Conceptual Design and Preliminary Data Analysis for Classification of Plasma Disruption Event at Aditya-U Tokamak

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Disruption prediction and its avoidance/mitigation is an essential part of the tokamak operations, particularly for large size tokamak as the disruptions could produce very large heat loads on diverter targets and other Plasma Facing Components (PFC), and large electromagnetic forces on the Vacuum Vessel (VV) can lead to the structural damages. It directs toward disruption research to develop methods for safe and rapid shutdown of high-power tokamak plasmas. To control or avoid the disruption, data-driven methodology using time series of relevant plasma parameters are useful with sufficient anticipation time. The Ohmically heated circular limiter tokamak ADITYA (R0 = 75 cm, a = 25 cm) has been upgraded to a tokamak named the ADITYA Upgrade (ADITYA-U) with an open diverter configuration. The data driven methodology uses supervised learning techniques for classification to develop accurate automatic classifiers from large set of discharge data which will be used for regression to determine key events of time for disruption. Based on extensive literature survey, preliminary data analysis is performed for 8000 previous plasma shots from large dataset of ADITYA/ADITYA-U tokamak archival. Binary classification model is developed to separate two sets of data using Support Vector Machine (SVM) and Neural Network (NN) for ADITYA TOKAMAK. Both models are compared with test data with previous shots and validated with accuracy performance which may lead towards future development of time series data-driven model for accurate prediction of disruption event for ADITYA-U tokamak.

Keywords: DAQ, Deep learning, Machine learning, Plasma Disruption, Tokamak.

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1 Introduction

A physics research, especially time-urgent and very challenging problem facing the development of a fusion energy reactor today is the need to reliably mitigate and avoid largescale major disruptions [1-3]. ADITYA-U has been upgraded to ADITYA-U is to carry out dedicated experiments including disruption prediction, and mitigation studies. [4]. “The ability of deep learning methods to learn from such complex data make them an ideal candidate for the task of disruption prediction” [5,6]. Several scientific experiments designed for disrupting research, which aims to develop methods toward safe tokamak plasmas experiments [7-11]. Various techniques development are in progress for avoidance and mitigation of such events [12-16].

The science of tokamak disruption is complex in some manner which needs many timescales and spatial scales with considering of multiple possibilities to be considered. It is not easier to implement directly by first-principal based scenario to model the disruption. There are many sequential changes in number of diagnostics parameters based on timescales for long time than the actual disruption timescale. The correlation between different signal are not easier to derive for all parameters for which many disruption data from tokamak archive needs to be studied and applied. The refinement of such database is needed to construct the appropriate machine learning based model for implementing of prediction of disruption.

Many efforts have been devoted towards disruption control and mitigation research for Aditya tokamak in the past years [17]. Data driven deep learning methods have been applied in the field of disruption prediction as well. However, in the part of deep learning methodology we still need to put more dedicated efforts to achieve higher percentages of correct classifications for reaching maximum performance rates. The aim of the current work is to obtain a higher reliable prediction and maintain a low rate of missed and false alarms. To achieve the goal, it has been necessary to exhaustively preprocess the required signals, study relevant characteristics of signals for disruptive properties for feature extraction using mathematical and supervised data learning. We are selecting important signals among available diagnostic signals among vast database of Aditya server. We are trying to build correlation between each signals by scaling those in to same length. The evidence in the signals would be further studied for classification using deep learning methods to achieve higher accuracy in the model development. Several technique will be studied with available literature on deep learning platform to achieve goal of model development. Rescaling of the signals are very important for the input diagnostic signals will be selected for the modelling as acquisition rate of the signals are different as per their respective requirement. The signals normalization on same scaling of 1kHz is required for simplicity and to avoid complex calculation for the training of the model. The threshold for the each time-series will be calculated to prediction of the disruption event can be calculated. Firstly, we have developed binary classification model for almost 1600 shots and got good results after having optimization on activation function and dropout selection with augmentation of data. We are planning to add relevant diagnostic signals with finding correlation between all signals for input parameter to the model. After such binary classification, we will work on out time-series based model for fining time until disrupt which will be deployed on Aditya-U real-time server.

2 Proposed method and Model development

We need to design and develop multi-dimensional, time dependent data driven model be trained to predict results within desirable time scale as per the length of the plasma shot durations. We have develop methodology to identify the important parameter for plasma disruption event. With respect to plasma current, the correlation between other signals are established with classification techniques. Based on the study of Aditya-U plasma shots we have identified almost 21 plasma diagnostics parameters which will be studied one by one. Out of 30000 shots previous data, we would use almost 8000 shots data to be utilized for training model for accurately predicting the results. It is decided to use SVM and neural network for classifying and modelling to have comparison for accuracy and optimization. We will compare both result and the final methodology will be decided. Optimizing DL model is an iterative process. Selection of well-performing hyperparameters need to be set manually based as per Aditya tokamak parameters. Non-linear mapping, Scaling study and tunable hyperparamter model would be designed and implemented for disruption research. Research and development of our own model and methods which can fit in Aditya machine in simulated and real time environment. Flow diagram of the proposed solution shown in Fig.1 and Fig.2 for Aditya tokamak disruption prediction. Initially we are focusing on building classification and in next phase time-series regression will be used for prediction.

Several scientific experiments designed for disrupting research, which aims to develop methods toward safe tokamak plasmas experiments. The ability of deep learning methods to train from such complex data based approach make them an ideal candidate for forecasting disruptions. The FRNN code on more than two terabytes of data collected from JET and DIII-D that achieved significant results and upgrades is in progress [5]. For ITER tokamak simulated version has been developed which needs more upgrade and improvements [6]. Other tokamak based disruption research codes will be studied for reference [18-23] like JET real-time Advanced Predictor of DISruptions (APODIS). Disruption Predictor Feature Developer (DPFD) is a set of Matlab scripts, Large-Scale Image Analysis [24].

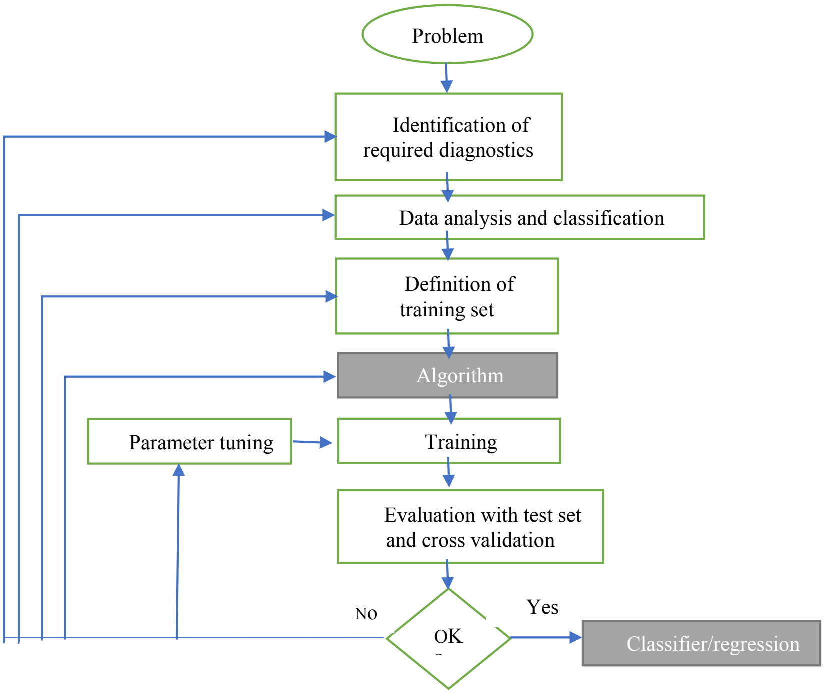

Fig 1: The processes of Model Machine learning

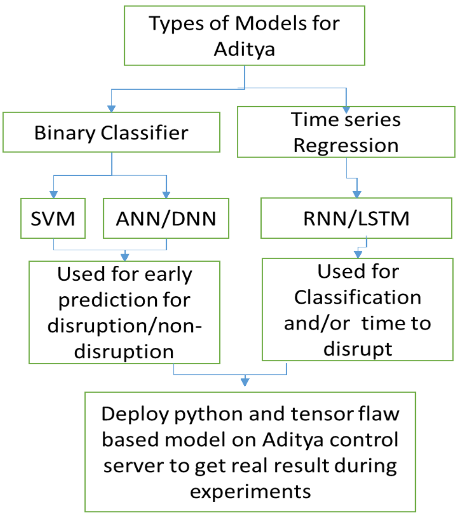

Fig 2: Proposed model development and deployment scheme for Aditya

The JET based model the dataset utilized in the study contains 220 disruptive and 220 nondisruptive discharges. Considering past research [5,6], each shot is represented by the temporal evolution of 13 signals. The sampling rate is not equal in the considered signals, so an interpolation algorithm has been applied to each one resampling the signals to achieve a resolution of 1 ms to standardize the available database. The 13 signals used present amplitudes which differ by several orders of magnitude.

To identify in Aditya shots data, a specific attempt has been made using machine learning techniques with adequate resolution by extensive analysis of discharges evolution every periodic (8ms to 16ms) windows. Healthy time series signals are being checked that will be followed by time to disruption calculation if unhealthy sign detected by the first model. We have successfully studied around 1650 shots at preliminary level for data analysis and classification. Around 851 shots have been detected as a non-disruption data-set using applied techniques of classification.

3 Tracking Procedure and Database

Plan is to predict the disruption event at least prior significant anticipation time. In the initial mode, classification model is designed using SVM and neural network with limited timescale up to 60ms for initial input parameters like Plasma current, loop voltage, HXR, SXR and HALPHA. Gradually other signals which for identified around 15 signals would be studied. After having development of correlation and accuracy the final model will be designed using RNN. The model accuracy and test data would using ROC curve which can provide accuracy almost 88% on the test set of minimal computation time. Aditya has its own architecture design which differs for other solution as mentioned below.

- Some of the state-of-art-techniques have prediction time is well in advance as Aditya has discharge time maximum to 500ms till now which is very low compared to other tokamak like JET, DIII-D, AUG and C-Mod. Average duration of Aditya tokamak is almost 200ms.
- Earlier prediction model on Aditya has limited amount so sample and data-set has been used which can give ambiguous result in some scenario of uncertainty.
- Recently the data acquisition speed has been increased for several important diagnostics which is useful for future development.
- We have 5kHz to 1MHz of acquisition signal which need to be scaled in such a way that classification and model input can be applied without post data processing.

3.1 Data clustering, classification and data analysis

Table 1. Aditya data clustering

Total shots	10-20ms	10-30ms	10-40ms	10-50ms	10-60ms	10-70ms	10-80ms	10-90ms	>100ms	*Unfit Shots
27510-29905 (2395)	115	159	217	338	496	610	756	894	969	294

*Unfit shots: The data are not valid binary structure or less than 10kA plasma current

Table 2. Aditya-U data clustering

Total shots	10-20ms	10-30ms	10-40ms	10-50ms	10-60ms	10-70ms	10-80ms	10-90ms	>100ms	*Unfit shots
30029-35621(**5592**)	902	1199	1505	1841	2082	2323	2581	2828	1470	935

*Unfit shots: The data are not valid binary structure or less than 10kA plasma current

Table 1 and Table 2 shows the data clustering of Aditya/Aditya-U pervious shots for around 8000 shots with duration based on plasma current as this is useful for classification of data as input to the model building. Data is separated in 10to20ms, 10to30ms, 10to40ms, 10to50ms, 10to60ms, 10to70ms, 10to80ms, 10to90ms, >100ms and unfit shots which length binary structure are not readable for data extraction or plasma current is low up to 10kA.

Table.3. Aditya data classification

Total shots	Disruptive	Non-disruptive	Unfit/small discharge
27510-29905 (2395)	1067	1073	306

Table.4. Aditya-U data classification

Total shots	Disruptive	Non-disruptive	Unfit/small discharge
30029-35621 (**5592**)	2141	2253	1198

Table 3 and Table 4 shows the data classification for Aditya/Aditya-U as classified in disruptive and non-disruptive shots based on criteria of decline slop of plasma current signal. Plasma current should reach at least 10kA and discharge time should be more than 20ms. Additionally, 10% of maximum plasma current on either side is calculated and difference between initial time duration of 10% should be less than the value of either side of same criteria. Unavailable shots are length binary structure are not readable for data extraction or plasma current is low up to 10kA which are not fit for model as it can can create ambiguity for the model in terms of performance and accuracy.

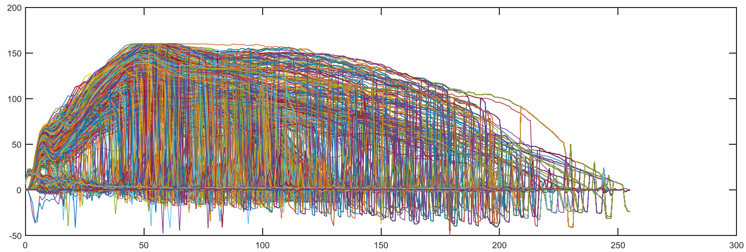

Fig. 2. Aditya all disruptive shots (Plasma current, Loop voltage and HXR signals)

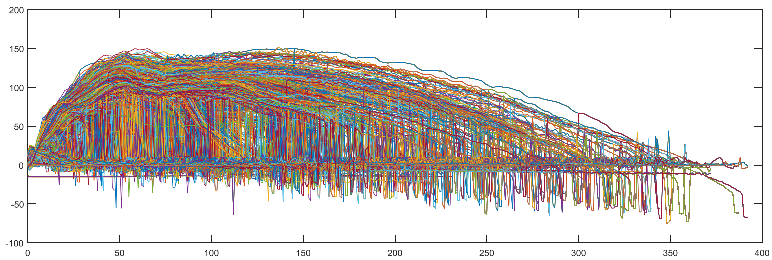

Fig.3. Aditya-U all disruptive shots (Plasma current, Loop voltage and HXR signals)

Table.5. Aditya/Aditya-U data acquisition shot range and length

	Shot range->	27510-29905	30029-30098	30099-30296	30297-30752	30753-31689	31690-34133	34135-35621
Ch. No.	Signal Name	Acquisition Frequency						
7	Plasma Current	5kHz	20kHz	20kHz	20kHz	20kHz	100k Hz	100k Hz
2	Vloop2	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz
301	HXR	1MHz	100k Hz	1MHz	1MHz	1MHz	1MHz	1MHz
302	SXR	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz

23	CIII	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	5kHz	100k Hz
156	OII	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz
22	HALPHA	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz
12	BV	5kHz	10kHz	10kHz	100k Hz	100k Hz	100k Hz	100k Hz
306	MINROV2	50k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz
217	REFLV	0kHz	0kHz	0kHz	0kHz	0kHz	100k Hz	100k Hz
58	FEBCUR	5kHz	0kHz	5kHz	5kHz	5kHz	5kHz	100k Hz
59	OTCUR	5kHz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz
202	PVAL	5kHz	100k Hz	5kHz	5kHz	5kHz	5kHz	100k Hz
15	Bolo	5kHz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz	100k Hz

Fig 2 and Fig 3 shows the plotting of plasma current, loop voltage and HXR signals all together to analyze the characteristics disruptive shots for model building. Table 5 shows the data acquisition shot range and length for Aditya/Aditya-U as this is useful for data analysis and extraction while building input parameters for the classification model. We have identified input parameters for model which are close to the disruption event. The correlation between all signals will be identified and then reduction in input parameters will be performed. Some of the signals are not acquired during initial phase of operation which are identified as zero but it will be considered in final model building as future prediction will be based on these diagnostics.

Table.6. Aditya-U disruption statistics of each input parameters

Sr. No.	Logical ch. Name	Acq. Board	Rate	Logical ch. No.	Calibration	Min	Max	Mean	Median	Std
1	Vloop2	SBC	10kHz	2	10	-0.491	8.3790	1.6918	1.1519	1.6703
2	Plasma Current	SBC	10kHz	7	57	-2.1594	28.492	15.728	16.932	9.8444
3	HALPHA	SBC	1MHz	22	1	-0.4826	1.0457	0.0800	0.0196	0.2276
4	CIII	SBC	10kHz	23	1	-0.511	0.1720	-0.092	-0.0736	0.1978

						0		5		
5	OII	SBC	10kHz	156	1	-0.1000	0.8997	0.0932	0.0206	0.2184
6	HXR	PXI	10kHz	301	1	-0.0247	1.1666	0.2328	0.1508	0.2620
7	SXR	PXI	10kHz	302	1	-0.0157	0.1063	0.0033	7.3216e-04	0.0182
8	MINROV2	SBC	10kHz	306	1	-0.8127	0.2320	-0.1198	-0.0469	0.2416
9	BV	PXI	10kHz	12	1.16	-0.0372	1.2005	0.4431	0.3381	0.4192
10	FEBCUR	PXI	10kHz	58	1	-0.2959	1.0845	0.3071	0.3024	0.4077
11	OTCUR	SBC	10kHz	59	1	-0.6587	0.4387	-0.0349	-0.0273	0.2242
12	PVAL	PXI	10kHz	202	2	0.3866	1.1719	0.7343	0.7166	0.2114
13	BOLO1	PXI	10kHz	17	1	-1.0244	-0.9647	-0.9914	-0.9900	0.0134

In parallel, we have analyzed and classified Adtiya-U data for almost 5000 shots which details are shown in below Table 6. Minimum, Maximum, Mean, Median and standard deviation are calculated for all disruptive shots at Aditya-U. These data are useful for prediction range of shots to classify the disruptive/non-disruptive analysis as model output.

3.2 Data correlation and binary classification model

Fig.4 shows the correlation of other diagnostic signals with plasma current for one of the non-disruptive Aditya shot no. 29881. Pearson correlation has been used for correlate the signals with respect of time. Many shots the correlation has been identified to study the change of numeric values by which regression can be established more confidently. Fig.5 shows the correlation of other diagnostic signals with plasma current for one of the disruptive Aditya shot no. 29877. HXR, HALPHA, Mirnov and BOLO has less proportionate change, while CIII, OI, GP and Minrov has reverse correlation with plasma current in case of non-disruptive and disruptive case. Many shots have been analyzed with disruptive and non-disruptive cases for correlation of signals. Based on the result the input parameter would be decided for the final model development for time-series analysis.

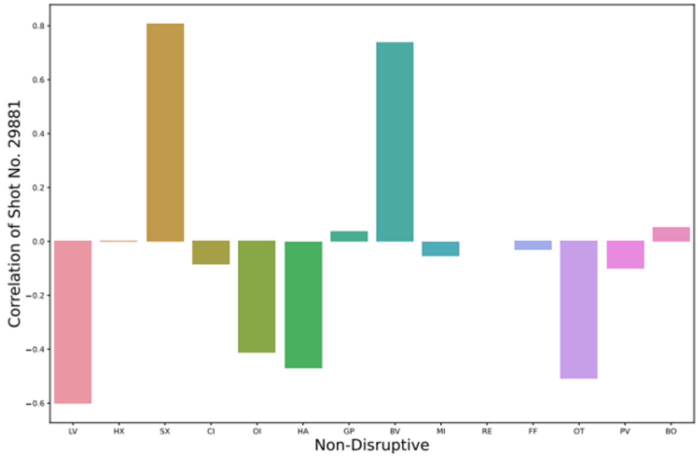

Fig 4. Pearson correlation of other diagnostics with plasma current for Non disruptive Aditya shot

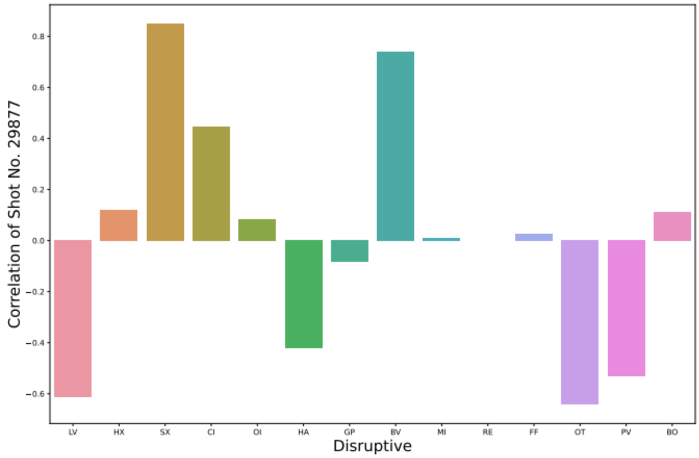

Fig. 5. Pearson correlation of other diagnostics with plasma current for disruptive Aditya shot

Fig. 6 shows the confusion matrix of SVM and ANN based predictor using 1648 shots in which around 32 shots of test data are true result while almost 6 shots gives wrong result. Subsequently, early prediction with initial 10ms, 20ms and 30ms of data for which we are getting less accuracy on binary classification for training as well as prediction. It is almost 50% to 55% with different activation function and consideration of other optimization as well. Finally using leaky relu activation we got almost 57% of accuracy in prediction which is under development.

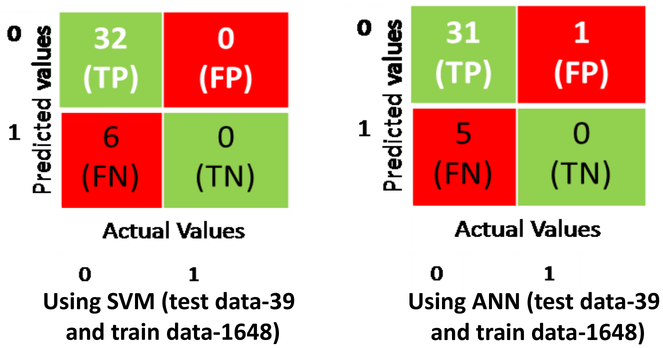

Fig 6. Confusion matrix for the binary classification task using Aditya/Aditya-plasma current data. The number of samples correctly detected are displayed as diagonal elements in green, while the misclassifications are shown in red as off-diagonal terms.

Table 7 shows the binary classifier accuracy with other tokamak model [25] which needs more attention for future development with higher accuracy for prediction. It is noted that the time-series based model development is yet to be done and that will be reported soon.

Table 7: Prediction accuracy of different Deep learning models for various tokamaks

Methods	ROC curve for Tokamak - Machines					
Tokamak ->	DIID	C-MOD	East	JET	Asdex-U	Aditya-U
HDL	0.947	0.801	0.973	NA	NA	
FRNN				0.952		
Multi level perception (MLP)					0.913	
HDL boosted			0.959			
Best classical mode				0.893		
SVM/ANN for Aditya (binary classifier)						~0.8433

In second phase we have extended the time till the full plasma shot length for plasma current signal which gives less accuracy in prediction although it gives higher accuracy for training. By applying synthetic data for several shots in order to make same length of plasma shots. The accuracy of prediction has been hampered for adding more shots up to shot number 29905. It has bene used leaky relu activation and balancing dropout we got the same accuracy which is given in table 7. This has been optimized with synthetic data and flatten data with other signals to be added in calculation using ANN model. This process is still going on to improve prediction accuracy. After having binary classification model we will work on building the time-series based model using Arima/LSTM for predict time until disruption.

4 Discussion

We have constructed disruption predictors using the SVM and the DNN based on experimental data from Aditya and Aditya-U, and applied explanatory data analysis along with correlation of identified plasma diagnostics parameters. We have shown that the variables related to disruption can be extracted using the most frequent variables by both the SVM and DNN, and these plasma parameters are considered as the direct causes of disruption using correlation graph for many of the past shots. The classifier model is developed and compared with other available model for limited shots which will be extended for almost 8000 shots which shown in Table 7.

5 Conclusion

Based on experience and extensive data analysis and classification tools we got good exposure and confidence for building future model with higher accuracy and performance. After building the model on python/tensor flow will deploy it on Aditya real time server by wrapper for prediction of deployed model in C language. It will alarm the disruption/non-disruption and if it is in disruption phase it will give time until prediction of disruption event. The regression of time-series analysis based on RNN and LSTM the final output can be categorized in subsequent future development of models. The LSTM model was expected to perform better than its competitors, but results in this work don't show an advantage over SVMs. This work lead us to develop high accuracy time-series model for future on Aditya-U disruption prediction event and control.

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