Implementation of AI/Deep Learning Disruption Prediction into a Plasma Control System

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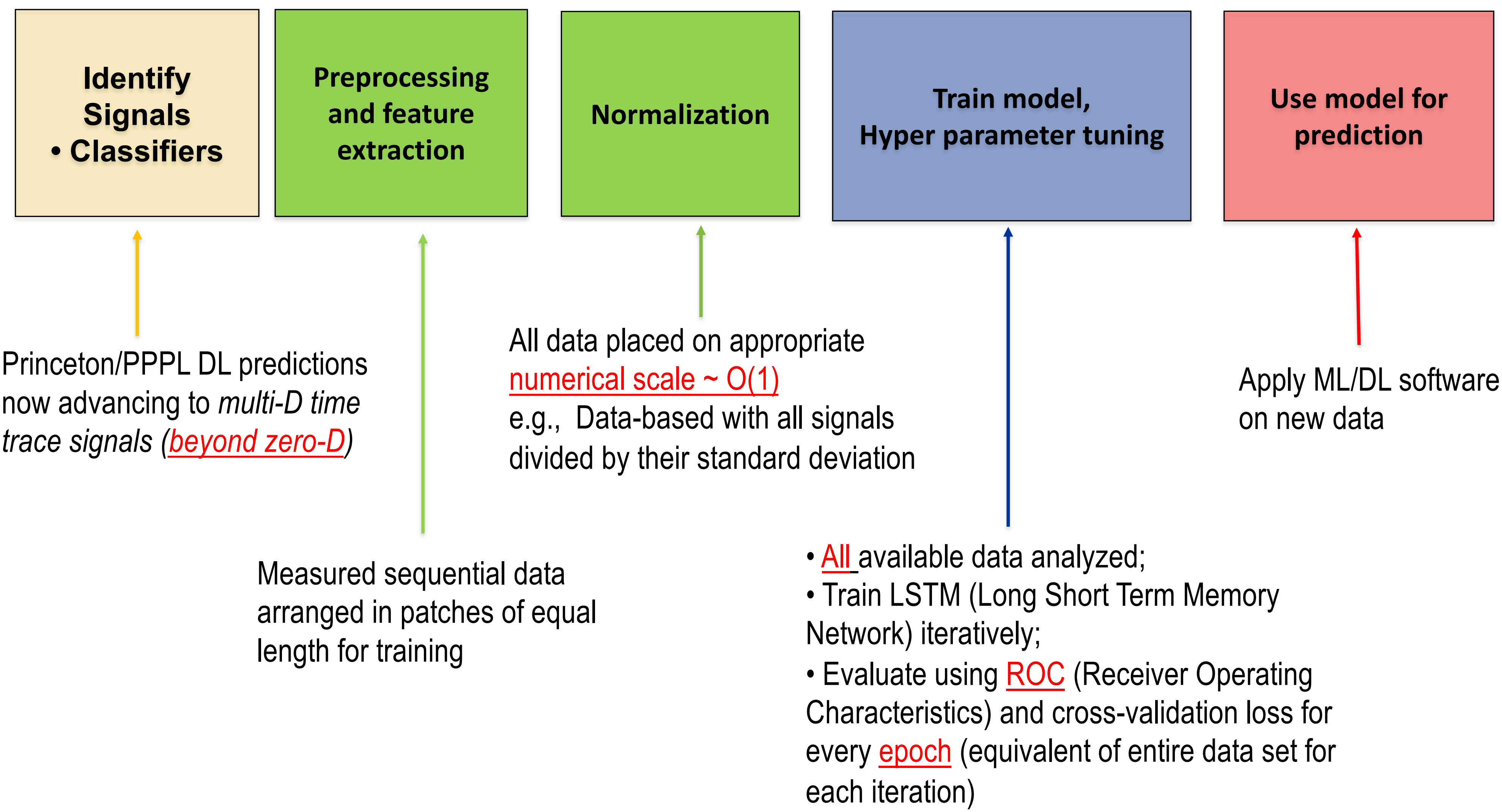
Introduction & Motivation:

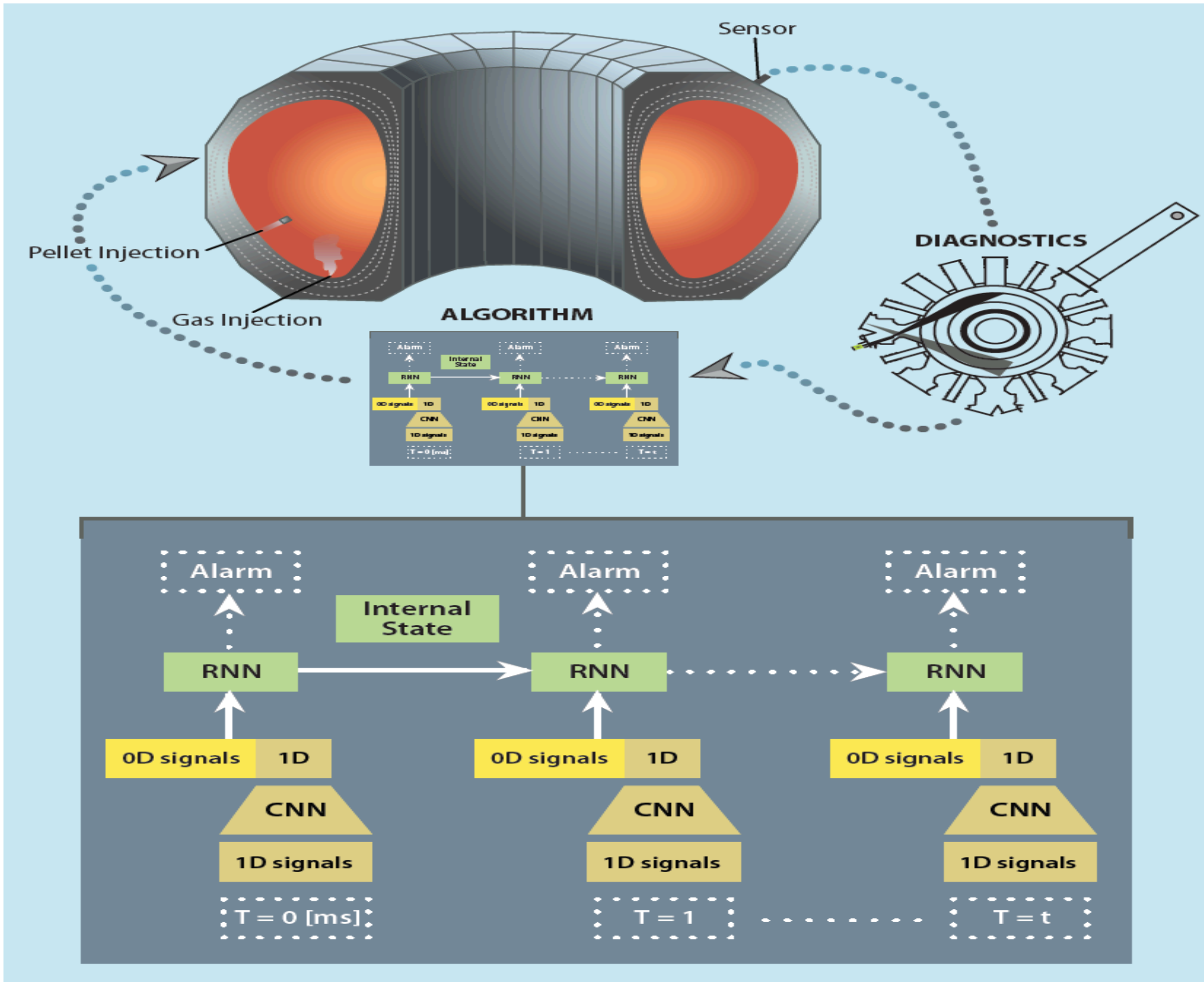
• FRNN produces accurate “disruption score” for probability of “when” imminent disruption will occur + a sensitivity analysis in real time for underlying reasons as to “why? ”

• Integration of AI/DL FRNN predictor into DIII-D plasma control system(PCS)

→ D3D’s "start-up" phase involving over 200 shots in May/June 2020 showed “FRNN inference engine” can be readily functional (~ 1.7 ms) during real-time operations;

→ Motivates systematic studies of *actuator engagement* to possibly modify the plasma state to avoid or delay onset of disruptions


Identify Signals
• Classifiers
Preprocessing and feature extraction
Normalization
Train model, Hyper parameter tuning
Use model for prediction
Princeton/PPPL DL predictions now advancing to *multi-D time trace signals (beyond zero-D)*
Measured sequential data arranged in patches of equal length for training
All data placed on appropriate numerical scale ~ O(1)
e.g., Data-based with all signals divided by their standard deviation
• All available data analyzed;
• Train LSTM (Long Short Term Memory Network) iteratively;
• Evaluate using ROC (Receiver Operating Characteristics) and cross-validation loss for every epoch (equivalent of entire data set for each iteration)
Apply ML/DL software on new data


Sensor
Pellet Injection
Gas Injection
DIAGNOSTICS
ALGORITHM
Alarm
Alarm
Alarm
Internal State
RNN
RNN
RNN
0D signals
1D
0D signals
1D
0D signals
1D
CNN
CNN
CNN
1D signals
1D signals
1D signals
T = 0 [ms]
T = 1
T = t

AI/Deep Learning FRNN Software Suite

FRNN [NATURE (April, 2019)]

AI/Deep Learning Model
- **Keras API**
- **LSTM based models**

Input
- **0D+1D data**

Output
- **Disruption score**

FRNN [2020-2021: In Progress R&D]

AI/Deep Learning Model
- **Keras API / Pytorch API**
- **LSTM / TCN / TTLSTM based models**

Input
- **0D+1D + 2D data**

Output
- **Disruption score + real time sensitivity score**
- **Physics-based signals**

Application
- **Implemented and tested in DIII-D PCS**

FRNN with Physics-based inputs: HPC Training & Prediction for disruption with enhanced accuracy and advanced alarm time

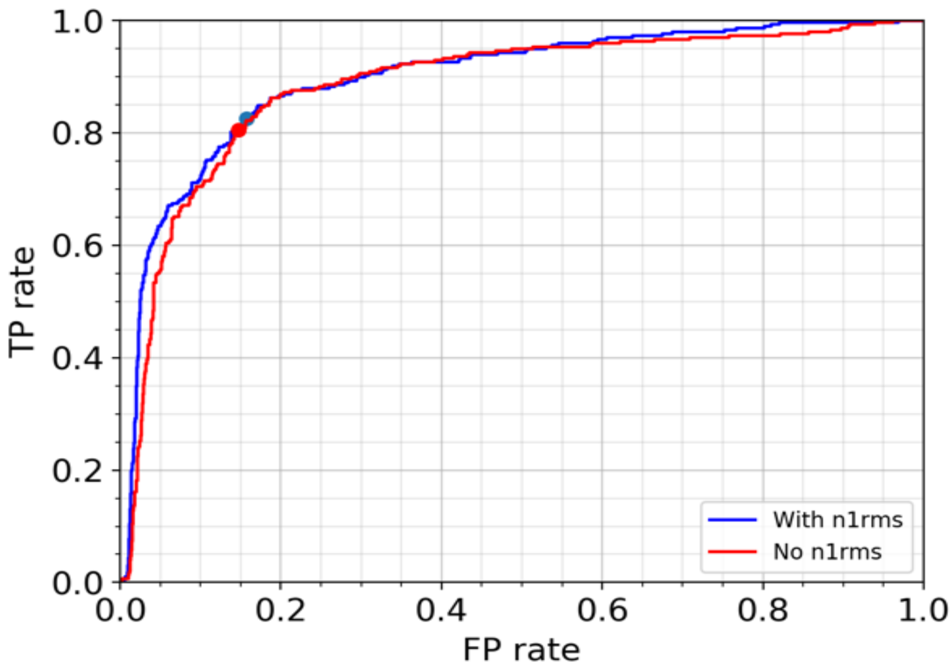


FIG. 1. Comparison of the ROC curves with and without the n=1 finite frequency mode amplitude ("n1rms")

Distinguishing disruptive and non-disruptive tearing modes

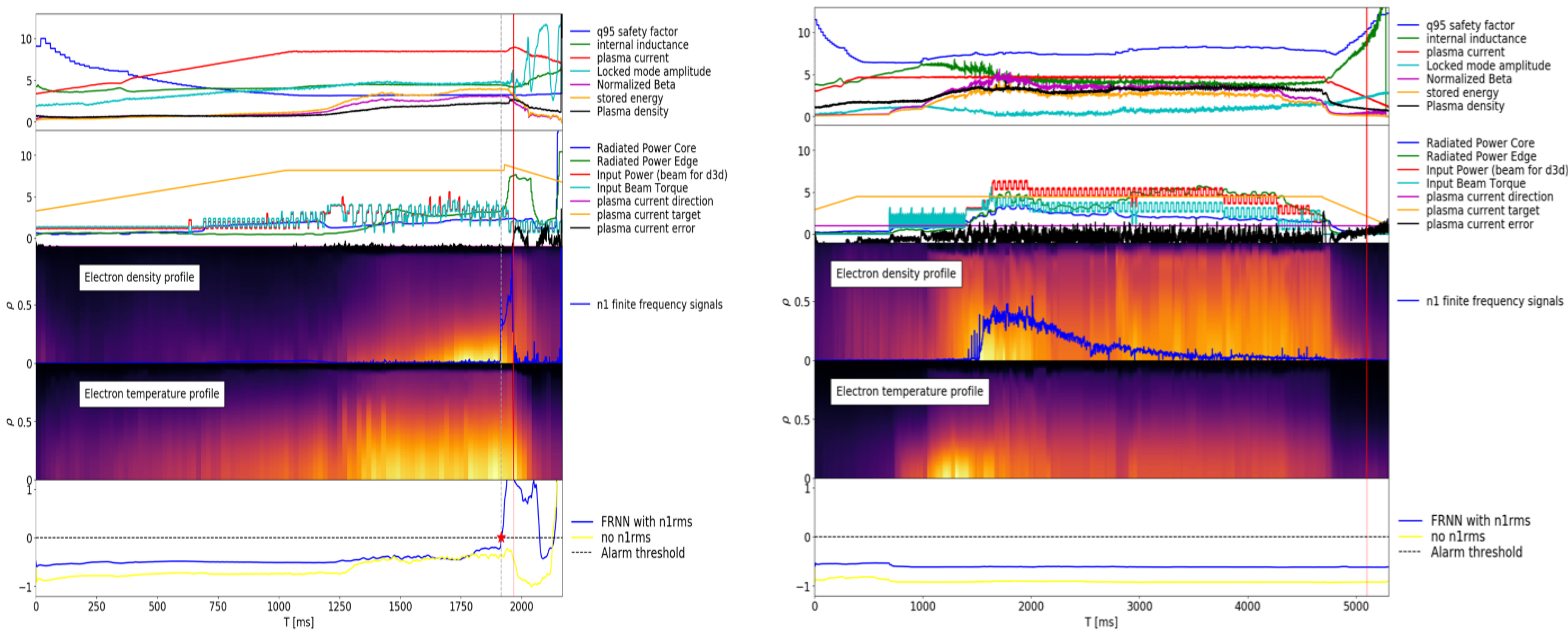


FIG. 2. DIII-D shot number 161362 in the left panel and DIII- shot number 170239 in the right panel. In each panel, the upper 4 sub-panels show measured signals as FRNN input, and the bottom sub-panel show FRNN model outputs

Studying contributions of physics-based signals to disruption score

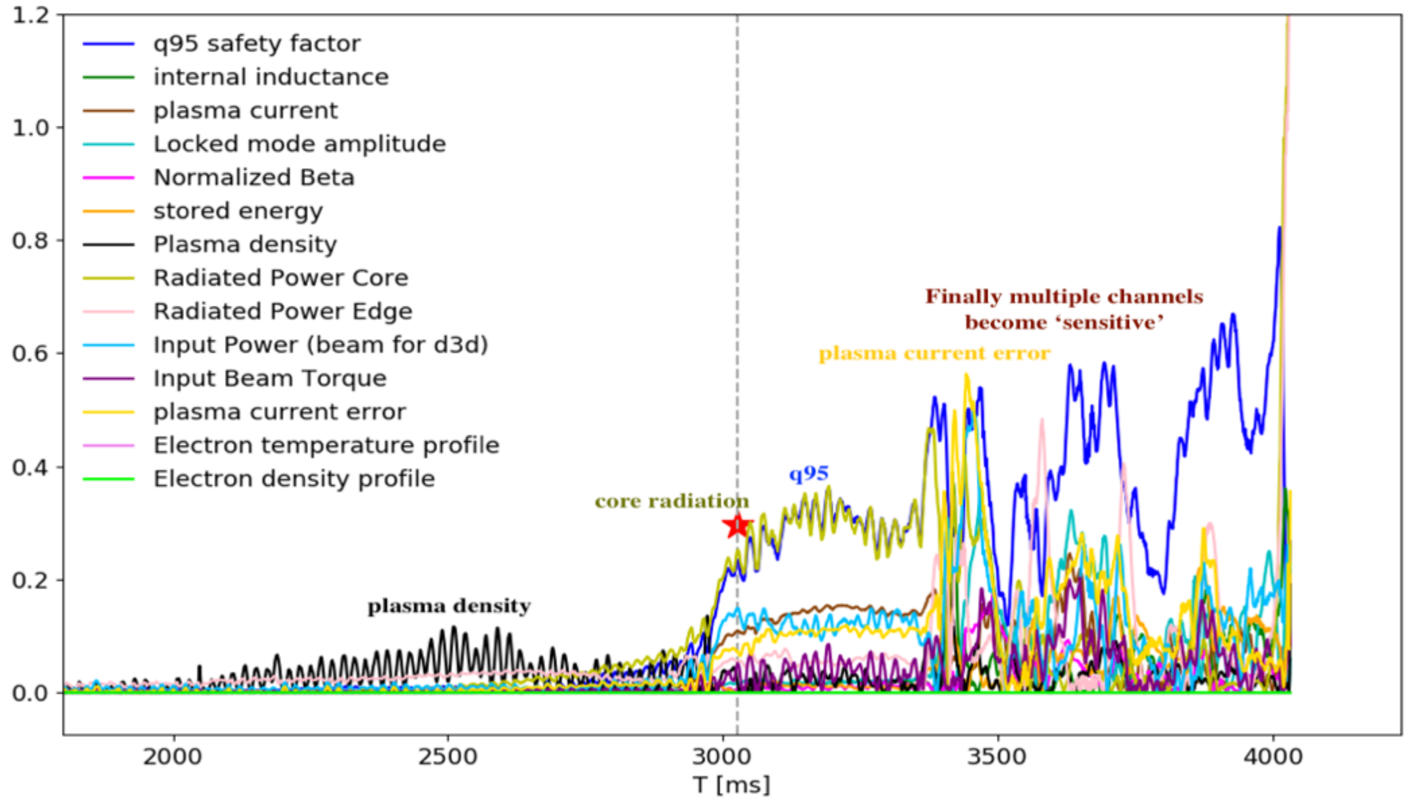


FIG 3. Evolution of the sensitivity score of the shot #164582

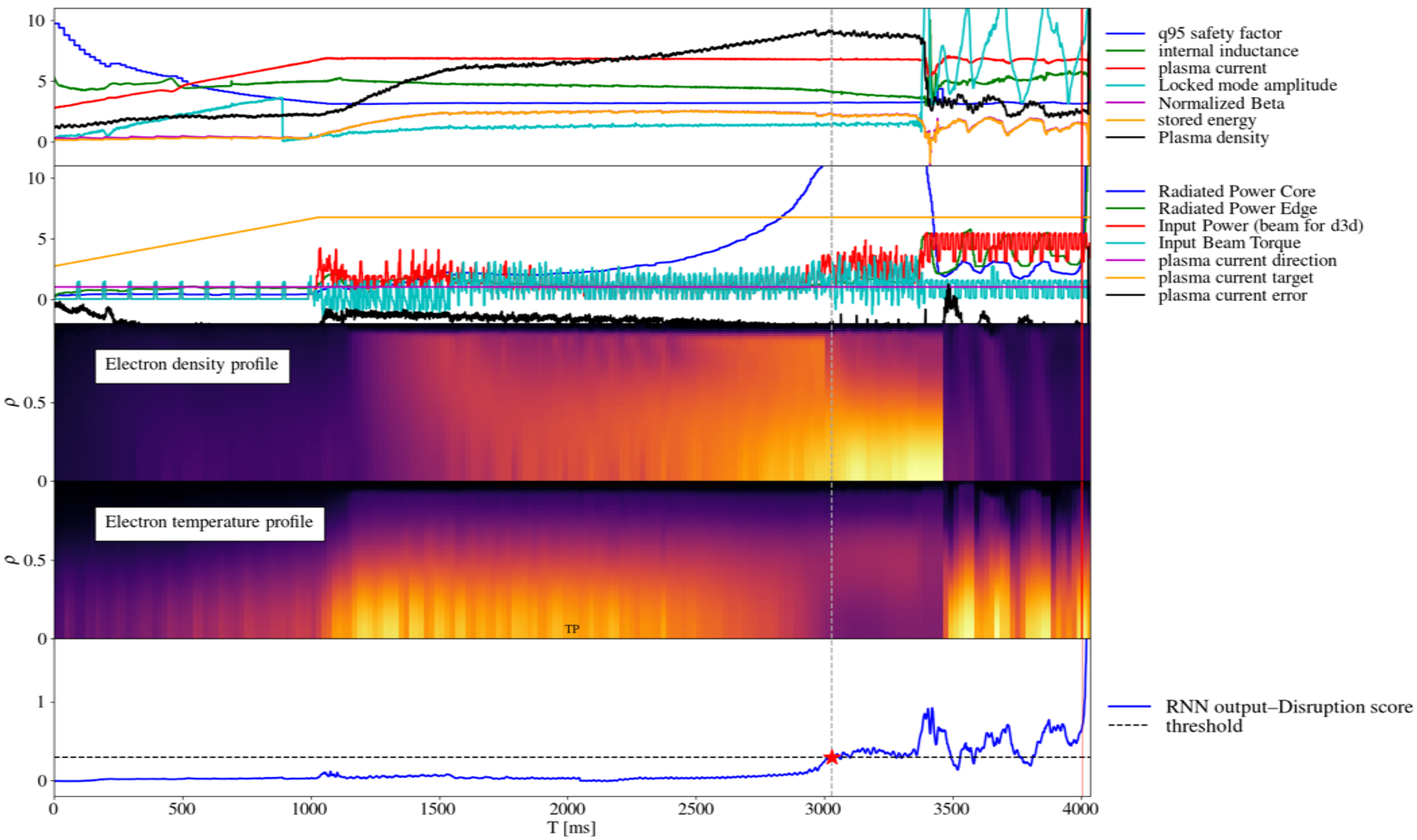


FIG 4. Evolution of each normalized physical signal for DIII-D shot #164582 in the upper 4 panels. The bottom panel shows the time history of the FRNN output

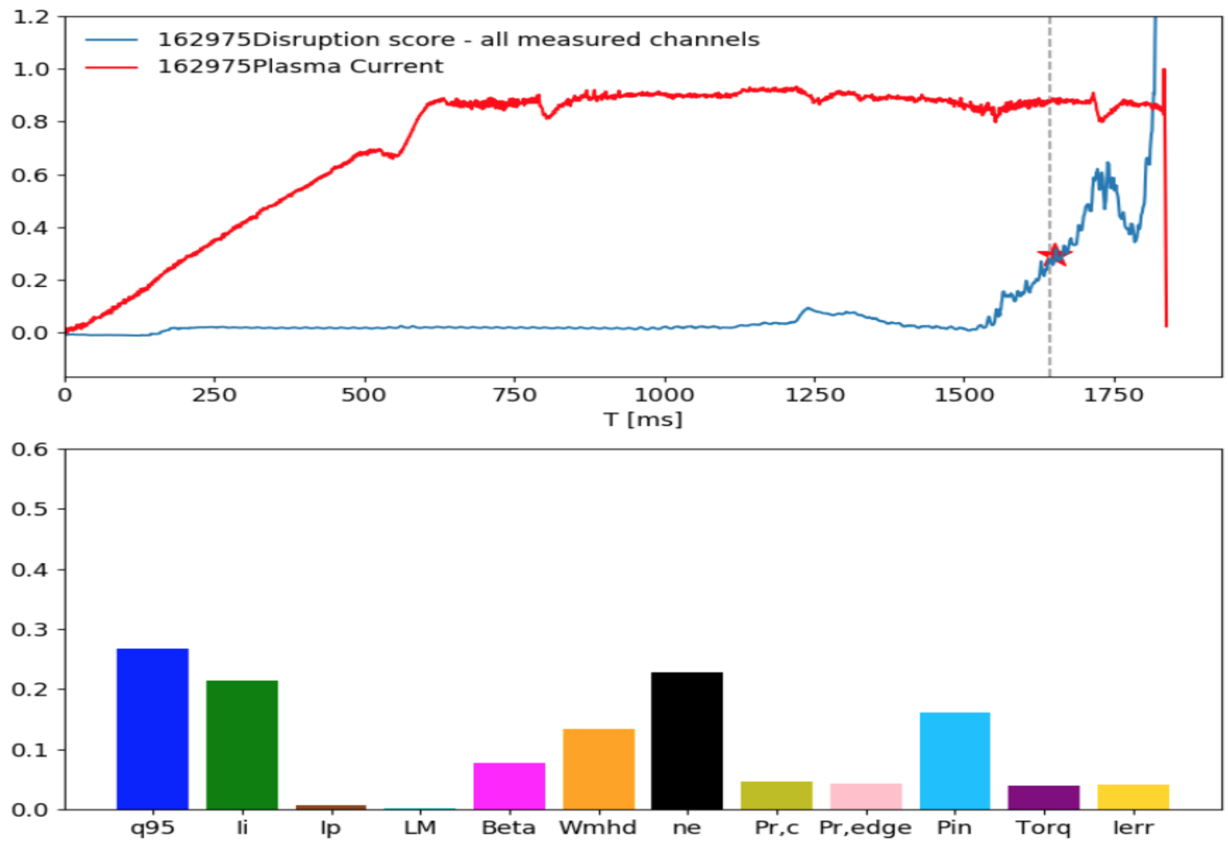


FIG. 5. DIII-D shot #162975. The upper panel shows the evolution of the plasma current (red line) and the FRNN output of the disruption score (blue line -- with the lower panel showing the sensitivity scores (for associated signals such as q95, etc.) at the time of the disruption alarm (red star in the upper panel).

Summary & Future Studies:

• Integration of AI/DL FRNN predictor into DIII-D plasma control system(PCS) + Interpretation via statistical sensitivity studies with real-time actionable integration into PCS

• When more signals are included in training database, better predictive capability can be achieved:

→ Exciting neural network to discriminate between disruptive and non-disruptive tearing modes.

→ FRNN “inference engine” demonstrably functional (~ 1.7 ms) on time-scales needed for real-time actuator engagement.

→ Motivates ongoing & future efforts to interconnect new features of present studies to enable DL sensitivity output in real time into the proximity control architecture designed for handling major disruption causes in the DIII-D PCS.