Supernova Gravitational Waves with Machine Learning

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Introduction

Core-collapse supernovae represent powerful terminal explosions of massive stars, where the interplay of all four fundamental forces of nature results in these extraordinary events. Due to this intricate interaction, these supernovae are often regarded as cosmic laboratories, providing valuable insights into fundamental physics and astrophysics. In this study, we examine the potential information that can be extracted from the gravitational wave (GW) signals emitted during these events. Specifically, we investigate the feasibility of utilizing machine learning (ML) techniques to determine the progenitor mass and the equation of state (EOS) of high-density matter in proto-neutron stars. Our focus is on the bounce phase of the GW signal, as it is a regime amenable to accurate modeling with relatively modest computational resources (Abdikamalov et al 2022).

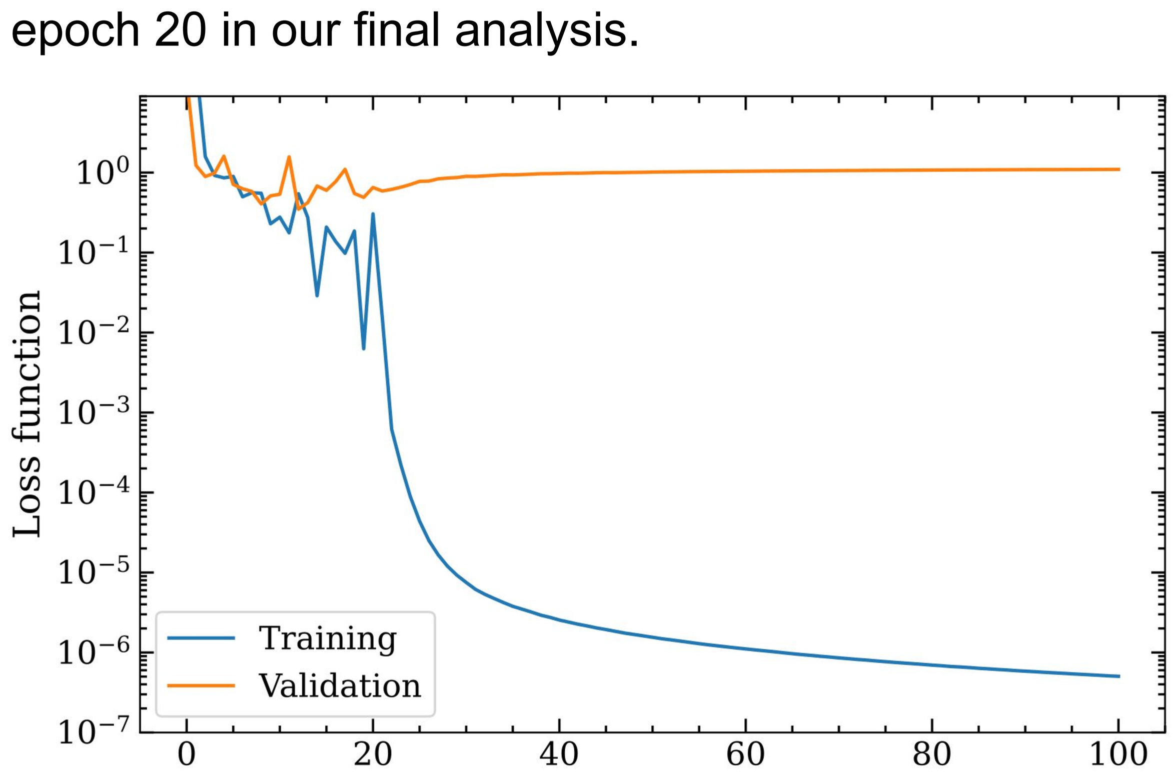
Method

To obtain GW signals, simulations are conducted using the CoCoNuT code (Dimmelmeier et al., 2005). For each progenitor mass and EOS, approximately 100 rotational configurations are generated, spanning from slow to rapid rotation (Abdikamalov et al 2014). The waveforms are analyzed utilizing a convolutional neural network (CNN) with the parameters specified by Edwards (2021).

Layer (type)	Output shape	Activation
Convolution 1D	(None, 1178, 32)	ReLU
Max Pooling 1D	(None, 589, 32)	
Convolution 1D	(None, 587, 64)	ReLU
Max Pooling 1D	(None, 293, 64)	
Convolution 1D	(None, 291, 128)	ReLU
Max Pooling 1D	(None, 145, 128)	
Flatten	(None, 18560)	
Dense	(None, 512)	ReLU
Dense	(None, 256)	ReLU
Dense	(None, 18)	Softmax

Hyperparameters	**Value**
Batch size	32
Loss function	Sparse categorical cross-entropy
Optimizer	Adam
Activation function	ReLU, softmax
Learning rate	0.001
Number of epochs	20
Evaluation	Accuracy and $F1$ score

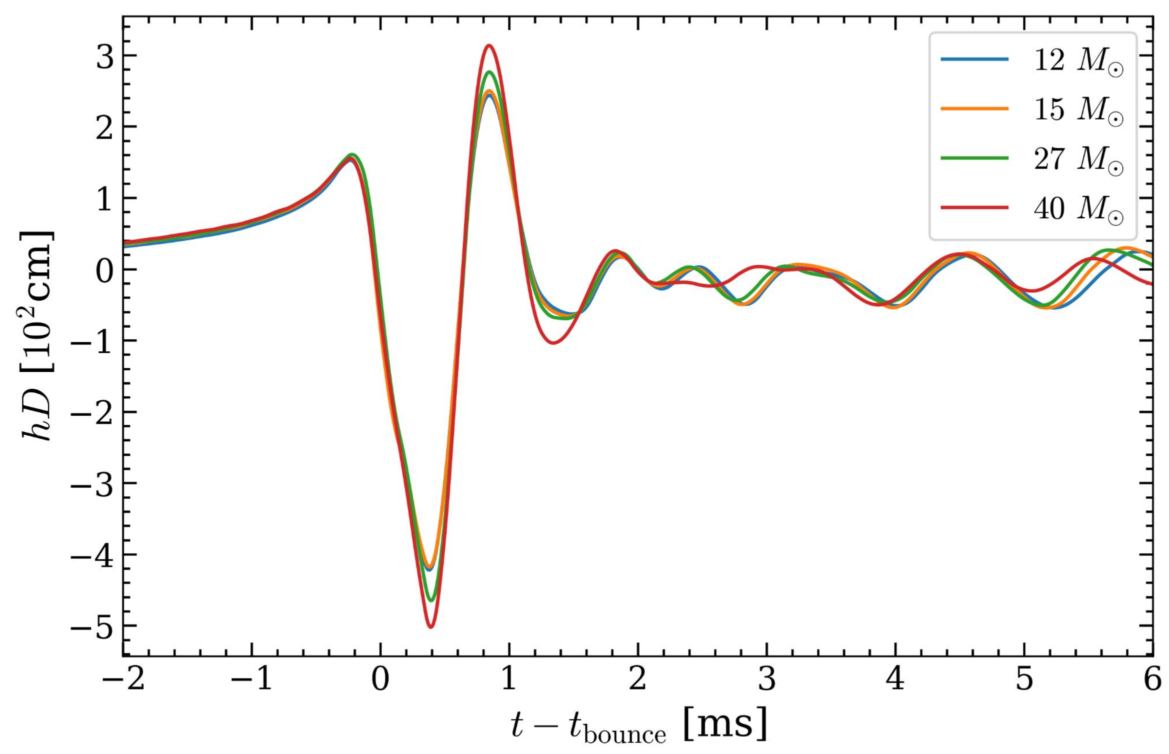
The loss function, shown below as a function of epoch, does not change much beyond epoch 20. We use epoch 20 in our final analysis.



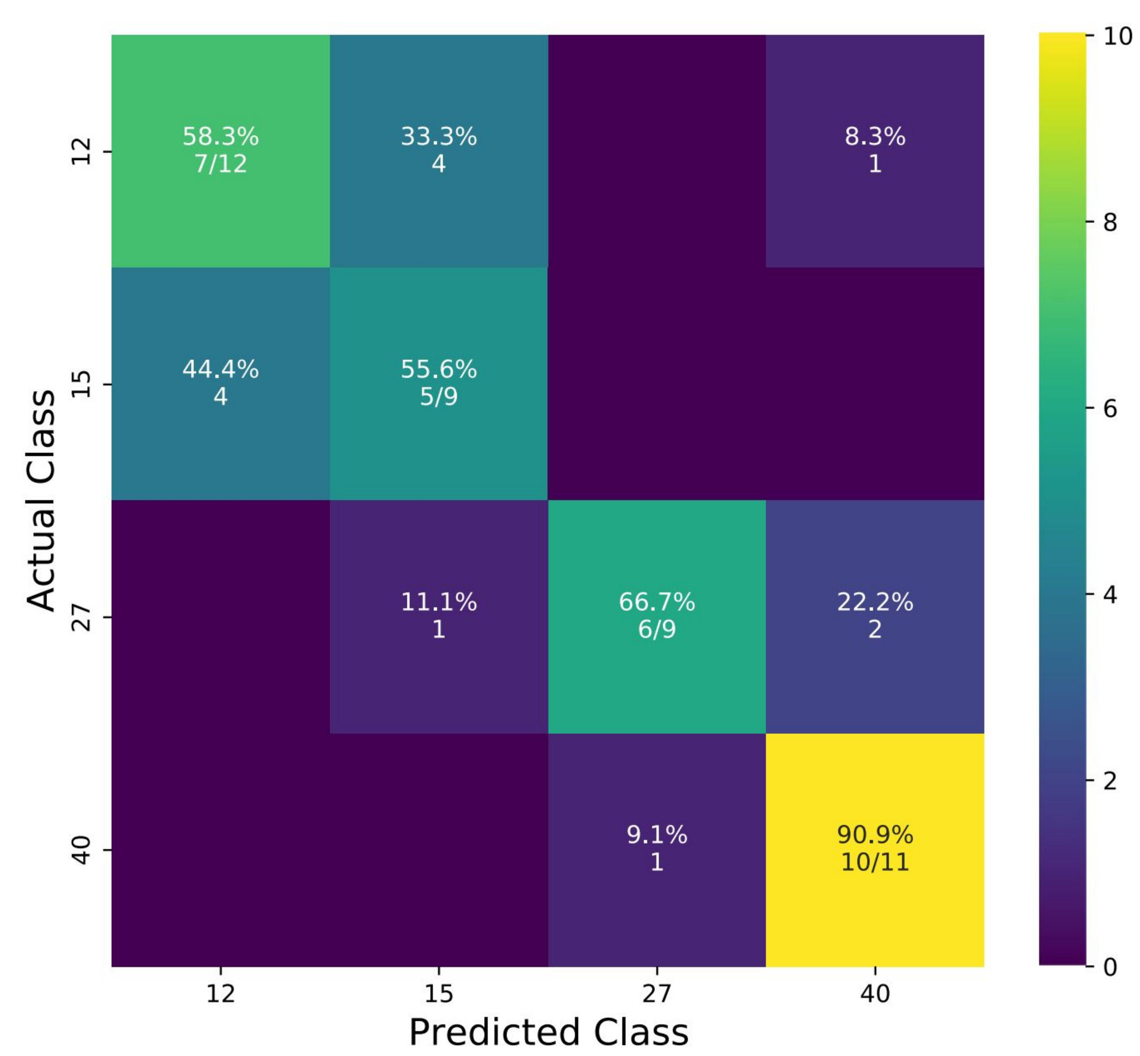
In addition to CNN, we also explored other machine learning methods, such as random forest, CATBoost, and XGBoost. We found that all these methods produced qualitatively similar results.

Measuring progenitor mass

We first explore if it is possible to extract progenitor mass from the bounce GW signal under ideal condition: consider only four progenitors with initial masses 12, 15, 27, 40 $M_\odot$ and ignore the detector noise. For the same inner core rotation, measured by the ratio of rotational kinetic energy to potential energy, the bounce GW signal of different models is similar to each other:



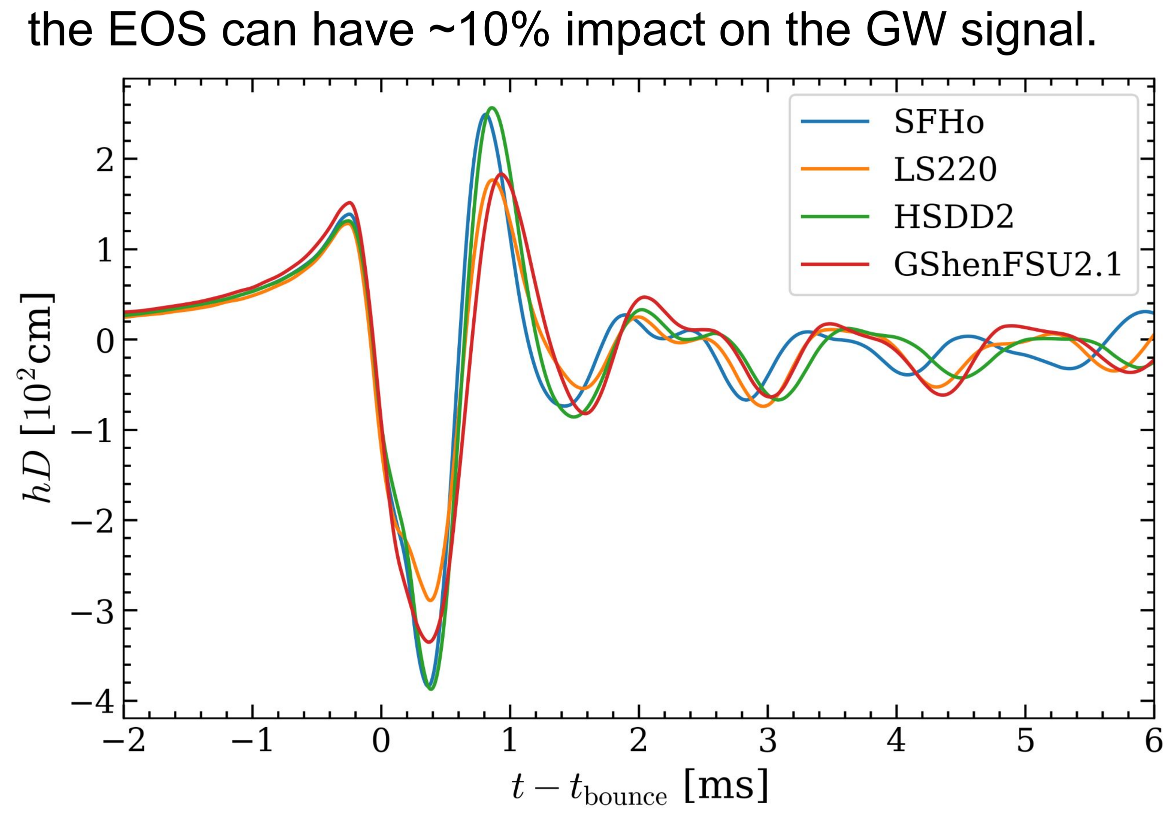
The confusion matrix for the prediction of the progenitor mass from the bounce GW signal is as follows:



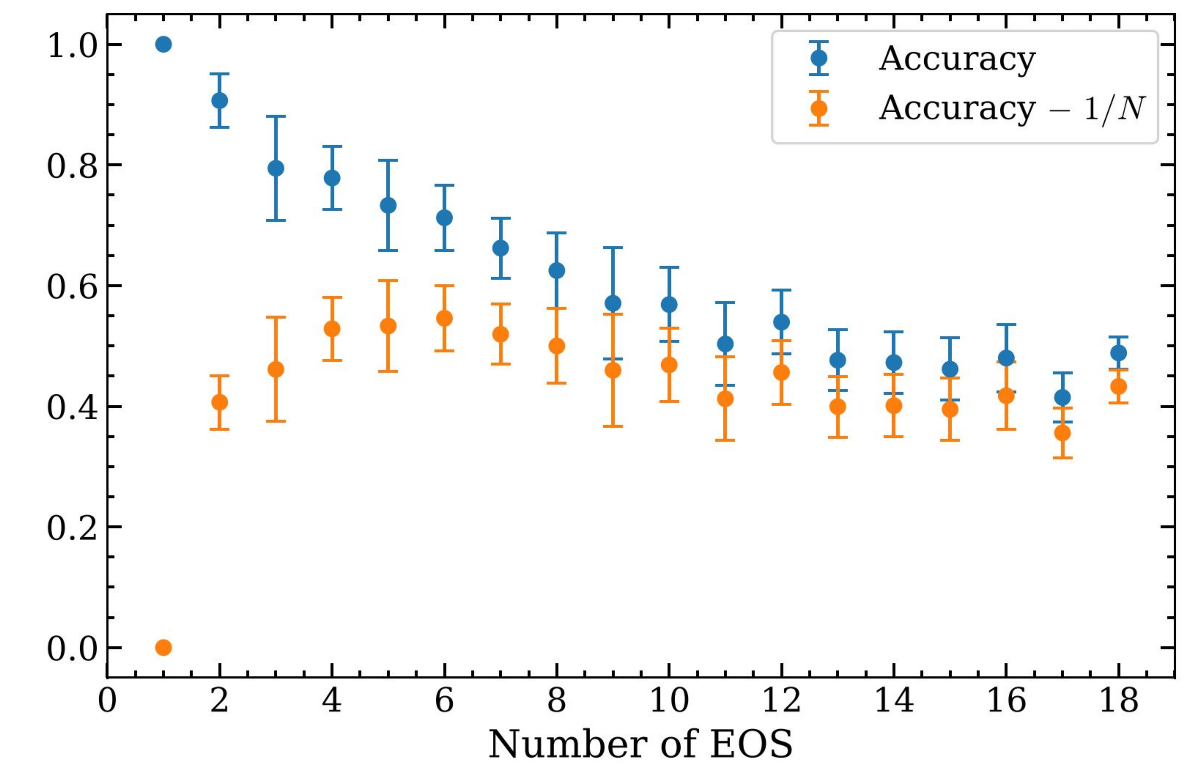
The overall accuracy is ~70%. This value corresponds to the idealized scenario characterized by only four progenitors and an absence of detector noise. Despite this, the ML method demonstrates limited capability in accurately extracting mass from the GW bounce signal. Under more realistic conditions, the accuracy is expected to be significantly lower (Mitra et al 2023).

Probing EOS of dense matter

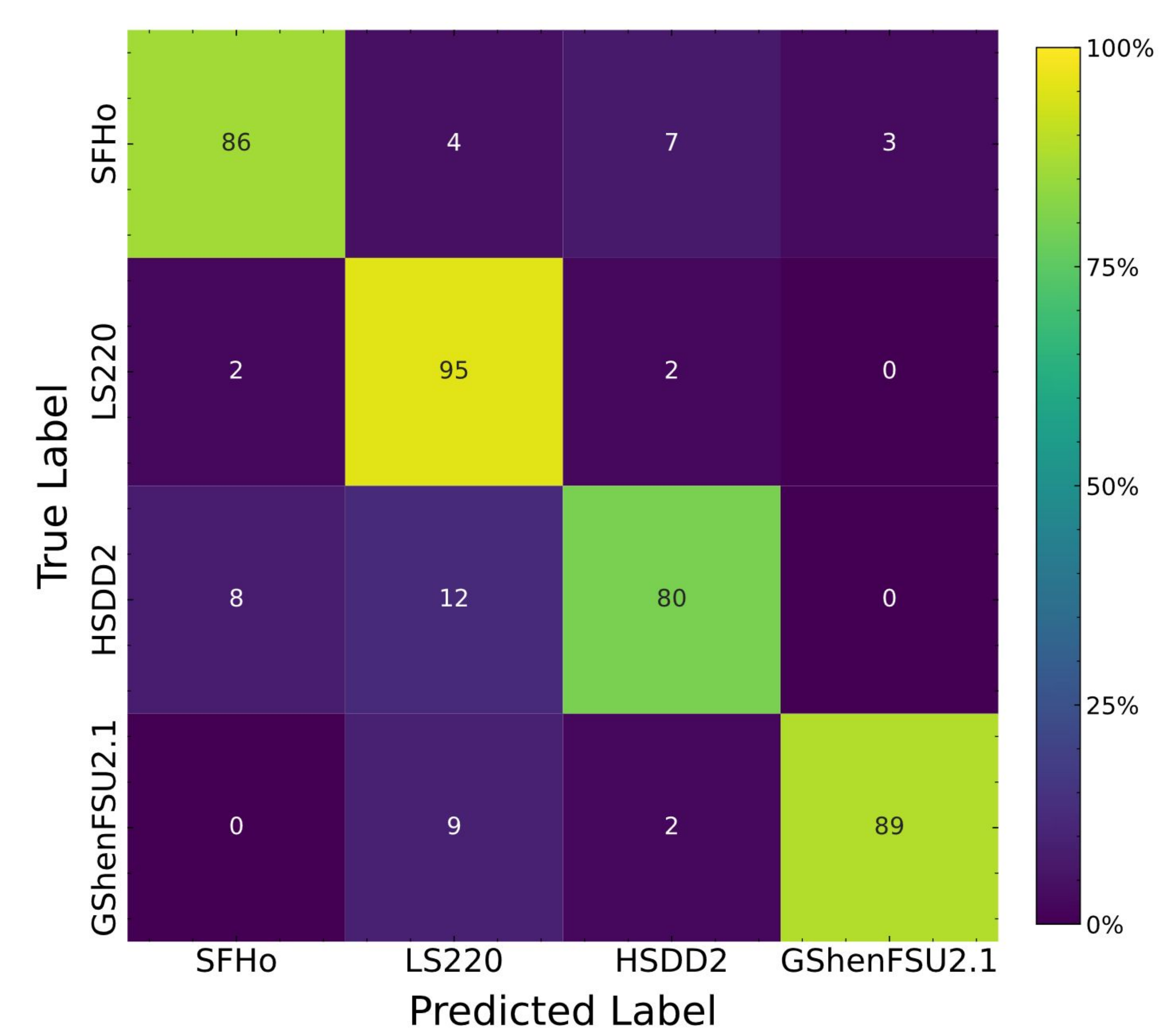
Next we perform simulations for different EOSs. The following plot shows GW signal corresponding to four representative EOSs, from which we conclude that the EOS can have ~10% impact on the GW signal.



The ML classification accuracy as a function of the number of EOSs included the training dataset is shown below.



The difference between ML accuracy and random selection accuracy (orange dots) is the highest when four EOSs are used. Following this, we perform classification analysis for four representative EOSs in the dataset of Richers et al (2017). The resulting confusion matrix is shown below.



The overall accuracy for classification of four EOS is ~87% (Mitra et al 2024).

Conclusion

ML techniques are a powerful tool for analyzing GW signals from supernovae. While ML method exhibit limited capability to extract mass from bounce GW signal, we find ~87% classification accuracy for a family of four EOS. Future analysis will expand the GW parameter space and incorporate detector noise.

References

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