Low-Latency Pipelines for LISA Mission A Deep Learning Approach

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Scientific Seminar of the Astronomical Institute,
Bucharest, March 15th 2023

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LISA CONSORTIUM

ISS LISA Science Group (ISS-Sci)

- Data analysis using NNs implemented on different hardware platforms
- Estimating the merging rate of BHs
- Waveform generation
- Building of GW source catalogues
- Multi messenger analysis of astrophysical sources
- Deep learning based low-latency alert pipeline for the detection and characterisation of GW from LISA data

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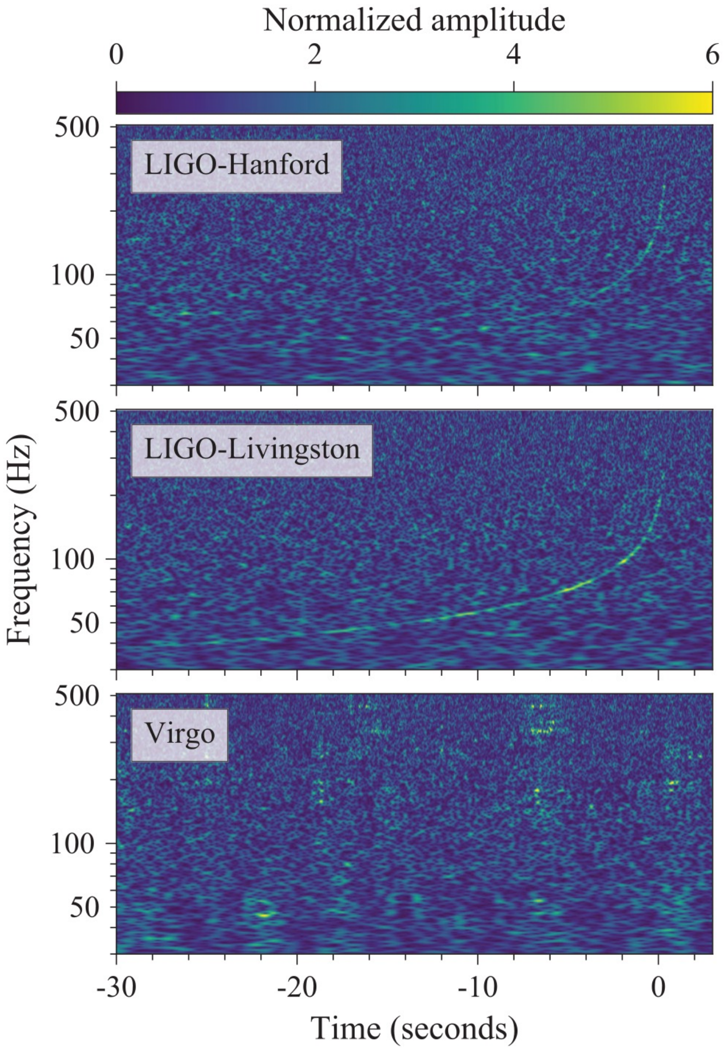
LISA CONSORTIUM

17 August 2017, 12:41:04 UTC

GW170817

17 August 2017, 12:41:04 UTC

GW170817



17 August 2017, 12:41:04 UTC

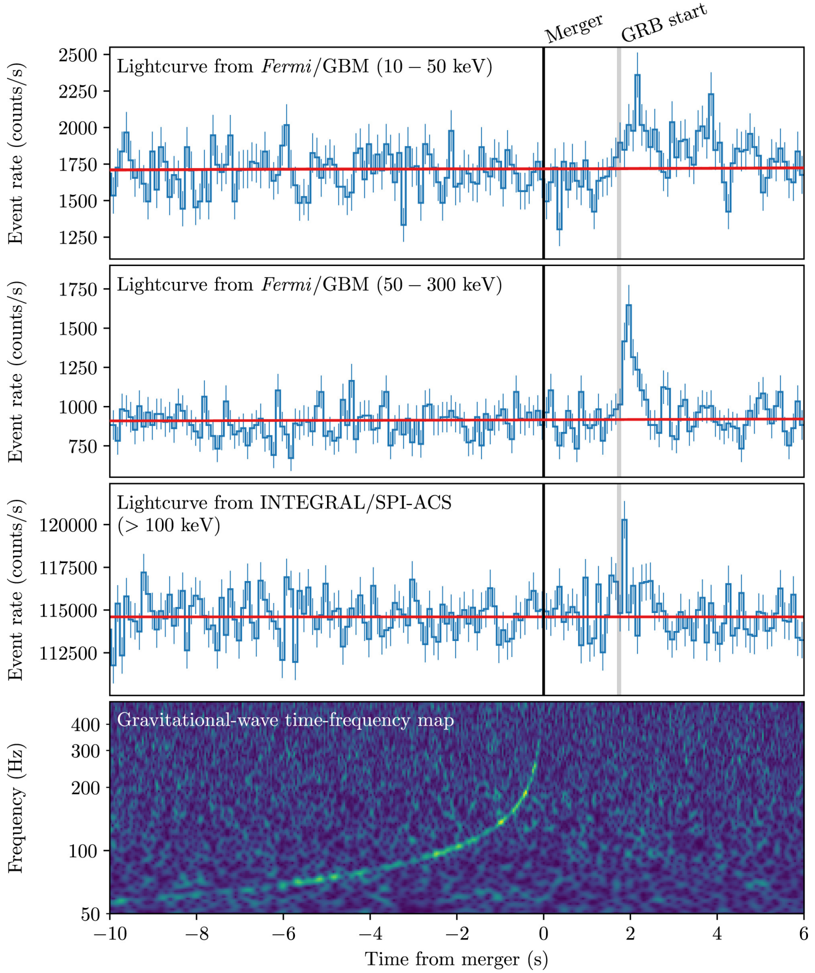
GW170817

$\downarrow$ + 1.7 sec

GRB170817A

+ 2 sec

GRB170817A



Credits: Abbott, B. P., et al. "Gravitational Waves and Gamma Rays from a Binary Neutron Star Merger: GW170817 and GRB 170817A." 2017, ApJL, [848, L13].

+ 2 sec

GRB170817A

+ 10.9 h

SSS 17a/AT 2017 GFO

+ 10.9 h

SSS 17a/AT 2017 GFO

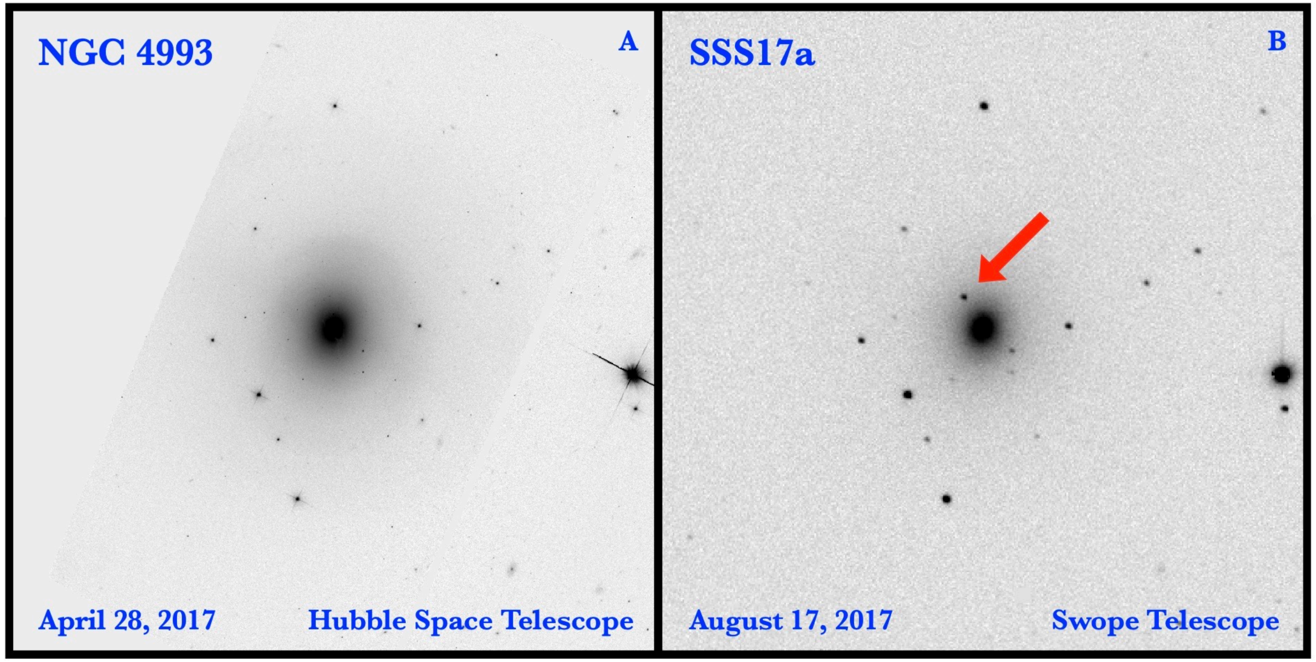
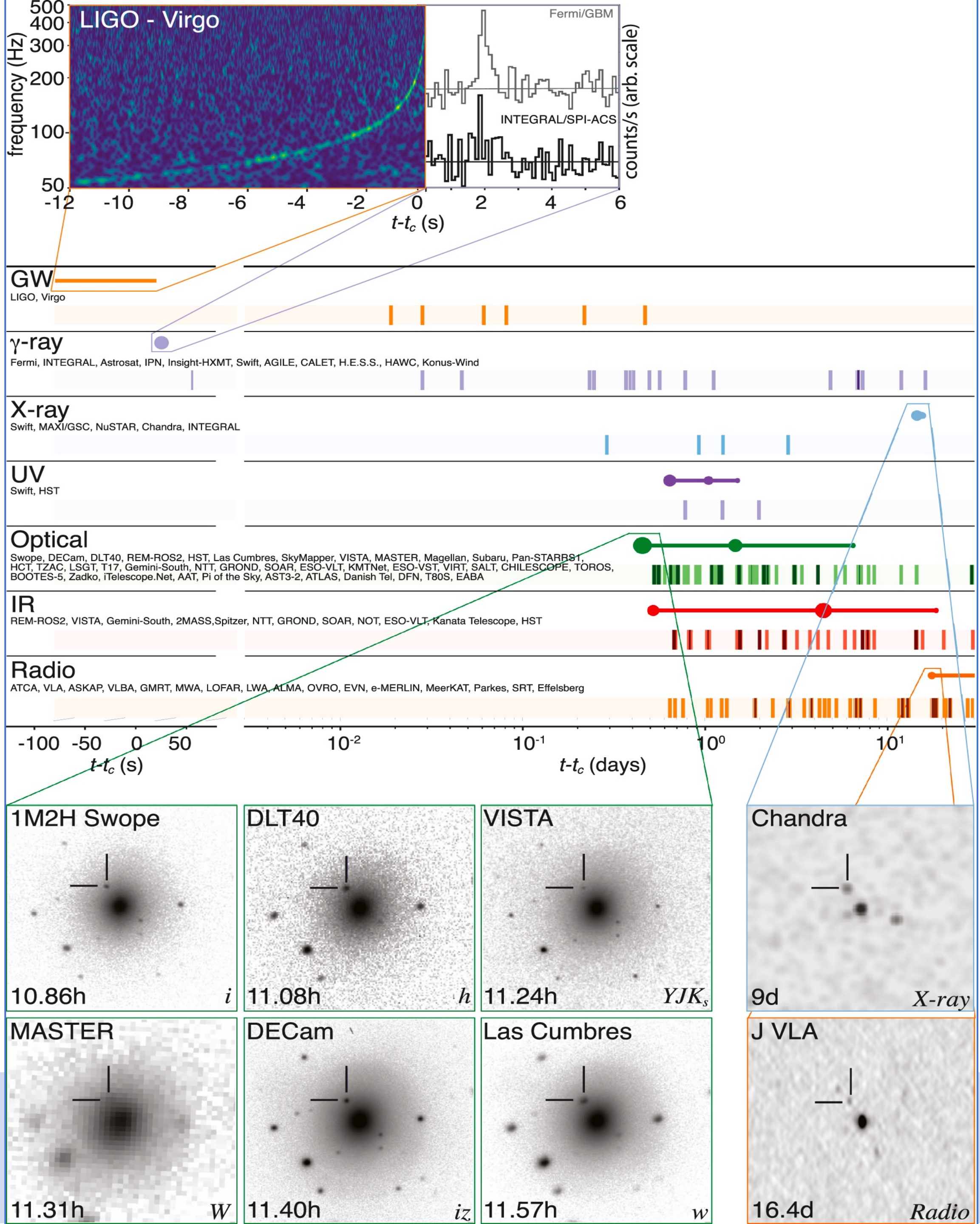


Figure 4 **3′ × 3′ images centered on NGC 4993 with North up and East left.** *Panel A*: *Hubble Space Telescope* F606W-band (broad *V*) image from 4 months before the GW trigger (*25, 35*). *Panel B*: Swope image of SSS17a. The *i*-band image was obtained on 2017 August 17 at 23:33 UT by the Swope telescope at Las Campanas Observatory. SSS17a is marked with the red arrow. No object is present in the *Hubble* image at the position of SSS17a (*25, 35*).

***CREDITS: D.A. COULTER ET AL.,* "Swope Supernova Survey 2017a (SSS17a), the optical counterpart to a gravitational wave source*", SCIENCE*, 2017, vol 358, Issue 6370, pp. 1556-1558**

FIG. 1: Timeline of the discovery of GW170817, GRB 170817A, and SSS17a/AT 2017gfo; as well as the subsequent follow-up observations relative to the merger time t_c. The the rows are separated by the observation band (gravitational and electromagnetic), and the names of the relevant instruments and observing teams are given in each row. The shaded dashes represent times when the information was reported in a GCN circular. Representative observations in each band are shown with solid circles, with the size approximately scaled with their brightness. Solid lines indicate when the source was detectable by at least one telescope. Samplings of the measured signal are given by the subplots with lines highlighting their placement on the timeline.



Credits: Justin Conor Flaherty, "
Multimessenger Observations of Neutron Star Merger GW170817"
Thesis · August 2020
DOI: 10.13140/RG.2.2.21742.02882

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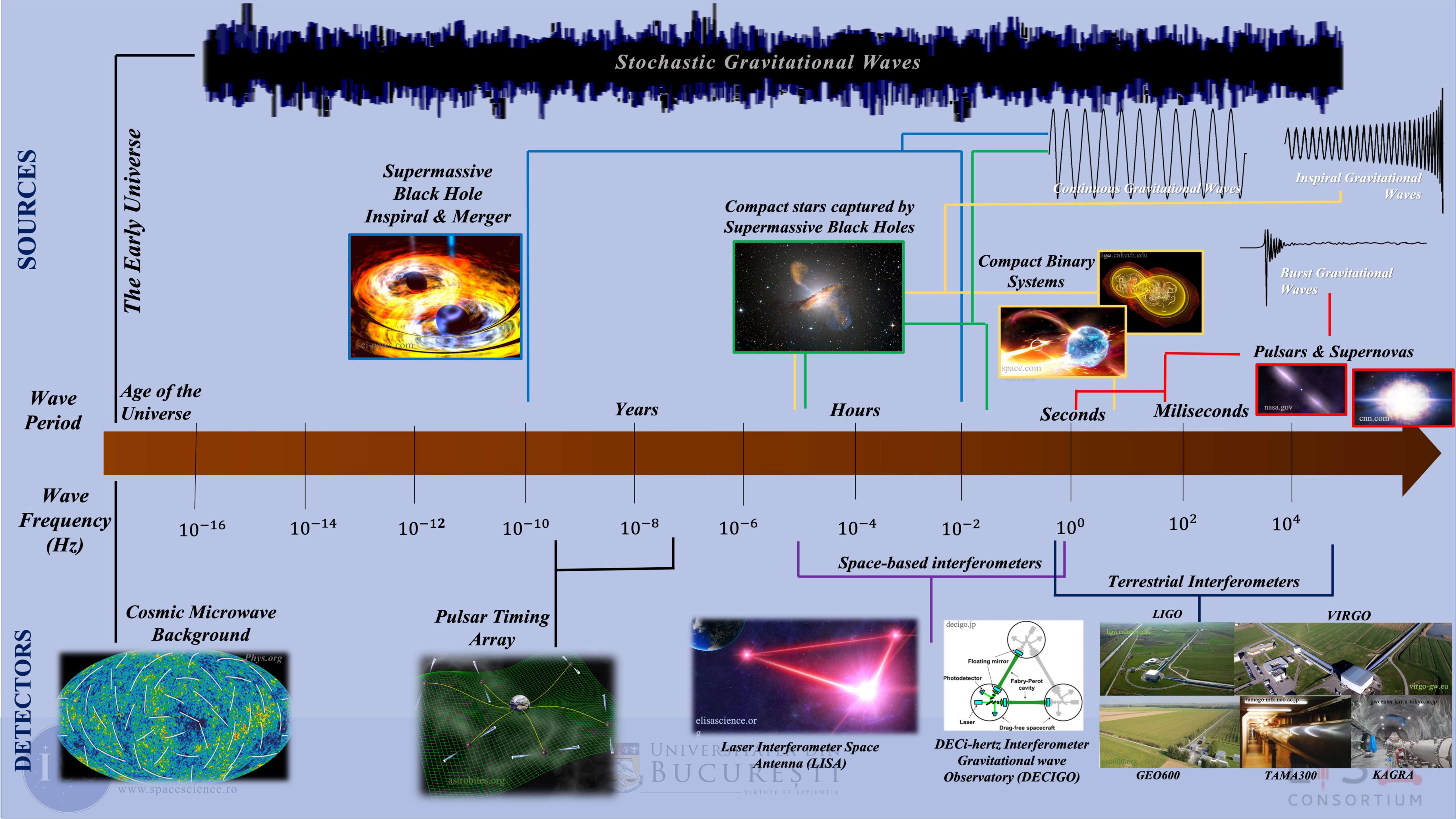
Stochastic Gravitational Waves
SOURCES
The Early Universe
Supermassive Black Hole Inspiral & Merger
sci-news.com
Compact stars captured by Supermassive Black Holes
Continuous Gravitational Waves
Inspiral Gravitational Waves
Compact Binary Systems
ligo.caltech.edu
space.com
Burst Gravitational Waves
Pulsars & Supernovas
nasa.gov
cnn.com
Wave Period
Age of the Universe
Years
Hours
Seconds
Miliseconds
Wave Frequency (Hz)
10^{-16}
10^{-14}
10^{-12}
10^{-10}
10^{-8}
10^{-6}
10^{-4}
10^{-2}
10^{0}
10^{2}
10^{4}
Space-based interferometers
Terrestrial Interferometers
DETECTORS
Cosmic Microwave Background
Phys.org
Pulsar Timing Array
astrobites.org
elisascience.org
Laser Interferometer Space Antenna (LISA)
decigo.jp
Floating mirror
Photodetector
Fabry-Perot cavity
Laser
Drag-free spacecraft
DECi-hertz Interferometer Gravitational wave Observatory (DECIGO)
LIGO
VIRGO
virgo-gw.eu
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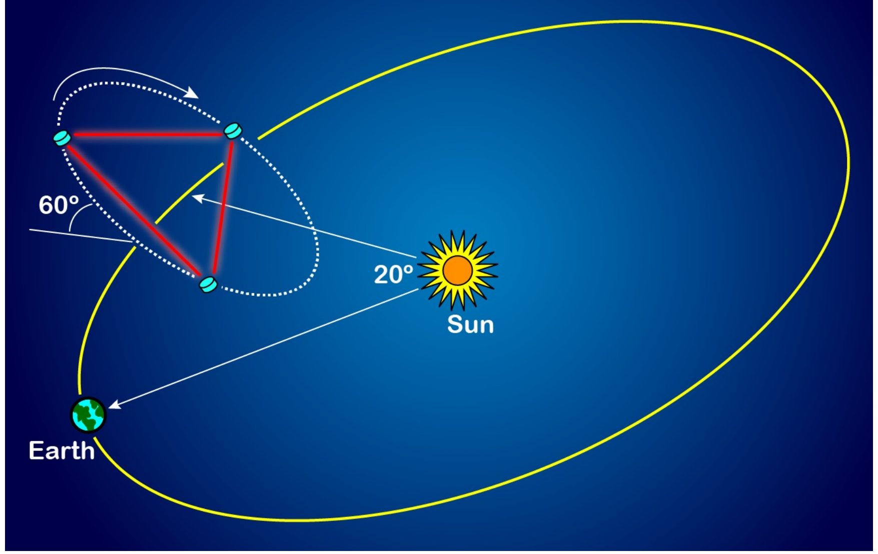
LISA Mission



- The LISA (Laser Interferometer Space Antenna) mission will be one of the first space-based gravitational wave observatories.

- The observatory will consist of three satellites connected by laser signals and will be capable of in-depth studies related to various physics phenomena (from black hole formation to the expansion rate of the Universe).

- Most importantly, LISA, with the help of gravitational waves, will "listen" to different evolution stages of the Universe.

A Deep Learning Toolkit for Gravitational Waves Analysis (GWEEP)

- Develop and test different types of neural network models, configurations and pre-processing approaches.

OUR APPROACH (so far):

Multilayer Perceptron (MLP)

Convolutional (CNN)

Multilayer Perceptron (MLP)

Input Layer
Dense Hidden Layer #1
Dense Hidden Layer #2
Dense Hidden Layer #3
Dense Hidden Layer #4
Dense Hidden Layer #5
Dense Layer #6
Dense Output Layer

Convolutional (CNN)

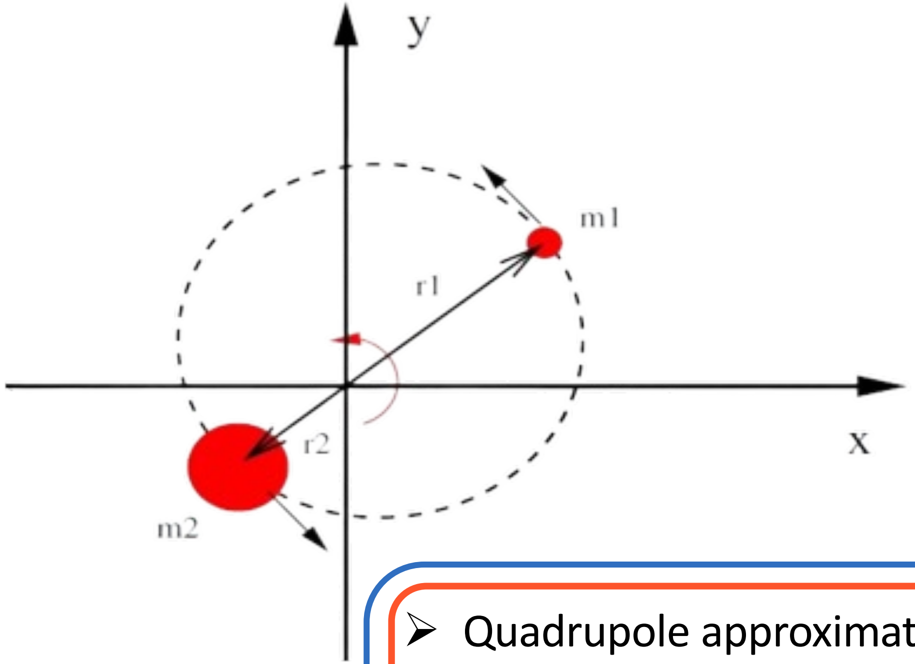
Input Layer
Convolutional Hidden Layer #1
Convolutional Hidden Layer #2
Convolutional Hidden Layer #3
Convolutional Hidden Layer #4
Flatten Layer #5
3 x Dense Hidden Layer #5
Dense Output Layer

- Develop and test different types of neural network models, configurations and pre-processing approaches.
  - Generate simplified data set

OUR APPROACH (so far):

Multilayer Perceptron (MLP)

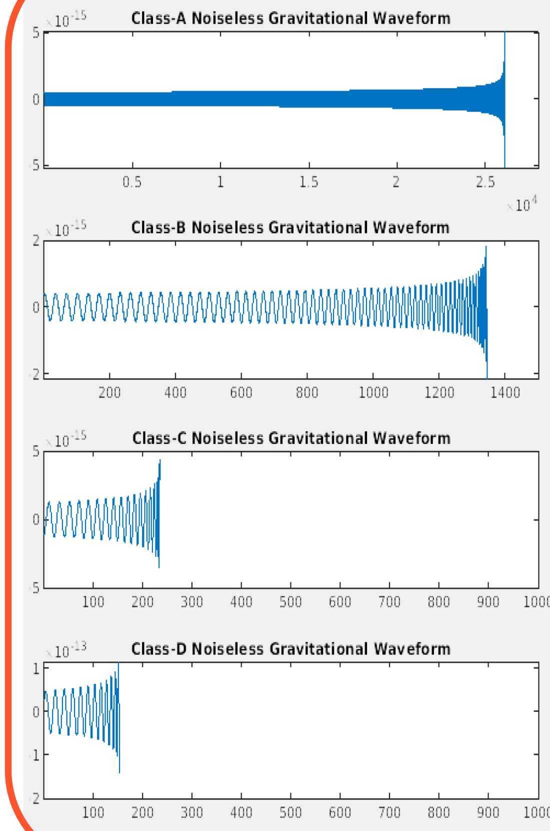
Convolutional (CNN)

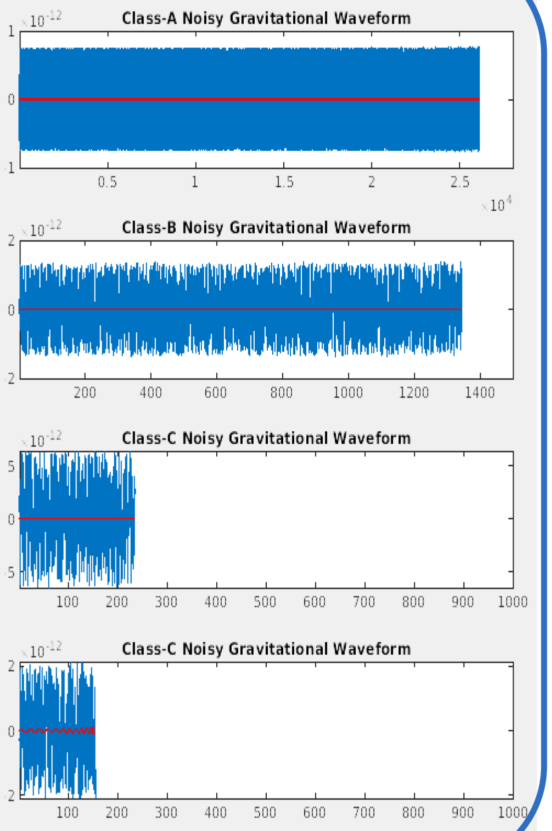


https://www.mathworks.com/matlabcentral/fileexchange/116105-quick-gravitational-wave-data-generation

- Quadrupole approximation
- Non-spinning point-masses
- Circular orbits

- **Additive Gaussian Random Noise**





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Multilayer Perceptron (MLP)

Convolutional (CNN)

Time series waveforms of various lengths

Mean PSD (Power Spectral Density)

Peak Frequency

Maximum Amplitude

Minimum Amplitude

Signal Amplitude Mean

Standard Deviation of the raw signal

Quartile 25%

Quartile 50%

Quartile 75%

Multilayer Perceptron (MLP)

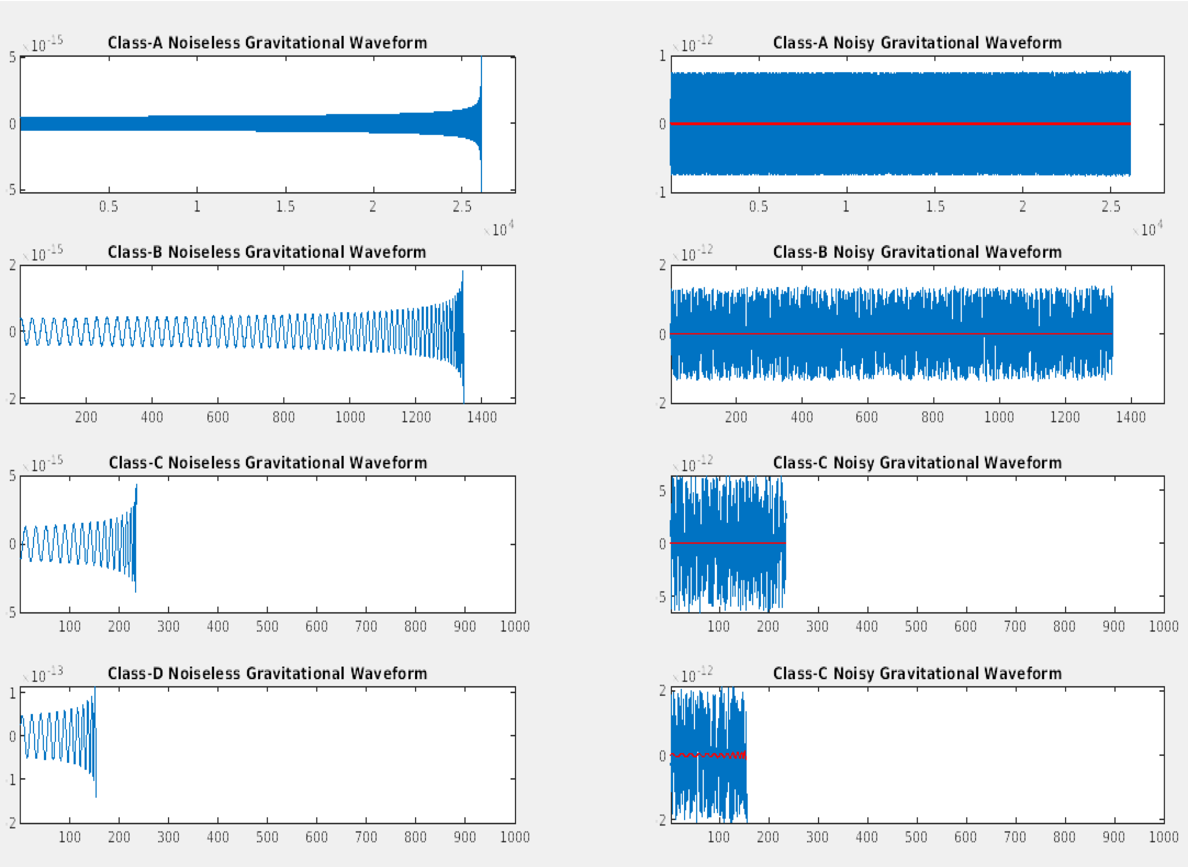
Convolutional (CNN)

The GW Dataset
1.960.959 total samples

out of which:

800.000 (40%): **train**

1.160.959 (60%): **inference**



5 x Classes of adjecent mass ratios:

A (q = 1 – 300)

B (q = 301 – 749)

C (q = 750 – 1200)

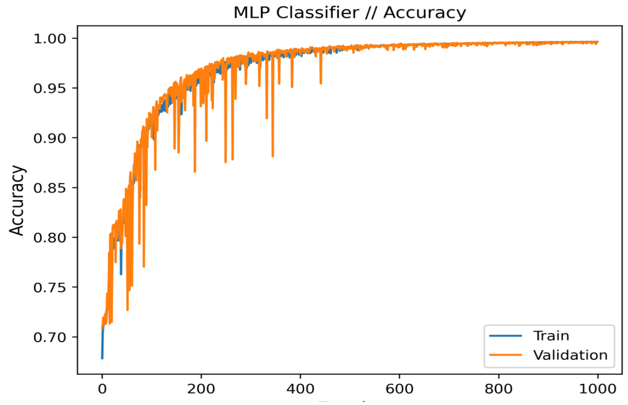
D (q = 1201 – 1501)

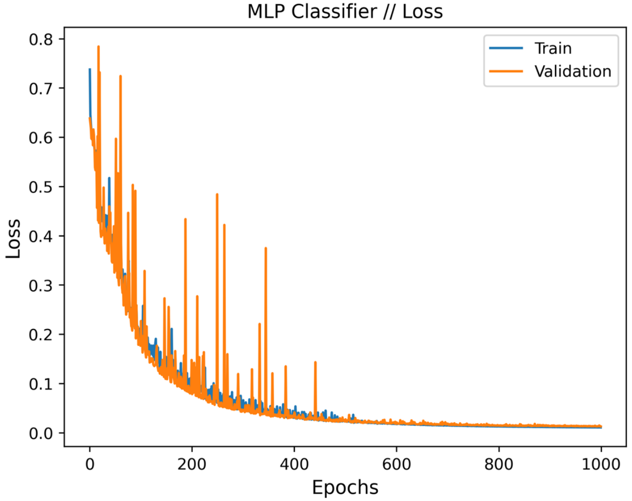
N (Noise)

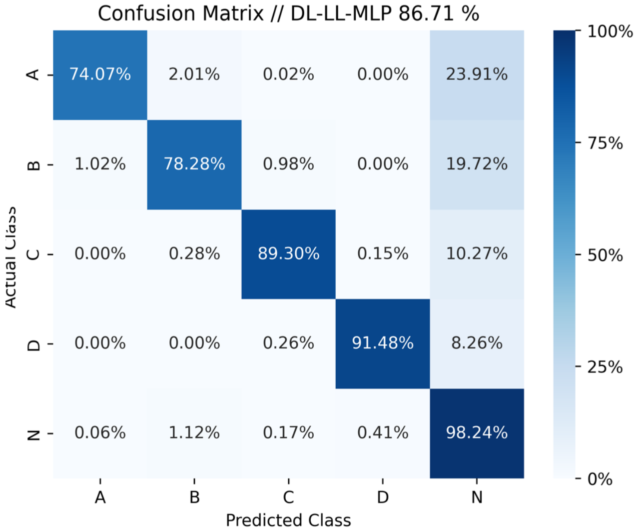
Min-Max Feature Standardization:

$$X = \frac{features - min}{max - min}$$

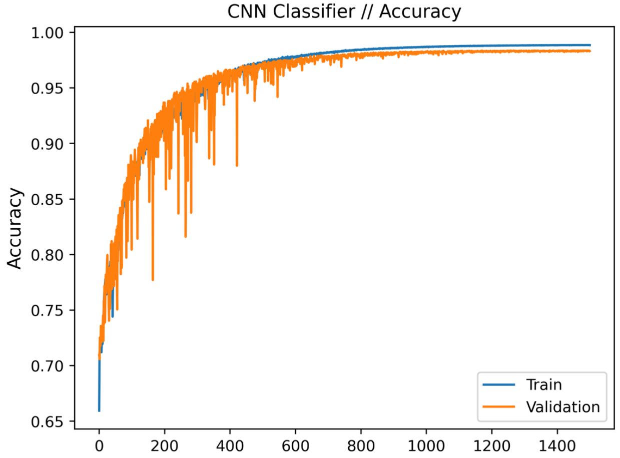
Multilayer Perceptron (MLP)

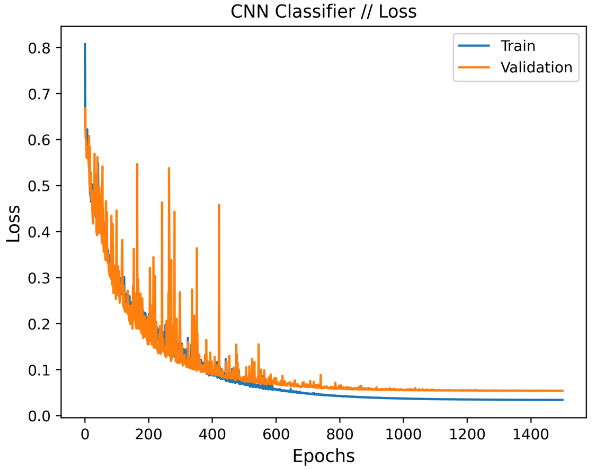


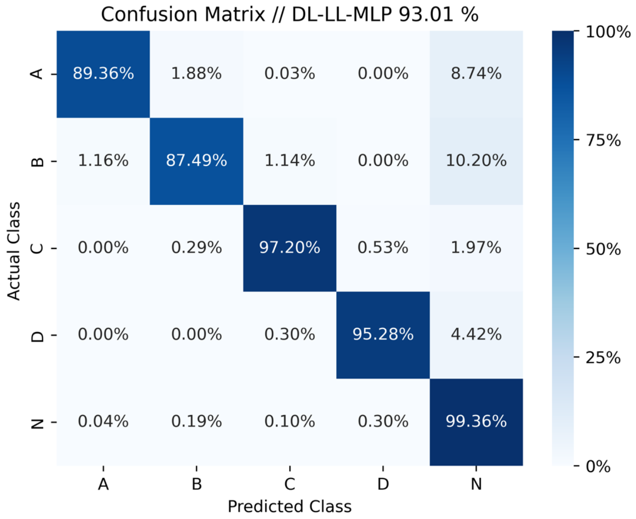




Convolutional (CNN)







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Multilayer Perceptron (MLP)

Convolutional (CNN)

Nvidia RTX 3050 Ti

Technology = 8 nm

RT Cores = 20

Tensor Cores = 80

Core Clock = 1035 MHz

VRAM = GDDR6

VRAM size = 4 Gb

Bandwidth = 192 Gb/s

Mem. Clock = 1500 MHz

FP32 = 5.299 TFLOPS

Nvidia Tesla T4

Technology = 12 nm

RT Cores = 40

Tensor Cores = 320

Core Clock = 1590 MHz

VRAM = GDDR6

VRAM Size = 16 Gb

Bandwidth = 320 Gb/s

Mem. Clock = 1250 Mhz

FP32 = 8.141 TFLOPS

Apple M1 Neural Engine

Technology = 5 nm

CPU Cores = 8

GPU Cores = 8

GPU Clock = 1278 MHz

CPU Clock = 3200 MHz

Neural Engine = 16 Cores

Unified Memory = 16 Gb

Memory = LPDDR4X

FP32 = 2.6 TFLOPS

AMD EPYC 7551P

Technology = 14 nm

Cores = 32

Threads = 64

Core Clock = 2000 MHz

Boost Clock = 3000 MHz

RAM = DDR4

RAM Size = 128 Gb

RAM Clock = 2666 Mhz

Multilayer Perceptron (MLP)

Convolutional (CNN)

Credits: V.A. Bâsceanu

Models	Platform	Memory	Cores	FP32	Lib	Training Time	Inference Time	Inference Accuracy
DL-LL CNN	Nvidia RTX 3050 Ti	GDDR6/ 4Gb	RT 20/ Tensor 80	5.299 TFLOPS	Keras/ Tensorflow	87 min 10.15 sec	2 min 45.92 sec	96.16 %
DL-LL CNN	Nvidia Tesla T4	GDDR6/ 16Gb	RT 40/ Tensor 320	8.141 TFLOPS	Keras/ Tensorflow	*379 min 15 sec	1 min 29.4 sec	96.40 %
DL-LL CNN	Apple M1 Neural Engine	LPDDR4X/ 16Gb	Neural Engine 16 Cores	2.6 TFLOPS	Keras/ Tensorflow	1099 min 10.20 sec	2 min 55.15 sec	95.27 %
DL-LL CNN	AMD EPYC 7551P	DDR4/ 128Gb	32 Cores/ 64 Threads	---	Keras/ Tensorflow	680 min 20.40 sec	1 min 51.2 sec	95.61 %
DL-LL MLP	Nvidia RTX 3050 Ti	GDDR6/ 4Gb	RT 20/ Tensor 80	5.299 TFLOPS	Keras/ Tensorflow	57 min 29.51 sec	2 min 25.77 sec	83.76%
DL-LL MLP	Nvidia Tesla T4	GDDR6/ 16Gb	RT 40/ Tensor 320	8.141 TFLOPS	Keras/ Tensorflow	*369 min 45.03 sec	42.03 sec	84.27 %
DL-LL MLP	Apple M1 Neural Engine	LPDDR4X/ 16Gb	Neural Engine 16 Cores	2.6 TFLOPS	Keras/ Tensorflow	239 min 49.85 sec	1 min 31.34 sec	84.61 %
DL-LL MLP	AMD EPYC 7551P	DDR4/ 128Gb	32 Cores/ 64 Threads	---	Keras/ Tensorflow	381 min 21.59 sec	2 min 34.22 sec	82.54 %

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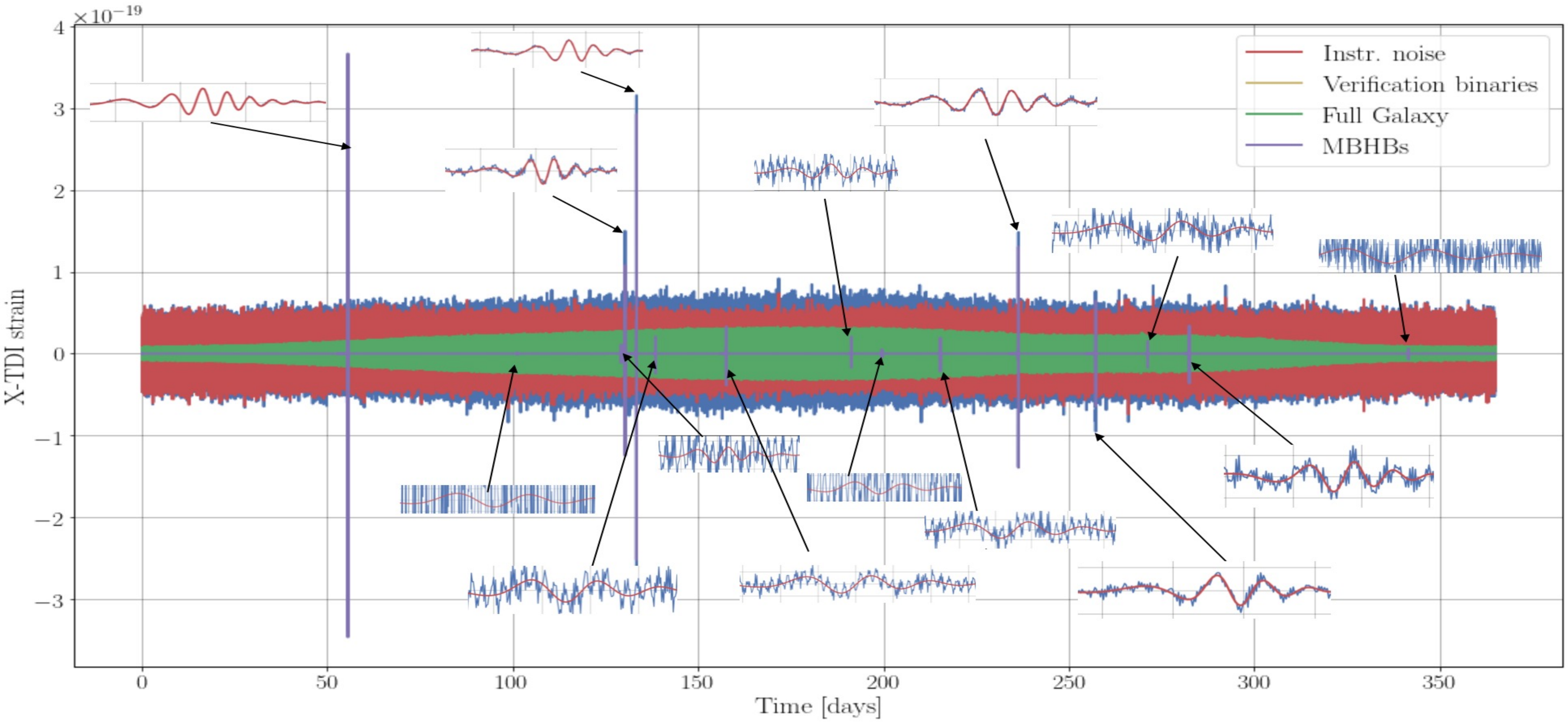
- Test on (much) more realistic data

SANGRIA DATA CHALLENGE

https://lisa-ldc.lal.in2p3.fr/challenge2a



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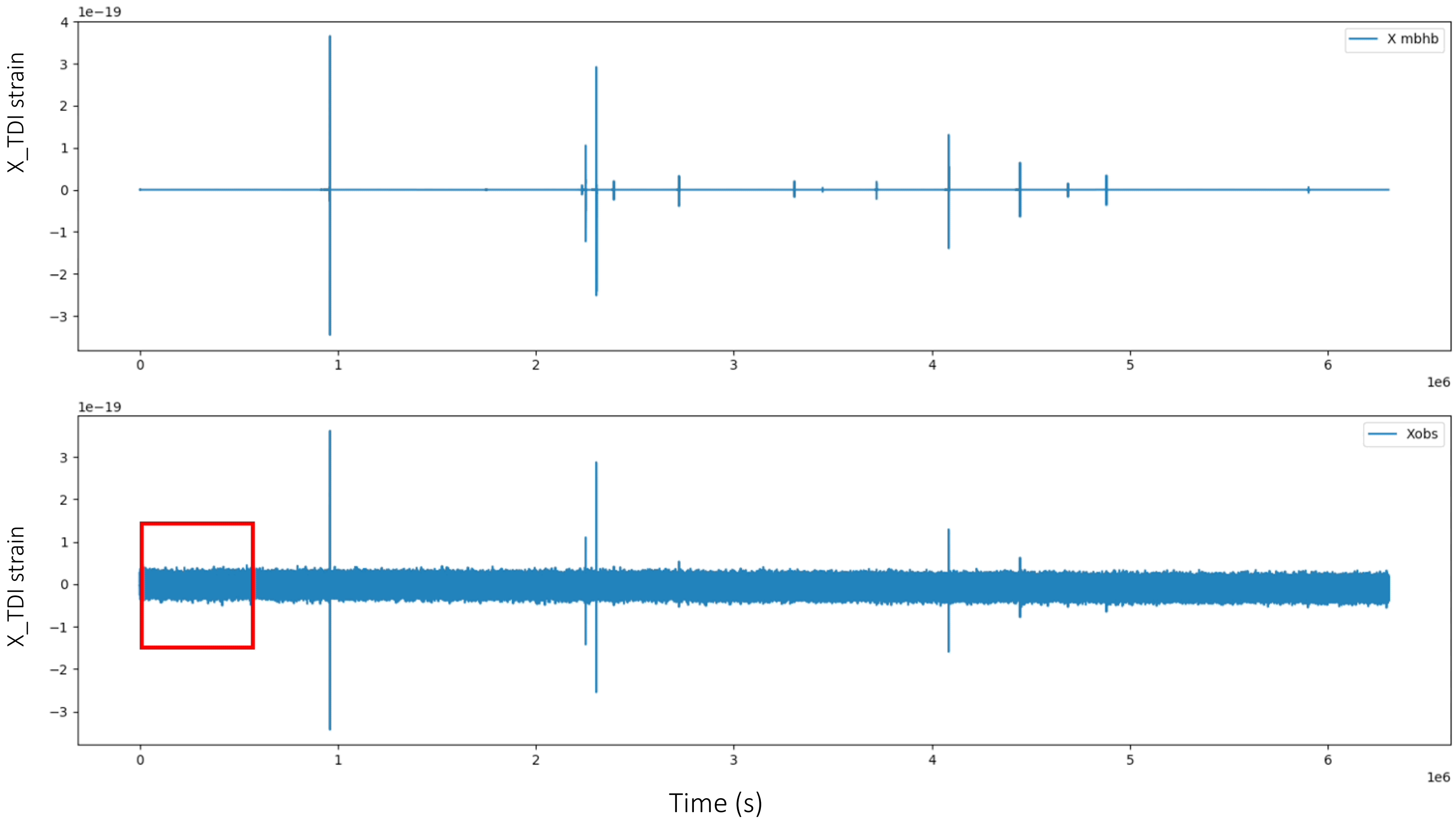
SANGRIA TRAIN DATA

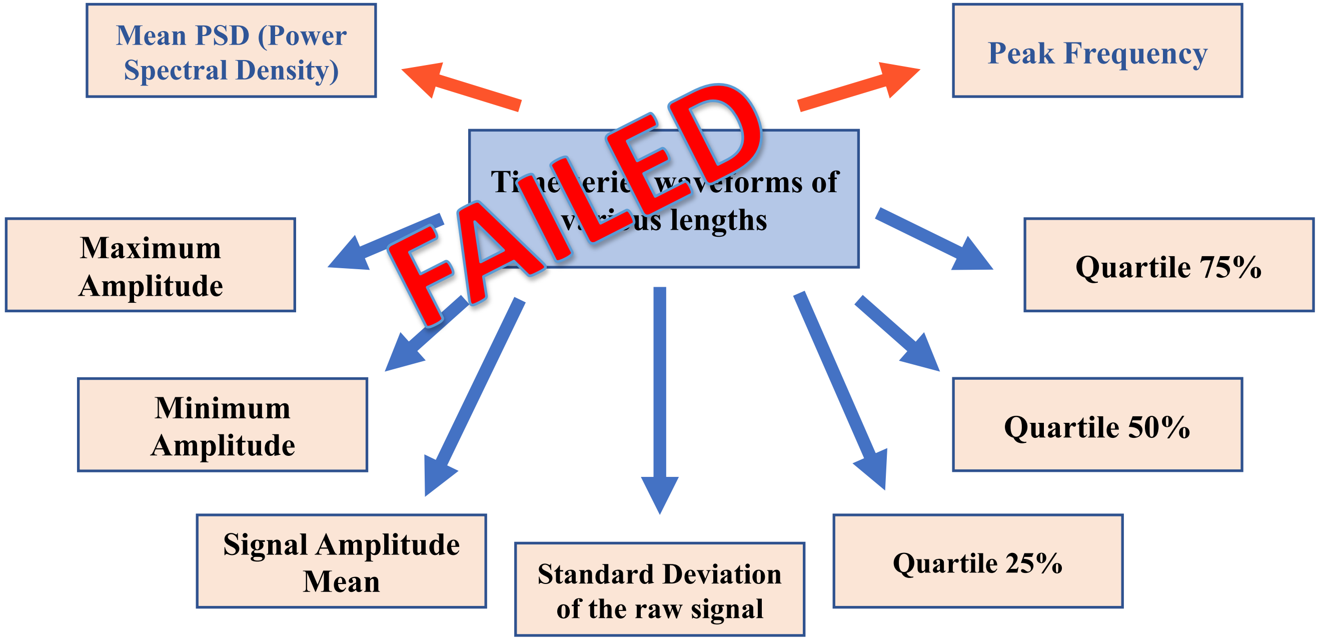


We use overlapping moving window to generate multiple sequences.

Multilayer Perceptron (MLP)

Convolutional (CNN)

Recurrent (RNN)



10 features into the input layer:

Michelson (X, Y, Z) & Orthogonal (A, E) TDI combinations + spectral entropies of those above

Labels: 0 or 1. Each data point is “manually” labeled in the beginning.

Recurrent (RNN)

Input feature DF split into train (68%) and test datasets (32%)

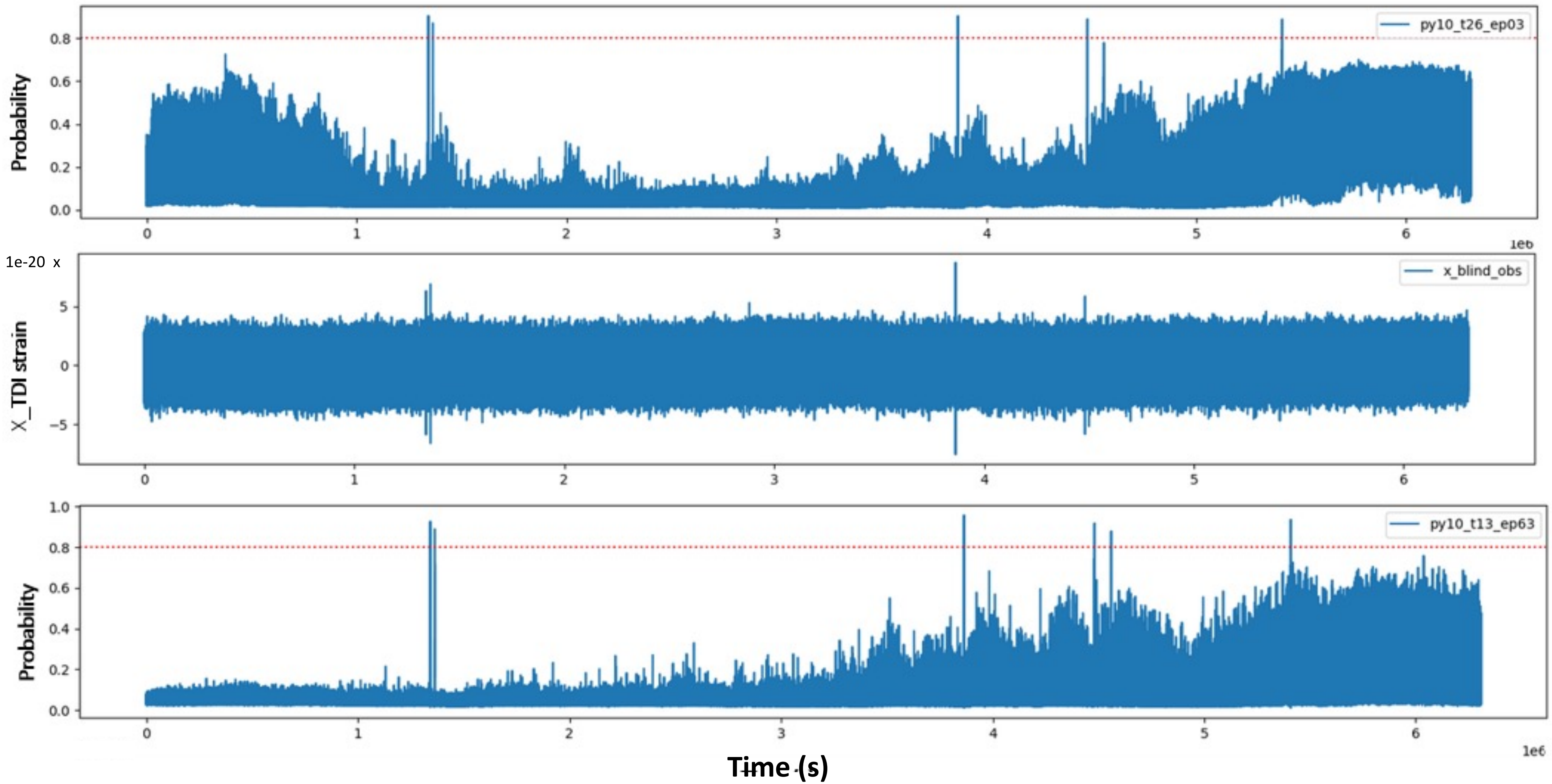
Loss function: Binary Crossentropy

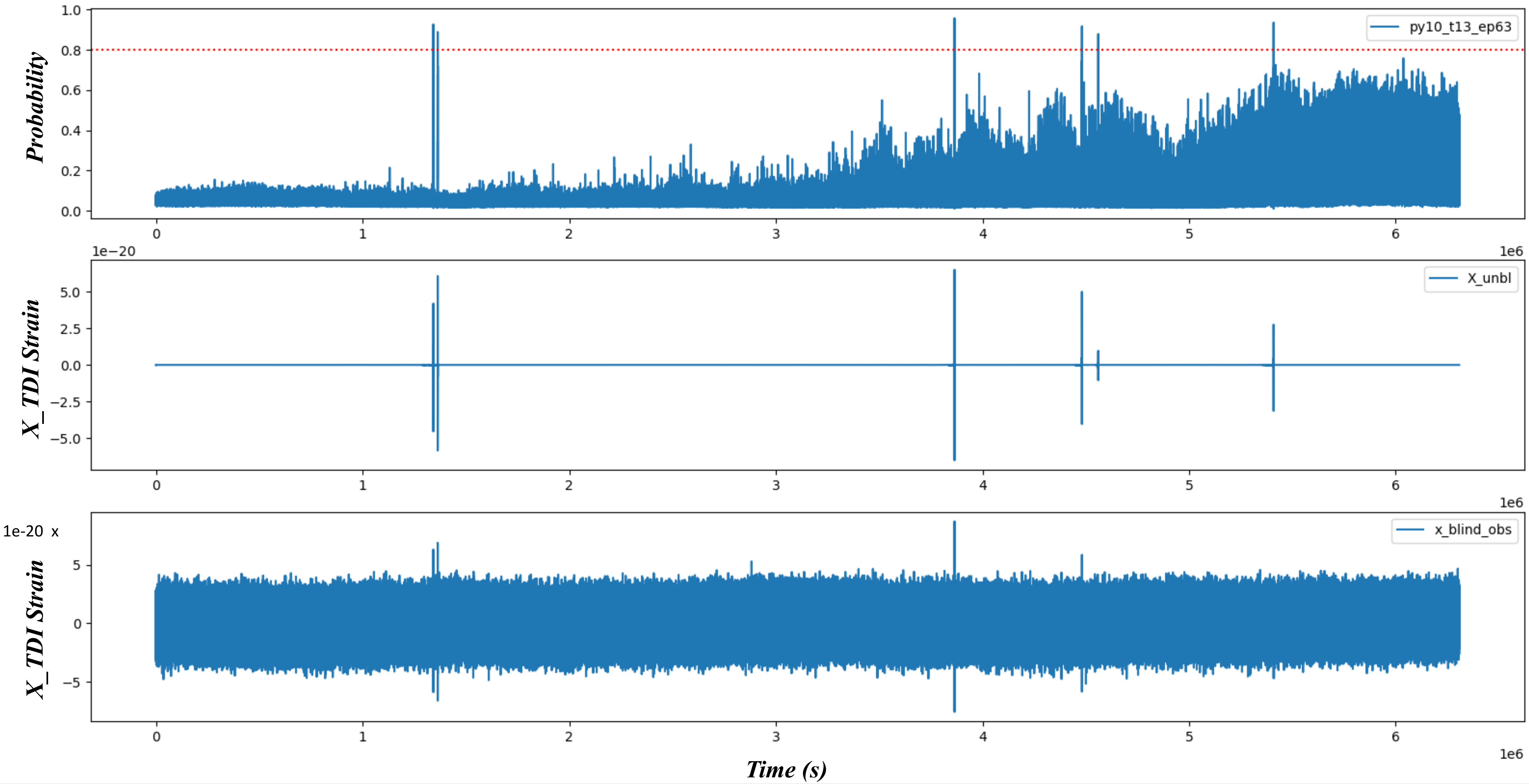
Optimizer: ADAM

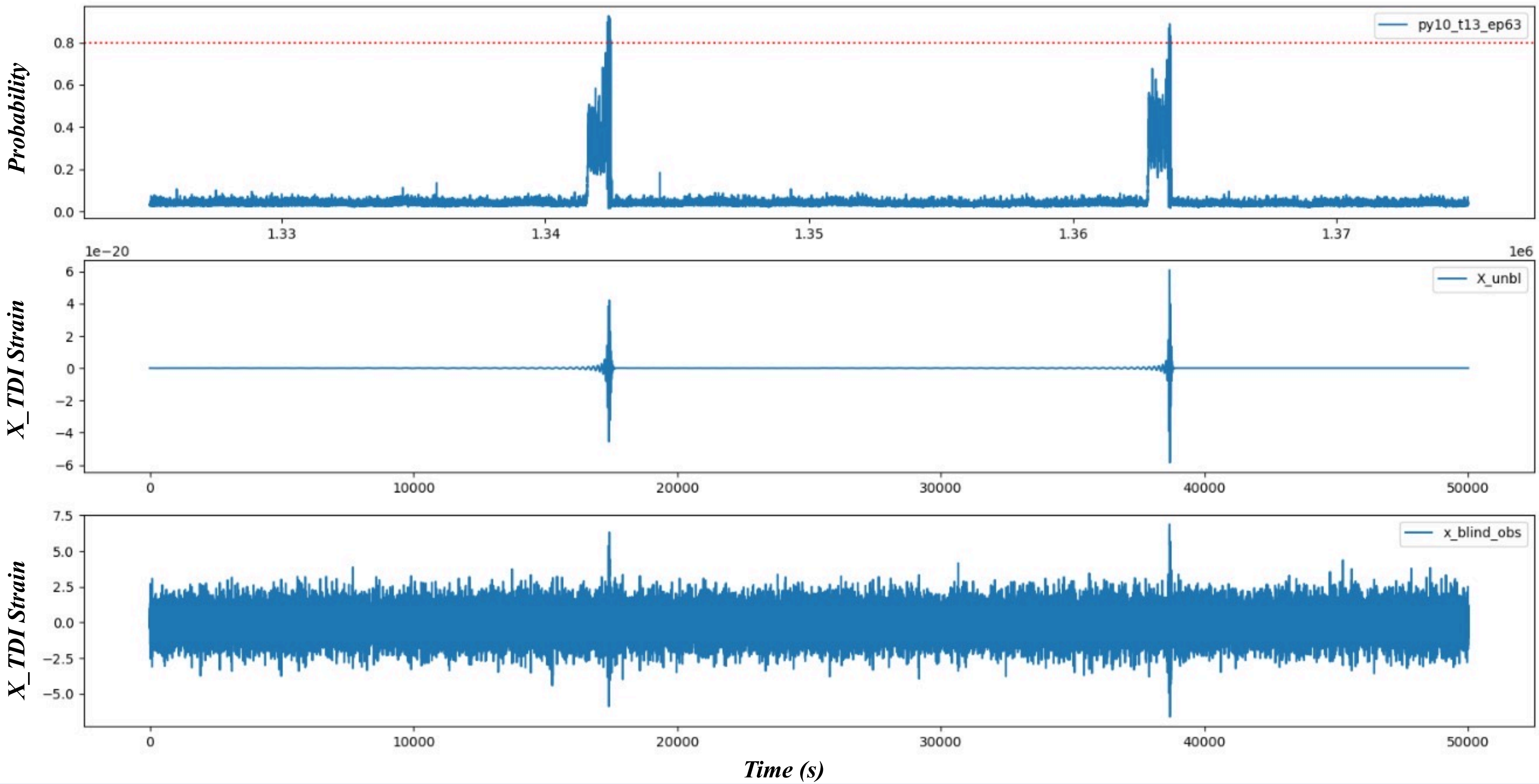
Architectures: ANN, LSTM, BiLSTM, GRU, SimpleRNN

Recurrent (RNN)

MODEL	py10_t13_ep63	py10_t26_ep03	py10_t37_ep05
Hidden Cells	10	30	10
No. of feature dimensions	10	10	10
Learning rate	10^{-4}	10^{-5}	10^{-4}
Layers	1xLSTM + 1xDense	2xBiLSTM + GlobalMaxPooling1D + 1xDense	1xLSTM + 1xDense


py10_t26_ep03
Probability
1e6
1e-20 x
x_blind_obs
X_TDI strain
py10_t13_ep63
Probability
1e6
Time (s)

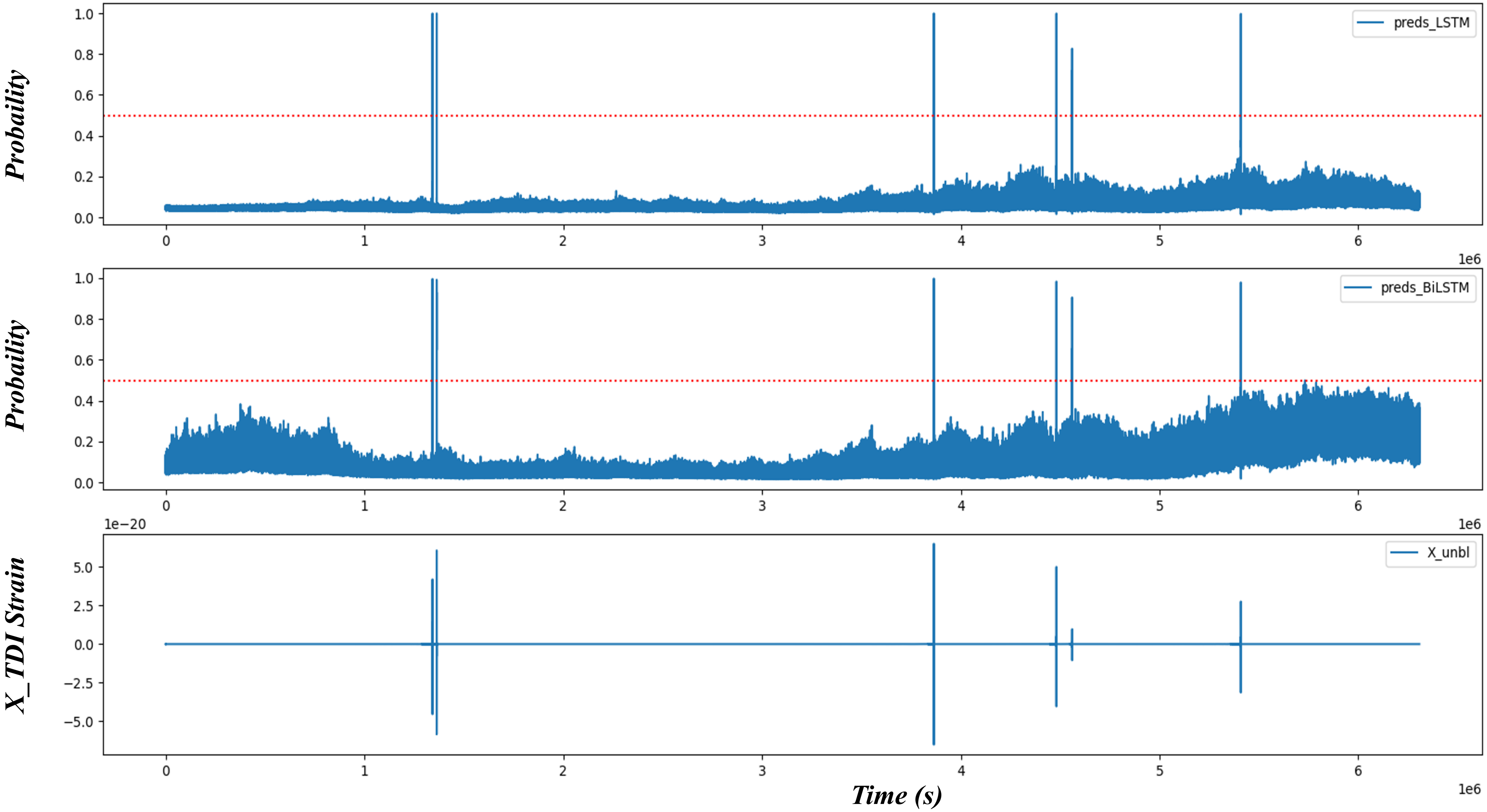

Probability
1.0
0.8
0.6
0.4
0.2
0.0
py10_t13_ep63
1e−20
X_TDI Strain
5.0
2.5
0.0
−2.5
−5.0
X_unbl
1e-20 x
X_TDI Strain
5
0
−5
x_blind_obs
0
1
2
3
4
5
6
1e6
Time (s)


py10_t13_ep63
Probability
0.0
0.2
0.4
0.6
0.8
1.33
1.34
1.35
1.36
1.37
1e6
1e−20
X_unbl
X_TDI Strain
6
4
2
0
−2
−4
−6
0
10000
20000
30000
40000
50000
x_blind_obs
X_TDI Strain
7.5
5.0
2.5
0.0
−2.5
−5.0
0
10000
20000
30000
40000
50000
Time (s)

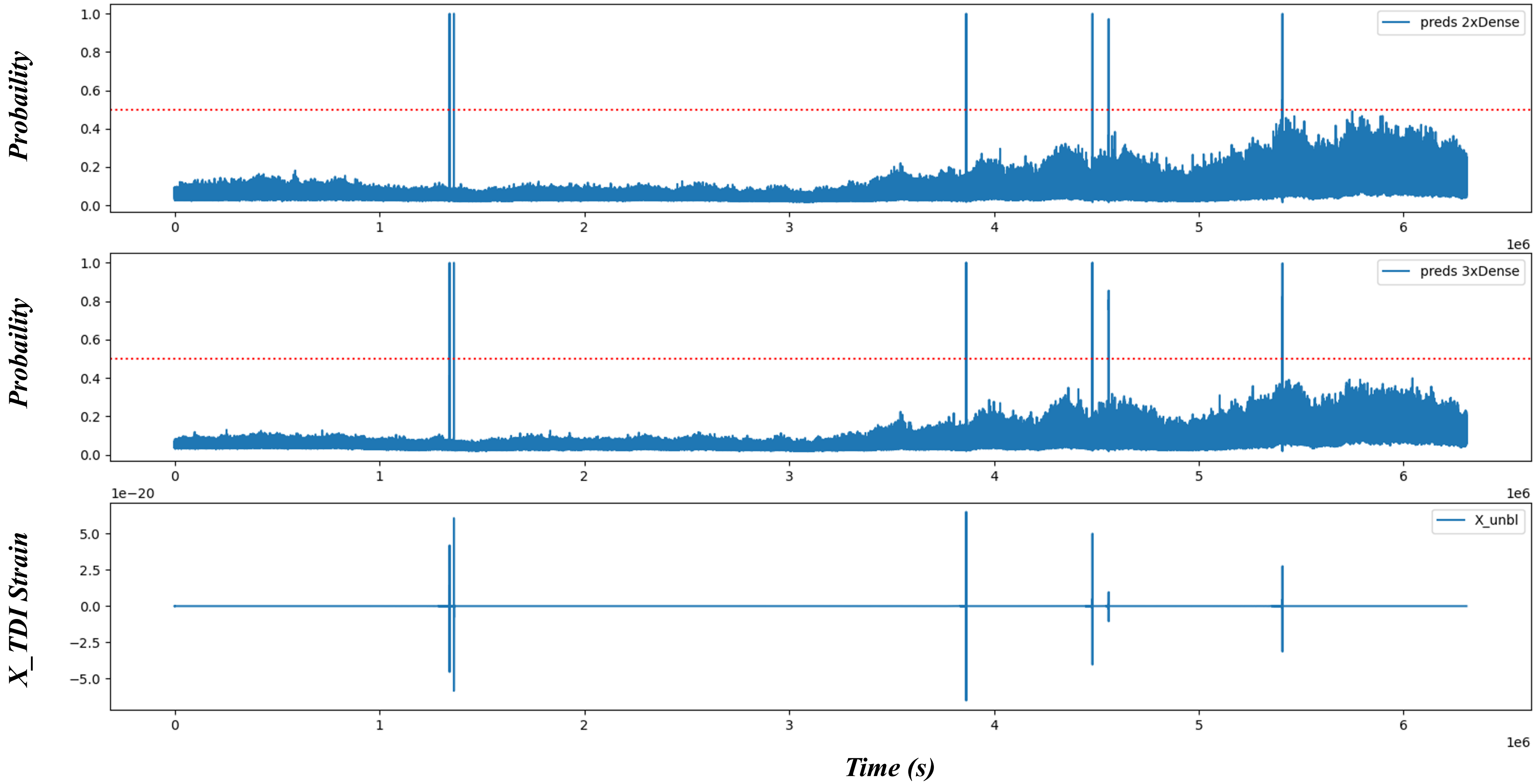
Recurrent (RNN)

ANN (a.k.a "the mother of all NNs)

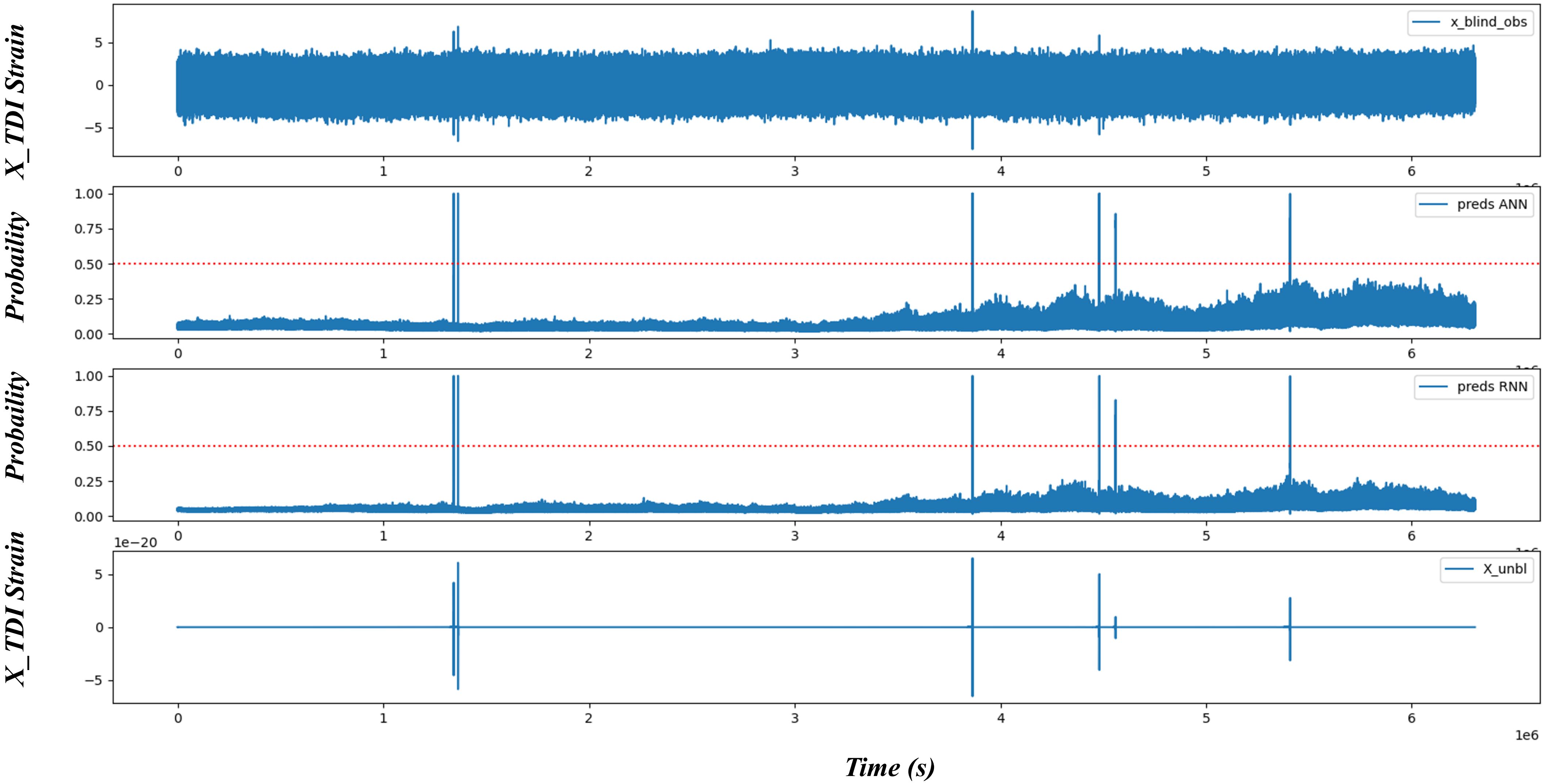
MODEL	gweep_rnn_01	gweep_rnn_02	gweep_ann_01	gweep_ann_02
Hidden Cells	1024	1024	128	1024
No. of feature dimensions	10	10	10	10
Learning rate	10^{-7}	10^{-5}	10^{-5}	10^{-7}
Layers	1x LSTM	2xBiLSTM, GlobalMaxPooling1D	2x Dense, Dropout(0.2)	3x Dense



preds_LSTM
Probaility
preds_BiLSTM
Probaility
X_unbl
X_TDI Strain
1e−20
1e6
Time (s)



Probaility
preds 2xDense
Probaility
preds 3xDense
X_TDI Strain
X_unbl
1e−20
1e6
Time (s)



X_TDI Strain
x_blind_obs
Probaility
preds ANN
Probaility
preds RNN
X_TDI Strain
1e−20
X_unbl
5
0
−5
1.00
0.75
0.50
0.25
0.00
0
1
2
3
4
5
6
1e6
Time (s)

Results:

- ✓ All peaks are detected if the threshold is above 0.5 (50%)
- ✓ We proved that the development of a low latency pipeline which can detect MBHB events is feasible
- ✓ Prediction time on Sangria blind: seconds
- ✓ Training time: 12-24h depending on model architecture and hardware (PC) resources

OUR APPROACH (so far):

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- Test the models with the simplified data set.
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- Parameter estimation (correctly identifying the rest of the GW source parameters)

Thank you!