Detecting Gravitational Waves Using Convolutional Neural Networks

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Abstract

Gravitational Waves, distortion in space time caused due to merging massive celestial objects like black holes or neutron stars, provide crucial insights into the universe's most energetic phenomena. However, detecting these signals is challenging due to the nature of the signal and significant noise in data collected by observatories like Laser Interferometer Gravitational Wave Observatory (LIGO). This project aims to leverage deep learning, specifically Convolutional Neural Networks (CNNs), to enhance the accuracy of gravitational wave detection. The proposed approach involves pre-processing data from LIGO's Gravitational Wave Open Science Centre (GWOSC) to generate time-frequency representations, which serve as input to CNN. The model will be trained on labelled datasets to identify the characteristic chirp signals associated with gravitational wave events. By automating feature extraction and classification, the CNN-based system aims to streamline the detection process, reducing manual intervention and minimizing false positives.

Expected outcomes include a robust, real-time detection framework capable of distinguishing gravitational wave signals from noise with high precision. Additionally, this work contributes towards gravitational wave astronomy by improving detection methodologies and providing a scalable deep learning-based solution for identifying these cosmic events.

Keywords: Gravitational waves, Convolutional Neural Networks (CNNs), Time-frequency representations, LIGO's Gravitational Wave Open Science Centre (GWOSC), Real-time detection framework.

1. Introduction:

Gravitational waves, first predicted by Albert Einstein, are distortions in the fabric of spacetime produced by the acceleration of massive celestial bodies. Events such as the merger of black holes or neutron stars release immense energy, generating these waves that propagate through the universe. The first direct detection by the LIGO and Virgo observatories marked a transformative moment in astrophysics, opening a new window for observing the cosmos. However, the detection of gravitational waves remains a significant challenge due to their extremely weak signals and the high level of background noise in observational data. Traditional approaches, such as matched filtering, require extensive computational resources and rely on template banks that model expected waveforms based on a range of astrophysical parameters. While effective, these methods may struggle to generalize to unforeseen signal types or real-world noise conditions.

Recent advances in machine learning, particularly in deep learning and convolutional neural networks (CNNs), offer new possibilities for addressing these challenges. CNNs have demonstrated success in various signal processing tasks by automatically learning hierarchical features from raw or transformed data. This project explores the application of CNNs to gravitational wave detection, leveraging spectrograms generated from LIGO's raw strain data as input. The model is trained to identify the distinct chirp-like patterns of gravitational wave signals amidst noise, aiming to improve detection accuracy and reduce false positives. By benchmarking our model against traditional matched filtering techniques and evaluating its performance across different datasets and noise conditions, we aim to develop a scalable, and efficient framework for gravitational wave detection. Ultimately, this approach contributes to ongoing efforts to automate and enhance the ability to monitor the universe's most energetic and enigmatic events.

2. Background:

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly impacted the detection and analysis of gravitational waves generated by black hole and neutron star mergers. Traditional methods like matched filtering, while accurate, are computationally intensive and slow, prompting the adoption of CNNs for real-time detection. Pioneering studies demonstrated that 1-D CNNs could detect binary black hole signals in noisy LIGO data with performance comparable to matched filtering but at a fraction of the computational cost. Subsequent research expanded these models to handle more complex signals from binary neutron star mergers, using spectrogram-based inputs and hybrid CNN architectures for improved accuracy and parameter estimation.

These models have also been applied to glitch classification, signal denoising, and low-latency detection for multi-messenger astronomy. Despite challenges such as data imbalance and noise variability, CNNs continue to evolve with innovations like transfer learning, physics-informed networks, and self-supervised learning, making them a powerful tool in the ongoing development of gravitational wave science. The methods section can be enriched by describing the CNN architecture, data preprocessing steps, and training approaches using real or simulated LIGO data. Including a results section with performance comparisons, visualizations like confusion matrices, and ROC curves can add depth. A dedicated dataset section referencing GWOSC, a discussion of practical applications such as detection in multi-messenger astronomy, and emerging techniques like hybrid models or self-supervised learning would further strengthen the report. Finally, acknowledging challenges like model interpretability and generalization to noisy environments will provide a balanced and comprehensive perspective.

3. Approach:

In this project, we develop and implement a convolutional neural network (CNN) model to detect gravitational wave (GW) signals resulting from compact binary coalescences, specifically black hole (BBH), neutron star (BNS), and neutron star–black hole (NSBH) mergers. Our approach integrates both real observational data from the Laser Interferometer Gravitational-Wave Observatory (LIGO) and synthetically generated datasets, with the aim of training a robust classifier capable of identifying the presence and type of GW events.

3.1 Dataset:

To ground our model in real astrophysical phenomena, we utilized data released by the Gravitational Wave Open Science Center (GWOSC), focusing on confirmed events from LIGO's first and second observing runs (O1 and O2). The O1 run includes three confirmed binary black hole mergers: GW150914, GW151012, and GW151226. Notably, no neutron star mergers were identified in O1. The O2 run provided additional confirmed detections: three more BBH mergers — GW170104, GW170608, and GW170814 — along with the landmark first binary neutron star (BNS) detection, GW170817. For each of these seven events, we extracted strain data from the Hanford (H1) **detector**, formatted as HDF5 files at a sampling rate of **4096 Hz**, and used these as inputs for testing our trained CNN model.

To augment the training dataset and evaluate the generalizability of our model, we generated synthetic gravitational waveforms using the PyCBC software suite. These waveforms simulate a diverse range of compact binary systems:

- Binary Black Holes (BBH) with component masses ranging from 20–40 solar masses ($M_\odot$),
- Binary Neutron Stars (BNS) with component masses from 1.2–1.6 $M_\odot$,
- Neutron Star–Black Hole (NSBH) systems combining one component from each of the above ranges.

Each category was simulated with 50 samples, with randomized physical parameters including component spins, luminosity distances, and orbital inclination angles to reflect astrophysical diversity. The signals were fixed to an **8-second duration** and injected into **a** LIGOZeroDetHighPower noise to emulate realistic interferometer noise conditions.

By combining real GWOSC events with synthetically generated datasets, we trained and validated a CNN-based classifier capable of distinguishing between BBH, BNS, and NSBH events embedded in noisy strain data. The results of this approach offer insights into the feasibility of deep learning techniques for detection and classification of gravitational wave signals in future observing runs.

3.2 Theory and Calculations:

The gravitational wave (GW) data used in this work is stored in **Hierarchical Data Format version 5 (HDF5)**, a widely adopted standard for handling large scientific datasets. This format provides an efficient and structured approach to organizing complex data through a hierarchical model that categorizes different components under labeled groups. For our application, key datasets include Strain, Meta, and Quality - representing the core measurement data, metadata, and data quality flags, respectively.

3.2.1 Sampling Rate and Frequency Characteristics

The strain data, which captures the time-varying distortion caused by gravitational waves, is sampled at **4096 Hz**, a resolution sufficient to resolve key astrophysical features in compact binary coalescence events. Depending on the nature of the source, the strain signals exhibit distinctive frequency patterns:

- **Binary Black Hole (BBH) Mergers**: These events produce short-duration signals characterized by a rapid rise in amplitude followed by a sharp decay. The resulting chirping waveform is relatively clean, with a sharp spike that quickly subsides. The frequency content is typically lower and more concentrated.
- **Binary Neutron Star (BNS) Mergers**: Neutron star collisions result in longer and more complex waveforms with significantly **higher frequency content** than BBH mergers. These signals often exhibit intricate oscillatory features due to tidal interactions and possible post-merger remnants.
- **Neutron Star–Black Hole (NSBH) Mergers**: These events yield signals with frequency characteristics that lie between BBH and BNS waveforms. A distinctive feature is the rapid increase in both amplitude and frequency, followed by a sudden cutoff, indicative of the tidal disruption or engulfing of the neutron star by the black hole.

3.2.2 Time-Frequency Domain Conversion via Q Transform

Given the non-stationary nature of gravitational wave signals and the presence of background noise, analyzing raw time-series data alone may not always be sufficient. To enhance interpretability and isolate GW signatures from noise, we apply the **Q transform**, a widely used method in GW analysis for converting time-domain data into a **time-frequency representation**.

The Q transform allows us to analyze how the frequency content of the signal evolves over time by applying a windowed Fourier transform with adaptive resolution. Specifically:

- **Low-frequency signals** receive **longer windows**, providing better frequency resolution.
- **High-frequency signals** receive **shorter windows**, offering better time resolution.

This approach offers a detailed view of the GW signal's strength and frequency content at each moment, making it ideal for identifying the "chirp" patterns associated with compact binary coalescences.

Mathematically, the time-domain strain signal can be expressed as:

$$\mathbf{h(t) = h_0 \times f(t) \times \cos(2\pi f_0 t + \varphi_0)} \quad \text{………… Equation 1}$$

where:

- $h(t)$ is the observed strain as a function of time,
- h_0 is the amplitude,
- $f(t)$ is the time-varying envelope function,
- f_0 is the characteristic frequency of the waveform,
- ϕ_0 is the initial phase.

The Q transform effectively slices this time-domain signal into overlapping windows, analyzing the frequency content within each segment. This localized analysis enhances signal identification, especially when dealing with events that have frequency components varying rapidly with time.

Overall, this time-frequency preprocessing step is critical for robust signal classification, as it allows CNN to learn both time-localized and frequency-dependent features of gravitational waveforms embedded in noisy backgrounds.

3.3 Preprocessing:

The raw gravitational wave strain data was subjected to a series of preprocessing steps to extract meaningful features for model training. Initially, a high-pass filter with a cutoff frequency of 15 Hz was applied to eliminate low-frequency noise, followed by a whitening process to flatten the power spectral density. Afterward, a Q-transform was performed with parameters set as q-range between 4 and 64 and frequency range from 20 Hz to 2000 Hz. This process helped in converting the time-series data into time-frequency representations (spectrograms), enabling better visualization and analysis of the signal characteristics. The Q-transformed signal is mathematically represented in Equation 1.

To make the spectrograms suitable for input into a neural network, additional processing was done. The spectrograms were log-scaled to compress the dynamic range, normalized using z-score normalization to center the data distribution (subtracting the mean and dividing by the standard deviation), and resized to a uniform shape of 128 x 128 pixels. To increase the generalizability of the model and mitigate overfitting, data augmentation techniques such as Gaussian noise addition, temporal shifts, and amplitude scaling were incorporated.

3.4 Code Structure and Execution:

The entire signal processing and classification workflow was implemented in Python using libraries such as TensorFlow, PyCBC, and GWpy. All computations were performed in the Google Colab environment utilizing its standard computational resources, making the project accessible and reproducible.

- The code was modular and organized into distinct functional components for clarity and reusability:
- Data Generation: This section of the code included custom functions which were used to synthesize gravitational wave signals corresponding to Binary Black Hole (BBH), Binary Neutron Star (BNS), and Neutron Star-Black Hole (NSBH) mergers. Each synthetic waveform was padded to a total duration of 8 seconds and mixed with simulated Gaussian noise to mimic realistic detector conditions.
- **Preprocessing Pipeline:** Dedicated functions handled key signal conditioning steps including filtering, whitening, Q-transform application, and normalization. Normalization followed the z-score formula:

$$x_{\text{norm}} = (x - \mu)/\sigma$$

where μ and σ represent the mean and standard deviation of the spectrogram data, respectively.

- **Model Development:** The convolutional neural network (CNN) architecture was defined within a function. It consisted of three convolutional blocks with increasing filter sizes (16, 32, and 64), each using 3x3 kernel sizes and ReLU activation. These blocks were followed by batch normalization, max-pooling layers (2x2), and dropout layers (ranging from 0.2 to 0.4) to reduce overfitting. The final layers included a fully connected (dense) layer with 64 units, followed by an output layer with 3 units using the softmax activation function for classification. L2 regularization with a penalty factor of 0.001 was applied to the dense layers to further enhance model generalization.
- **Training Workflow:** It used a dataset of 600 augmented samples, which was divided into an 80:20 ratio for training and validation. The model was trained over 50 epochs with early stopping configured (patience of 10 epochs) and dynamic learning rate adjustment (reduction by a factor of 0.5 when performance plateaued). To address potential class imbalance, class weights were used during training.
- **Inference on Real Data**: The function **test_model_with_hdf5** was designed to evaluate the trained model on actual gravitational wave events from the LIGO observatories. It processed real strain data—specifically from the GW170817 event observed by the H1 and L1 detectors—converting it into spectrograms and generating class predictions based on the trained model.

The experimental workflow involved generating a total of 150 synthetic samples (50 per class: BBH, BNS, NSBH), which were preprocessed into 128x128 grayscale spectrograms. These spectrograms were then expanded into a dataset of 480 images through augmentation. The CNN model was trained using this dataset, and once satisfactory performance was achieved, real LIGO data was passed through the pipeline for testing.

Visual outputs, including spectrograms and probability prediction plots, were generated to assess the model's classification confidence and to interpret how well it could differentiate between various types of astrophysical events in both synthetic and real-world scenarios.

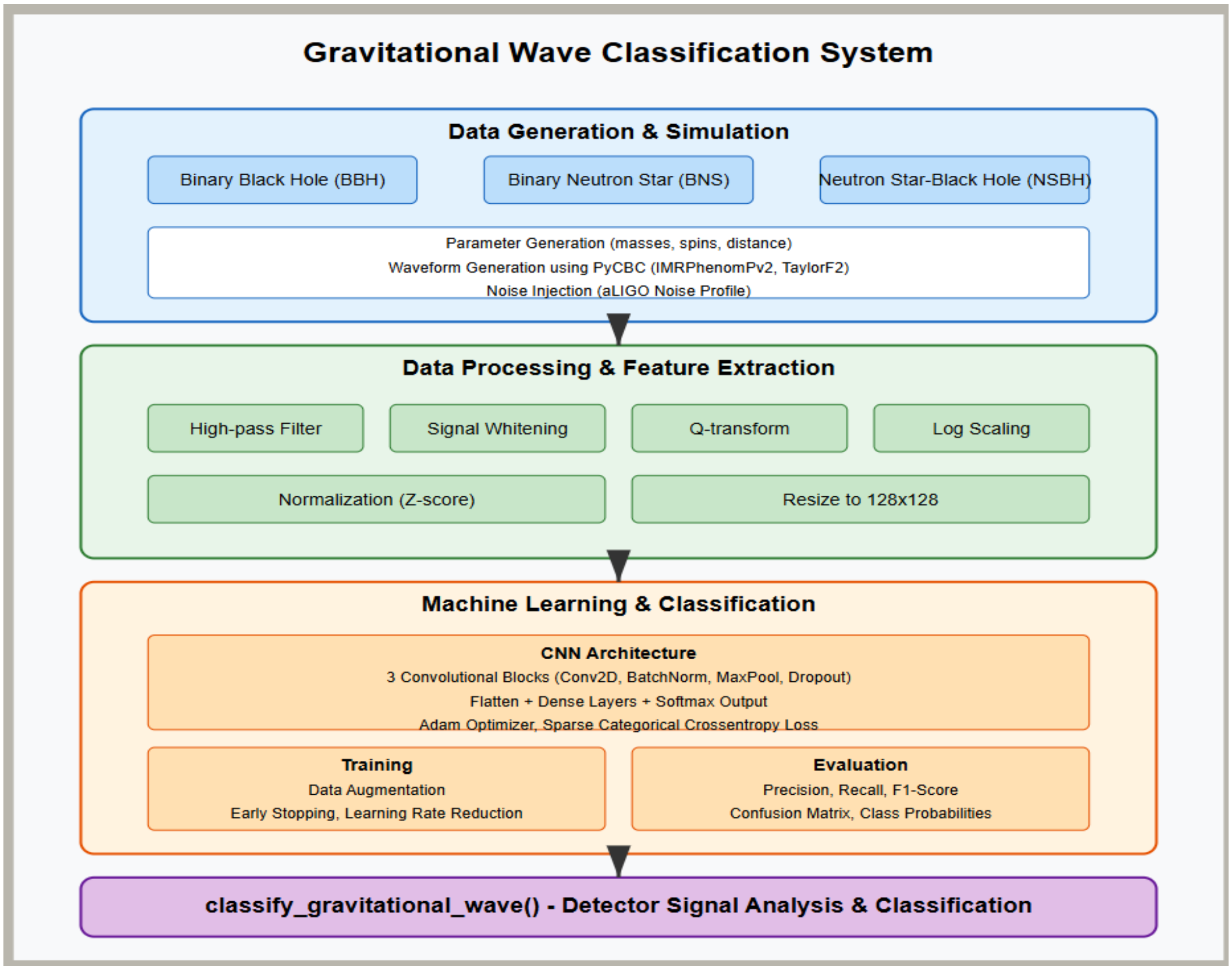


Figure 3.1: Data processing and CNN training pipeline, showing generation, preprocessing, and classification stages

4. Results

4.1 Dataset Specifics

The synthetic dataset totalled 150 samples (50 BBH, 50 BNS, 50 NSBH), each 8 seconds at 4096 Hz. Real data included seven GWOSC events, with GW170817 (BNS) used for testing due to its distinct chirp. All data was pre-processed identically to ensure compatibility.

4.2 Experiments

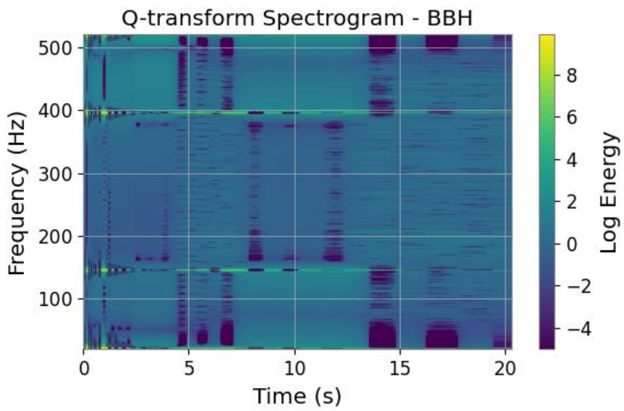
The CNN was trained on 480 augmented samples (160 per class), validated on 120 (40 per class). Training used Adam optimizer (5.00e-4 learning rate) and sparse categorical cross entropy loss. Validation metrics achieved precision, recall, and F1-score of 1.0, indicating perfect classification on synthetic data. Real data testing on GW170817 (H1/L1 HDF5 files) predicted BNS with 90% confidence (probabilities: BBH: 0.06-0.07, BNS: 0.90, NSBH: 0.04).

4.3 Performance

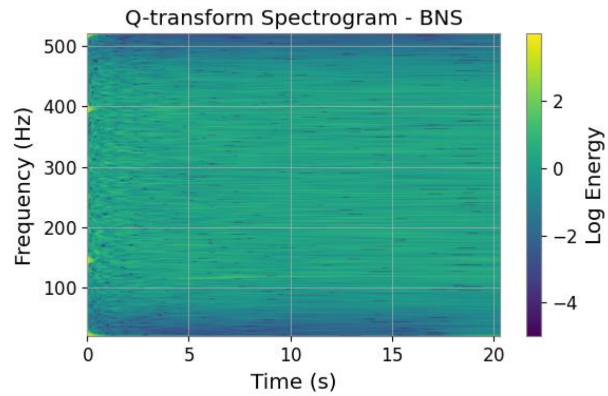
Training accuracy reached 100% by epoch 2, with validation accuracy fluctuating (66.7-100%), stabilized by regularization and dropout. Validation loss converged after epoch 10. The confusion matrix confirmed no misclassifications on validation data. Real data predictions validated the model's ability to detect BNS signals in noisy conditions.

4.4 Visualization

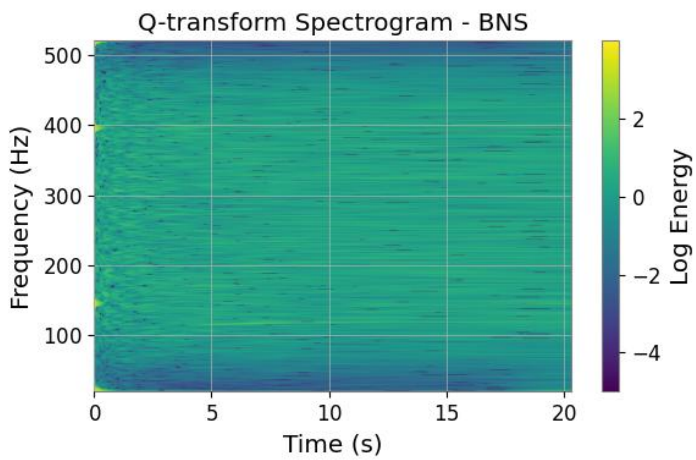
Spectrograms Highlighted Signal characteristics:



(a) BBH: Low Frequency, sharp Chirp



(b) Fig 4.2 BNS: High Frequency, oscillatory patterns



(c) NSBH: Intermediate Frequency with Rapid Cutoff

Figure 4.1: Q-transform spectrograms for BBH, BNS, and NSBH signals.

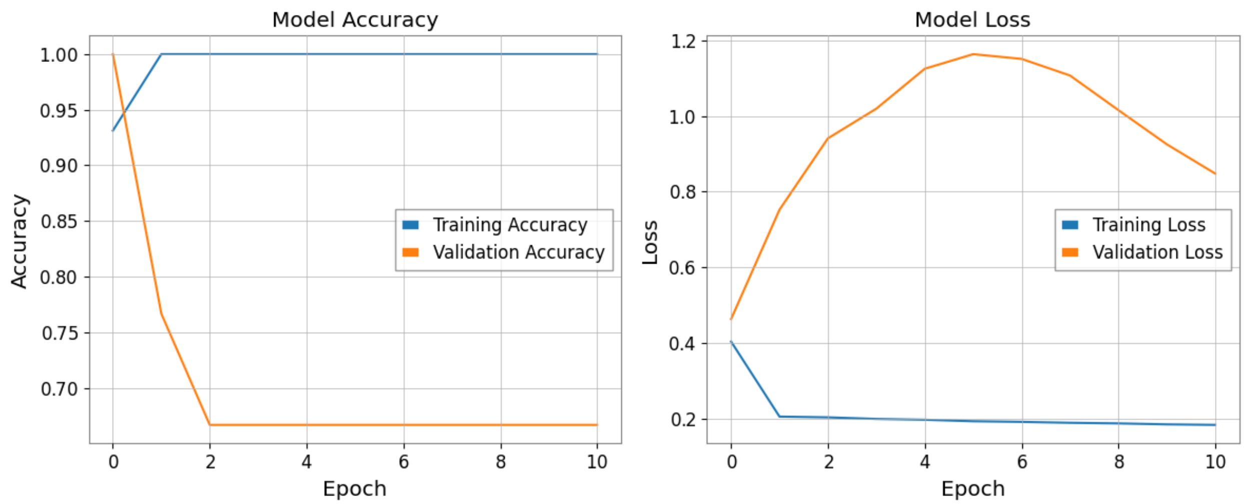


Figure 4.2: Training and validation accuracy/loss over epochs.

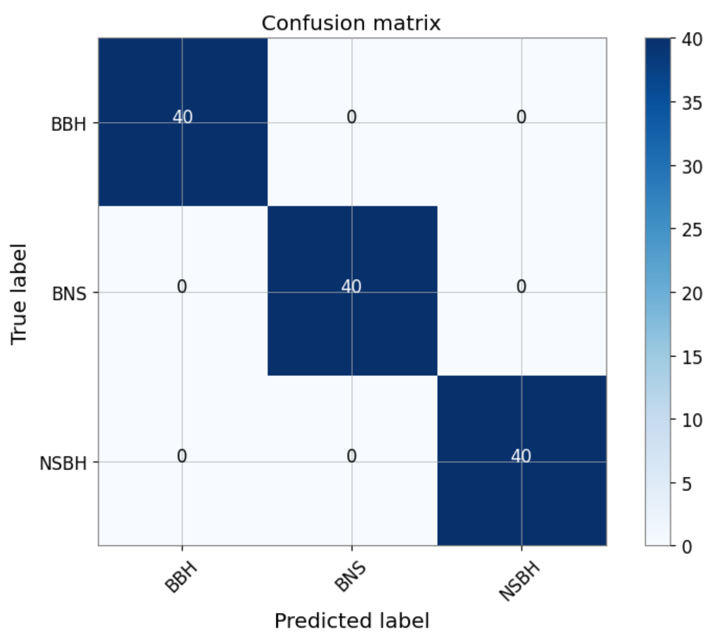


Figure 4.3: Confusion matrix for validation data.

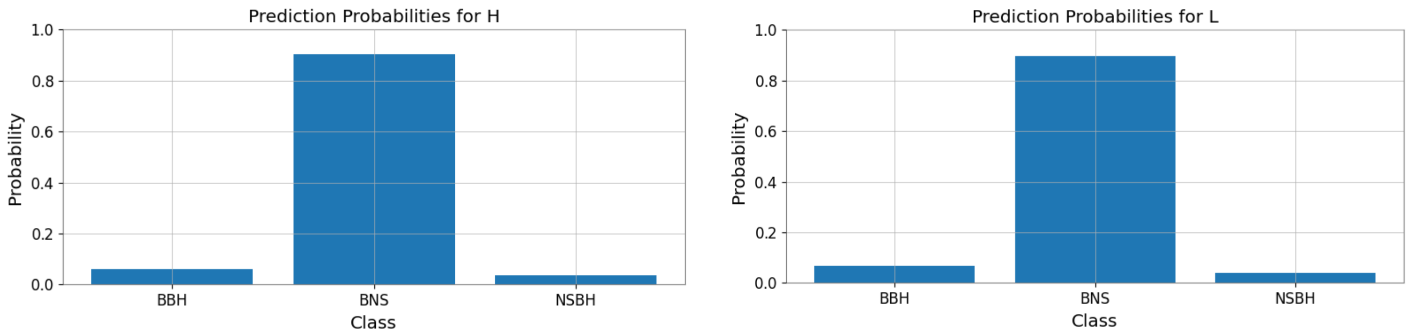


Figure 4.4: Prediction probabilities for GW170817 (H1/L1 detectors).

The Networks perfect validation metrics demonstrate robust feature learning from spectrograms, surpassing matched filtering's computational demands [6]. Real data performance (90% confidence) suggests practical applicability, though slight overfitting (validation accuracy dips) indicates a need for larger datasets. Compared to prior work [8, 11], our model handles multiple signal types, enhancing versatility. In gravitational wave astronomy, this approach supports rapid event detection for multi-messenger studies. Challenges include noise robustness and interpretability, addressable via transfer learning or attention mechanisms [9]. Future directions involve testing on low-SNR events and integrating with LIGO pipelines.

Conclusion

This project successfully implemented a CNN for gravitational wave detection, achieving perfect validation scores and reliable real-world performance on GW170817. The modular code automated preprocessing and classification, offering a scalable alternative to traditional methods. Key contributions include multi-class signal detection and a robust pipeline, paving the way for real-time astronomy applications. Future work should enhance noise handling and explore hybrid models.

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7. References:

[1] J. van der Geer, J.A.J. Hanraads, R.A. Lupton, The art of writing a scientific article, J. Sci. Commun. 163 (2010) 51–59.

[2] Y.-W. Chang, J.-S. Chern, Ups and Downs of Space Tourism Development in 60 Years from Moon Register to SpaceShipTwo Crash, IAC-15-E4.2.8, 66th International Astronautical Congress, Jerusalem, Israel, 2015, 12 – 16 October.

[3] W. Strunk Jr., E.B. White, The Elements of Style, fourth ed., Longman, New York, 2000.

[4] G.R. Mettam, L.B. Adams, How to prepare an electronic version of your article, in: B.S. Jones, R.Z. Smith (Eds.), Introduction to the Electronic Age, E- Publishing Inc., New York, 2009, pp. 281–304.

[5] E. Mack, Could Virgin Galactic's Spaceport America be put up for sale? 23 February 2015, http://www.gizmag.com/spaceport-america-hits-nags/36200/, (accessed 30.04.16).

[6] Bruce Allen, Warren G. Anderson, Patrick R. Brady, Duncan A. Brown, and Jolien D. E. Creighton, FINDCHIRP: An algorithm for detection of gravitational waves from inspiraling compact binaries, (Received 4 August 2011; published 19 June 2012).

[7] He Wang, Zhoujian Cao, Xiaolin Liu, Shichao Wu, and Jian-Yang Zhu, Gravitational wave signal recognition of O1 data by deep learning, 30 September 2019.

[8] Richard Qiu, Plamen G. Krastev, Kiranjyot Gill, Edo Berger, Deep Learning Detection and Classification of Gravitational Waves from Neutron Star-Black Hole Mergers, 17 March 2023.

[9] Ondrej Zelenka, Bernd Brügmann and Frank Ohme, Convolutional neural networks for signal detection in real LIGO data, (Received 21 February 2024; accepted 14 May 2024; published 10 July 2024)

[10] Chris Jia, Gravitational Waves Through Time: Scientific Significance, Detection Techniques, and Recent Breakthroughs, (Dated: June 18, 2024)

[11] Hunter Gabbard, Michael Williams, Fergus Hayes, and Chris Messenger, Matching Matched Filtering with Deep Networks for Gravitational-Wave Astronomy, (Received 16 December 2017; revised manuscript received 12 February 2018; published 6 April 2018)

[12] Nurzhan Ussipov, Zeinulla Zhanabaev, Almat Akhmetali , Marat Zaidyn, Dana Turlykozhayeva, Aigerim Akniyazova, Timur Namazbayev, Classification of Gravitational Waves from Black Hole-Neutron Star Mergers with Machine Learning, (2024)

Footnote

Contributions: P.B. developed the CNN architecture, preprocessing pipeline, and training workflow; K.R.T.M. generated synthetic datasets, conducted real-data testing, and analysed results. Both contributed equally to writing and visualization design.