A REPORT

ON

NUCLEAR PLASMA DISRUPTION CONTROL IN TOKAMAKS USING VARIOUS MACHINE-LEARNING TECHNIQUES

By

Manamrit Singh

2022B1A31013G

At

Bhabha Atomic Research Centre (BARC), Visakhapatnam

A Practice School-I Station of

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE,

PILANI May 2024

A REPORT

ON

NUCLEAR PLASMA DISRUPTION CONTROL IN TOKAMAKS USING VARIOUS MACHINE-LEARNING TECHNIQUES

By

MANAMRIT SINGH
2022B1A31013G
Msc. Biology + B.E. EEE

Prepared in partial fulfilment of the
Practice School-I Course No.
BITS F221

Submitted to

Mr. Utkarsh Bhardwaj
SO E, Visakhapatnam

Bhabha Atomic Research Centre (BARC), Visakhapatnam

A Practice School-I Station of

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE,

PILANI May, 2024

Acknowledgment

I am writing this to express my gratitude to all those who contributed to the success of my internship so far:

First, I thank BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI, for this opportunity. Having to work in a research-oriented work environment so far has been quite fulfilling for me and a great learning experience.

I am deeply grateful to our Faculty-in-Charge, Prof. Kranthi Kumar Palavalasa, for their guidance and support throughout the project.

I am deeply grateful to Mr. George Yuvaraj, our co-instructor, for his valuable inputs and guidance at crucial times which helped enhance the quality of my work and for giving me his insights so that I may be smoothly complete this project by the end of these two months.

My sincere gratitude goes to my mentors , Mr Utkarsh Bhardwaj and Mr. Manoj Warrier , for their expertise and advice in the field of Computational Physics and making the process of learning Machine Learning much easier. My gratitude goes to Mr. Manoj Warrier for always being up for a discussion regarding the Physics behind tokamaks and explaining everything in simple manner.

This project would not have been possible without the collective effort of all these individuals and institutions.

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI
(RAJASTHAN)

Practice School Division

Station: BHABHA ATOMIC RESEARCH CENTRE, VISAKHAPATNAM

Centre: BHABHA ATOMIC RESEARCH CENTRE, VISAKHAPATNAM

Date of Start**: 28/05/2024**

Title of the Project: **NUCLEAR PLASMA DISRUPTION CONTROL IN TOKAMAKS USING VARIOUS MACHINE-LEARNING TECHNIQUES**

ID No./ Name(s)/ Discipline(s)/of the student(s): **2022B1A31013G/ Manamrit Singh / MSc. Biology + BE EEE**

Name(s) and designation(s) Guide(s): **Mr. Utkarsh Bhardwaj**
SO/E

Name(s) of the PS Faculty: **Prof. Kranthi Kumar**

Key Words: Machine Learning, Deep Learning, LSTM, SVM, Logistic Regression Classification, Decision Tree Classification, Random Forests, Tokamak, Nuclear Fusion, Plasma,

Project Areas: Machine learning Models for catastrophe predictions, Nuclear Fusion and Plasma Physics inside of a Tokamak.

Abstract: The primary objective of the project lies in Disruption prediction of the Plasma confined inside the tokamak well before in time using Machine Learning models and contain the disruption. Studying already developed models and aiming to implement smart feature-engineering into the models and main aim is to achieve higher accuracy and efficiency for prediction of disruptions inside tokamaks.

Signature(s) of Student(s) Signature of PS Faculty

Date: 24/06/2024 Date:

TABLE OF CONTENTS:-

INTRODUCTION

Nuclear fusion as a potential energy source holds promise of revolutionizing the global energy scenario, offering a virtually limitless source of power. Central to this ambition are actually tokamaks, devices designed to confine plasma necessary for fusion reactions. However, one of the significant challenges impeding the reliable operation of tokamaks is the phenomenon of plasma disruption. Disruptions can lead to severe damage to the reactor, loss of plasma confinement, and significant downtime, thereby compromising the efficiency and safety of the fusion process.

What are Tokamaks?

Tokamaks are advanced devices used to confine hot plasma with strong magnetic fields, enabling controlled nuclear fusion reactions. They are donut-shaped (toroidal) machines where plasma is heated to extremely high temperatures, causing atomic nuclei to collide and fuse, releasing energy. The magnetic fields are generated by external coils and the plasma current, creating a stable environment for the fusion process. Tokamaks are considered one of the most promising designs for achieving practical fusion energy, as they aim to replicate the conditions found in the sun to produce a sustainable and virtually limitless source of clean energy.

Why are they prone to disruptions and what are a few of the disruptions?

Tokamaks are prone to disruptions due to the complex and unstable nature of the confined plasma. These disruptions can be triggered by various factors, including instabilities in the plasma current, magnetic fields, and pressure gradients. A few common types of disruptions include:

1. **Magnetohydrodynamic (MHD) Instabilities**: Fluctuations in the magnetic field can lead to tearing modes, where magnetic field lines reconnect and cause plasma to escape confinement.

2. **Edge Localized Modes (ELMs)**: Bursts of energy and particles from the edge of the plasma can erode the reactor walls and degrade performance.

3. **Runaway Electrons**: High-energy electrons can be accelerated during disruptions, potentially damaging the reactor components.

4. **Thermal Quenches**: Rapid cooling of the plasma, leading to a sudden loss of thermal energy, can stress the reactor structure.

This report delves into the application of advanced machine-learning techniques to control and mitigate plasma disruptions in tokamaks. Machine learning, with its capability to analyze vast amounts of data and identify complex patterns, offers a promising solution to predict and manage these disruptive events. By leveraging various algorithms and models, we aim to develop a robust framework for early detection and real-time intervention to prevent disruptions.

The study explores several machine-learning approaches, such as the use of RNNs (Recurrent Neural Networks) and CNNs (Convolutional Neural Nets), LSTMs (Long-Short term memory), SVMs (Support Vector Machines), Decision Trees, Random Forests, Logistical Regression classification, all of these technologies can be employed to study the huge amounts of data real-time data coming from the data signals of the tokamak to forecast the disruption.

By integrating these machine-learning techniques, the project aims to enhance the operational stability and performance of tokamaks.

LITERATURE REVIEW

Algorithms and Methodology used in the ADITYA Tokamak:-

ADITYA is a medium size tokamak installed at the Institute for Plasma Research in India. Since the tokamak is smaller than normal the feature-engineering for this tokamak is a bit different than bigger sized tokamaks. The model used is also different.

For this tokamak they came up with a deep learning-based solution. We forecast the disruption in plasma duration 7–20 ms before it occurs. Using the LSTM network, a type of RNN, they achieved an accuracy of around 89% on the test set containing disruptive and non-disruptive shots, with minimal computation time.

Methodology:-

(a) Plasma current (I_p)
(b) Loop voltage (V_{loop})
(c) Bolometer probe (*bolo*)
(d) Mirnov probe at 16° poloidal angle ($Mirnov_{16}$)
(e) A single hard x-ray signal (*HXR*)
(f) A single soft x-ray signal (*SXR*)
(g) Hydrogen-alpha radiation monitor (H_α)
(h) Radiation from ionized oxygen (*OI*)
(i) Radiation from ionized carbon (*CIII*)

These are some of the features of the data signal which were used in the LSTM Model for the tokamak. All of these features were downsampled with the help of SVD and FFT with the equation below:-

$$A = [f, f', FFT(f)] = U\Sigma V^T. \quad (1)$$

The downsampled rate was brought down to 0.2ms intervals or 5kHz frequency.

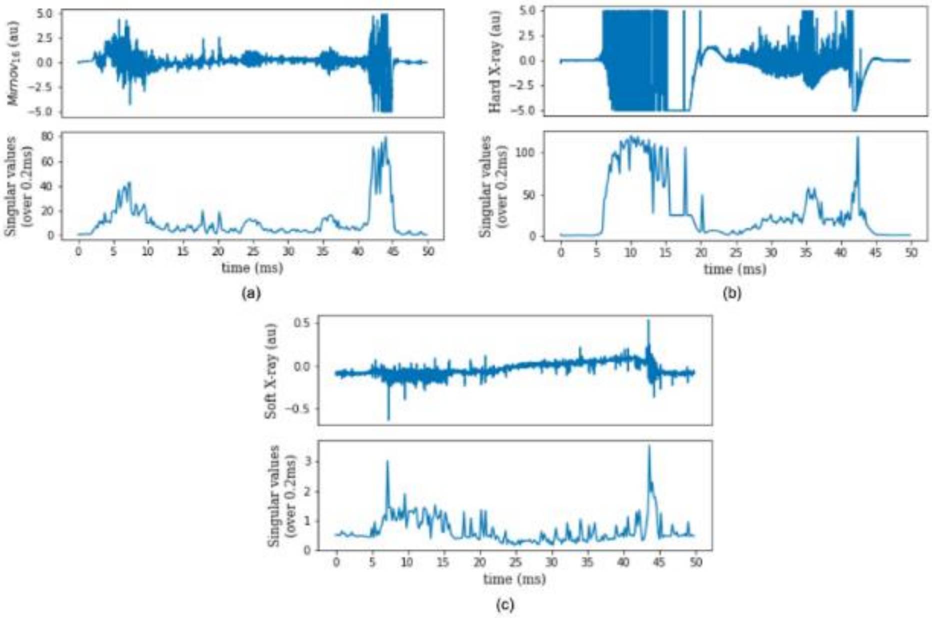


Figure 2. The downsampling of (a) $Mirnov_{16}$, (b) *HXR*, and (c) *SXR* signal values over a window of 0.2 ms for shot #14749, in the form of singular values (SVs) from the SVD method.

The Mirnov Probe, the HXR and SXR were downsampled as shown and hence their graphs could be used with the rest of the data.

The potent features were then analysed as to which one has a greater contribution towards disruption , for example as seen in the graph below:-

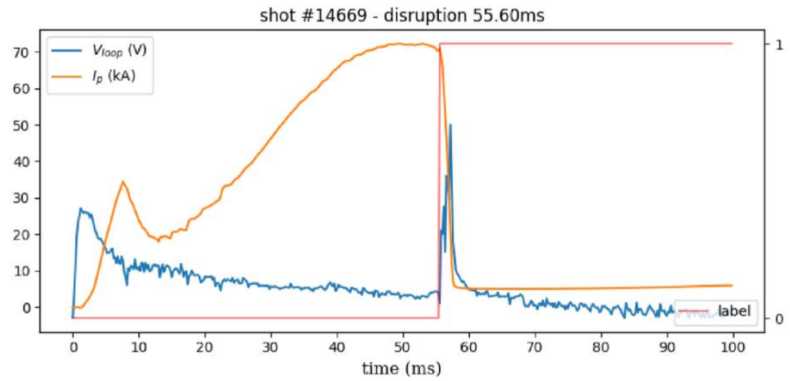


Figure 3. The label was created by identifying the spike in V_{loop} and I_p signals. It had a value of 0 before the point of disruption and 1 after that.

The graph makes it evident that the Plasma Current and the Voltage in the Loop both see a spike at the same time before the disruption is about to happen. *Thus we can conclude that both Plasma current and Voltage are very valuable and good potential features for our Model Training*.

Similarly feature-engineering is done for the rest of the features and the most notable features are filtered out. For this Tokamak we can see the most important features as the following which I prepared in my own document:-

TOKAMAK	*Feature*	*Weigtage/Importance(if adequate data supports)*
ADITYA	**Plasma current (I_p or Quench Current)**	
ADITYA	**Loop voltage (V_loop)**	
ADITYA	**Mirnov probe at 16° poloidal angle (Mirnov16)**	
ADITYA	**A single hard x-ray signal (HXR)**	
ADITYA	**A single soft x-ray signal (SXR)**	
ADITYA	**Hydrogen-alpha radiation monitor (H_α)**	
ADITYA	**Bolometer probe (bolo)**	
ADITYA	**Radiation from ionized oxygen (OI)**	
ADITYA	**Radiation from ionized carbon (CIII)**	

Weightage Legend	Colour Code
High	
Med	
Low	

Deep sequence to sequence learning-based prediction of major disruptions in ADITYA tokamak.Aman Agarwal et al 2021 Plasma Phys.

In this compilation I have tried to assemble all the features with respect to their weightage and impact on the model. The Plasma Current and Voltage (as seen above have the most impact), as well as the Mirnov , HXR and SXR. Followed by the rest of the features, blue signifying medium weightage and green signifying less.

All these features with respect to their weightage are then put inside the LSTM which trains the model.

Here is a basic overview of how LSTM works:-

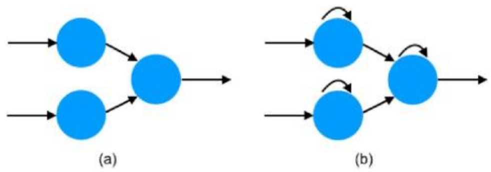


Figure 4. Comparison of (a) feed-forward neural network and (b) recurrent neural network architecture.

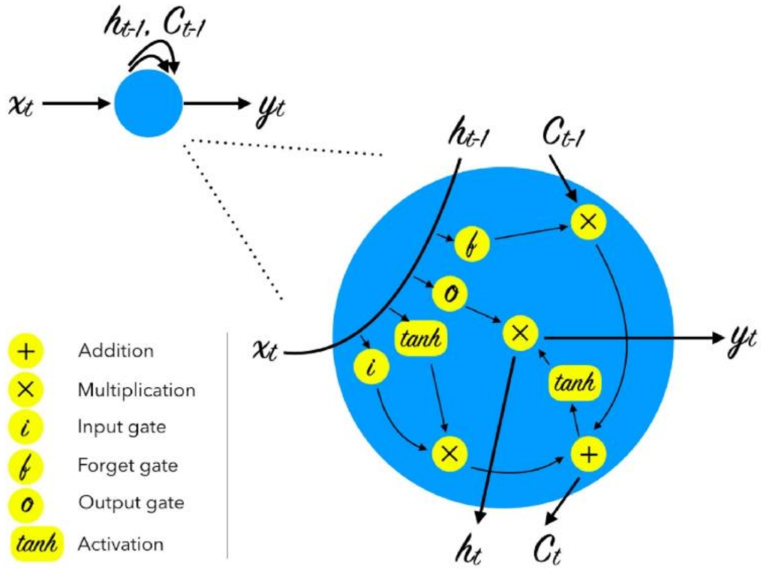


Figure 5. A schematic representation of an LSTM cell.

The Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to effectively learn and remember long-term dependencies in sequential data. They use gates to control the flow of information, overcoming the vanishing gradient problem and enabling more accurate modelling of time series and sequential tasks.

The coding that goes behind this can be simply explained using the following pseudo-code:-

Algorithm 1: Disruption forecast for ADITYA.

```
reset LSTM cell state
while every timestep of 0.08 ms do
    if timestep % 0.2 != 0 then
        aggregate Mirnov_16 , HXR , and SXR
        continue
    else
        data = get raw diagnostic signal values
        // add SVs over a period of 0.2 ms to the data
        data = concat(data, SVs of Mirnov_16 , HXR , and SXR )
    end
    normalize the data
    // get probability of disruption
    output = LSTM(data)
    threshold = 0.5
    if output < threshold then
        continue
    else
        raise alarm
        break
    end
end
```

Results and Conclusion:-

The network predicted the results 7–20 ms in advance with 89% accuracy on the testing set of 36 disruptive and 6 non-disruptive shots. A prediction made this early can alert the system of the imminent disruption well in advance so that preventive measures to control the thermal energy are deployed in time. The results can be calculated by simply using the True Positives (TP), False Positives (FP), True Negatives(TN) and False Negatives (FN) predicted by the model. The results can be summarized below:-

$$Precision = \frac{TP}{TP+FP} = \frac{32}{32+2} = 0.94, \tag{8}$$

$$Recall = \frac{TP}{TP+FN} = \frac{32}{32+3} = 0.91, \tag{9}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{32+5}{32+5+2+3} = 0.88. \tag{10}$$

Through this work, we show how LSTM networks can be used to solve real-time disruption prediction problem. A prediction made this early can alert the system of the imminent disruption well in advance so that preventive measures to control the thermal energy are deployed in time.

Algorithms and Methodology used in the JET Tokamak:-

Database:-

Table 1: JET plasma parameters.

Signal name	*Acronym*	*Signal name*	*Acronym*
Plasma current	Ip	Poloidal Beta	β_{pol}
Safety factor at 95% of the major radius	q_{95}	Electron density/Greenwald density	f_{Gw}
Total input power	P_{inp}	Locked Mode signal	LM
Total radiated power	P_{rad}	Plasma centroid vertical position	Zcc
Total Radiated Power/Total Input Power	P_{frac}	Line-integrated plasma density	ne
Internal inductivity	li	Stored diamagnetic energy time derivatives	dW_{dia}/dt

The above parameters were used in the JET Tokamak and Methodologies used were as follows:-

Methodologies:-

- **Data Cleaning and Preparation**:
  - Data cleaning procedures were applied to detect, remove, or correct inaccurate data and outliers
  - Scaling of variables was mandatory due to the varying ranges of signal magnitudes.
- **Distinguishing Phases**:
  - A distinction was made between samples belonging to the disruptive and non-disruptive phases for training set generation.
  - Manual or statistical identification of the time instant (tpre-disr) that discriminates between non-disruptive and disruptive phases of a disrupted pulse.
- **Prediction Performance Metrics**:
  - **Premature Detection (PD)**: Fraction of disruptive pulses that trigger the alarm too much in advance.

- **Tardy Detection (TD)**: Fraction of disruptive pulses that trigger the alarm too late.
- **Missed Alarm (MA)**: Fraction of disruptive pulses predicted as non-disruptive.
- **Successful Predictions (SPs)**: Remaining alarms that were successful predictions.

- **Machine Learning Models**:

  - Initial approaches used black box neural network models to classify samples as disruptive or non-disruptive.
  - Generative Topographic Mapping (GTM) showed great potential for both disruption prediction and classification with an overall prediction rate of about 89% and a classification success rate reaching 100% in some cases.

- **Manifold Learning**:

  - Linear and non-linear manifold learning algorithms were used to extract knowledge from high-dimensional data and project it into a lower-dimensional space.
  - GTM was effective in identifying characteristic regions of the plasma scenario on 2D mapping, providing natural discrimination between non-disruptive and disruptive regions.

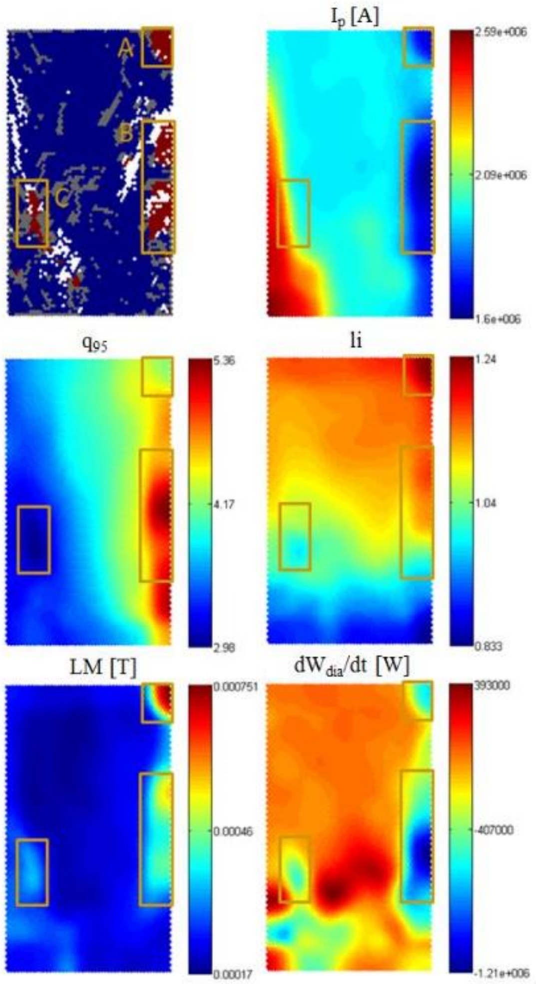


Figure 3: SOM of the 10D JET operational space and related *C-planes* for inputs *Ip*, *q95*, *li*, LM and dW_{dia}/dt

The above heatmap goes on to show the distribution of specific input parameters (Ip, q95, li, LM, dWdia/dt) across the clusters. By examining the C-planes, we can very well see how these parameters vary across the map, providing insight in the conditions leading to disruptions. The red regions (high disruption risk) are distinctly separated from the blue regions (non-disruptive) by transitional (grey) and empty (white) regions. This separation helps in identifying safe and risky operational zones. The SOM not only confirms known plasma behavier but also serves as a simple yet powerful tool to visualize the plasma's actual state. All of this at the end aids in disruption control for this JET tokamak.

Result:-

- **Prediction and Classification**:

    - The results showed that GTM could be used both as a predictor and a classifier.
    - By following the trajectory of a discharge throughout the map, a class could be associated with each sample, and disruption alarms could be triggered.

- **Operational Space Mapping**:

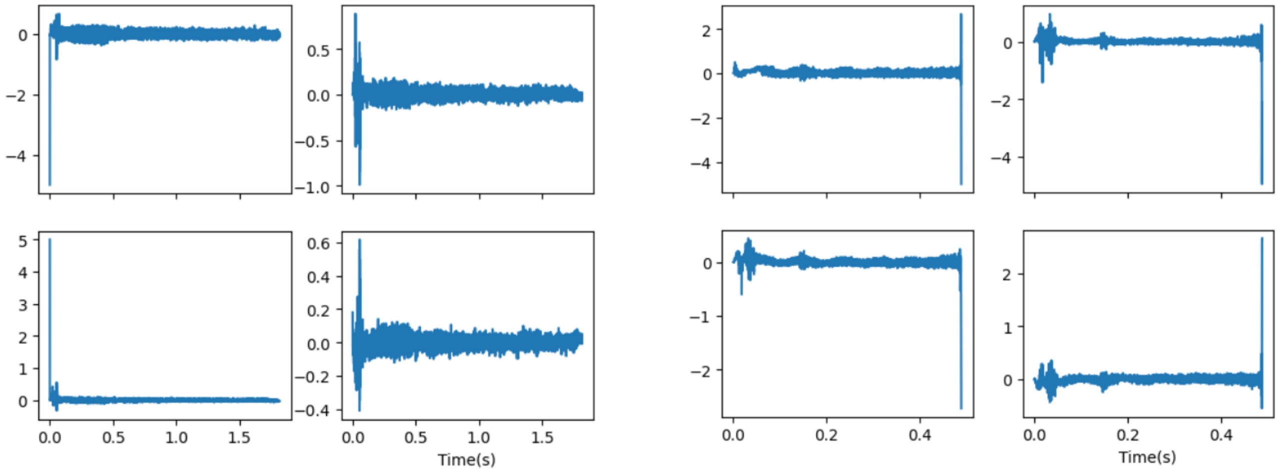
    - The GTM approach provided insights into the plasma operational space, allowing for the prediction of both the proximity to disruptions and the type of disruption.

- **Practical Application**:

    - The analyses demonstrated how machine learning tools could be effectively used to extract information from experimental data and use this knowledge for disruption prediction and classification.

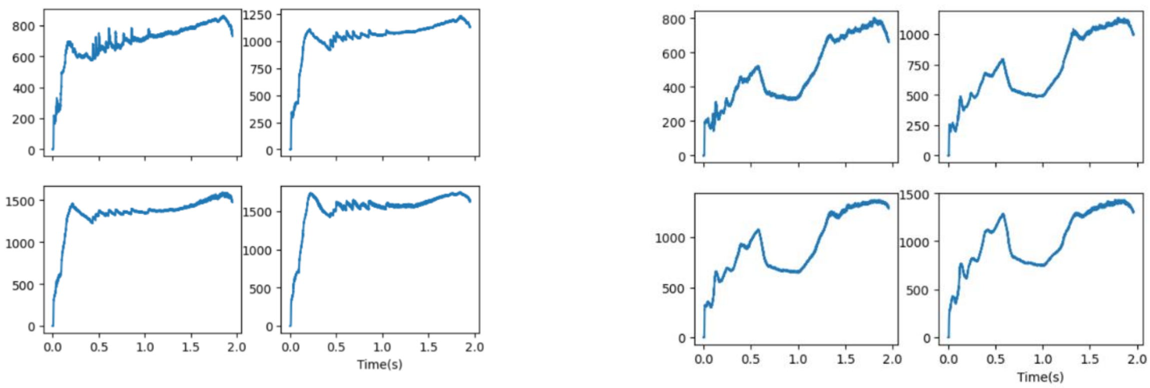
Personal Methodology and Feature-Engineering As of Yet:-

Data Analysis And Feature-Engineering:-



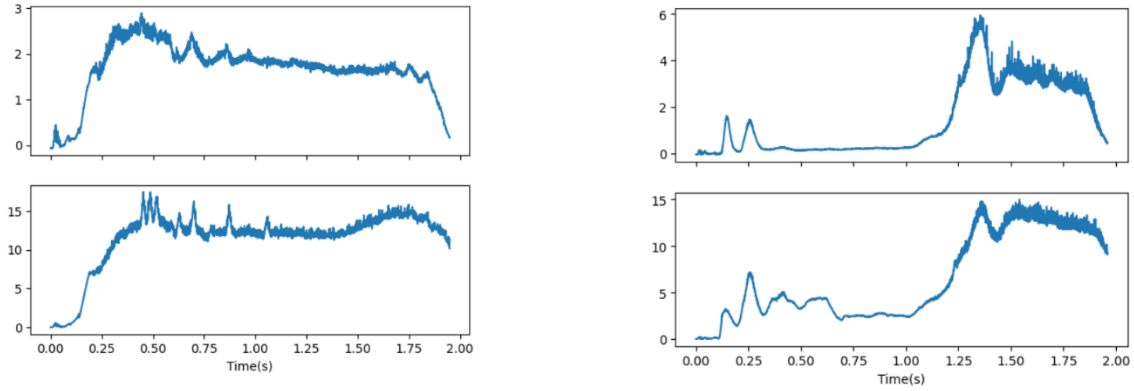
Mirnov Probe Readings Plotted by me with Non-Disruptive shot (left) and Disruptive Shot(Right)

As you can see the Disruptive shot gets cut off at around the 0.5th second with the Radiation readings quickly going up and down so a perpendicular line is formed. However the time-frame of disruption readings is quite small and sudden. This is an indication of differences in Mirnov readings and Mirnov's potential as a okay feature for our model.



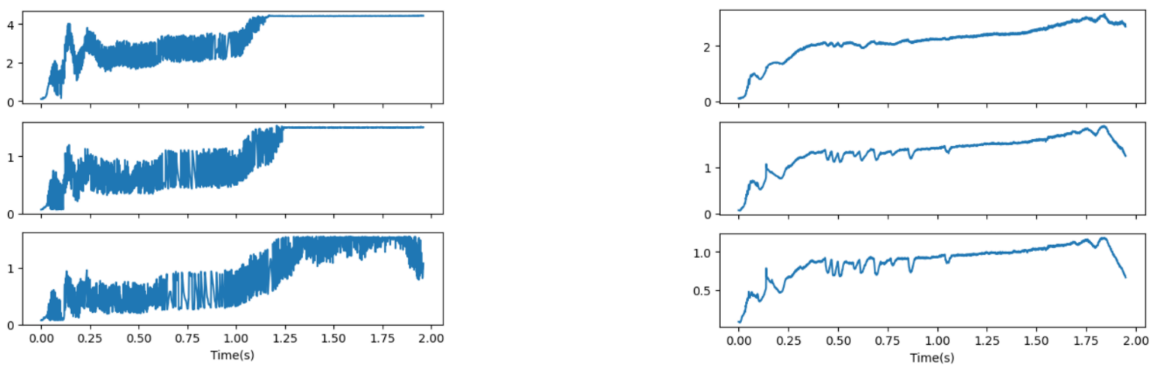
Plasma Density Readings Plotted by me with Non-Disruptive shot (left) and Disruptive Shot(Right)

As you can see in the above graph the Disruptive shot has the plasma density fluctuating more and being more chaotic overall whereas the non disruptive shot has a more stable plasma density. Hence density is also a good feature for our model.



SXR (Soft X-Ray readings) Readings Plotted by me with Non-Disruptive shot (left) and Disruptive Shot(Right)

Soft X-Ray also acts as a good feature in our data as we can see that the disruptive shot has really low readings and suddenly shoots up (chaotic) whereas non disruptive is stable throughout.



AXUV (UV readings) Readings Plotted by me with Non-Disruptive shot (left) and Disruptive Shot(Right)

As it can be observed clearly the UV readings on the left side are much more stable and the readings on the right(Disruptive ones) taper off towards the end gradually. The tapering off happens in around 50ms timeframe and it gives us enough time to predict the disruption, hence AXUV readings are a very good feature and can be given good weightage to be taken up for our feature engineering for this specific dataset of the Tokamak.

Conclusion:-

As we can see feature engineering and selection of right features through the correct data handling and analysis is very important for the model to give a high enough accuracy and perform efficiently. Hence via the above Graphical comparisons we can quite easily see how to select data and reject data for our models in general. Here the important features can be arranged with respect to their importance as I tried to explain through the graphs:-

1. **AXUV (MOST important)** – Good identifier and a big enough time frame to make prediction.

2. **SXR** – Chaotic and fairly unstable for disruptive shots hence good identifier

3. **Plasma Density** – Erratic, and sudden dip

4. **Mirnov Probe readings (LEAST Important)** – Not significant enough stability differences in the Disruptive and non-disruptive shot and the time-frame on the disruptive shot is very small to actually make a prediction in time. Hence Mirnov readings are poor identifier and should be given lesser weightage in the weightage matrix

CONCLUSIONS AND FUTURE DIRECTIONS:-

From the analysis of both research papers, it is evident that machine learning techniques, particularly deep learning models like CNNs, RNNs, and LSTMs, are highly effective in predicting disruptions in tokamaks. Key takeaways include:

- **Versatility provided by Machine Learning**: All the studies that were did above in my literature review demonstrated that machine learning models can be adapted to different tokamak sizes and configurations. While JET benefited from a combination of CNNs and RNNs, ADITYA effectively used LSTMs for real-time prediction.
- **Importance of Data Preprocessing**: Proper preprocessing of diagnostic signals is crucial for accurate prediction. Techniques like normalization, re-sampling, and feature extraction significantly enhance model performance. Also usage of SVDs and FFTs was scene in my first review for Downsampling.
- **Real-time Application Potential**: The studies highlight the potential for real-time disruption prediction, which is essential for preventing damage to tokamak vessels and surrounding equipment. The ability to predict disruptions with high accuracy and minimal computation time is a significant advancement for plasma confinement and fusion energy research.

Some Future Directions which I plan to steer the project in for my rest of the research include:-

- **Data Preparation**: Continue to focus on comprehensive data cleaning, normalization, and feature extraction to ensure high-quality input data for models.
- **Exploratory Data Analysis (EDA)**: Perform detailed visualizations and statistical analyses to understand data distributions and feature relationships.
- **Basic Model Implementation**: Start with implementing simple machine learning models such as Decision Trees, Random Forests, and Logistic Regression to establish a strong baseline.
- **Model Evaluation**: Use metrics like accuracy, precision, recall, and F1-score, and visualize performance using confusion matrices and ROC curves.
- **Advanced Techniques**: Progress to more complex models like CNNs, RNNs, and LSTMs for handling high-dimensional and time-series data.
- **Real-time Systems Integration**: Develop real-time data pipelines and model inference systems for live tokamak operations.
- **Hybrid Models**: Explore combining different machine learning models to leverage their unique strengths and improve prediction accuracy.

<u>REFERENCES:-</u>

- **Deep sequence to sequence learning-based prediction of major disruptions in ADITYA tokamak.** *Aman Agarwal et al 2021 Plasma Phys. Control. Fusion 63 115004*

- **Disruption Prediction in Fusion Devices through Feature Extraction and Logistic Regression.** *Diogo R. Ferreira IST, University of Lisbon, Portugal*

- **Disruption prediction approaches using machine learning tools in Tokamaks**. *G. Sias1 , B. Cannas , S. Carcangiu1 , A. Fanni1 , A. Murari , A. Pau , and the JET Contributors*

GLOSSARY:-

1. **CNN (Convolutional Neural Network)**: A deep learning model particularly effective in processing spatial data, such as images.
2. **RNN (Recurrent Neural Network)**: A deep learning model designed to handle sequential data by maintaining a memory of previous inputs.
3. **LSTM (Long Short-Term Memory)**: A type of RNN capable of learning long-term dependencies in sequential data.
4. **Self-Organizing Map (SOM)**: An unsupervised learning algorithm used to produce a low-dimensional representation of high-dimensional data.
5. **Generative Topographic Mapping (GTM)**: A probabilistic model used to visualize high-dimensional data by mapping it to a lower-dimensional space.
6. **Safety Factor (q95)**: A measure of the stability of the plasma, indicating the number of times magnetic field lines wrap around the torus in the poloidal and toroidal directions.
7. **Internal Inductance (li)**: A parameter related to the distribution of the plasma current within the tokamak.
8. **Locked Mode (LM)**: A plasma instability where the plasma rotates slowly or becomes stationary relative to the tokamak's magnetic fields.
9. **Diamagnetic Energy (dWdia/dt)**: The rate of change of the diamagnetic energy, reflecting the plasma's pressure changes.
10. **Feature Extraction**: The process of identifying and selecting relevant features from raw data to be used in a machine learning model.
11. **ROC Curve (Receiver Operating Characteristic Curve)**: A graphical plot that illustrates the diagnostic ability of a binary classifier by plotting true positive rate against false positive rate.
12. **Black Box Model**: A type of machine learning model whose internal workings are not easily interpretable or understood by humans.