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Fault Detection of Aerospace Systems Based onBinary Grasshopper Optimization Algorithm

Silna.KV[1], Limna Das.P[2]
[1]PG Scholar, Dept. of Computer Science Engineering, M.Dasan Institute of technology Ulliyeri,koyilandi ,Kozhikode,673620
[2]Assistant Professor, Dept. of Computer Science Engineering, M.Dasan Institute of technology Ulliyeri ,koyilandi,Kozhikode,673620
APJ Abdul Kalam Technological University

Abstract:
The entire flight movement procedure is managed by the aerospace system.Its ability to detect faults can help the aerospace prognostic health management system make decisions and carry out targeted maintenance, which is crucial for enhancing the safety and dependability of the air- craft systems. Aerospace systems are constantly subject to several failures due to the risks and difficulties of the space environment, including the deterioration of subsystem performance, sensor errors, connection loss, or equipment damage.The fault diagnosis method for aerospace systems based on binary grasshopper optimisation algorithm is proposed in this study using Deep Learning (DL) technique by taking use of the strong learning and intelligent recognition capacity.The suggested system offered a novel LSTM autoencoder architecture with supervised machine learning and deep learning techniques to carry out two distinct stages of fault diagnosis. The detection phase, employing the LSTM autoencoder with KNN, compacted the two phases. Then, the fault diagnosis phase, which is represented by the classification schema, is updated using a decision tree with KNN.The fault detection and diagnostics for LSTM in aircraft systems was completed successfully. The experimental findings proved the superiority and efficacy of the suggested strategy. The experimental findings proved the efficacy and superiority of the suggested strategy.
Index Terms: Aerospace System,Binary Grasshopper Optimization Algorithm,KNN,Decision Tree, LSTM.

1. Introduction

One of the key problems in aerospace engineering is the creation of predictive and health moni- toring for space systems, which improves their effectiveness, dependability, and safety based on the condition of their resources and mission activities. It is challenging to assess the health statesof the space systems using standard approaches like mathematical models, limit checking, and expert systems because of their nonlinearity and complexity. The health prognosis and monitoringprocedures for all aeronautical applications have been extensively developed using data-driven methodologies.It is almost impossible to completely eliminate the danger of flaws because tothe harsh and difficult space environment. One or more unauthorised departures from normal or acceptable conditions of a system property or parameter might be considered a fault.Faultsof aerospace indicate the degraded system performance or failure, a complete interruption ofthe system’s capability to perform required functions. The fault diagnosis can be recognized as the essential task of the health monitoring operations, which keep the space systems of the unexpected health hazards that may lead to complete failures.
The development of predictive and health monitoring for space systems is one of the essential issues of aerospace engineering, which increases its efficiency, reliability, and safety based on thestatus of the resources and mission operations. The space systems’ nonlinearity and complexity characteristics make it difficult to determine these systems’ health states using conventional approaches like mathematical models, limit checking, and expert systems.Due to the harsh and challenging space environment, it is virtually impossible to eradicate the risk of faults. The fault can be defined as one or more unpermitted deviations of the system property or parameterfrom normal or acceptable

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conditions. Two types of aerospace datasets, satellite power systems and aircraft engines, are used to demonstrate the effectiveness of the proposed approach. The dataset for aircraft engines is the PHM08 prognostic challenge dataset, which was made public byNASA and contains sequential data from the dynamic simulation process for aircraft engines.The output result of this study was contrasted with the output result of the BGOA-EANNs strategy thatwas suggested while using the PHM08 challenge dataset. The comparison findings demonstrate the advantages of the suggested strategy. Regarding the second evaluation dataset, the satellite power system dataset was gathered, presented, and a defect diagnosis approach was suggested.Recently, an effective FDD framework is trending, which evolves around preforming the detection and diagnosis phases separately, to ensure detecting rare fault occurrences in various systems. The first phase is the detection, where it is often represented by a healthy signal reconstructed schema, using different Machine Learning (ML) and Deep Learning (DL) methodologies, i.e., LSTM.The LSTM is trained using the fully efficient input of the dataset, which represents the healthy form of the training data.Comparing the reconstructed healthy signal with the given one provides an indication of any fault.The more the given signal is identical to the healthy recon- structed one, the more likely that it is a healthy signal and lacks the presence of anomalies, and vice versa.Meanwhile, in the fault diagnosis phase, the faults or deviations captured in the first phase (detection phase), are then used to train a certain ML or DL classification model.

2. Basics And Background

The grasshopper optimization algorithm is one of the recently population-based optimization techniques inspired by the behaviours of grasshoppers in nature. It is an efficient optimization algorithm and since demonstrates excellent performance in solving continuous problems, but cannot resolve directly binary optimization problems. Many optimization problems have been modelled as binary problems since their decision variables varied in binary space such as featureselection in data classification. The main goal of feature selection is to find a small size subsetof feature from a sizeable original set of features that optimize the classification accuracy. In this paper, a new binary variant of the grasshopper optimization algorithm is proposed and used for thefeature subset selection problem. This proposed new binary grasshopper optimization algorithmis tested and compared to five well-known swarm-based algorithms used in feature selection problem. All these algorithms are implemented and experimented assessed on twenty data sets with various sizes. The results demonstrated that the proposed approach could outperform the other tested methods.

In GOA, grasshoppers' position in a swarm represents a potential solution to a specific opti- mization problem. The position of the i^{th} grasshopper is symbolized as X_i and is based on three components as shown in

$$X_i = S_i + G_i + W_i \tag{1}$$

where Si represents social interaction and is formulated as Equation.2, G_i stands for the gravityforce on i^{th} grasshopper and is formulated as Equation.6, and W_i is the wind advection is formulated as Equation.7. $rand_1$, $rand_2$, and $rand_3$ are random numbers between 0 and 1.

$$S_i = \Sigma s(d_{ij})d_{ij} \tag{2}$$

where d_{ij} is the Euclidian distance between i^t and j^{th} grasshopper, and it is measured as Equation.3. While, db_{ij} is a unit vector from the $^h i^{th}$ grasshopper to j^{th} grasshopper and is calculated as Equation.4.Where s is a function that determines the power of social forces and is computed as Equation.5.

$$d_{i=}P_j - P_i \tag{3}$$

$$\hat{d}_{ij} = \frac{P_j - P_i}{d_{ij}} \tag{4}$$

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$s(r) = fe^{-r}$ (5)

Where f represents the intensity of attraction, and l denotes the attractive length scale.The intense experiments to analyze the function's behavior s with varying values of f and l, andto show how the s function influences the social interaction (i.e., attraction and repulsion) of the grasshoppers.The results of the experiments showed that the repulsion occurs when the distance between two grasshoppers in the interval [0, 2.079]. Whereas if the distance between twograsshoppers becomes 2.079, there is no attraction and repulsion and this is named the comfort zone. The force of attraction increases from 2.079 distance units to approximately 4. Whereasif the distance between two grasshoppers is greater than 4, the function s returns values closeto zero and cannot apply strong forces to them. To control this defect, the distance between the grasshoppers is normalized.

$$G_i = -g\hat{u}_g \quad (6)$$

Where g is the gravitational constant, and $\hat{u}_g$ represents a unity vector towards the center ofthe earth.

$$W_i = m\hat{u}_w \quad (7)$$

Where m is a constant drift, and ubw is a unit vector in the direction of the wind. A metaheuris- tic optimizer must strike a delicate balance between exploration and exploitation to specify an accurate approximation of the global optimum to solve optimization problems. The mathematical representation of GOA shown in Equation.7 must have special parameters to achieve this purpose. Hence, the GOA's mathematical representation has been restructured for this respect, as shown in the Equation.8.

$$P_i^d = c\left(\sum_{j=1,\ j\neq i}^{N} c\frac{ub_d - lb_d}{2}\, s\left(\left|p_j^d - p_i^d\right|\right)\frac{p_j - p_i}{d_{ij}}\right) + \widehat{L_d}$$

where N is the number of grasshoppers, ub_d is the upper bound in the d^{th}dimension, lb_d isthe lower bound in the d^{th} dimension. The s function is still calculated as Equation.5, and Lb_d is the value of d^{th} dimension in the target (optimal solution found so far). In contrast, the adaptive parameter c is computed as Equation..9 and has been used twice for two different roles. The first c reduces research coverage around the leader while increasing the iteration counter. The secondc is a descending factor for shrinking all zones (i.e. comfort zone,repulsion zone, attraction area). By the Equation.8, it is observed that the S component is still taken into account, while the G component has been dispensed with. For the W component, it has been assumed that the wind direction is always towards the leader $\hat{L}d$.

$$c = c_{Max} - t\frac{c_{Max}}{c_{Min}} \quad (9)$$

Where cMax indicates the maximum value of the adaptive parameter c, cMin indicates the minimum value of the adaptive parameter c, t is the current iteration, and T is the maximum number of iterations. In the original GOA paper, the values for cMax and cMin were set to 1 and 0.00001, respectively.

$$\Delta P = c\left(\sum_{j=1,\ j\neq i}^{N} c\frac{ub_d - lb_d}{2}\, s\left(\left|p_j^d - p_i^d\right|\right)\frac{p_j - p_i}{d_{ij}}\right)$$

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The current grasshopper position will be adjusted as in Equation.12, depending on the proba-bility value Sigmoid (ΔP_t) computed from Equation.11.

$$Sigmoid(\Delta P_t) = \frac{1}{1 + e^{-\Delta P_t}} \tag{11}$$

3. Dataset

The proposed approach are performed using two datasets:

1) Open-source benchmark PHM08 prognostic challenge dataset that is available in NASA'sdata repository.
2) The collected power system data of GEO satellite that is used .

PHM08 challenge data was developed by NASA using a model-based simulation program, C-MAPSS. It includes certain a number of engines, which is arranged in a matrix with n rows, where each row is assumed to be the lifecycle of the engine, and in 26 columns that represent engine number, operational sensor settings, and the sensor measurements. Each engine's operating stateis stable in the early stages. It starts to decline throughout operational cycles until it ends with failure. Each engine's life cycle is classified into four classes (urgent, short, medium, and long) based on the remaining cycles till failure occurs. The classes are labeled by 0, 1, 2, and 3 for urgent, short, medium, and long.Which is described in table.1.

The GEO satellite power system's collected data that includes ten parameters reflect the powersystem status as described that is available in NASA depository site.The parameters is describedin excel sheet that consist of 16 coloums included as battery voltage,battery current,battery pressure,battery quantity,battery status,output power,shunt current,duty cycle,bus current,bus volt-age,density,temperature,speed,source etc.

FORMAT OF THE C-MAPSS DATASET

Coloumn No	Contents
1	Engine Unit No
2	Time in cycles
3	Operational setting 1
4	Operational setting 2
5	Operational setting 3
6	Sensor measurement 1
.	.
.	.
.	.
26	Sensor measurement 21

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4. Proposed System

The suggested system is divided into two phases: feature selection, followed by training and prediction.

4.1. *Feature Selection*

Prior to learning and predicting, the original dataset is processed using one of the feature selection approaches in this step. From all of the features that are used to characterise a dataset, the term ”feature selection” refers to the process of choosing an optimum subset. The subset of features that has the lowest classification error rate and the fewest chosen features is the optimum subset.There are two types of feature selection techniques: filter-based and wrapper-based. In this stage,the BGOA and KNN classifiers were used in conjunction with the wrapper-based technique. In order to find the best subset of features that minimise the fitness function as defined by Equation. 15, the feature space is explored using the BGOA search strategy. As a classifier, the KNN is asa classifier to guarantee the quality of the selected subset features.

$$\downarrow Fitness = \alpha\ \gamma_R(D) + (1-\alpha)\frac{|S|}{|T|} \qquad (12)$$

Where $\gamma_R(D)$ represents the KNN classifier’s error rate, S is the size of the feature subset. T is the total number ofthe features. is a hyperparameter corresponding to the significance of classification performance and subset size.

4.1. *Training and Prediction*

The second stage starts once the best subset of features for the dataset is chosen based on the best target’s position and the fitness function. An ensemble of classifiers is trained on the optimiseddataset (the dataset with the optimal subset characteristics) during the second step, which is the training and prediction phase. The basic objective of the ensemble technique is to aggregate the predictions of several and different classifiers to produce outputs for classification that are more accurate. Therefore, after splitting the optimised dataset into three sets (70% training set, 15% validation set, and 15% test set), three ANN models were trained independently on each set. During the training phase, each model is trained on the training set and its performance using the training and validation sets.The majority voting techniques are used to aggregate these predictionsafter each of these three ANN models has been trained and its predictions have been obtainedon the test set. Each ANN model in the ensemble casts a vote for one class given a test sample, and the class with the most votes is chosen as the anticipated final result. The majority voting approach creates a strong ensemble classification model by incorporating the advantages of eachANN model.

5. Experimental Results with Analysis

This section outlines the steps for putting the suggested strategy into practise, the datasets used to assess the effectiveness of the BGOA-EANNs suggested approach, and an analysis of the outcomes. The phases of the suggested strategy were implemented using Python with Keras.

5.1. *PHM08 Prognostic Challenge Dataset*

There are training and test sets in the PHM08 prognostic challenge dataset. However, only this set was employed in this work because the training set had a large number of data. In order to start the first phase of the suggested approach, the training set was divided into a training setthat was 80% training and a test set that was 20% training. 19 of the 26 characteristics were nominated as an ideal subset of the total features utilised to characterise the PHM08 prognostic challenge dataset after 1 iterations of the feature selection process. Engine Unit No., Time in Cycles, Operational Setting 1, Operational Setting 3, and Sensory Signals from 15 of 21 Sensors are included in this specified subset of characteristics.

5.1.1. KNN with LSTM

The k-nearest neighbors algorithm, also known as KNN or k-NN.KNN is used to choose mostly related neighboring stations with the test station. It is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

LSTM stands for long short-term memory networks, used in the field of Deep Learning. It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems.A multilayer LSTM is applied to predict traffic flow in all selected stations. The final prediction results are obtained by weighting the prediction valuesin all selected stations.LSTMs are predominantly used to learn, process, and classify sequential data because these networks can learn long-term dependencies between time steps of data.

5.1.2. Decision Tree with LSTM

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches representthe decision rules and each leaf node represents the outcome. In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches. The decisions or the test are performed on the basis of features of the given dataset. It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions. It is called a decision tree because, similar toa tree, it starts with the root node, which expands on further branches and constructs a tree-like structure. A decision tree is a tree-like graph with nodes representing the place where we pickan attribute and ask a question; edges represent the answers the to the question; and the leaves represent the actual output or class label. They are used in non-linear decision making with simplelinear decision surface.

Decision trees classify the examples by sorting them down the tree from the root to some leaf node, with the leaf node providing the classification to the example. Each node in the tree actsas a test case for some attribute, and each edge descending from that node corresponds to oneof the possible answers to the test case. This process is recursive in nature and is repeated for every subtree rooted at the new nodes.

5.1.3. Performance Evaluation

The performance of ANNs in classification tasks can be assessed using a variety of performance metrics, including accuracy, precision, recall, F1 score, and confusion matrix. One of the most used criteria for gauging the effectiveness of classification models is accuracy. According to Equation.14,it is determined by dividing correctly categorised samples by the total number of samples. As maybe observed in Equation.15, precision is calculated by dividing the total number of true positives by the sum of true and erroneous positives. In other words, Precision is one indicator of a machinelearning model's performance — the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions (i.e.,the number of true positives plus the number of false positives).Recall, also known as the true positive rate (TPR), is the percentage of data samples that a machine learning model correctly identifies as belonging to a class of interest—the "positive class"—out of the total samples for that class.Accuracy score in machine learning is an evaluation metric that measures the number of correct predictions made by a model in relation to the total number of predictions made. We calculate it by dividing the number of correct predictions by the total number of predictions.It is a table that is used in classification problems to assess where errors in the model were made.The rows represent the actual classes the outcomes should have been. While the columns represent the predictions we have made. Using this

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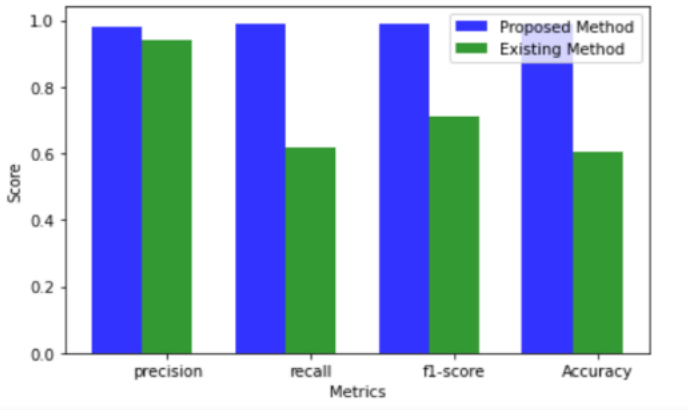
table it is easy to see which predictions are wrong.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

$$Precision = \frac{TP}{TP + FP} \tag{15}$$

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{17}$$



5.2. *Satellite Power System Dataset*

The satellite power subsystem dataset's training and testing sets have been loaded into theGSO to start the first phase of the suggested approach. Battery voltage, battery pressure, battery status, shunt current, duty cycle, bus current, and bus voltage are among the optimum subset of characteristics. The second stage starts after selecting the optimum subset of features based on the best target position and fit function. The training set was split into an 80% training group anda 20% validation group during the initial preparation of the dataset throughout the training and prediction phase.

```
Report :
              precision    recall  f1-score   support

     train_a       0.95      0.90      0.92      5258
     train_b       0.87      0.98      0.92      9570
     train_c       0.99      0.90      0.94     10580

    accuracy                           0.93     25408
   macro avg       0.94      0.93      0.93     25408
weighted avg       0.94      0.93      0.93     25408
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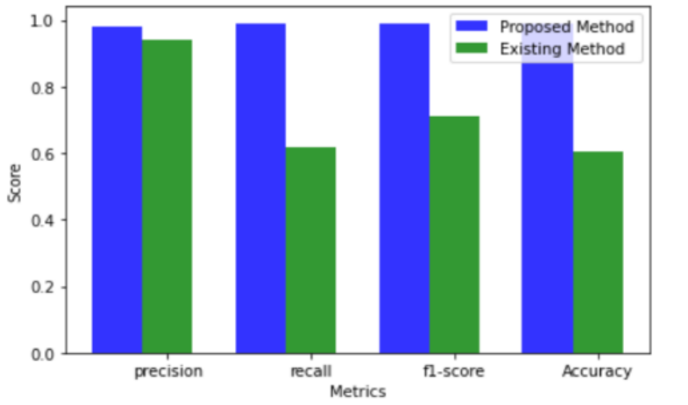

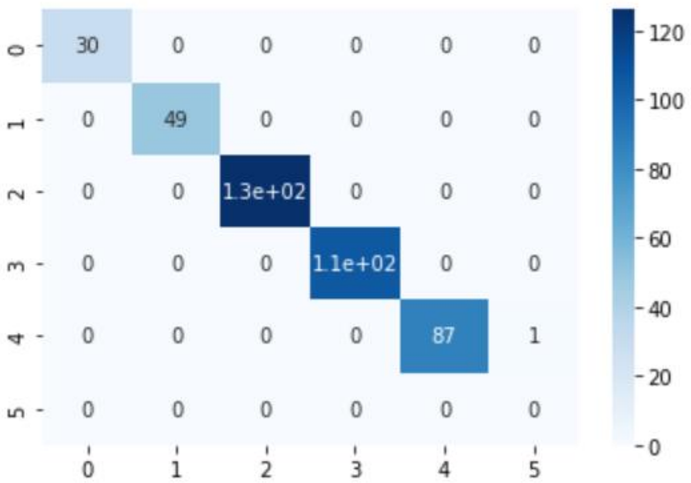

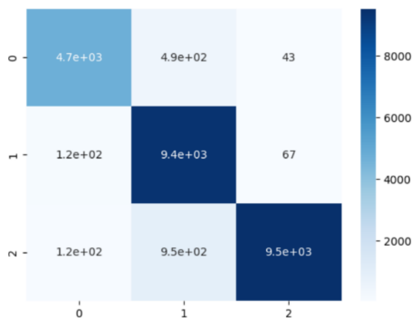

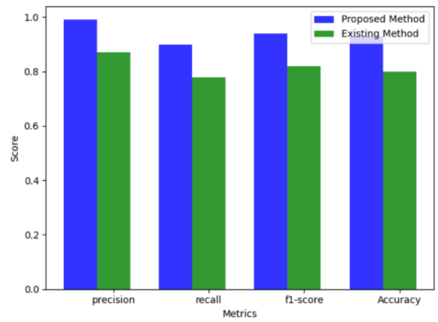

Confusion matrix and Performance Evaluation (satellite power system)

6. Conclusion

In this proposed system contributes to aerospace systems' prognostic health management pro- cess that requires fault diagnosis to detect any failures or unusual behaviors to improve system safety and increase efficiency and reliability.A novel fault diagnosis approach for the aerospace system, the proposed approach BGOA-EANNs is mainly based on BGOA and ANNs.The pro- posed approach is evaluated against two existing fault diagnosis techniques, using two types of the aerospace dataset; aircraft engines and satellite power system. The experimental results demonstrated the effectiveness of the proposed approach and proved its efficiency.

The initial PHM08 dataset using the proposed approach result combining KNN with LSTM gave accuracy rate of 60%, helping to increase the model's accuracy. The primary goal was to comparethe results with another classifier, Decision tree using LSTM, which had an accuracy rate of 99%.Ifenough

data is available for training, deep learning techniques are able to perform an extensive assessment of the deep learning models used for the identification and classification of aircraft systems.
In future work, fault diagnosis for multivariate samples of more different types of aerospace applications with different and multiple modes and other real conditions of the space environment will be extensively studied.

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