

Recurrent Convolution Neural Network for Space Debris and Asteroids Detection and Classification on the Monitored Satellite Information Using Deep Space Network

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ABSTRACT

Satellites are used for many monitoring, prediction and forecasting application operation in space , hence it has to be continuously monitored and controlled against the catastrophic damage due to collision of space debris and asteroids debris in the space. Timely and efficient Controlling of satellite will eliminate the heavy irreparable damages as number of space debris and asteroids debris is continuously increasing in the space. Hence monitoring of the satellites increases the sustainability and its safety navigation in the space operations. In order to achieve this objective, deep space network (Satellite ground station) has to be designed as space situational awareness mechanism on basis of the detection and classification of the space objects towards providing optimal path for satellite trajectory with high processing speed and reduction of memory in data processing.

In this work, a new deep learning architecture entitled as optimized recurrent convolution neural network is designed to satellite ground station towards detection and classification of space debris and asteroids debris. Initially architecture is interfaced with feature extraction technique named as principle component analysis to extract the space features and those extracted feature were detected and classified using deep learning model. In this work, convolution neural network composed of convolution layer is used to filter the discrete features, max pooling layer for downsizing the features and represent the feature map and finally fully connected layer to detect and classify the space debris and predict the optimal path for satellite trajectory on basis of the velocity of the debris in the particular orbit. Experimental results of the proposed model has been evaluated using accuracy and precision metric. Further design is implemented and verified using Xilinx Software. The performance analysis of the proposed model yields better accuracy on the classifying the monitored information on comparing with conventional approaches such as support vector machine and K- Nearest Neighbour Technique.

Keywords: *Satellite Collision Analysis, Deep learning, Space Debris , Asteroid Debris, Convolution Neural Network, Principle Component analysis , Deep Space Network*

I INTRODUCTION

Satellites are employed for monitoring, predicting and forecasting operation of various environment from space. However satellite moving in orbit for space exploration is exposed to collision due to increased number of satellite launches[1]. Hence it becomes to mandatory to monitor and control the movement of the satellite from the ground station against its collision with space debris and asteroid debris as it leads to catastrophic damage. Further timely and efficient controlling eliminate the heavy damages. Ground station[2] has to designed to compute the optimal trajectory of the satellite against various space objects with high processing speed and reduced computation memory towards processing data[3].

In order to achieve this objective, deep space network (Satellite ground station) has to design with space situational awareness mechanism on basis of the detection and classification of the space objects on satellite trajectory. The conventional manual space situational awareness estimation[4] using information of monitored sensors has been augmented with debris identification approach and model based debris identification and satellite movement trajectory will lead to increase the computation error and computation cost burden on satellite operating official[5]. However automated space exploration system will produce more advantages on detection and classification of the debris in the space and forecast the path for satellite trajectory [6].

In this paper, a new deep learning architecture entitled as recurrent convolution neural network is designed as automated system to handle the space exploration data collected by satellite ground station towards detection and classification of space debris and asteroids debris. Initially architecture is associated with feature extraction technique named as principle component analysis[7] to extract the space features and those extracted feature were detected and classified using deep learning model. In this work, convolution neural network[8] composed of convolution layer is used to filter the discrete features on orbit regimes, max pooling layer for downsizing the features on time scales and velocity of targets and represent the feature map and finally fully connected layer to detect and classify the space debris and predict the optimal path for satellite trajectory[9]

The remaining article is sectioned as follows, section 2 describes the review of literature related to space exploration and satellite controlling approaches and it is followed by section 3 to define the current methodology towards space debris detection and classification using deep learning architectures termed as recurrent convolution neural network in addition to feature extraction technique represented as principle component analysis and section 4 discusses the experimental result with respect to the area, power , delay analysis along detection accuracy and finally section 5 summarizes the article.

1. Related work

In this section, various literatures related to manual and machine learning model for processing the space exploration data is mentioned in terms of feature extraction, detection and classification. Those architecture represented as follows

1.1. Regression Techniques for Satellite Fault Diagnosis

In this literature, regression model has been employed as machine learning technique for satellite power fault analysis on telemetry data which is high dimensional in nature. Initially telemetry data is clustered using k means clustering technique with aggregation of dynamic stochastic neighbor embedding technique for dimensionality reduction. Further reduced data is processed using regression analysis in order to classify failure of the power system and failure cause on telemetry parameters which lead to satellite failure on constructing the fault tree analysis[10].

1.2. Artificial Neural Network for Satellite Fault Classification

In this literature, artificial neural network has been employed as machine learning technique for satellite power fault analysis on telemetry data which collect considerable of heterogeneous sensed data using remote terminal unit and phasor measurement units. It is considered as fast fault diagnosis model as detection and classification of power system fault conditions is very crucial for reliable operation. Artificial neural network is capable determining the micro fault in the power system especially on fault orientations and severity degrees[11].

II. PROPOSED MODEL

In this section, Recurrent Convolution Neural Network for debris detection and classification along prediction of optimal path for satellite trajectory to space data explored in the deep space network(satellite ground station) is designed as space situational awareness model is explained as follows

2.1. Dimensionality Reduction – Singular Value Decomposition

In this part, space explored data collected in ground station is reduced using Singular value decomposition technique. It eliminates the irrelevant and outlier information of the space. Dimensionality reduction also avoids the over fitting and under fitting issues during detection and classification process. Further it is highly capable in reducing the features on basis of correlation analysis . Analysis identifies the distance among the selected space point [12].

2.2. Feature Extraction – Principle Component Analysis

Principal component analysis is employed to extract the highly distinguishing features from the space. It computes the space features on basis of covariance and correlation matrix. The principle component of the technique

describes the greatest amount of variance of the feature computed on basis of Eigen value. It contains in the Eigen vectors to the specified orbit which collected using covariance matrix computation[13].

$$\text{Cov}(x,y) = \frac{\sum_{i=1}^n a(x_i - x)(y_i - y)}{n-1} \dots \text{Eq.1}$$

2.3. Feature Classification – Recurrent Convolution Neural Network

Recurrent Convolution Neural Network is deep learning architecture employed to detect and classify the space feature into debris. In addition it is capable of predicting the optimal path for satellite trajectory in the space. In order to carry those operation, feature vector representing the principle feature is processed on various layer of the convolution neural network. Convolution Neural network composed of convolution layer, max pooling layer and fully connected layer. Those layer will produce space situational awareness model. Figure 1 represents the block diagram of the proposed model[14].

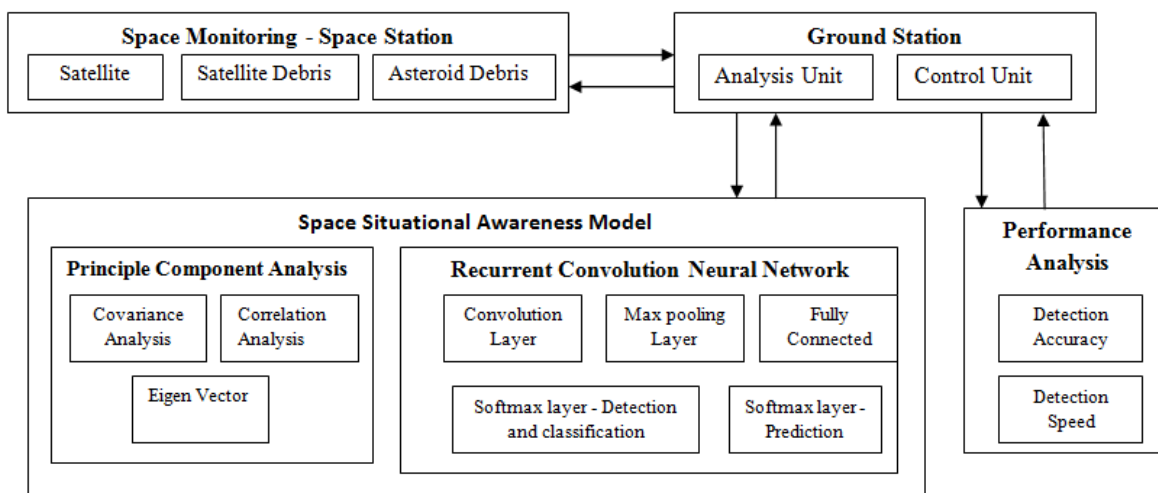


FIGURE 1: ARCHITECTURE DIAGRAM OF THE PROPOSED MODEL

2.3.1. Convolution Layer

The convolution layer incorporates multiple filter or kernel to convolve with optimal features to derive the feature map which is considered as activation map. Convolution is mathematical operation is mentioned as multiplication of the feature vector containing space information matrix and multiple filter. Feature matrix of space information in 5*5 matrix is multiplied with kernel 3*3 matrix to provide convolution matrix or feature map[15]

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

4	3	4
2	4	3
2	3	4

FEATURE MATRIX

KERNEL MATRIX

FEATURE MAP

The convolution layer Yields the feature map on the convolution operations to regime of the orbit. Convergence of the feature map is established using epoch and it enhance the feature generation on normalization of the activation function mentioned as ReLu to yields the linear feature map on various time scales and proximity operations[16].

2.3.2. Max pooling Layer

Pooling layer reduces the feature computed from PCA. Hence it is considered as spatial pooling for the space exploration data. It is considered as down sampling of space features on decreasing the feature on retaining only selected weighted features. Selected weighted feature has greatest feature in the orbit regimes on basis of its velocity and surface parameters. Max Pooling layer connects the spectral features into small patches on account of the spectral signatures. Max pooling is employed to compute the greatest no of the features to the translational states of space objects. It further enhances the model generalization [17]. Feature pooling of the convoluted matrix is presented as

4	3	4
2	4	3
2	3	4

=

4	3
3	4

CONVOLUTED FEATURE

MAX POOL FEATURES

2.3.3. Fully Connected Layer

It is composed of two softmax function and one loss function to compute the debris in the orbit and predict the optimal path for satellite trajectory.

- **Softmax Function**

Fully connected layer of the model is to process the feature map on the softmax function on utilizing the numerous spaces constraints with respect to detection, classification and prediction. Feature map composed of the spatial and temporal features of the particular orbit is processed on the constraints detect the debris and classifies the debris type. On detection and classification of debris, model will predict the optimal path for satellite trajectory on basis of

velocity and space parameters of the particular orbit. Constraints contains the feature selection rule for the space features[18]

Detect D= Softmax_ Detection Constraint (High Level Space features)

Class C= Soft max_ Classification Constraint (High Level Space features)

Predict P = Softmax_ Prediction Constraint(High level Space feature

)Loss Function

Predicted satellite path and debris in form class is processed in loss layer to determine the occurrence of over-fitting and under-fitting issues[19]. On appearance it can be reduced using the cross entropy function.

$$W_{n+1, i} = W_{n, i} + r_n X_n - I$$

$$P_i = U_n - I W_{n, i}$$

Algorithm: Debris Detection and Classification

Input : Space Exploration Data

Output : Debris Classes

Process

Extract _ Principle feature (Space Data)

Covariance Matrix (Space Data)

Correlation Matrix (Space Data)

Eigen Vector = { Eigen Value 1, Eigen Value 2, Eigen Value 3}

Eigen Value = Principle feature of Space

Recurrent Convolution Neural network (Principle Features)

Convolution Layer ()

Kernel Matrix * Feature matrix = feature map

Max pooling Layer ()

Feature reduction (feature map)

Reduced feature map

Fully connected layer ()

Activation Function _ ReLu()

Softmax function ()

XgBoost classifier(Feature Map)

Debris Class = { Satellite components , Asteroids }

III. EXPERIMENTAL RESULTS

In this work, ground station analysis towards space situational awareness has been carried using recurrent convolution neural network model on space exploration data. The debris detection and classification model is simulated in Xilinx software using Verilog HDL and modelsim[20]. The simulation results of the current model is described in detail in below sections on relevant parameters of various orbits

Space explored information represent the space regime on various orbit. Each regime on the orbit is represented with velocity of the satellite and space parameters. Those information will be used for controlling the satellite in optimal path from ground station on various time intervals. Especially processing the multivariate time series data using deep learning model produces high detection accuracy and detection speed. Detection accuracy of the model is computed using confusion matrix to synthesis data used for validation

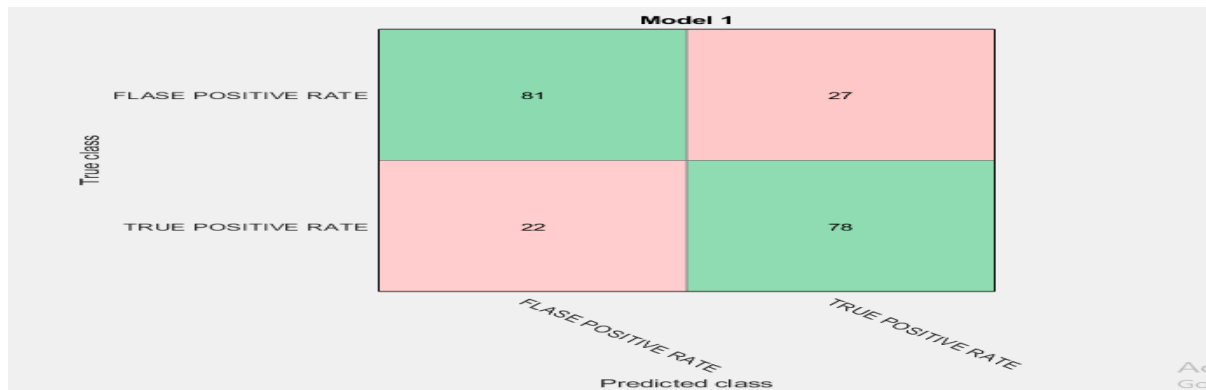


FIGURE 2: CONFUSION MATRIX OF THE VALIDATION DATA

The figure 2 represents the confusion matrix to compute the accuracy of the debris detection and classification using proposed approach on cross fold validation. Accuracy is computed on basis of true positive, true negative, false position and false negative values.

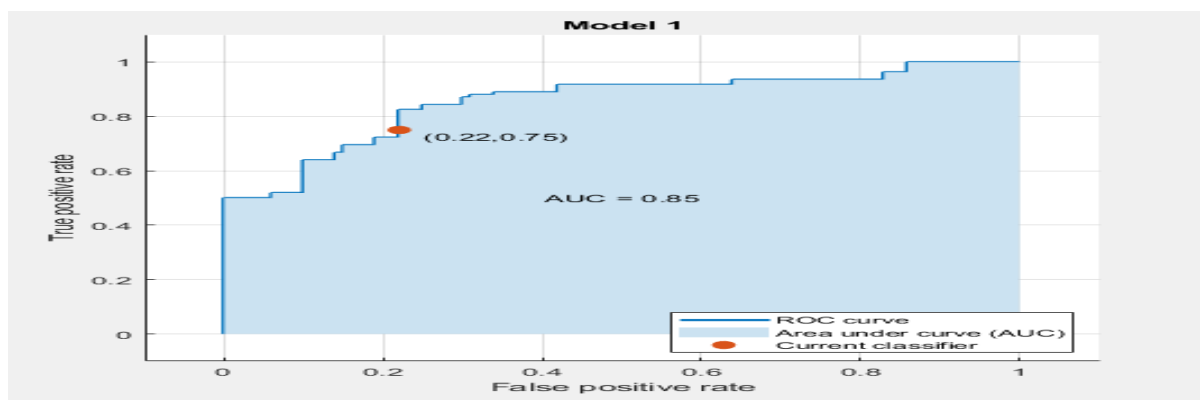


Figure 3: ROC Analysis and AUC analysis of the classification result

Figure 3 illustrates the ROC analysis and AUC Analysis of the classification of the space debris. Compared with conventional approaches, the current approach produces the highest AUC value of 0.976.

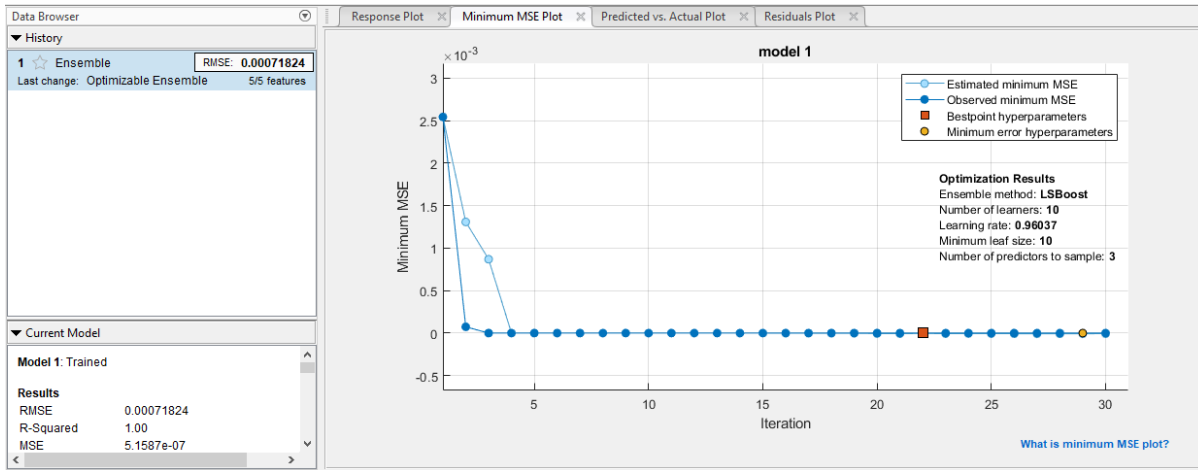


Figure 4: Mean square Error Analysis

Figure 4 provides the mean square analysis on the current approach to changes of the validation data with respect to 3 fold. Finally current model is capable of computing the satellite trajectory path various space parameter and orbit velocity. Schematic representation of satellite navigation is illustrated in the figure 5



Figure 5: schematic representation of satellite navigation

3.1. Analysis of area

The models are illustrated in Verilog and experimented in the Xilinx 14.2 and simulated using modelsim. The synthesis outcome for area shows that the current detection and classification of satellite information on the hardware architecture is represented in the figure 7.

Device utilization summary:				

Selected Device : 3s400pq208-5				
Number of Slices:	565	out of	3584	15%
Number of Slice Flip Flops:	766	out of	7168	10%
Number of 4 input LUTs:	954	out of	7168	13%
Number of IOs:	357			
Number of bonded IOBs:	80	out of	141	56%
Number of GCLKs:	1	out of	8	12%

FIGURE 7: AREA ANALYSIS OF THE MODEL

3.2. Analysis of power

The synthesis results for power shows that the current detection and classification hardware configuration utilizes 40% of power on compared with conventional hardware design for controlling operation on satellite on optimal trajectory is represented in the figure 8 .

A	B	C	D	E	F	G	H	I	J	K	L	M	N
Device		On-Chip	Power (W)	Used	Available	Utilization (%)			Supply	Summary	Total	Dynamic	Quiescent
Family	Spartan3	Clocks	0.000	1	--	--			Source	Voltage	Current (A)	Current (A)	Current (A)
Part	xc3s400	Logic	0.000	945	7168	13			Vccint	1.200	0.015	0.000	0.015
Package	pq208	Signals	0.000	1090	--	--			Vccaux	2.500	0.015	0.000	0.015
Temp Grade	Commercial	IOs	0.000	80	141	57			Vcco25	2.500	0.002	0.000	0.002
Process	Typical	Leakage	0.060										
Speed Grade	-5	Total	0.060										
Environment		Thermal Properties	Effective TJA	Max Ambient	Junction Temp				Supply	Power (W)	Total	Dynamic	Quiescent
Ambient Temp (C)	25.0		(C/W)	(C)	(C)						0.060	0.000	0.060
Use custom TJA?	No		35.2	82.9	27.1								
Custom TJA (C/W)	NA												
Airflow (LFM)	0												
Characterization													
PRODUCTION	v1.2.06-25-09												

FIGURE 8: POWER ANALYSIS

3.3. Delay analysis

In delay analysis , proposed model play its role by reducing the computational complexity and delay in controlling satellite on the optimal path in order to avoid the collision with space debris in the various orbits . The synthesis results for delay shows that the current model on the fpga hardware architecture is represented in the figure 9.

FIGURE 9: DELAY ANALYSIS OF THE MODEL

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