Alfvén Eigenmode Detection Using Long-Short Term Memory Networks and CO_2 Interferometer Data on the DIII-D National Fusion Facility

by

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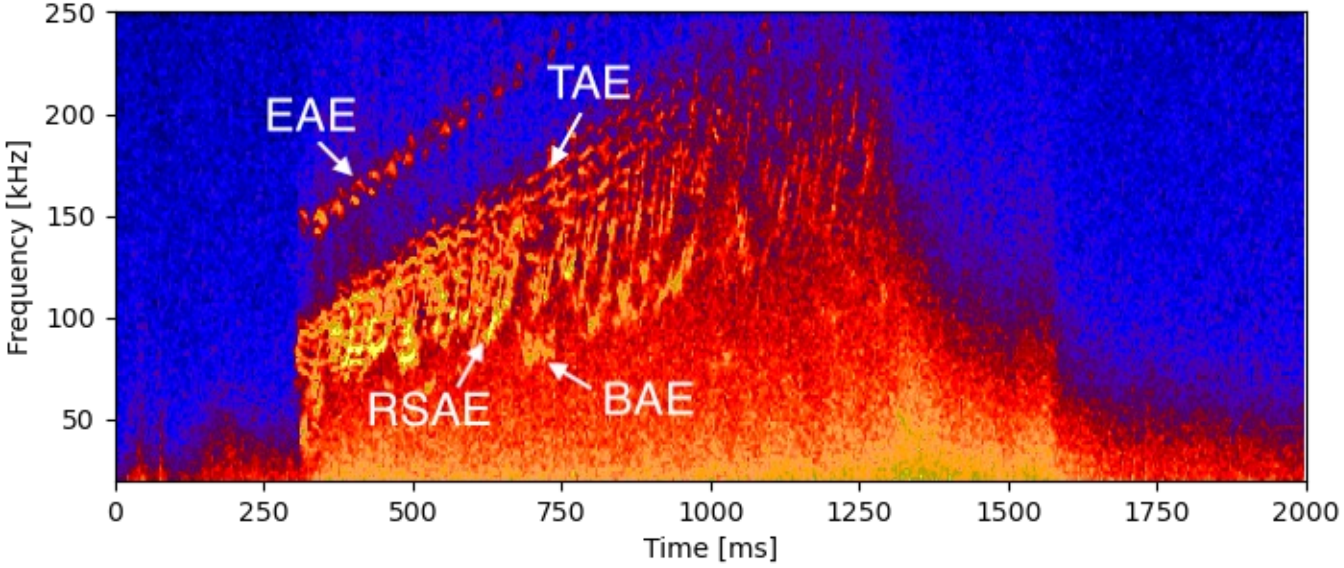

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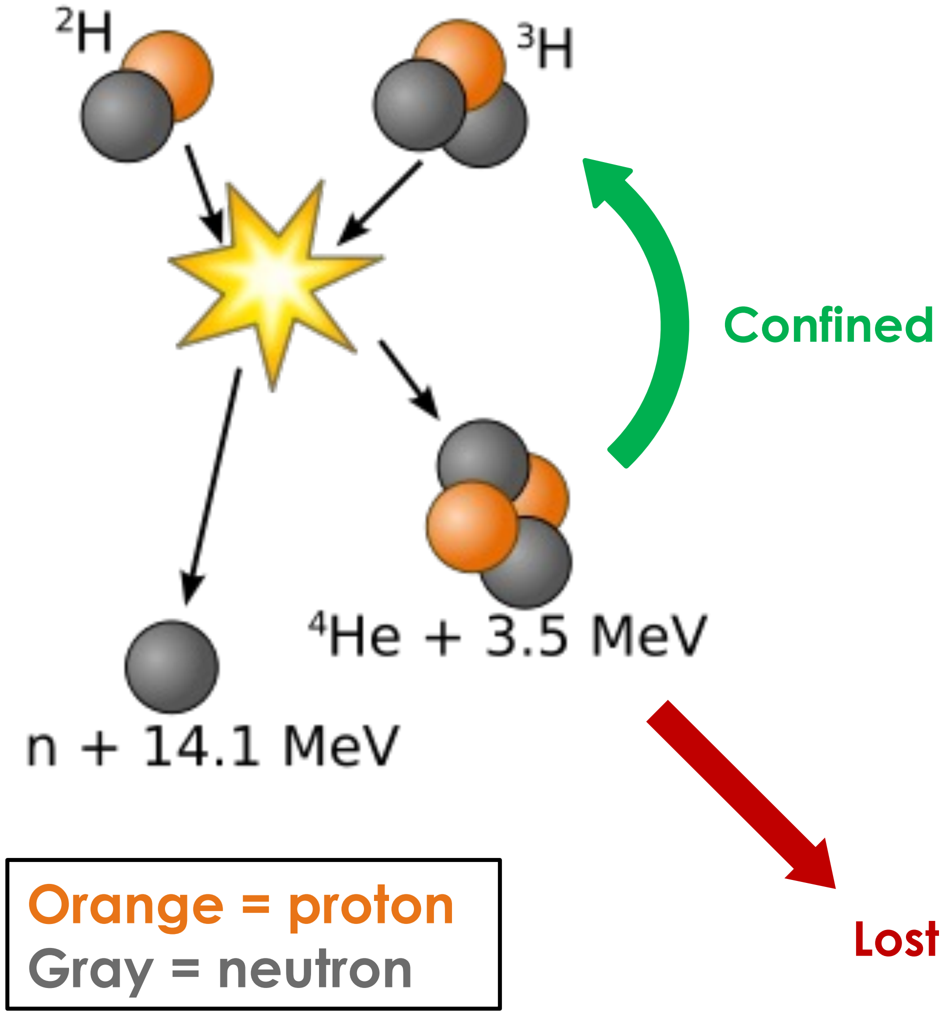
DIII-D NATIONAL FUSION FACILITY SAN DIEGO
UC IRVINE
U.S. DEPARTMENT OF ENERGY | Office of Science
Graduate Student (SCGSR) Research Program
PRINCETON UNIVERSITY
PPPL PRINCETON PLASMA PHYSICS LABORATORY
TUD

High temperatures are required for fusion reactions

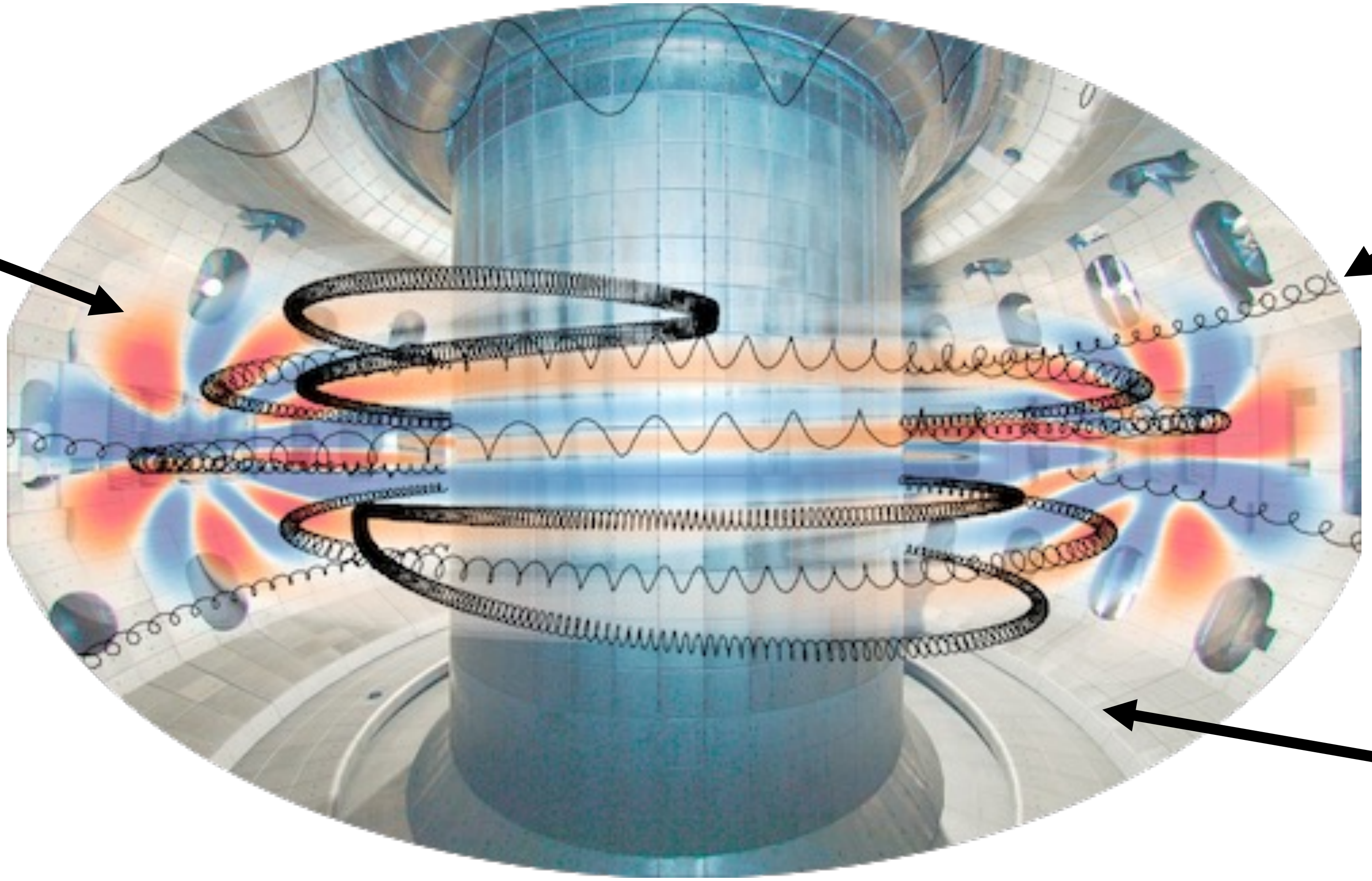
- **Hot ions need to get close to produce a fusion a reaction**
  - Electrostatic coulomb force repel ions
  - If density and temperature are high enough, the nuclear strong force causes a reaction

- **Fusion conditions**
  - $\text{Density} \approx 10^{13} cm^{-3}$ (10^{11} times lower than the sun)
  - $\text{Temperature} \approx 150 \text{ Million } °C$ (10 times hotter than the sun)



Energetic ions are important for an ignited fusion device, but can also resonate with Alfvén eigenmodes

- **Poorly behaved fast-ions can resonate with plasma waves (Alfvén eigenmodes), degrade the plasma performance and create a quench of fusion burn**



Pace, David C., et al., Physics Today 68.10 (2015).

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Machine Learning is useful in Fusion Energy research

- **Many spatially located sensors collect data and can be used for Machine Learning analysis**

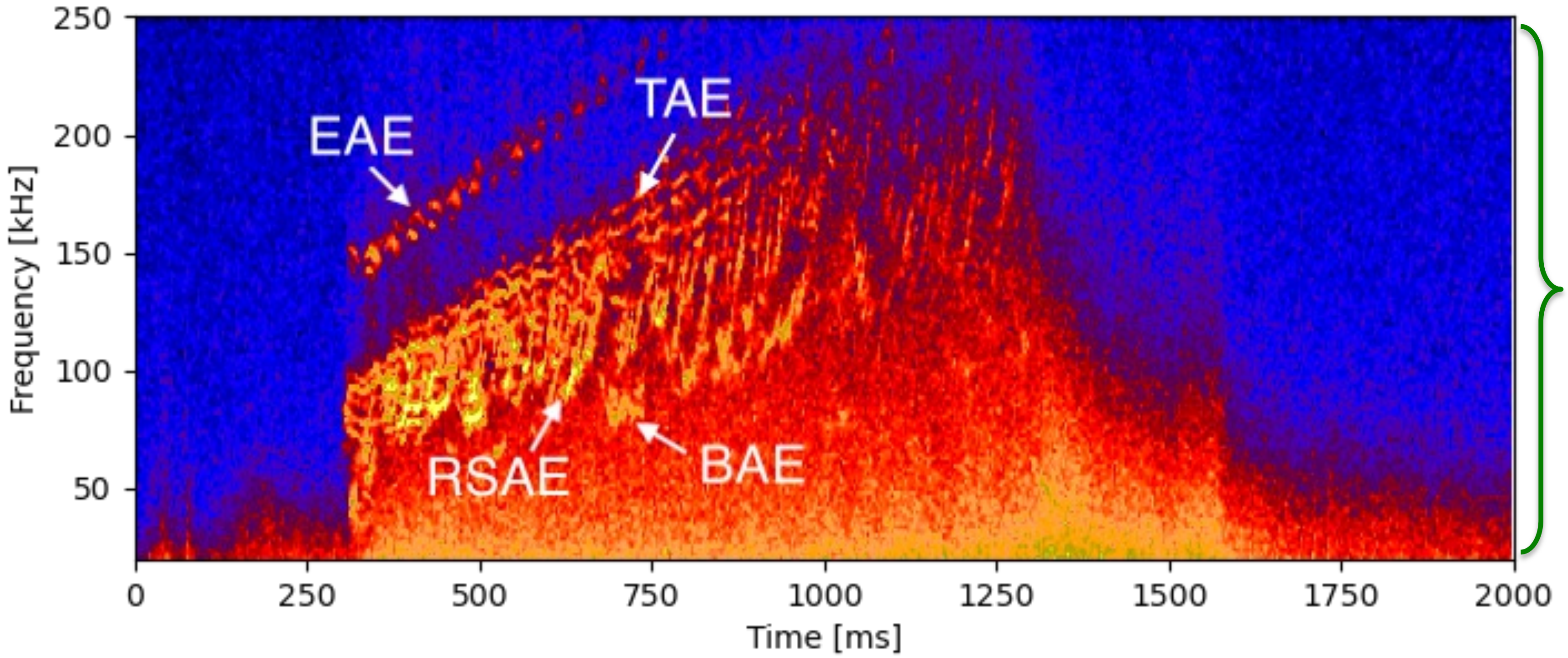
- **ML applications in Fusion Energy:**
  - Disruption mitigation
  - Surrogate models
  - Reactor design
  - Alfvén Eigenmode (AE) $\boxed{\text{detection}}$, prediction and control

This talk focuses on AE detection

- **Progress on classifying Alfvén Eigenmodes using Machine Learning is part of a large collaboration**
  - United States Department of Energy Project on ML for Real-time Fusion Plasma Behavior Prediction and Manipulation (DE-SC0021275)

Advantages of using the CO2 Interferometer to detect AEs

1. **Crosspower is useful to detect AEs by eye**



Recurrent Neural Networks presented in this talk reproduce the expert-made labels!

2. **Signals are available in real time for nearly every shot**

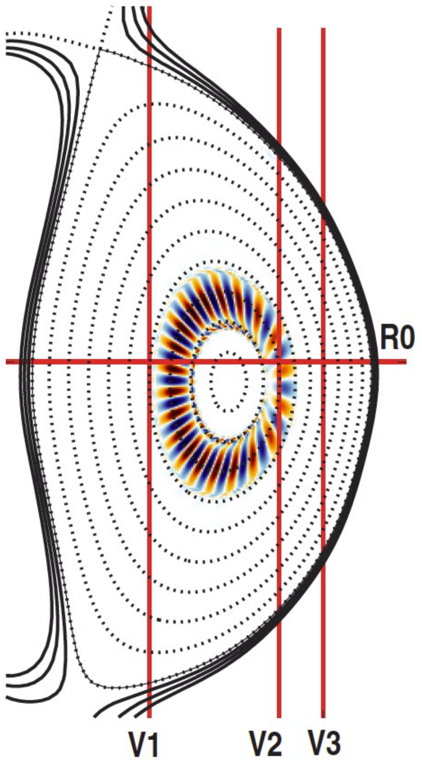
3. **Cutoff frequencies are not an issue unlike other sensors (ECE)**

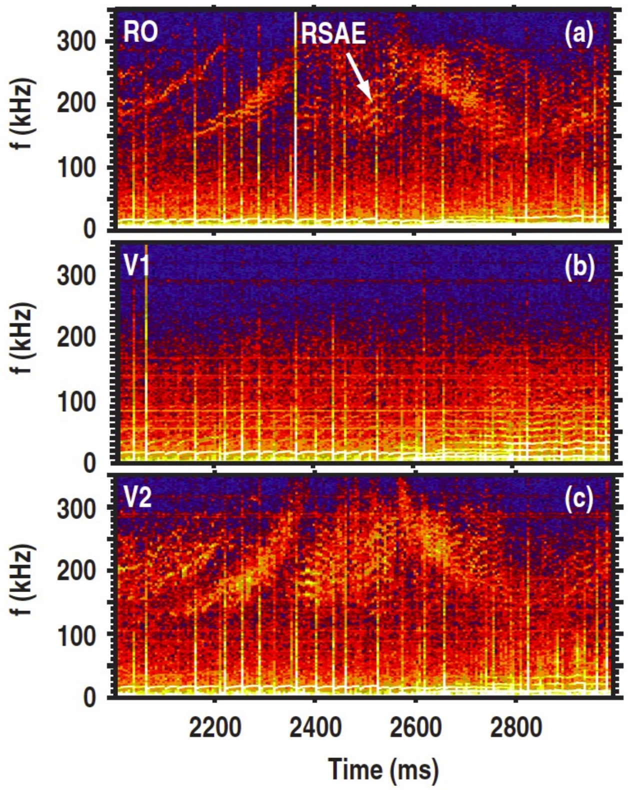
2009–2017 DIII-D AE Energetic Particle (AE-EP) Database is suitable for machine learning analysis [1]

- **Recent work produced a database of the occurrence of EAE, TAE, RSAE, BAE, LFM, and EGAM activity [1]**
  - 1139 discharges with timestamps during the first 1.9 sec
  - Timestamps sample plasma conditions and AE evolution

We classify the first 5 AE types

- **CO_2 interferometer measures line integrated electron density perturbations in the plasma**
  - Digitized for 9 seconds per discharge
  - Sampling rate is 1.67 MS/s.





[1] W.W. Heidbrink et al 2021 Nucl. Fusion 61 016029
Van Zeeland, M. A., et al 2006 Nuclear fusion 46.10 S880

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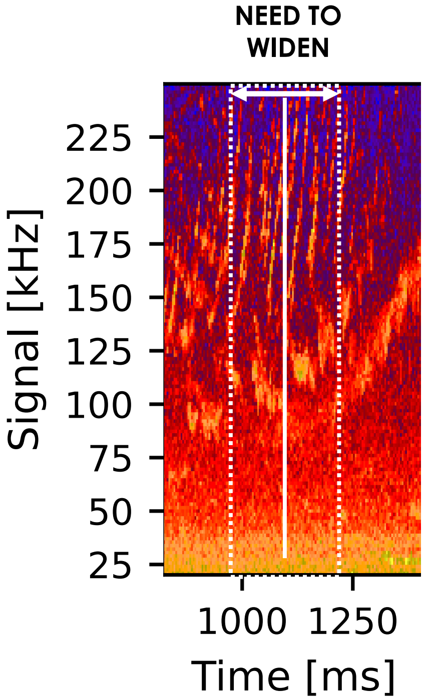
Challenges using the Large AE-EP Database are interesting

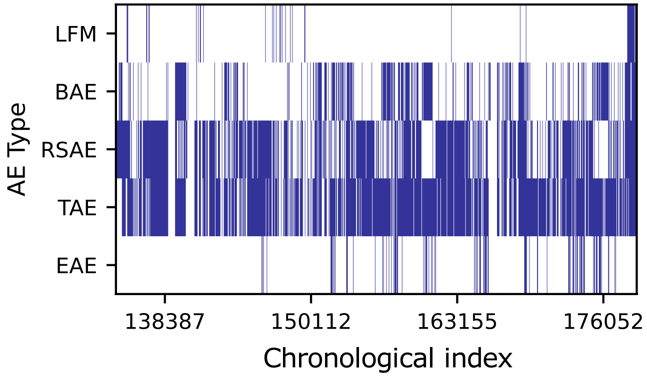
1. **Convert to times to binary flags**

2. **Need to widen re-assigned flag**

3. Class imbalance



AE Type	Expert Timestamp	ML Label
EAE	0	0
TAE	-1	0
RSAE	2	1
BAE	2	1
LFM	3	0



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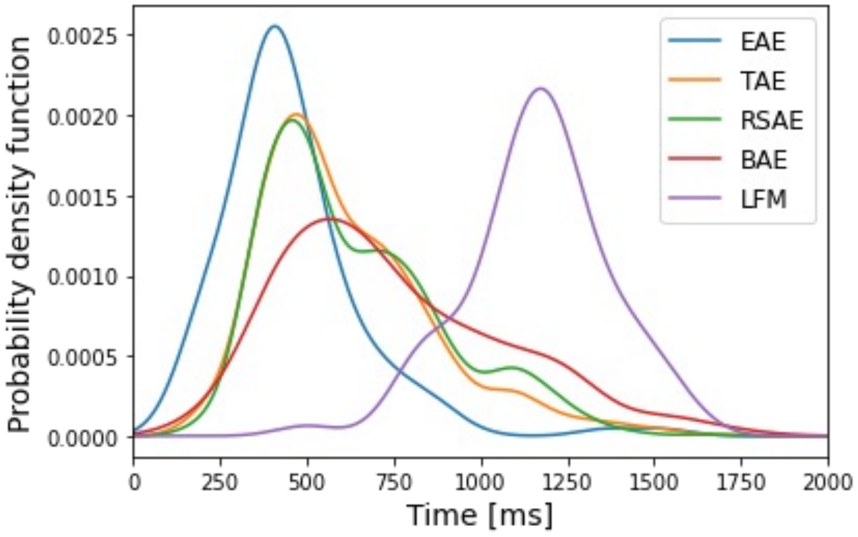
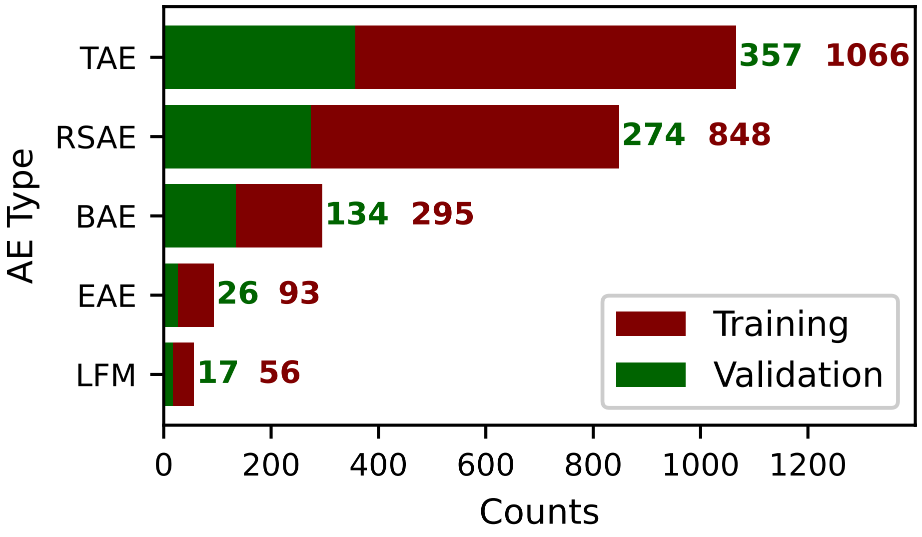


$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$

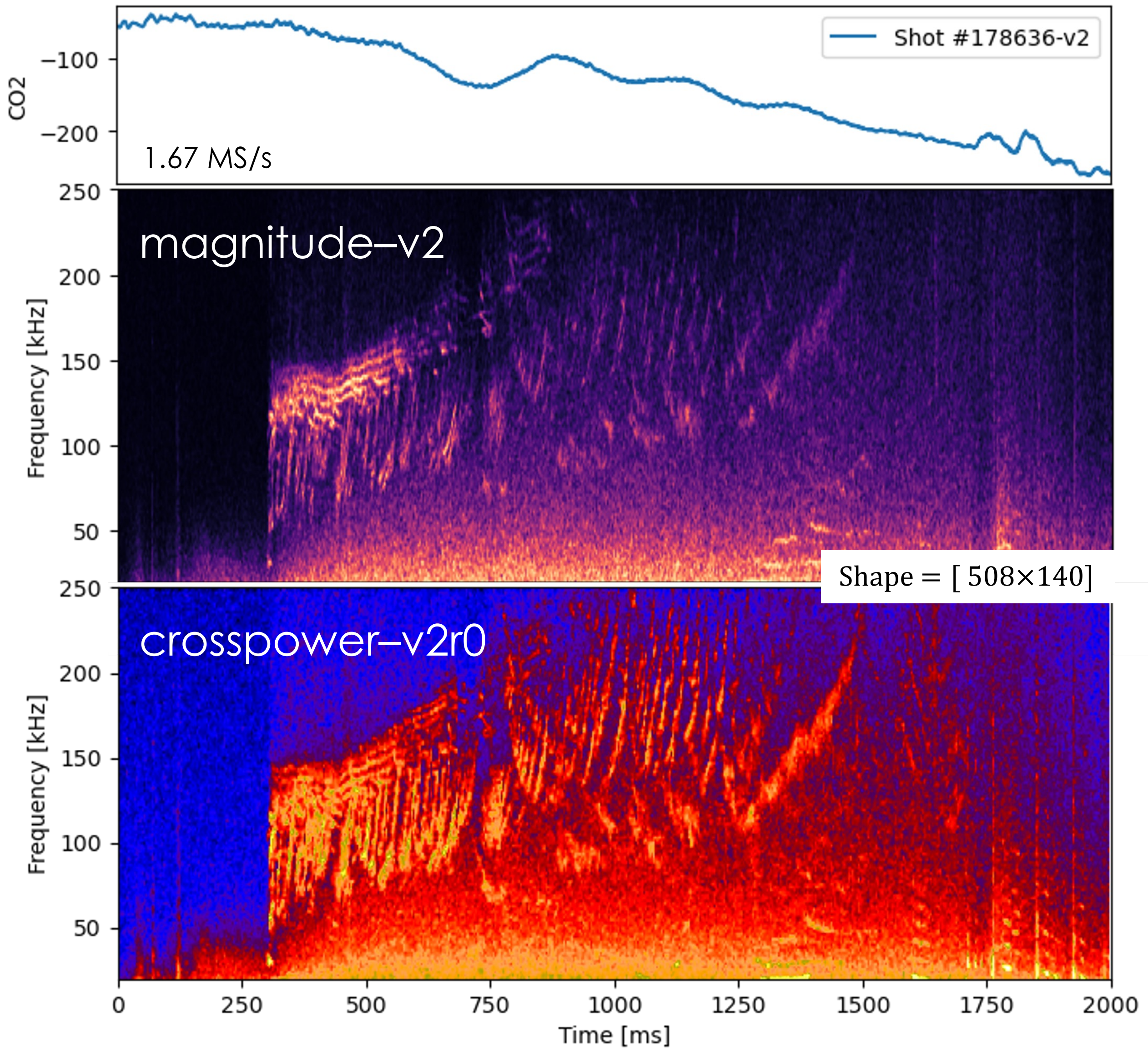
Since there is class imbalance, need to use TPR and FPR



The CO_2 interferometer signals are preprocessed for Machine Learning classification

- **Using time-domain CO_2 interferometer data is a challenge**
  – Sensitive to machine vibrations (difficult to globally normalize)
  – AEs are fast oscillating (activity can be undetectable)

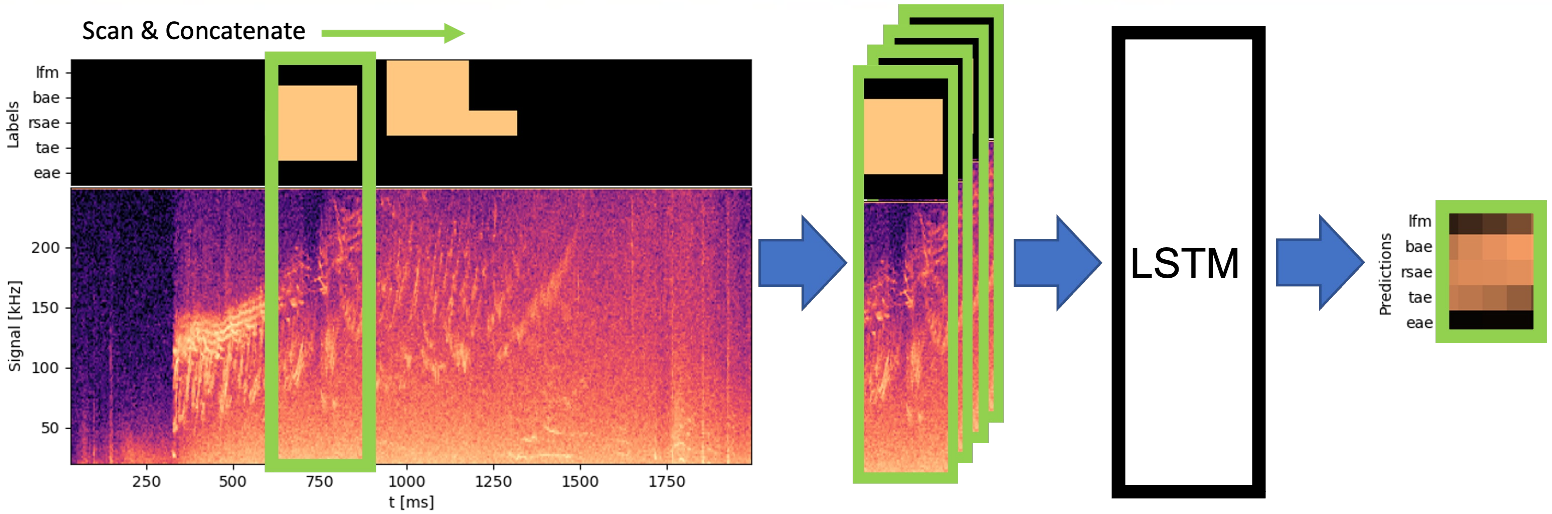
- **Use spectrograms instead!**
  – 4 simple magnitude spectrograms (`V1, V2, V3, R0`)
  – 10 crosspower spectrograms (`V1V1, V1V2, V1V3, V1R0, V2V2, V2V3, V2R0, V3V3, V3R0, R0R0`)

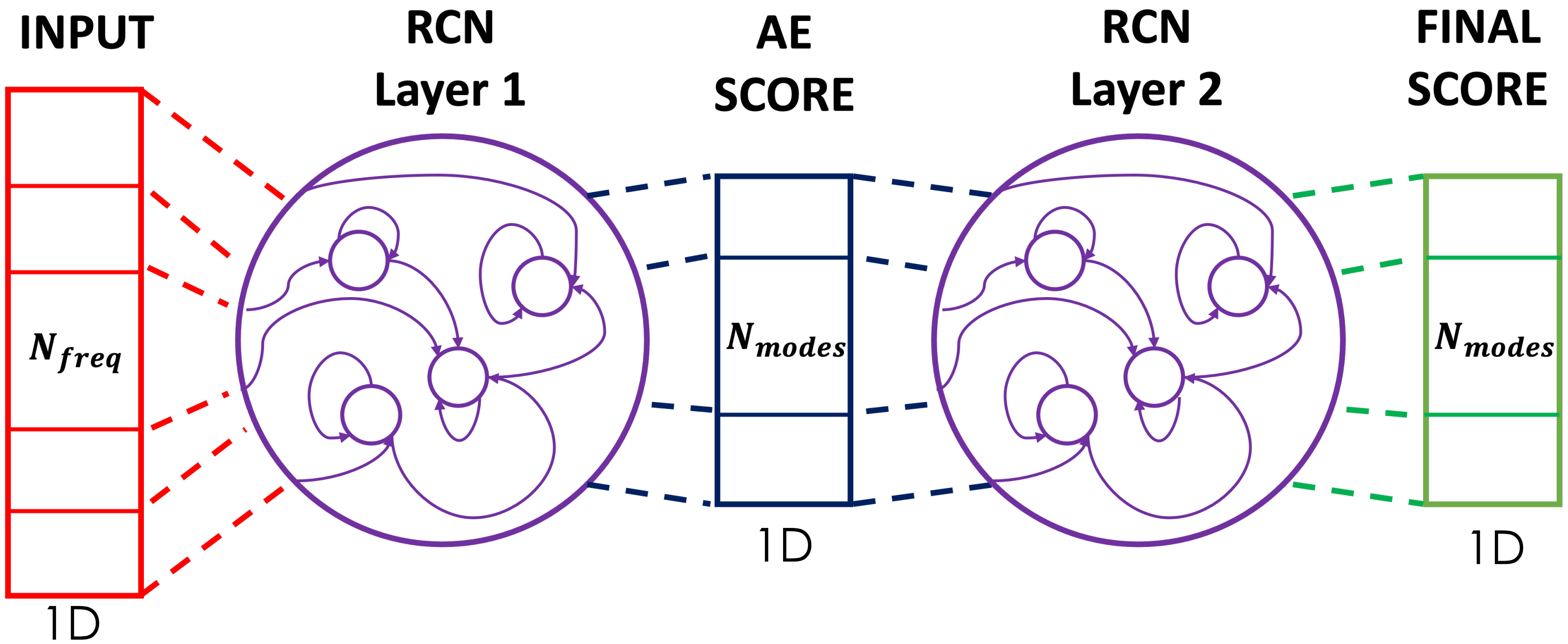


Garcia, Alvin, et al., 2023 International Joint Conference on Neural Networks (IEEE) (2023).

Recurrent Neural Networks work best

- **Multiple models trained**
  - Linear Regression
  - Multilayer Perceptron (MLP)
  - Convolutional Neural Networks
  - Long Short-term Memory Networks (LSTM)
  - Reservoir Computing Networks (RCN)

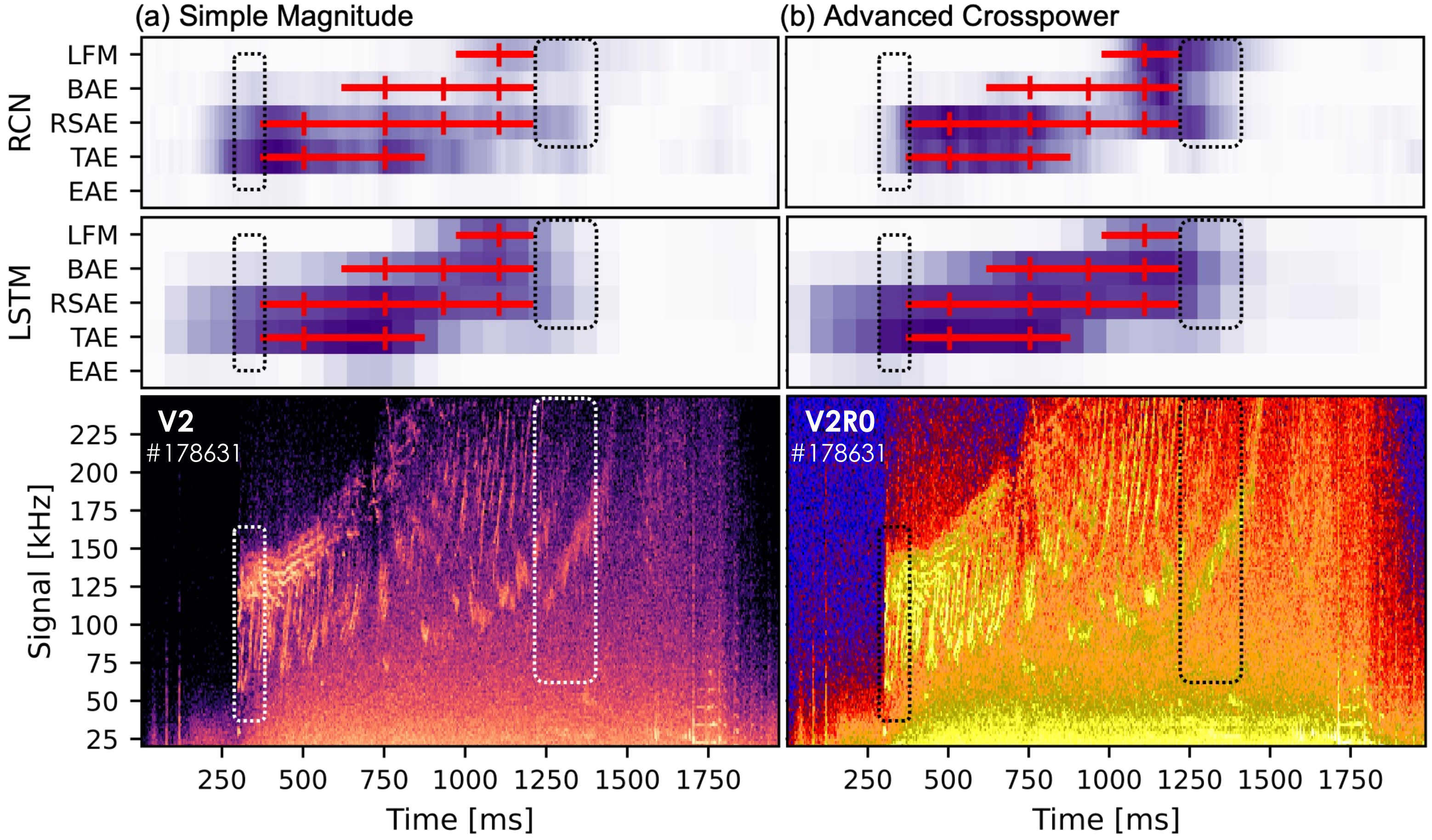




Garcia, Alvin, et al., 2023 International Joint Conference on Neural Networks (IEEE) (2023).

Compare the features of different inputs (simple magnitude and advanced crosspower spectrograms)

- **Red strikethroughs (expert label)**
- **Red vertical ticks (time stamps)**
- **Purple pixels (AE scores)**
- **Good agreement happens when purple overlaps with:**
  1. Red strikethroughs
  2. Dotted regions



Garcia, Alvin, et al., 2023 International Joint Conference on Neural Networks (IEEE) (2023).

Determine the best performing recurrent neural network (RCN or LSTM)

- **Threshold values per AE listed in table**
  - RCN: 0.05, 0.15, 0.11, 0.07 and 0.08
  - LSTM: 0.06, 0.13, 0.13, 0.10 and 0.07

- **True Positive Rate = 90%**

- **False Positive Rate = 14 %**

	SIMPLE				CROSSPOWER			
	RCN		LSTM		RCN		LSTM	
AE	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR
EAE	0.60	0.07	0.77	0.07	0.72	0.07	0.70	0.06
TAE	0.93	0.18	0.94	0.26	0.89	0.14	0.94	0.28
RSAE	0.94	0.19	0.91	0.29	0.89	0.15	0.92	0.28
BAE	0.80	0.23	0.79	0.23	0.69	0.13	0.79	0.27
LFM	0.81	0.05	0.80	0.10	0.64	0.02	0.78	0.07
TOTAL	0.90	0.14	0.90	0.18	0.85	0.10	0.90	0.18

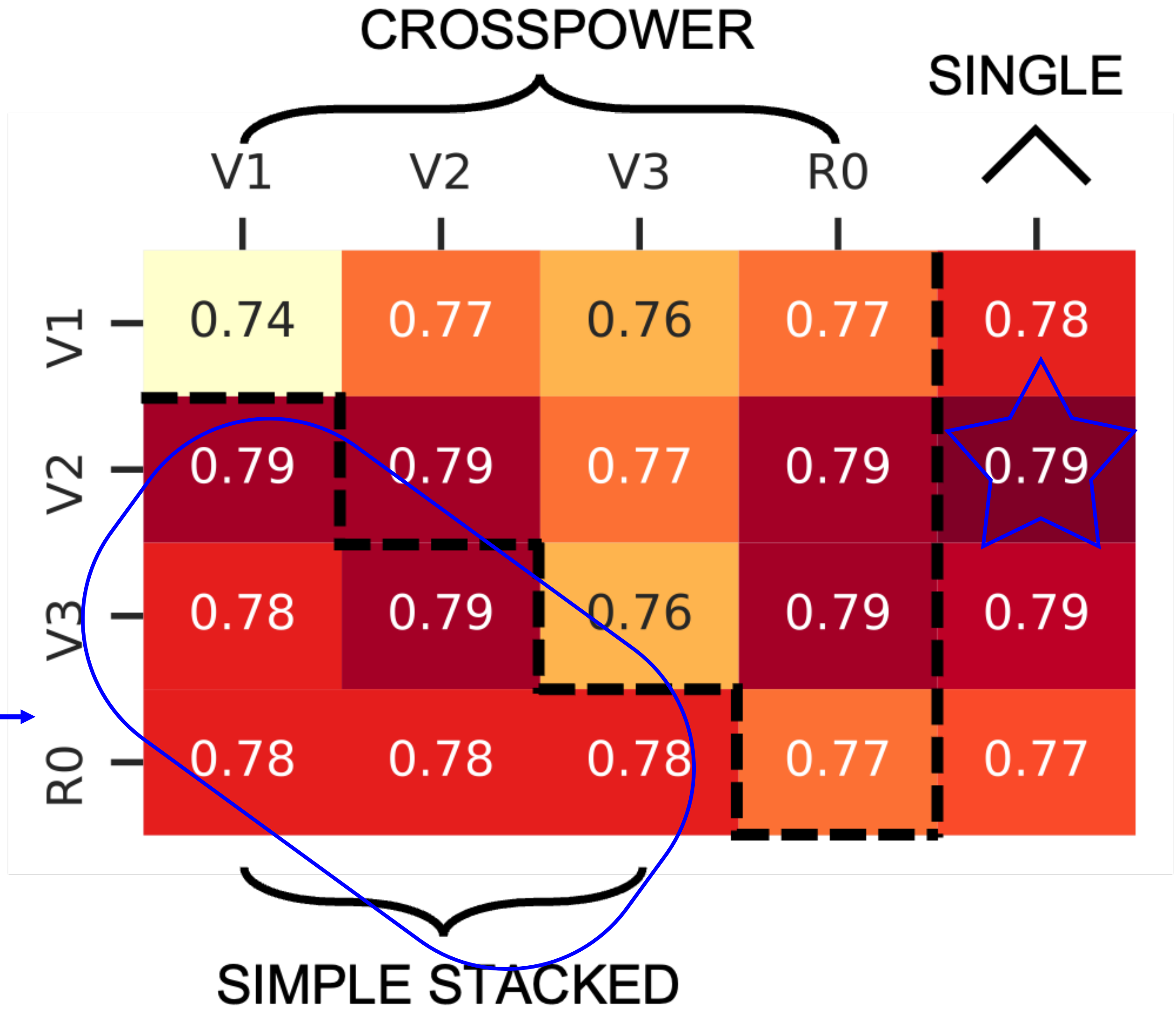
Garcia, Alvin, et al., 2023 International Joint Conference on Neural Networks (IEEE) (2023).

Compare stacking outputs, crosspower combinations and single chord predictions

- **F2 is used to evaluate chord comparisons**

$$F_2 = \frac{5}{\frac{4}{\text{Recall}} + \frac{1}{\text{Precision}}}$$

- **Almost everything works well**
- **Stacking two channels can sometimes be better than crosspower**
- **Chord V2 performs best (darkest red)**



Garcia, Alvin, et al., 2023 International Joint Conference on Neural Networks (IEEE) (2023).

Conclusions

- **Recurrent Neural Networks are trained using CO_2 interferometer data and the Large AE-EP Database**
- **Simple magnitude spectrograms can be used to reliably detect AEs**
- **RCN achieves highest performance (True Positive Rate = 90% and False Positive Rate = 14%)**
- **ML can be useful for nuclear fusion reactor designs (the vertical chord passing near center achieves highest performance in this work)**