and correlations between various signal channels, both inter-, and intra-subsystem. One way to avoid training thousands of unique deep learning models from scratch would be to use a single anomaly detector for multiple channels, or an entire subsystem, with some finetuning for the predictor to tailor its performance for each channel. Therefore, establishing a measure of dataset similarity for anomaly detection and prediction, as well as investigate attention and transformers as an option to further highlight patterns in time-series data is still very challenging task and need to be address. Also, paying more attention to the specific crucial prediction input feature sequence to extract the key feature sequences effectively and eliminate the influence of the redundant feature sequences due to attention weight can a better prediction approach with better accuracy as supported in the literature. Hence, in our future work, we will propose a novel deep learning algorithms based on transfer learning spacecraft anomaly prediction method with attention on critical features using historical data collected from NASA over a much longer time frame.

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