

A Proof-of-Concept Convolutional Neural Network for Estimating the Total Mass of Binary Black Hole Systems from their Gravitational Waves

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ABSTRACT

Gravitational wave detections provide information about the physical properties of their source binary system, such as the total mass of the system. Typically, these parameters are extracted by comparing observed gravitational wave signals with waveform models. This study presents a proof-of-concept investigation of how a convolutional neural network (CNN) can estimate the total mass of a binary black hole system from its gravitational wave waveform. Simulated gravitational waves are generated over a range of total masses using a gravitational wave waveform model. The simulated waves are then used as inputs to a one-dimensional CNN. The proof-of-concept implements fixed values for many parameters for both the binary system and the detector. This is done to isolate the relationship between the waveform and the total mass. A preliminary CNN implementation was developed and evaluated using simulated gravitational wave waveforms. The preliminary implementation generated 1,000 simulated waveforms with total masses linearly spaced from 50 to 600 $M_{\odot}$ and used them as inputs to a one-dimensional CNN. Many source and detector parameters were held fixed to isolate the relationship between waveform morphology and total mass. On the held-out test set, the implementation produced a mean absolute error (MAE) of 33.94 $M_{\odot}$ and a root mean squared error (RMSE) of 45.13 $M_{\odot}$. Because the implementation was not independently validated and used a restricted set of simulated source parameters, its results are presented as a proof-of-concept rather than as evidence of a validated predictive model. The study also discusses its limitations, including the use of simulated data, restricted source parameters, and simplified detector conditions, as well as potential extensions applicable to more realistic gravitational wave waveforms.

INTRODUCTION

Gravitational Waves

Gravitational waves are propagating perturbations of spacetime generated by accelerating mass distributions (NASA, n.d.). Compact binary systems, such as binary black holes or binary neutron stars,

are some of the strongest sources of gravitational waves detectable to ground-based interferometers. As the components orbit and approach one another, their orbital frequency increases, producing a gravitational wave signal whose amplitude and frequency evolve through the inspiral, merger, and ringdown stages of coalescence (Abbott et al., 2016). When the gravitational wave emitted eventually passes through a detector, it produces time-dependent distortions that change the space between objects.

During the inspiral stage, the black holes gradually approach one another as their orbital frequency and gravitational wave frequency increase. As the system reaches coalescence, it enters the merger stage, which produces the strongest and most rapidly varying portion of the signal. The final ringdown stage occurs as the remnant black hole settles into a stable configuration, causing the gravitational wave amplitude to decrease. The changing frequency and amplitude across these stages contain information about the physical parameters of the binary system (Abbott et al., 2016; Abbott et al., 2019; Forteza et al., 2023). This motivates investigating whether a machine-learning model can learn features of the waveform that are informative about these parameters.

Gravitational waves have two tensor polarization states, h_+ and $h_\times$, which produce orthogonal transverse distortions of spacetime (Sathyaprakash and Schutz, 2009). The two polarizations differ in their orientation relative to the direction of propagation. Because the strain measured by an interferometer depends on the polarization and detector geometry, these properties influence the observed waveform. The h_+ polarization distorts by alternating stretching and compressing patterns in perpendicular directions, while the $h_\times$ polarization does this at 45° to the h_+ configuration (see Figure 2). These extremely small distortions can be detected and measured by the change in relative distance of the two perpendicular arms of a laser interferometer.

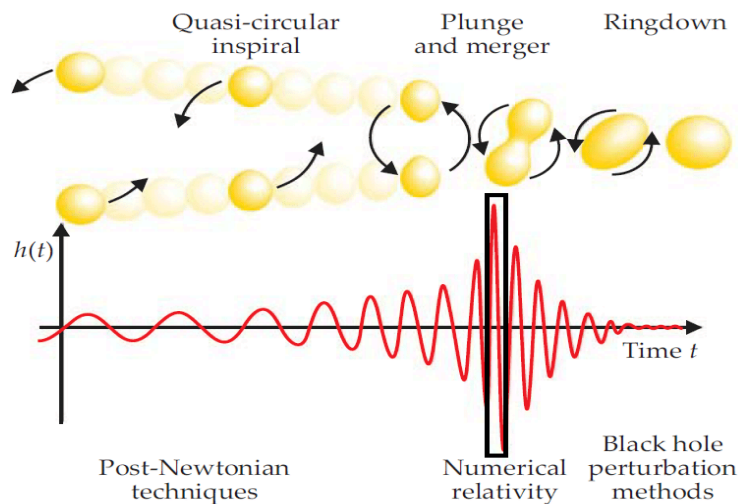


Figure 1: Schematic representation of the three stages of a binary black-hole merger: inspiral, merger, and ringdown. The inspiral stage is characterized by increasing orbital frequency, followed by the merger and subsequent ringdown of the resulting black hole (Scharpf, 2017).

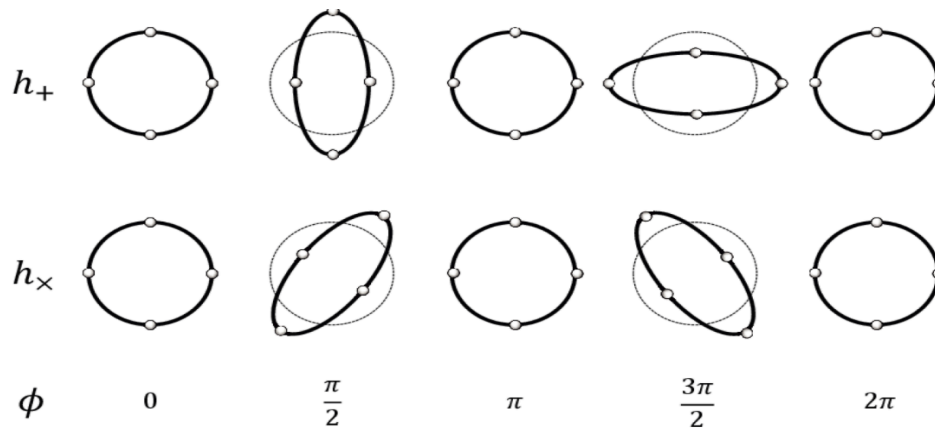


Figure 2: The two tensor polarization states of gravitational waves, h_+ and $h_\times$, and their associated spacetime distortions. The two polarizations describe the transverse deformation of spacetime produced by a passing gravitational wave (Królak and Patil, 2017).

Because the gravitational wave perturbation is small compared to the background spacetime metric, the spacetime metric can be approximated as:

$$g_{\mu\nu} = \eta_{\mu\nu} + h_{\mu\nu} \quad (1)$$

In Equation 1, $g_{\mu\nu}$ represents the full spacetime metric, $\eta_{\mu\nu}$ represents the Minkowski metric of flat spacetime, and $h_{\mu\nu}$ represents a small perturbation to the background metric (Thorne, 1995). In this linearized model, the propagating components of the perturbation describe gravitational waves. This mathematical approximation accounts for small distortions caused by these gravitational waves.

Gravitational Wave	Mass 1 ($M_\odot$)	Mass 2 ($M_\odot$)	Distance (Mpc)	Total Mass ($M_\odot$)
GW231123_135430 (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration, 2025a)	137^{+22}_{-17}	103^{+20}_{-52}	2200^{+1900}_{-1500}	238^{+28}_{-49}
GW231028_153006 (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration, 2025b)	99^{+32}_{-22}	55^{+24}_{-21}	4200^{+1400}_{-1900}	153^{+29}_{-14}
GW231029_111508 (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration, 2025b)	65^{+17}_{-14}	42^{+15}_{-15}	3100^{+2400}_{-1600}	106^{+22}_{-16}
GW231223_032836 (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration, 2025b)	46^{+15}_{-11}	31^{+12}_{-15}	4000^{+2900}_{-2000}	77^{+18}_{-13}

Table 1: Selected gravitational wave events and their estimated total source masses.

Sources of Gravitational Waves

Gravitational wave sources can be broadly classified by their physical origin. Most sources detected from ground-based detectors are from compact binary systems, which are gravitationally bound systems that result from two compact objects, such as neutron stars or black holes. Compact binary systems, including binary black holes and binary neutron stars, produce gravitational waves as their components orbit and coalesce. The gravitational wave waveform of each system is determined by total mass, distance to the detector, orbital dynamics, and other parameters. Compact binaries produce gravitational waves as their components orbit and eventually coalesce. These systems produce different gravitational wave waveforms based on different characteristic properties. Other sources produce different types of signals, including stochastic backgrounds formed from many unresolved events and burst signals associated with short-duration astrophysical phenomena ('Sources and types of gravitational waves', 2023). This study focuses specifically on binary black hole coalescences, which are the source systems modeled in the proof-of-concept experiment.

Detection Methods

Ground-based gravitational wave detectors such as LIGO and Virgo use laser interferometers to measure extremely small changes and distortions in the relative lengths of their two perpendicular arms caused by passing gravitational waves. Laser interferometry is a method that uses a beam splitter to divide a laser beam into two distinct beams that travel along perpendicular arms of equal length. At the end of the arms, there are mirrors that reflect the beam back toward the beam splitter, recombining the two distinct beams into one (see Figure 3).

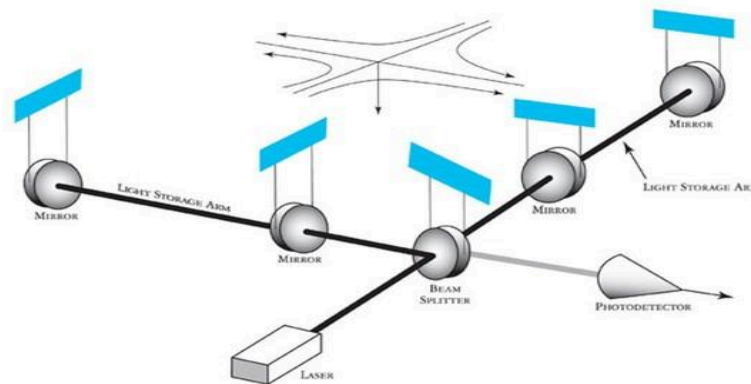


Figure 3: Schematic representation of a laser interferometer used to detect gravitational waves. A laser beam is split into two perpendicular arms, reflected by mirrors, and recombined at a photodetector to measure changes in the relative arm lengths caused by gravitational wave strain (Caltech/MIT LIGO Laboratory, 2024).

In the absence of gravitational waves, the beams are oriented in such a way that they destructively interfere with one another at the photodetector. When a gravitational wave passes through the interferometer, it produces changes in the lengths of the two arms. This changes the optical path lengths traveled by the separated beams, producing a phase difference in the light waves, causing the interference pattern to change. The photodetector can then detect the change in interference to detect gravitational wave distortions. Since the arms of the interferometer are many kilometers long, even extremely small distortions can be detected, producing measurable changes in interference signals. The gravitational wave strain, h , is described as the ratio of change in length of the arm to the original length as in the following equation:

$$h = \Delta l / l \quad (2)$$

Gravitational waves detection depends on the polarization of the waves, causing the strain to vary based on the geometry of the detector. Thus, a network of spatially-separated interferometers can improve the ability to detect gravitational waves and characterize them based on the different orientations of multiple detectors. Some examples of detectors are LIGO Hanford in Washington state, LIGO Livingston in Louisiana, and Virgo in Pisa in Italy.

Because gravitational wave strain contains information about the physical properties of its source, the resulting time series can be analyzed to estimate source parameters. Machine learning methods provide one possible approach for learning relationships between waveform characteristics and these physical parameters. This study therefore investigates whether a one-dimensional convolutional neural network can estimate the total mass of a binary black hole system from simulated gravitational-wave strain waveforms.

CONCEPT

Introduction to Concept

Gravitational wave waveforms contain information about the physical parameters of their source systems, including the total mass of the system. This study investigates whether a convolutional neural network (CNN) can learn the relationship between simulated gravitational wave waveforms and the total mass of a binary black hole system. By training the network on a dataset of waveforms generated with varied total mass parameters, the model can be evaluated on its ability to estimate the total mass of the system from its waveform. This serves as a proof-of-concept for using machine learning methods to estimate the system parameters from emitted gravitational waves. Convolutional neural networks have previously been investigated for gravitational wave parameter estimation (Andrés-Carasona et al., 2024), but the present

study is not intended to introduce the general application of machine learning. Instead, it develops a proof-of-concept framework for investigating total mass estimation from one-dimensional simulated strain waveforms under fixed source and detector parameters.

A convolutional neural network is a class of neural network framework, designed to learn spatial or local patterns within data provided. CNNs are widely used for image analysis, but one-dimensional CNNs are also able to be applied to data, such as a gravitational wave strain time-series. Convolutional neural networks can apply filters to local regions of the input waveform to identify features that may relate to the prediction. Additional filters can transform and reduce the local patterns before they are passed to fully connected layers, which combine the features extracted to estimate the predicted output. In this study, the proposed proof-of-concept framework uses the simulated gravitational wave waveforms as inputs to a CNN, with the corresponding total binary mass serving as the target variable. The one-dimensional CNN is applied to the temporal structure of the simulated gravitational wave strain waveform. The waveform data is then processed into a consistent numerical representation before being provided to the network for predictions.

A preliminary implementation was developed to demonstrate the proposed workflow. It generated 1,000 simulated binary black-hole waveforms with total masses from 50 to 600 $M_{\odot}$, added Gaussian noise with an amplitude of 0.3 in normalized strain units, and trained a one-dimensional CNN using a 68%/17%/15% training/validation/test division. The network was trained on base-10 logarithmic mass targets using mean-squared error (MSE). On the held-out test set, it produced an MAE of 33.94 $M_{\odot}$ and an RMSE of 45.13 $M_{\odot}$ after predictions were converted back to solar masses. These results demonstrate the implementation of the proposed workflow but do not constitute independent validation of predictive performance. These outputs are not considered validated measurements of predictive performance, and, thus, are purely for demonstrational purposes.

Data Generation and Preprocessing

For this proof of concept, a framework for generating and analyzing simulated gravitational wave waveforms can be made using PyCBC (Usman et al., 2016), a Python-based software package used to analyze gravitational waves of LIGO and Virgo. A thorough implementation of the software could generate binary black hole waveforms with varied total masses, distance, inclination, and spin parameters. Varying these parameters would allow a neural network to learn the relationship between waveform characteristics and the physical properties of the source under a broader range of conditions. In the preliminary unvalidated implementation in the Appendix, the total mass was varied while the other source and detector parameters were held fixed. For the proposed experiment, total masses between 50 $M_{\odot}$ and 600 $M_{\odot}$ can be sampled using a linear spacing to provide coverage across the selected total mass range, and other parameters can be set constant to investigate solely the relationship of mass and strain. A large

dataset of simulated waveforms could then be generated with an appropriate noise model to approximate the conditions of natural background noise similar to that of detector data.

For the preliminary implementation, PyCBC (Usman et al., 2016) was used to generate simulated binary black hole waveforms. The total mass was varied linearly from $50 M_{\odot}$ to $600 M_{\odot}$, while the component masses were set equal, the source distance was fixed at 100 Mpc, the inclination was 0, both aligned spin parameters were 0.9, and the sky location and polarization were held constant. The waveforms were generated with IMRPhenomD and projected onto the LIGO Hanford detector. Gaussian noise with an amplitude of 0.3 relative to the normalized signal was then added. Thus, the preliminary implementation intentionally varied total mass while holding the other modeled parameters fixed.

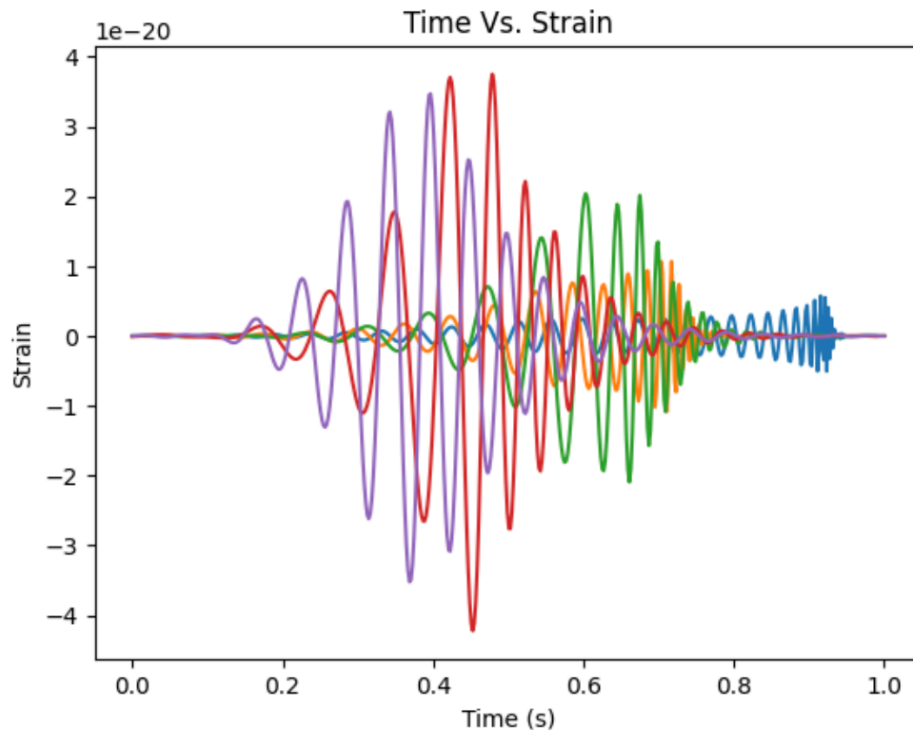


Figure 4: Five sample gravitational wave strains from the simulated binary black hole dataset plotted on the same graph. The horizontal axis represents time, and the vertical axis represents gravitational wave strain. The waveforms illustrate the variation in the simulated detector strain over time for different total masses. Each colored curve represents a waveform generated for a different total mass.

The waveform generation by PyCBC creates a time coordinate and the corresponding detector strain time-series for each simulated gravitational wave signal. To provide the network with a consistent numerical representation, generated waveforms can be processed by removing portions of the waveform that fall below a near-zero threshold, normalizing the time coordinate, and interpolating the remaining samples, simplifying and smoothing the waveform. *Akima1DInterpolator*, a one-dimensional

interpolation, can be used to obtain a smooth representation of the processed waveform while preserving its overall structure (Jones et al., 2020). The data from the resulting time series can then be arranged as inputs for the neural network.

In the preliminary implementation, the waveform-generation procedure produced a detector-strain time series for each simulated signal. To focus on the chirp, samples were retained when the absolute value of the change between adjacent strain samples exceeded 0.0001 times the maximum absolute strain. The retained time coordinate was then normalized to the interval $[0, 1]$. An `Akima1DInterpolator` (Jones et al., 2020) was applied to the retained samples, and the waveform was resampled at 3,000 equally spaced points between 0 and 1. Any NaN values produced by the interpolation were replaced with zero. This processing order provided a consistent 3,000-point numerical representation for the CNN input.

Convolutional Neural Network

A CNN can be implemented using a machine learning framework, such as `TensorFlow` (Abadi et al., 2016). The processed gravitational wave time-series can be formatted as one-dimensional input data, having the target values be the total mass of the binary merger system. The CNN then applies its learned convolutional filters to determine the relevant features of the waveform that describe the target total mass. These resulting feature representations can then be flattened into a one-dimensional vector and passed through the connected layers of the neural network, having the final output layer producing an estimated total mass. The network can be compiled using an optimization algorithm and a loss function, such as mean-squared error (MSE) or mean absolute error (MAE). During development, a validation set can be made from a portion of the original dataset in order to monitor model performance on data that was not used previously to update the model parameters.

In the preliminary model, the simulated gravitational-wave strain waveforms were assigned as input data (x), while the base-10 logarithm of the corresponding total masses was assigned as the regression target (y). The model was compiled with the Adam optimizer and mean-squared error (MSE) loss and was trained with a batch size of 32 for a maximum of 100 epochs. Early stopping monitored validation loss with a patience of 5 epochs and restored the best model weights. For evaluation, predictions were transformed from a log of base-10 (total mass) back to solar masses; the reported MAE and RMSE were calculated in solar-mass units, whereas the training and validation loss remained MSE in logarithmic-mass space.

Limitations of Framework

The proposed framework would require further development before it could be applied reliably to gravitational wave parameter estimation using observational data. The framework would need to account for realistic detector noise and differences between detectors rather than relying on simplified simulated conditions. Independent simulated populations would be necessary to evaluate whether the learned

relationship generalizes beyond the population used during model development. Ultimately, evaluation using observational gravitational wave data would be necessary to determine whether the approach remains effective under real detector conditions. Additional investigation would also be required to determine how accurately the framework can distinguish the effects of total mass from other physical parameters that can influence waveform morphology. Thus, the proposed framework should currently be regarded as a foundation for further investigation rather than a complete parameter-estimation method.

CONCLUSION

Gravitational wave waveforms contain information about the physical parameters of their source systems, including the total mass of binary black hole mergers. This study presented a proof-of-concept framework for investigating whether a one-dimensional convolutional neural network can learn the relationship between simulated gravitational wave waveforms and the total mass of their corresponding binary black hole systems. Simulated waveforms provide a controlled environment, where the characteristics of waveforms can be compared to the source total mass using machine learning methods. The preliminary implementation demonstrates how such a framework can be constructed using simulated waveforms in a controlled environment. Its outputs, provided in the Appendix as an implementation example, should not be interpreted as validated measurements of predictive performance.

The framework can be extended to estimate additional source parameters, such as chirp mass, mass ratio, and component spins, while incorporating a broader range of source parameters, realistic detector noise, independent data, and observational gravitational wave data. These extensions would allow the approach to be evaluated under more realistic conditions and provide a stronger assessment of whether machine learning methods could complement existing approaches to gravitational wave parameter estimation.

APPENDIX

Practice Model Setup

For this preliminary implementation, PyCBC (Usman et al., 2016), a Python-based software package meant to analyze gravitational waves of LIGO and Virgo, was used to generate simulated gravitational wave waveforms from binary black hole systems. The simulations used different linearly spaced total masses between $50 M_{\odot}$ and $600 M_{\odot}$. A total of 1000 gravitational wave waveforms were generated for the preliminary neural network implementation. The source distance was fixed at 100 Mpc, the inclination was set to 0, and the aligned spin parameters of both black holes were set to 0.9 for simplification. Gaussian noise with an amplitude of 0.3 was subsequently added to the simulated waveforms.

A function, `make_waveform()`, is made to generate the simulated waveforms with the specified set of parameters. The waveforms were generated using `IMRPhenomD` (Pürrer et al., 2023). The resulting waveforms were projected onto the LIGO Hanford detector (h1), while the sky location and polarization parameters were held constant. The resulting detector strain was represented as a time-series. Data was taken from the time-series as the proof-of-concept (as done in the data generation and preprocessing section in the paper). The processed time-series data were then prepared for input into the neural network. After simulating the waveforms, five sample gravitational wave waveforms were plotted on a graph (see Figure 4) for visual inspection.

Neural Network for Practice Model

TensorFlow (Abadi et al., 2016) was used to develop the convolutional neural network. The simulated gravitational wave strain waveforms were assigned as input data (x), while the base-10 logarithm of the corresponding total masses was assigned as the regression target (y). The CNN applies the convolutional filters to the waveform time-series to extract relevant features from the input signals. The resulting feature maps are then flattened into a one-dimensional vector and passed through fully connected layers. The final output layer produces a single value corresponding to the predicted logarithm of the total mass, which is subsequently transformed back into solar masses for interpretation. The architecture of the preliminary implementation is summarized in Table A.1.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 2985, 32)	544
max_pooling1d (MaxPooling1D)	(None, 746, 32)	0
conv1d_1 (Conv1D)	(None, 739, 64)	16,448
max_pooling1d_1 (MaxPooling1D)	(None, 184, 64)	0
conv1d_2 (Conv1D)	(None, 181, 128)	32,896
max_pooling1d_2 (MaxPooling1D)	(None, 45, 128)	0
flatten (Flatten)	(None, 5760)	0
dense (Dense)	(None, 128)	737,408
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Table A.1: Architecture of the one-dimensional convolutional neural network used in the preliminary implementation. The table lists the network layers and their corresponding configurations, including the

convolutional, pooling, flattening, and fully connected layers used to process the simulated gravitational wave time-series data and produce the model output.

Training the Practice Model

The neural network was compiled with the Adam optimizer and mean-squared error (MSE) loss and was trained using the simulated waveforms as input data and the base-10 logarithm of total mass as the target. The Adam optimizer used its default learning rate of 0.001. The 1,000 simulated waveforms were divided into training, validation, and test sets before model fitting. Fifteen percent of the dataset (150 waveforms) was held out as a test set using `train_test_split` with `random_state = 42` and `shuffle = True`. The remaining 850 waveforms were used for training and validation, with 20% of that subset (170 waveforms) used for validation, yielding 680 training, 170 validation, and 150 test waveforms. The held-out test set was not used for model fitting or validation and was evaluated only after training. Early stopping and model selection used validation loss from the training/validation subset, not the test set. Because the masses were sampled across the $50 M_{\odot}$ and $600 M_{\odot}$ range before partitioning, the held-out test set primarily assessed interpolation within the simulated mass range. No separate simulated population or observational dataset was used for independent validation, so the test-set results should be interpreted as performance on this simulated dataset rather than as evidence of a validated predictive model.

--- TEST SET MASS COMPARISON TABLE ---

True Mass ($M_{\odot}$)	Predicted Mass ($M_{\odot}$)	Absolute Error ($M_{\odot}$)	Percent Error (%)
55.505506	68.813408	13.307902	23.975824
62.662663	57.026138	5.636524	8.995028
63.763764	71.043251	7.279487	11.416339
66.516517	79.820641	13.304124	20.001234
71.471471	77.728394	6.256922	8.754433
74.224224	66.739861	7.484364	10.083452
79.729730	88.270859	8.541129	10.712603
80.280280	109.672256	29.391976	36.611701
82.482482	104.107559	21.625077	26.217781
84.684685	109.090630	24.405945	28.819786
86.336336	127.569191	41.232855	47.758402
86.886887	110.916405	24.029518	27.656093
88.538539	120.095413	31.556875	35.641965
89.639640	118.517685	28.878045	32.215709
91.841842	97.746689	5.904847	6.429365
97.347347	135.962311	38.614963	39.667196
98.448448	134.898315	36.449867	37.024318
102.852853	132.113907	29.261054	28.449434
105.605606	146.195709	40.590104	38.435558
108.908909	159.464096	50.555187	46.419699

Table A.2: Selected predictions from the preliminary neural network on the held-out test set. True and predicted total masses are reported in solar masses, along with the absolute and percentage errors for each prediction.

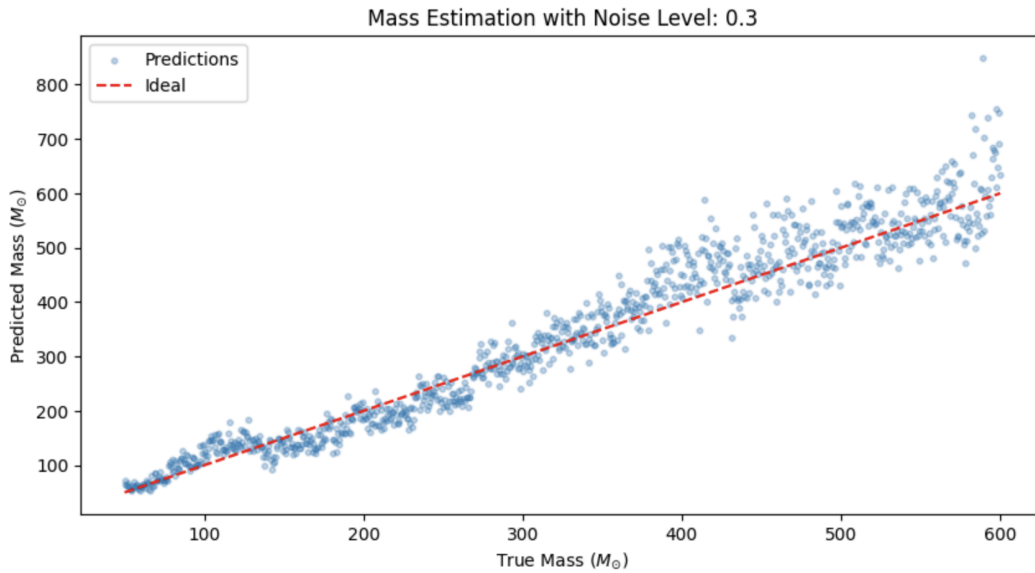


Figure A.1: True total mass versus CNN-estimated total mass for the simulated binary black hole dataset, generated with a Gaussian noise amplitude of 0.3 (in normalized strain units) added to each waveform. The x-axis shows the true total mass in solar masses, while the y-axis shows the model-estimated total mass in solar masses. The dashed line represents the ideal one-to-one relationship between true and estimated total mass.

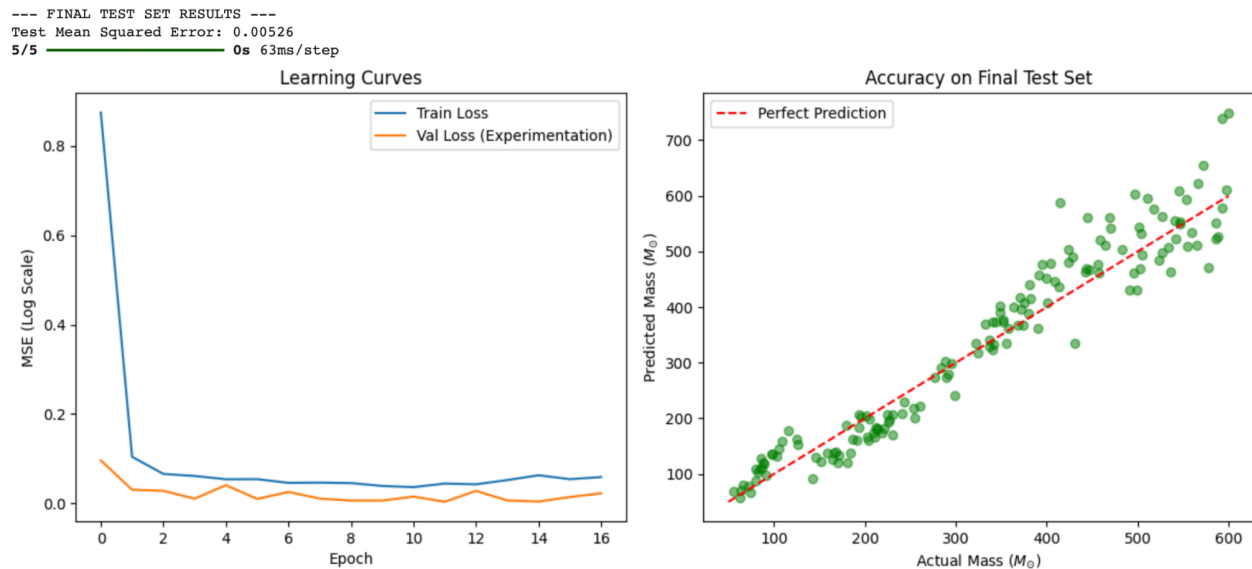


Figure A.2: Training and validation learning curves (left) and CNN predictions on the held-out test set (right). The left panel shows the mean squared error for the training and validation sets over training

epochs. The right panel compares the true total mass with the CNN-estimated total mass in solar masses. The dashed line represents the ideal one-to-one relationship between true and estimated total mass.

Results of Practice Neural Network

On the held-out test set, the preliminary implementation produced a logarithmic MSE of 0.00526, a mean absolute error (MAE) of $33.94 M_{\odot}$, and a root mean squared error (RMSE) of $45.13 M_{\odot}$. The MSE of 0.00526 represents the average squared difference between the predicted and true logarithmically transformed total masses. Because the model was trained using the logarithm of the total mass, this value is not expressed directly in solar masses. The MAE indicates that the predicted total mass differed from the true total mass by an average of $33.94 M_{\odot}$ within the simulated test set. The RMSE was higher than the MAE, indicating that larger prediction errors contributed more strongly to the squared-error metric. These results demonstrate that the proposed computational workflow can be implemented, but it does not establish predictive accuracy for astrophysical total mass estimation or evidence of a validated predictive model (Figure A.2). The predictions showed greater deviation from the target values at the upper end of the simulated total mass range, especially for systems with total masses above approximately $400 M_{\odot}$. This deviation may reflect limitations of the preliminary training dataset and model architecture, as well as the changing characteristics of the simulated waveforms across the total mass range. Specifically, higher-mass binary systems produce waveforms with lower characteristic frequencies, which may affect the information available to the model for distinguishing systems at the upper end of the total mass range. These observations provide potential directions for improving the model and dataset in future work. The results demonstrate the implementation of the model described by the paper but should not be interpreted as a validated measurement of predictive performance.

Limitations of Practice Model

The preliminary implementation has several limitations that restrict the interpretation of its results. The dataset consisted entirely of simulated gravitational wave waveforms, and several source and detector parameters were held constant during waveform generation. In particular, the preliminary implementation used a fixed source distance, inclination, spin parameters, sky location, and polarization, while the total mass was varied between $50 M_{\odot}$ and $600 M_{\odot}$. Gaussian noise was also added to the simulated waveforms as a simplified representation of detector noise. Consequently, the implementation does not capture the full range of source parameters or the complexity of noise present in observational gravitational wave data. In addition, because the simulated total masses were sampled within a fixed range, the held-out test set evaluates the model primarily through interpolation within that range rather than extrapolation to previously unseen total mass ranges. Finally, the implementation has not been independently validated using a separate simulated population or observational gravitational wave data.

Therefore, its preliminary performance metrics should be interpreted as an evaluation of the implementation on the simulated dataset rather than as evidence of validated predictive performance.

Code Availability

The Python code used to generate the simulated gravitational wave waveforms and implement the preliminary convolutional neural network is publicly available in the accompanying GitHub repository. The repository contains the waveform-generation and preprocessing procedures, neural-network implementation, and associated analysis code used for the preliminary results presented in this Appendix

<https://github.com/RY-research/Model-of-Gravitational-Wave-Mass-Detector-using-Neural-Network.git>

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