

Classification and Denoising of Gravitational Waves

Prepared By,

- Mithil Joshi (18106)
- Surbhi Singh (18106)
- Tejas Kausal (18106)
- Anagh Agrawal (181050007)



Veermata Jijabai
Technological Institute
Matunga, Mumbai

Under Guidance of,
Prof. Dr. M.S.Panse

INDEX

- ❑ Introduction
- ❑ Motivation
- ❑ Objective
- ❑ Summary of Stage-I
- ❑ Final Schematic Diagram
- ❑ Dataset
- ❑ Software Development
- ❑ Results
- ❑ Validation
- ❑ Conclusion and Future Scope
- ❑ References

INTRODUCTION

Gravitational Wave:

- They are carriers of motion information from the objects of the universe, without absorption or reflection by matter. Albert Einstein showed that a massive accelerating body disrupts space-time producing a wave in space-time that travels at the speed of light in all directions from the source, in his theory of general relativity.

Deep Learning:

- Deep Learning is a subfield of Machine Learning, which puts an emphasis on learning successive layers of increasingly meaningful representations. These layered representations are learnt via models called Neural Network. It's fundamentally a mathematical network.
- This projects uses two such frameworks:
 - 1D Convolutional Network
 - Bi-directional LSTM Network

INTRODUCTION

1D Convolutional Network:

- Convolutional Neural Networks extends a deep feed forward network by adding more layers which implement convolutional block.

Bi-Directional LSTM Network:

- Bi-directional LSTM network is a chain of repeating modules, each having for four layers.
- It has the ability to add or remove data from the main pipeline.
- It starts from both ends of the input
- It overcomes the problem of long-term dependencies and avoids vanishing gradient problem.

MOTIVATION

- The first gravitational wave was detected on 14th September 2015. Gravitational wave astronomy will help explore some of the great questions in physics
- Traditional methods for detection of Gravitational waves such as Matched Filtering which is the most sensitive algorithm used by LIGO targets a 3D subspace of the 8D parameter space.
- To overcome the limitations and computational challenges of existing algorithms we turned to the rapidly advancing field of Deep Learning, that can learn directly with optimization techniques based on backpropagation and gradient descent.
- With exploration and efficient detection of gravitational waves we can harness the very processes the universe uses to function and develop technologies like quantum Internet, efficient space travel, cryogenics, etc.

OBJECTIVE

- To study gravitational waves and its properties.
- To simulate Gravitational data using PYCBC.
- To classify detected gravitational wave into noise and merger signal using deep learning model.
- To denoise the detected gravitational wave using Denoising Autoencoders to extract pure Binary Black Hole Merger signal.

Summary of Stage 1

Paper[1]	N. Lopac, F. Hržić, I. P. Vuksanović and J. Lerga, "Detection of Non-Stationary GW Signals in High Noise From Cohen's Class of Time-Frequency Representations Using Deep Learning," in IEEE Access, vol. 10, pp. 2408-2428, 2022, doi: 10.1109/ACCESS.2021.3139850.
Objective	Classification of noisy non-stationary time-series signals
Scheme	A method for the classification of noisy non-stationary time-series signals based on Cohen's class of their time-frequency representations (TFRs) and deep learning algorithms.
Highlights	<ul style="list-style-type: none"> ● Example of detecting gravitational-wave (GW) signals in intensive real-life, non-stationary, non-white, and non-Gaussian noise. ● A dataset is produces based on the actual data from the LIGO detector and the synthetic GW signals obtained by realistic simulations. ● Original noisy time-series data used to train three convolutional neural network (CNN) architectures. ● The TFR-CNN models achieve the values of the classification accuracy of up to 97.10%
Use in Project	<ul style="list-style-type: none"> ● Generation of Real time Gravitational waves for dataset. ● Understanding of the Convolutional Neural Network. ● Preprocessing of Gravitational wave data.

Paper[2]	H. Shen, D. George, E. A. Huerta and Z. Zhao, "Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-encoders," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 3237-3241, doi: 10.1109/ICASSP.2019.8683061.
Objective	Denoising of Gravitational Waves
Scheme	Denoising of gravitational waves is achieved by using a combination of a recurrent neural net (RNNs) with a Denoising Auto-Encoder (DAEs)
Highlights	<ul style="list-style-type: none"> ● A novel model applying curriculum learning by first denoising high SNR signals, before gradually decreasing the SNR until the signals become noise dominated. ● It showcases the performance of EDR-DAE using time-series data that describes gravitational waves embedded in very noisy backgrounds. ● In addition, it shows that EDRDAE can accurately denoise signals whose topology is significantly more complex than those used for training, demonstrating that our model generalizes to new classes of gravitational waves that are beyond the scope of established denoising algorithms.
Use in Project	<ul style="list-style-type: none"> ● A non-linear algorithm to denoise GW signals which combines a DAE with an RNN architecture using unsupervised learning. ● The encoder in SMTDAE may be used as a feature extractor for unsupervised clustering algorithms

Paper[3]	S. Fan, Y. Wang, Y. Luo, A. Schmitt and S. Yu, “Improving Gravitational Wave Detection with 2D Convolutional Neural Networks,” 2020 25th International Conference on Pattern Recognition (ICPR), 2021, pp. 7103-7110, doi: 10.1109/ICPR48806.2021.9412180
Objective	Classification Of Real Time Gravitational Waves
Scheme	Classification of Real Time Gravitational Waves by processing in 2 Dimensions using 2D Convolutional Networks.
Highlights	<ul style="list-style-type: none"> ● Two 1D CNNs for signal processing ● One 2D CNN ● Short time Fourier Transform
Use in Project	<ul style="list-style-type: none"> ● Binary classification between Noise and Gravitational Waves (including Gaussian White noise) ● More accuracy at low SNRs

Paper[4]	F. U. M. Ullah, A. Ullah, I. U. Haq, S. Rho and S. W. Baik, "Short-Term Prediction of Residential Power Energy Consumption via CNN and Multi-Layer Bi-Directional LSTM Networks," in IEEE Access, vol. 8, pp. 123369-123380, 2020, doi: 10.1109/ACCESS.2019.2963045.
Objective	Use of CNN with Multi-Layer Bi Directional LSTM Networks
Scheme	Prediction of Power Energy consumption using Convolutional Neural Network (CNN) with a Multi-layer Bi-directional Long-short Term Memory (M-BDSM)
Highlights	<ul style="list-style-type: none"> ● Combination of Convolutional Neural Network (CNN) with a Multi-layer Bi-directional Long-short Term Memory (M-BDSM) method. ● The pre-processing and data organisation mechanisms to refine the data and remove abnormalities. The second step employs a deep learning network The third step generates the evaluates the prediction using error metrics. ● It achieved the smallest value of the Mean Square Error (MSE) and Root Mean Square Error (RMSE).
Use in Project	<ul style="list-style-type: none"> ● Understanding feature extraction from time series data using Convolutional Neural Network ● Applying Bi-Directional LSTM Network on same time series data. ● Comparison between both approaches was useful to decide which architecture to use for denoising model.

Paper[5]	H. Chiang, Y. Hsieh, S. Fu, K. Hung, Y. Tsao and S. Chien, "Noise Reduction in ECG Signals Using Fully Convolutional Denoising Autoencoders," in IEEE Access, vol. 7, pp. 60806-60813, 2019, doi: 10.1109/ACCESS.2019.2912036.
Objective	A denoising autoencoder (DAE) is applied to reconstruct clean data from its noisy version.
Scheme	A DAE using fully convolutional network (FCN) is proposed for ECG signal denoising. Meanwhile, the proposed FCN-based DAE can perform compression with regard to the DAE architecture.
Highlights	<ul style="list-style-type: none"> ● Denoising Auto Encoders ● Signal Denoising ● Fully Convolutional Layer ● ANN
Use in Project	<ul style="list-style-type: none"> ● DAE is powerful in learning low-dimensional representations and can be used to recover noise-corrupted input. ● An autoencoder (AE) is a machine learning model that aims to reproduce input data as close as possible. An AE generally comprises two parts: encoder and decoder. ● FCN is a special type of CNN. Convolutional layers consist of a set of filters that can extract feature maps to describe the characteristics of input data.

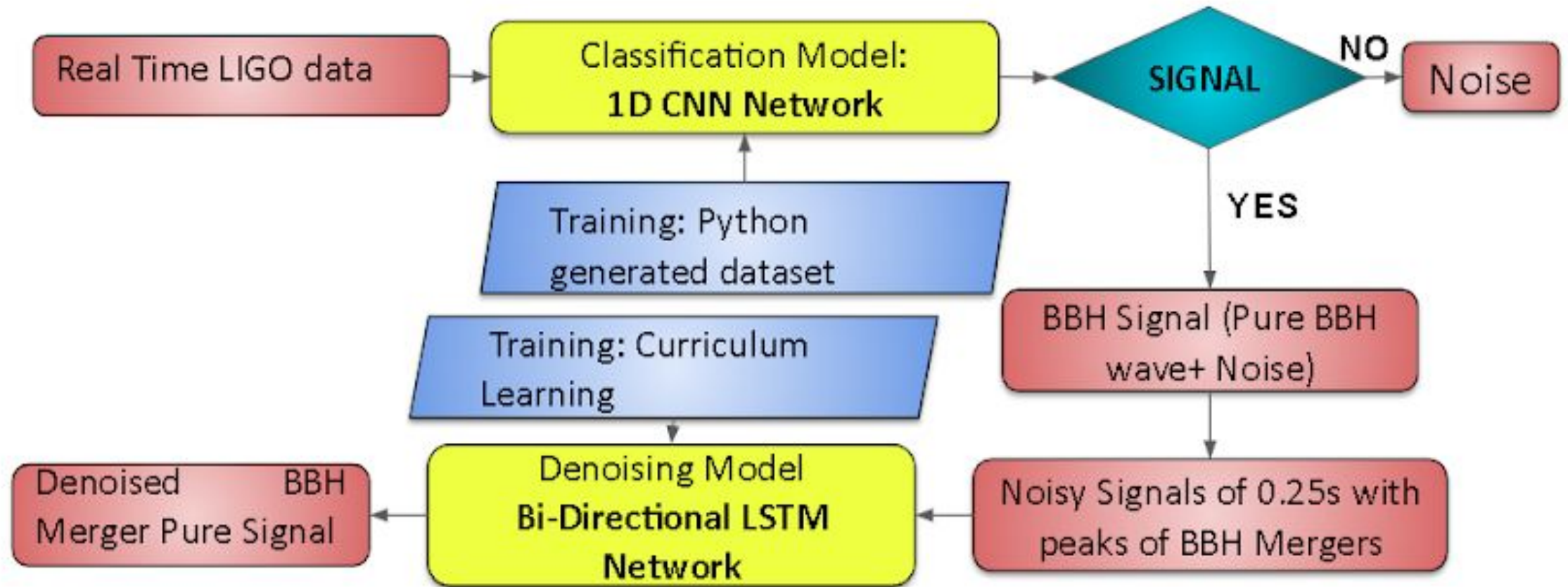
Paper[6]	S. Kiranyaz, T. Ince and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," in IEEE Transactions on Biomedical Engineering, vol. 63, no. 3, pp. 664-675, March 2016, doi: 10.1109/TBME.2015.2468589.
Objective	Classification of ECG signals
Scheme	A fast and accurate patient-specific electrocardiogram (ECG) classification system. Methods: An adaptive implementation of 1D Convolutional Neural Networks (CNNs)
Highlights	<ul style="list-style-type: none"> ● 1D Convolutional Neural Network ● Feature extraction ability can further improve the classification performance.
Use in Project	<ul style="list-style-type: none"> ● Classifier with an adaptive implementation of 1-D CNNs that are able to fuse the two major blocks into a single learning body: feature extraction and classification. ● CNN negates the necessity to extract handcrafted manual features, or pre- and post-processing. ● Besides the speed and computational efficiency achieved, the proposed method only requires 1-D convolutions (multiplications and additions) that make any hardware implementation simpler and cheaper

Paper[7]	G. Baltus, J. -R. Cudell, J. Janquart, M. Lopez, S. Caudill and A. Reza, "Detecting the early inspiral of a gravitational-wave signal with convolutional neural networks," 2021 International Conference on Content-Based Multimedia Indexing (CBMI), 2021, pp. 1-6, doi: 10.1109/CBMI50038.2021.9461919.
Objective	Introduce a novel methodology for the operation of an early alert system for gravitational waves. It is based on short convolutional neural networks.
Scheme	Building short 1-dimensional convolutional neural networks to detect these types of events by training them on part of the early inspiral. We show that such networks are able to retrieve these signals from a small portion of the waveform.
Highlights	<ul style="list-style-type: none">● Generation of two 1D whitened time series sets for training and testing with the PyCBC package● 1 Dimensional 4 layer CNN
Use in Project	<ul style="list-style-type: none">● Can be applied on extremely weak time-series signals embedded in highly non-Gaussian and non-stationary noise.● Shows similar results as that of standard Matched filtering

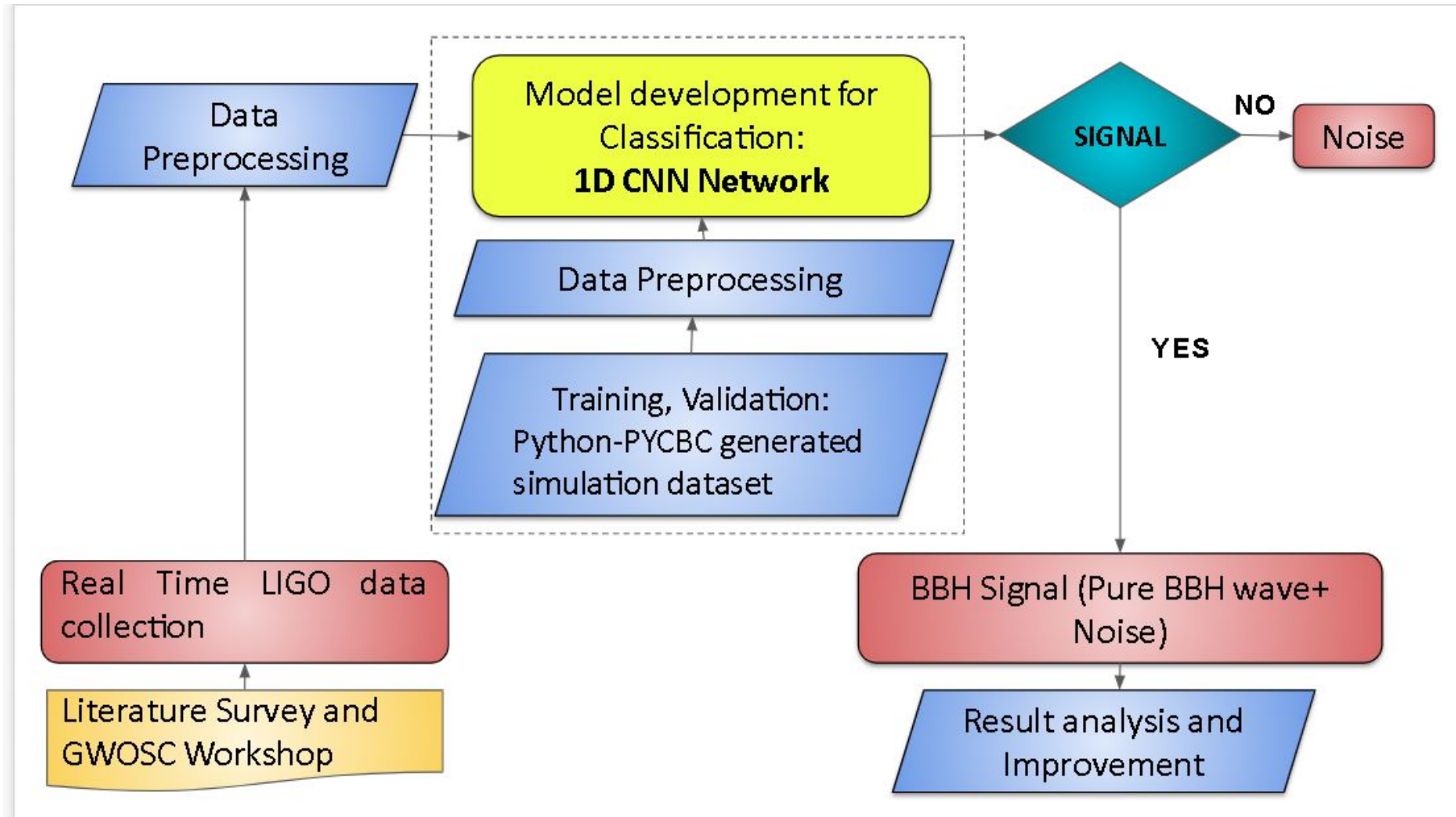
SUMMARY OF STAGE-I

- The concept of Gravitational Wave has been understood.
- Literature Survey successfully done
- Designing of Schematic Diagram has been done
- Software tools to be used have been decided
- Real time gravitational waves were extracted for understanding of composition parameters so that simulations with the same parameters can be generated.
- Simulated Dataset for Training and Validation of Neural Network has been generated which include signal and noise waves.
- The first stage of 1D convolutional Neural Network has been developed using Tensorflow and Keras

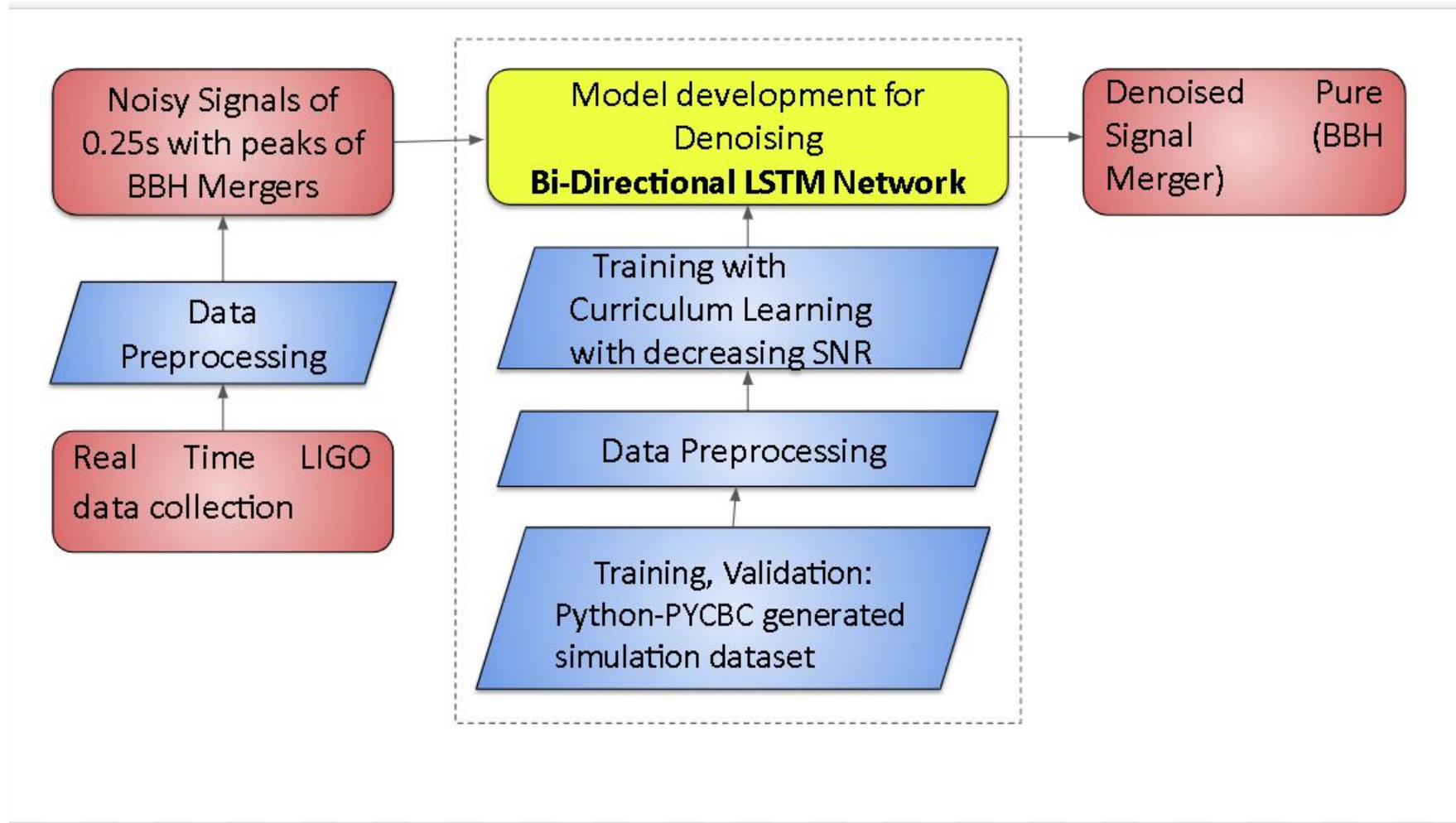
Final Project Schematic



Classification Schematic



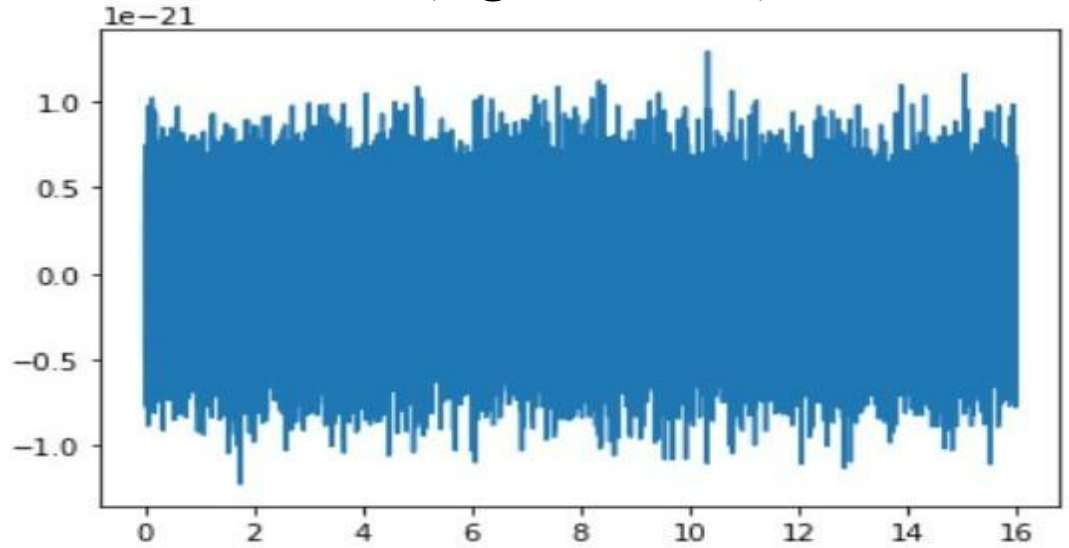
Denoising Schematic



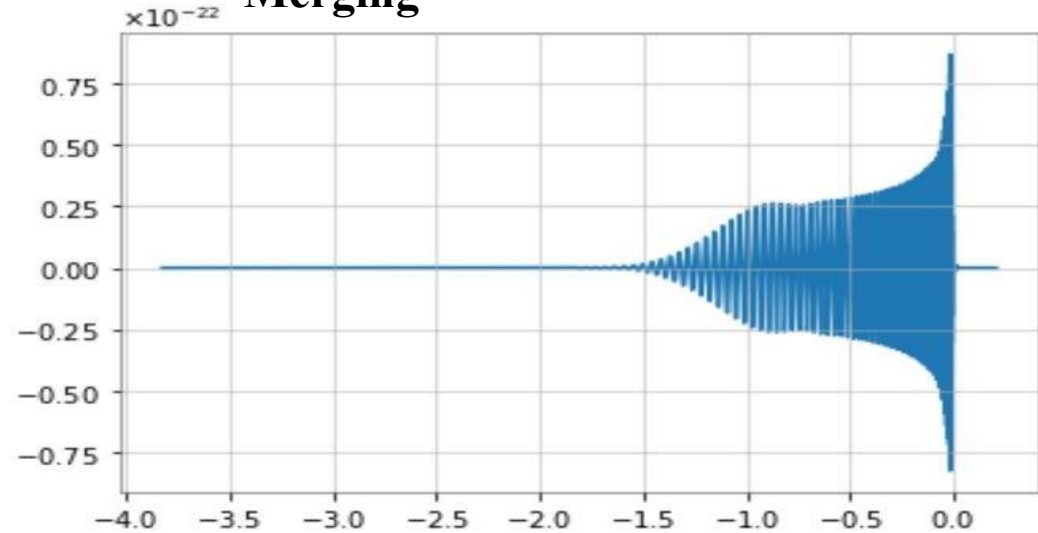
DATASET

CLASSIFICATION

Whitened (Signal + Noise)



Sample Wave of two Binary Stars Merging



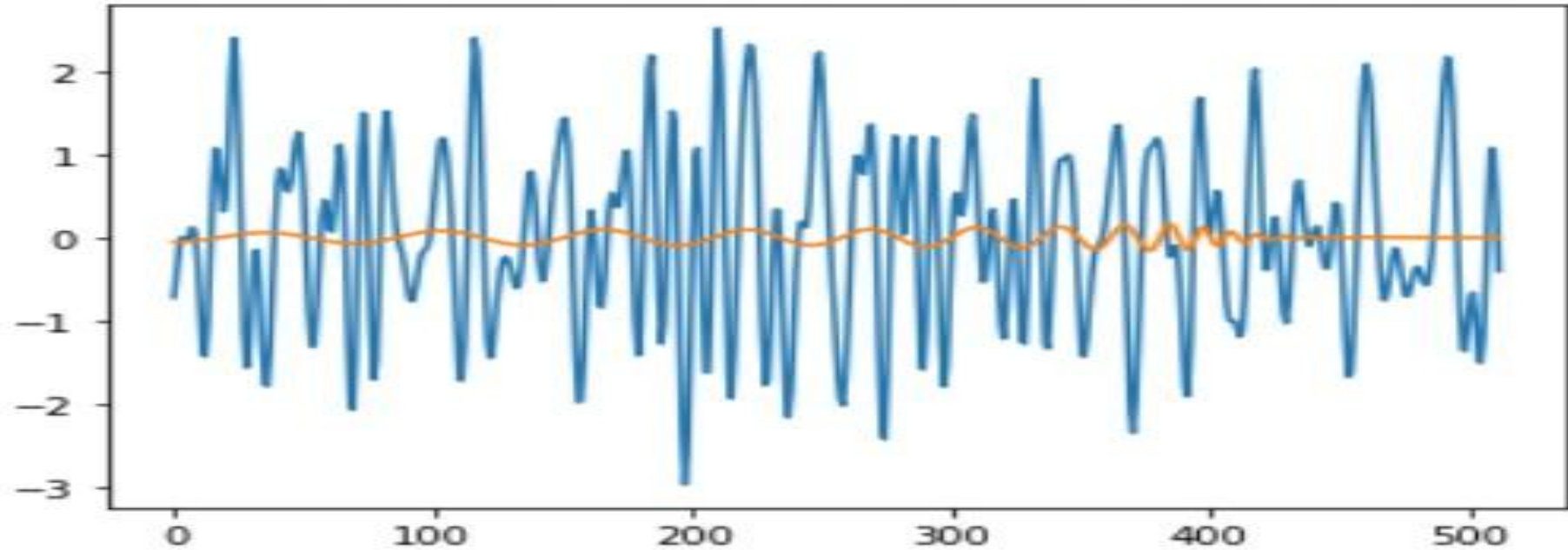
Input data specifications: -

- 16384 Timesteps
- 8 seconds of data
- Category 0 - Pure Noise
- Category 1 - Signal + Noise
- Frequency of sampling - 2048 Hz
- 24576 (Signal+ Noise) & 8192 Pure Noise samples i.e. 32768 total samples for training.

DATASET

DENOISING

Whitened (Signal + Noise) - Signal plus noise in blue. Pure signal in yellow

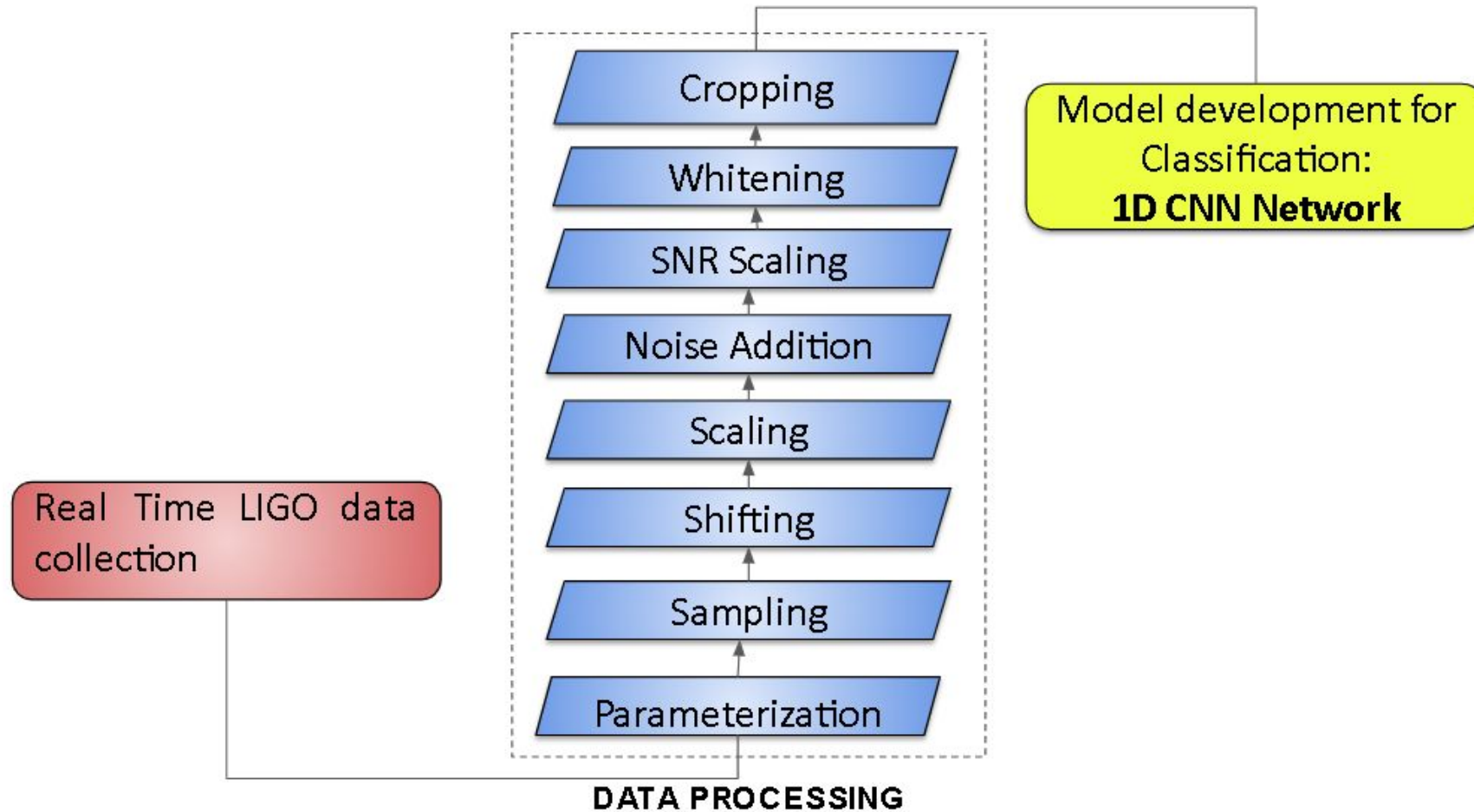


Input data specifications: -

- 512 Timesteps
- 0.25 seconds length of data
- Output will be a reconstructed signal of same dimensions
- Frequency of sampling - 2048 Hz
- 8000 (Signal + Noise) Waves for training.

DATASET

DATASET PREPROCESSING PIPELINE



A hand is shown holding a glowing blue sphere. The sphere is covered in a complex network of blue lines and dots, resembling a molecular structure or a data network. The background is dark with some blurred lights and a faint grid pattern. The text "SOFTWARE DEVELOPMENT" is written in white, bold, capital letters across the center of the sphere.

SOFTWARE DEVELOPMENT

GOOGLE COLAB



- We have tested and implemented our project code in **Google Colab**.
- What is **Google Colab**?
 - Product of Google Research
 - Colab is a free notebook environment that runs entirely in the cloud.
 - It lets you edit documents, the way you work with Google Docs.
 - Colab supports many popular machine learning libraries which can be easily loaded in your notebook.
 - Colab supports GPU and it is totally free.
 - It does not require a setup and the notebooks that you create can be simultaneously edited by your team members
 - Colab is a free Jupyter notebook environment that runs entirely in the cloud.

Why use Jupyter Notebook?

- All in one place:** As you know, Jupyter Notebook is an open-source web-based interactive environment that combines code, text, images, videos, mathematical equations, plots, maps, graphical user interface and widgets to a single document.
- Easy to share:** Jupyter Notebooks are saved in the structured text files (JSON format), which makes them easily shareable.
- Easy to convert:** Jupyter Notebook allows users to convert the notebooks into other formats such as HTML and PDF. It also uses online tools and nbviewer which allows you to render a publicly available notebook in the browser directly.



- What is **Kaggle** ?
 - A subsidiary of Google LLC
 - Kaggle is an online community platform for data scientists and machine learning enthusiasts.
 - Kaggle allows users to collaborate with other users, find and publish datasets and use GPU integrated notebooks
- **Advantages**
 - Faster and more accessible GPU
 - Easy to upload and use data

PROGRAMING LANGUAGES

- **Python** is the programming language which we have used for the development of the project.



What is Python?

- Python is an interpreted, high-level, general-purpose programming language
- The syntax in python is very simple and easy.
- Its language constructs and object-oriented approach aim to help programmers
write clear, logical code for small and large-scale projects.
- Python is used widely for creating mobile applications, web designing.

Python libraries used:

- **Numpy:** Numeric Python is a library that helps in performing mathematical and logical operations on arrays. The library consists of multidimensional array of objects and a collection of routines for processing the arrays.
- **Tensorflow:** TensorFlow is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks
- **Matplotlib:** Matplotlib is a plotting library that allows creating 2D graphs and plots by using Python scripts
- **PyCBC:** PyCBC is a software package used to explore astrophysical sources of gravitational waves. It contains algorithms to analyze gravitational-wave data, detect coalescing compact binaries, and make bayesian inferences from gravitational-wave data. PyCBC was used in the first direct detection of gravitational waves (GW150914) by LIGO.
- **Keras:** Keras is an effective high-level neural network Application Programming Interface (API) written in Python. This open-source neural network library is designed to provide fast experimentation with deep neural networks, and it can run on top of TensorFlow

Deep learning libraries used:

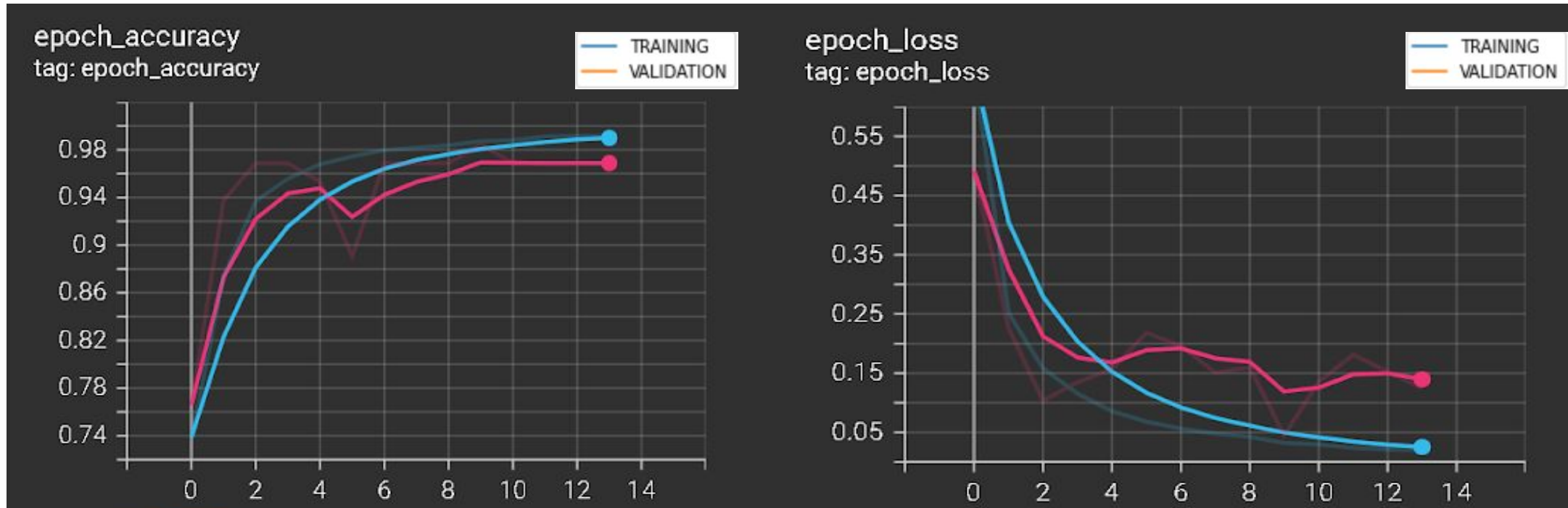
- **Sequential:** Easiest way to build a model in Keras. It allows you to build a model layer by layer.
- **Dense:** The results of the convolutional layers are fed through one or more neural layers to generate a prediction.
- **LSTM:** Flattening transforms a two-dimensional matrix of features into a vector that can be fed into a fully connected neural network classifier.
- **Activation:** In a neural network, the activation function is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input.
- **Dropout:** Dropout is a technique where randomly selected neurons are ignored during training.

Deep learning libraries used:

- **1D Convolutional Layer:** A 1-D convolutional layer applies sliding convolutional filters to 1-D input. The layer convolves the input by moving the filters along the input and computing the dot product of the weights and the input, then adding a bias term.
- **Max Pooling:** Max pooling is done in part to help over-fitting by providing an abstracted form of the representation. It reduces the computational cost by reducing the number of parameters to learn and provides basic translation invariance to the internal representation.
- **Bi-Directional LSTM:** Bidirectional long-short term memory(bi-lstm) is the process of making any neural network to have the sequence information in both directions backwards (future to past) or forward(past to future).

Results

Result (Classification)



Training:

Training duration (min) : 11.400427718957266

GPU 0: Tesla K80

loss: 0.0196 - accuracy: 0.9919 - val_loss: 0.1245 - val_accuracy: 0.9688

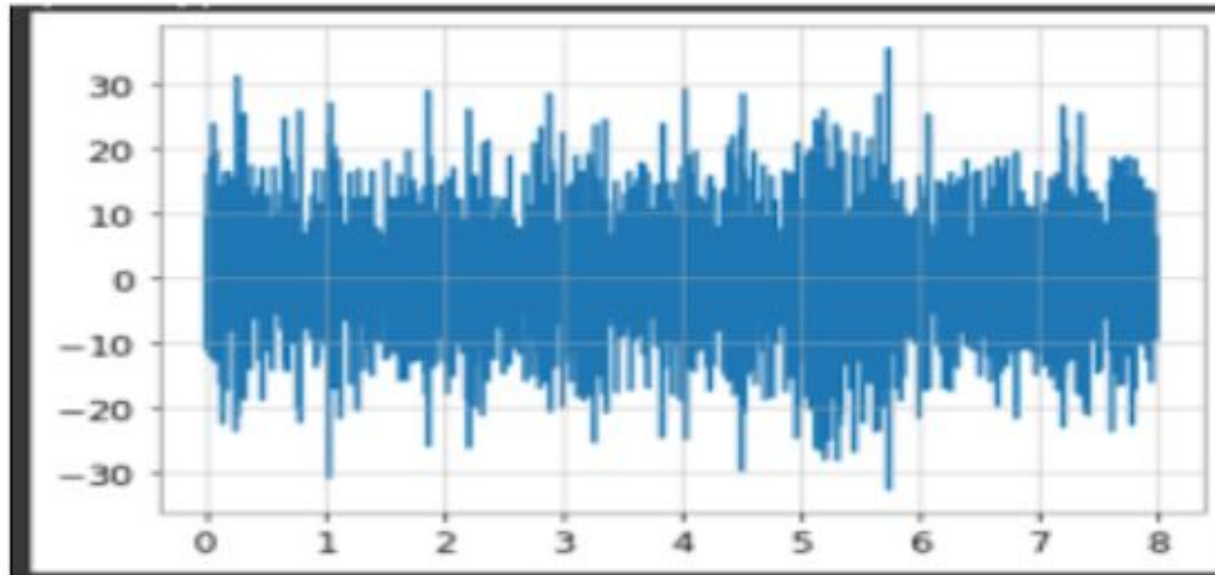
Testing:

Test loss: 0.1342875063419342

Test accuracy: 0.97503662109375

Result (Classification)

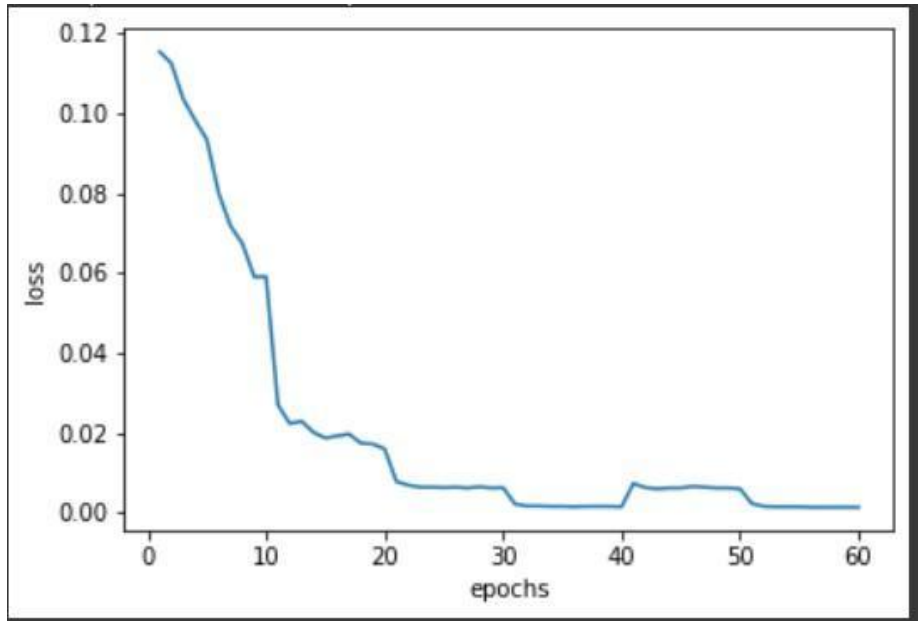
Processed data as per Model Input (Event 170809)



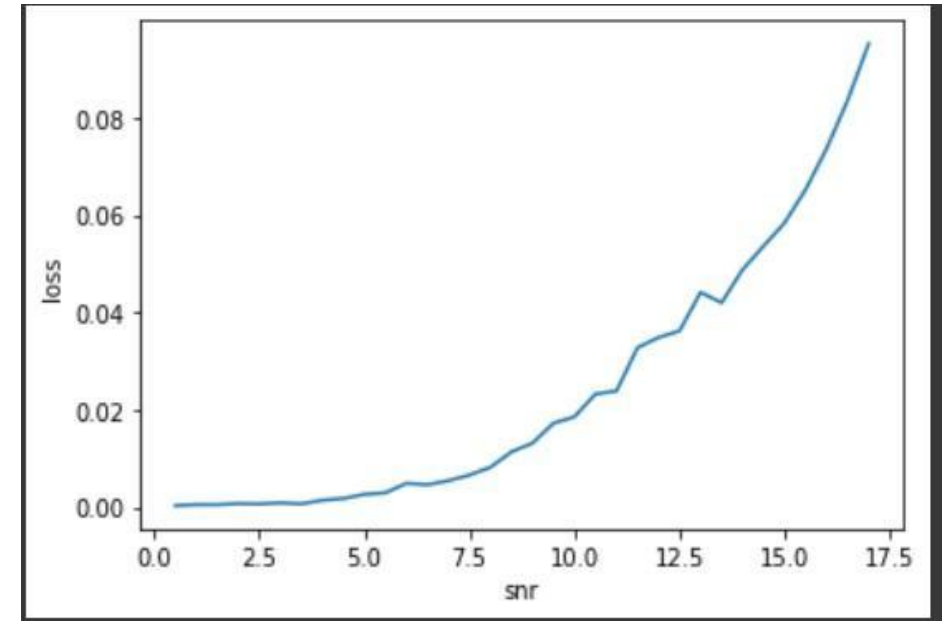
Model Prediction - `[[0.99996686]]`

The model predicted that the wave was 99% a BBH merger wave.

Result (Denoising)

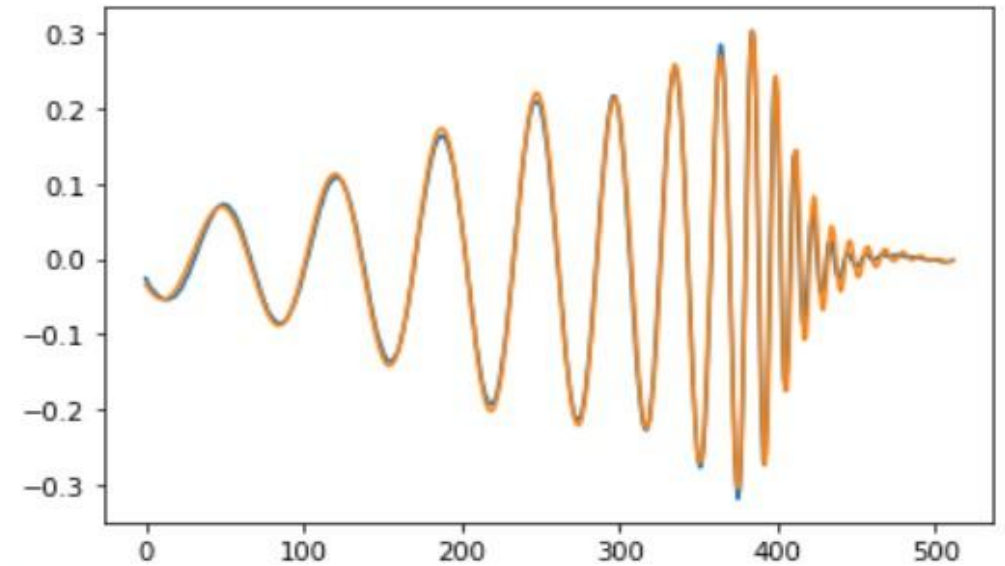
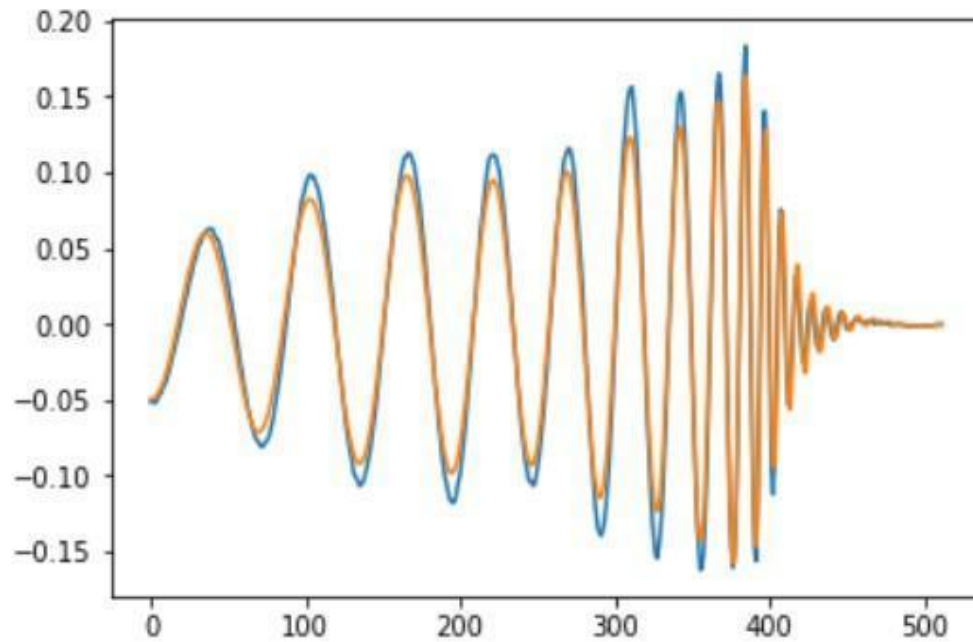


The MSE at the end of 60 epochs was 0.0014



The MSE for each SNR was calculated
Curriculum Learning

Result (Denoising)



Model testing on simulated samples (not included in the training or testing set)

Result (Video Demo)

VALIDATION

Validation

Classification Model

Obtained Result

Author's Result

Accuracy

97.50%

93.15%

Validation : N. Lopac, F. Hržić, I. P. Vuksanović and J. Lerga, "Detection of Non-Stationary GW Signals in High Noise From Cohen's Class of Time–Frequency Representations Using Deep Learning," in *IEEE Access*, vol. 10, pp. 2408-2428, 2022, doi: 10.1109/ACCESS.2021.3139850.

VALIDATION

Validation

Denoising Model

Obtained Result

Author's Result

MSE

0.0012

0.0050

Validation : H. Shen, D. George, E. A. Huerta and Z. Zhao, "Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-encoders," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 3237-3241, doi: 10.1109/ICASSP.2019.8683061.

CONCLUSION

- In this study, we have presented a methodological approach to classify and denoise a gravitational wave.
- Neural Networks provide an efficient way for the detection of gravitational waves.
- Our method is computationally faster and uses less memory than traditional approach

FUTURE WORK

- Number of output classes of classification model can be increased, which will segregate different types of gravitational wave.
- Implementation of the denoising model for different types of noise e.g. non-stationary noise, non-gaussian noise, glitches, etc.
- Denoising model can be used for other deep space signals using transfer learning
- Hyperparameter tuning to achieve better accuracy.

References

- [1] S. Fan, Y. Wang, Y. Luo, A. Schmitt and S. Yu, "Improving Gravitational Wave Detection with 2D Convolutional Neural Networks," 2020 25th International Conference on Pattern Recognition (ICPR), 2021, pp. 7103-7110, doi: 10.1109/ICPR48806.2021.9412180

- [2] G. Baltus, J. -R. Cudell, J. Janquart, M. Lopez, S. Caudill and A. Reza, "Detecting the early inspiral of a gravitational-wave signal with convolutional neural networks," 2021 International Conference on Content-Based Multimedia Indexing (CBMI), 2021, pp. 1-6, doi: 10.1109/CBMI50038.2021.9461919.

- [3] H. Shen, D. George, E.A. Huerta and Z. Zhao, "Denoising Gravitational waves with Enhanced Deep Recurrent Denoising Auto-Encoders," *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 3237-3241, doi: 10.1109/ICASSP.2019.8683061

- [4] P. Singh, A. Singhal and S. D. Joshi, "Time-Frequency Analysis of Gravitational Waves," 2018 International Conference on Signal Processing and Communications (SPCOM), 2018, pp. 197-201, doi: 10.1109/SPCOM.2018.8724396.

References

- [5] S. Kiranyaz, T. Ince, O. Abdeljaber, O. Avci and M. Gabbouj, "1-D Convolutional Neural Networks for Signal Processing Applications," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 8360-8364, doi: 10.1109/ICASSP.2019.8682194.

- [6] Daniel George, E.A. Huerta, Deep Learning for real-time gravitational wave detection and parameter estimation: Results with Advanced LIGO data, Physics Letters B, Volume 778, 2018, Pages 64-70, ISSN 0370-2693, <https://doi.org/10.1016/j.physletb.2017.12.053>.

- [7] Plamen G. Krastev, Real-time detection of gravitational waves from binary neutron stars using artificial neural networks, Physics Letters B, Volume 803, 2020, 135330, ISSN 0370-2693, <https://doi.org/10.1016/j.physletb.2020.135330>.

- [8] Xia, Heming, Lijing Shao, Jun-jie Zhao and Zhoujian Cao. "Improved deep learning techniques in gravitational-wave data analysis." *ArXiv abs/2011.04418* (2020): n. Pag.

References

- [9] Rituerto-González, E., Peláez-Moreno, C. End-to-end recurrent denoising autoencoder embeddings for speaker identification. *Neural Comput & Applic* 33, 14429–14439 (2021).
<https://doi.org/10.1007/s00521-021-06083-7>
- [10] S. Singh, A. Singh, A. Prajapati and K. N. Pathak, "Deep learning for estimating parameters of gravitational waves," in *Monthly Notices of the Royal Astronomical Society*, vol. 508, no. 1, pp. 1358-1370, Aug. 2021, <https://doi:10.1093/mnras/stab2417>
- [11] S. Kiranyaz, T. Ince and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," in *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 664-675, March 2016, doi:10.1109/TBME.2015.2468589.
- [12] H. Chiang, Y. Hsieh, S. Fu, K. Hung, Y. Tsao and S. Chien, "Noise Reduction in ECG Signals Using Fully Convolutional Denoising Autoencoders," in *IEEE Access*, vol. 7, pp. 60806-60813, 2019, doi:10.1109/ACCESS.2019.2912036.