Gravity Wave Detection Using Convolutional Neural Network

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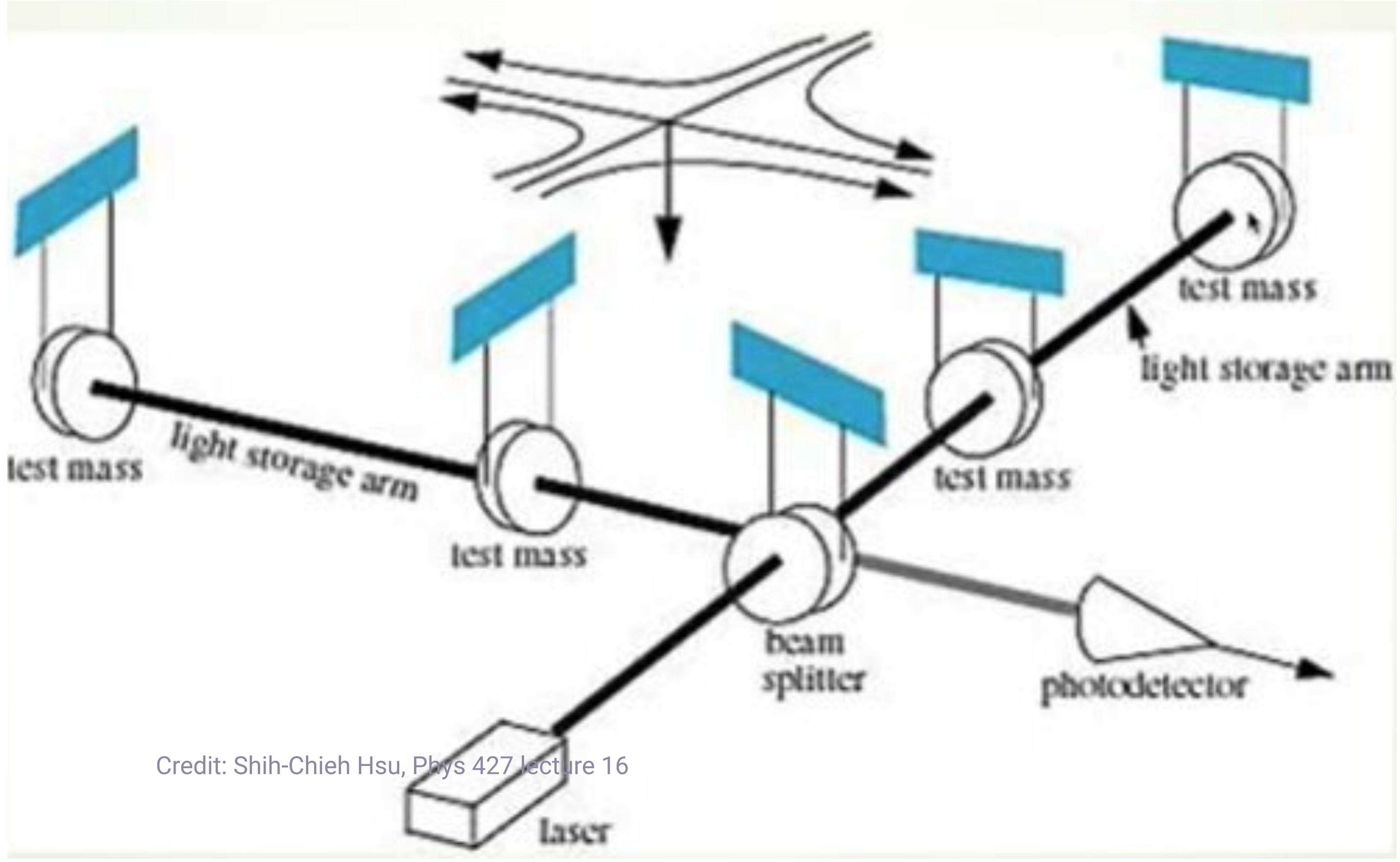
Introduction

In 1915, Albert Einstein published his general theory of relativity predicting gravity to be the inertial motion of objects along curved spacetime. Ripples in spacetime can be caused by massive events such as black holes colliding or supernovae. These ripples in space-time are called gravitational waves. These signals become very small as they reach Earth, making them very hard to detect given a multitude noise sources. **Through the use of neural networks, vast amounts of data can be used train the network to identify these weak gravitational wave signal.**

About the Dataset

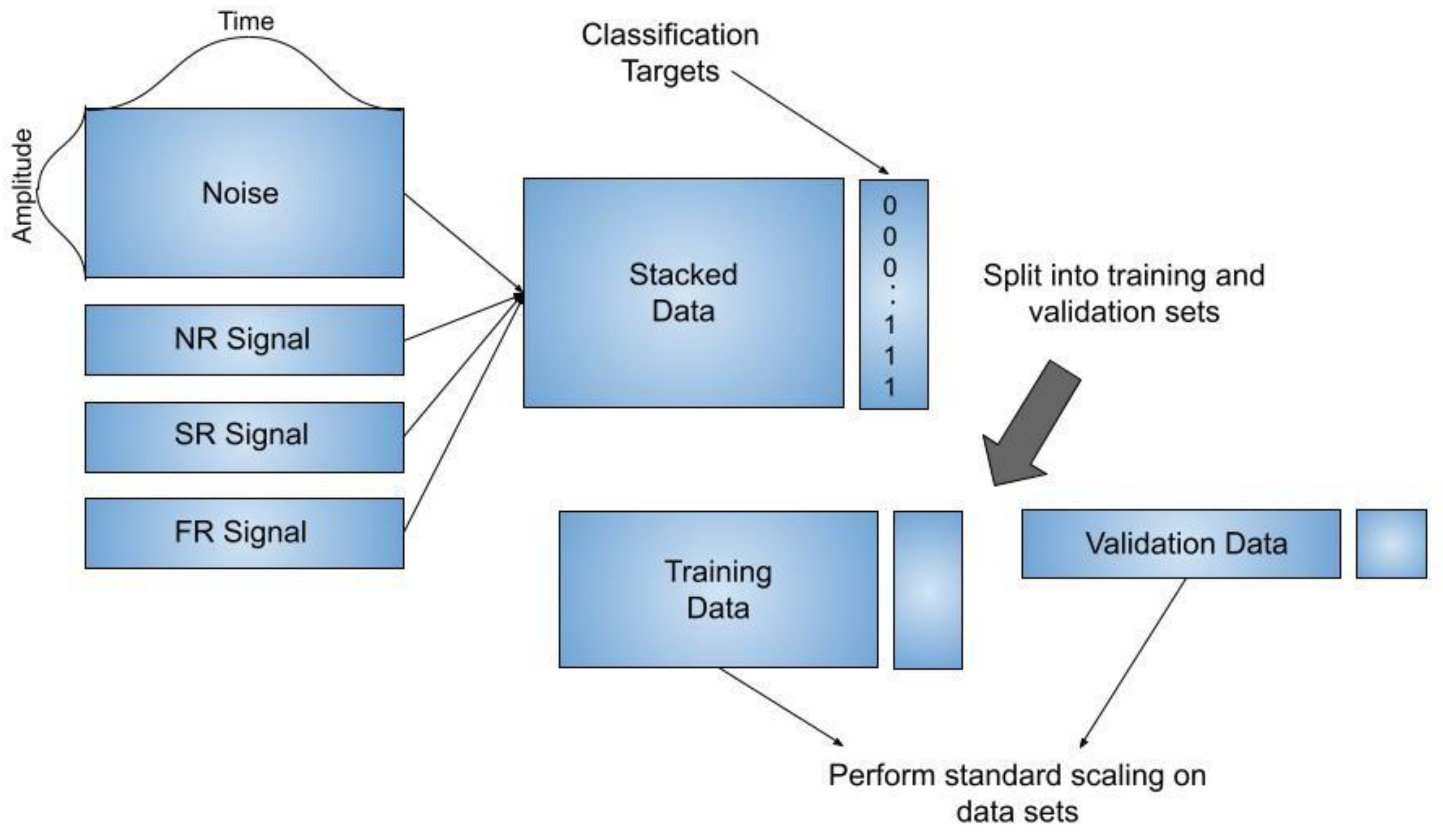
The data consists of 300k, 2 second segments of strain data from an interfermoeter. Then half of this strain data has synthetic, characteristic gravitational waves that would be produced by a core collapse supernova (CCSN), with three different types corresponding to the rotation speed of the star: no rotation (NR), slow rotation (SR), and fast rotation (FR).



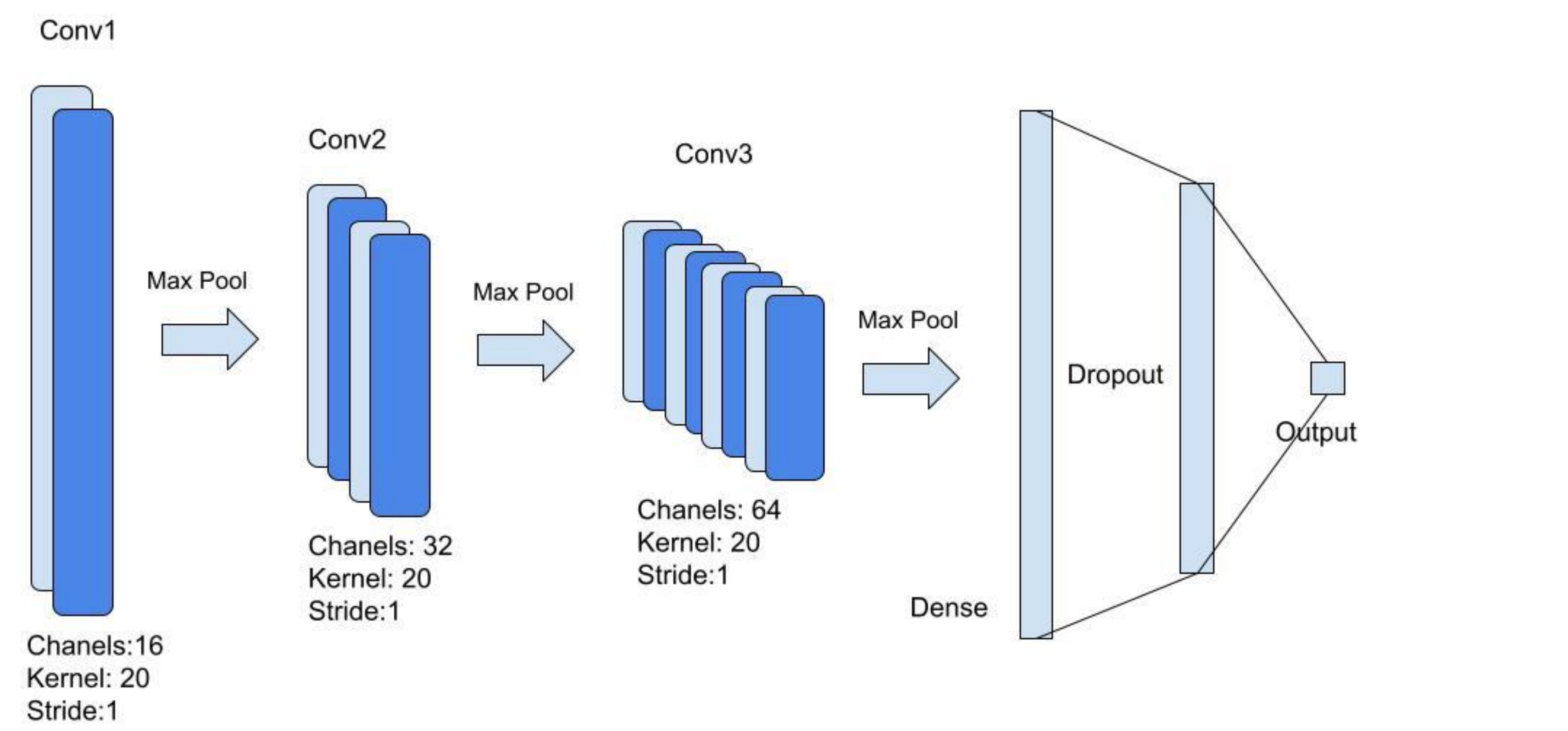
We can use a laser interferometer to measure path length distortions due to ripples.

Data Preprocessing

Import 10800 entries of noise and signal (split amongst , nr, sr, and fr CCSN). Stack the data then create a corresponding targets array with 0 corresponding to noise and 1 corresponding to signal. Separate into training and validation with 90%/10% split. Then perform standard scaling.



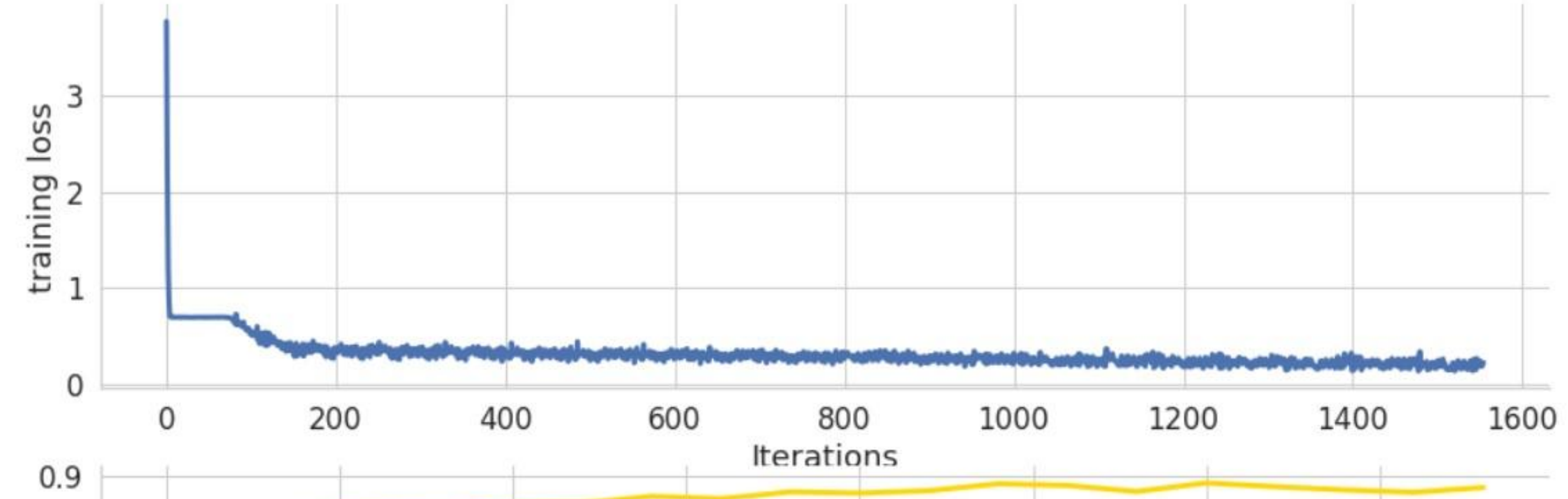
CNN Architecture

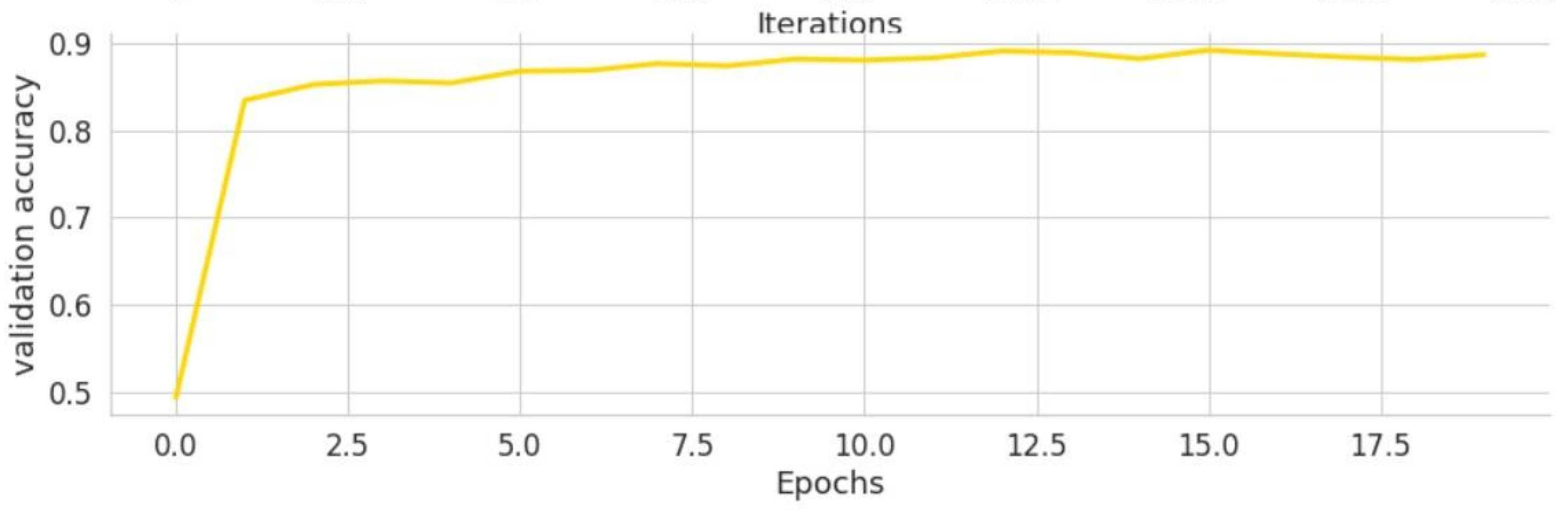


The architecture used was that of a 1-D convolution neural network. Consisting of 3 convolution layers with 3 pooling layers that condense into 2 fully connected layers that output a binary classification probability.

Results

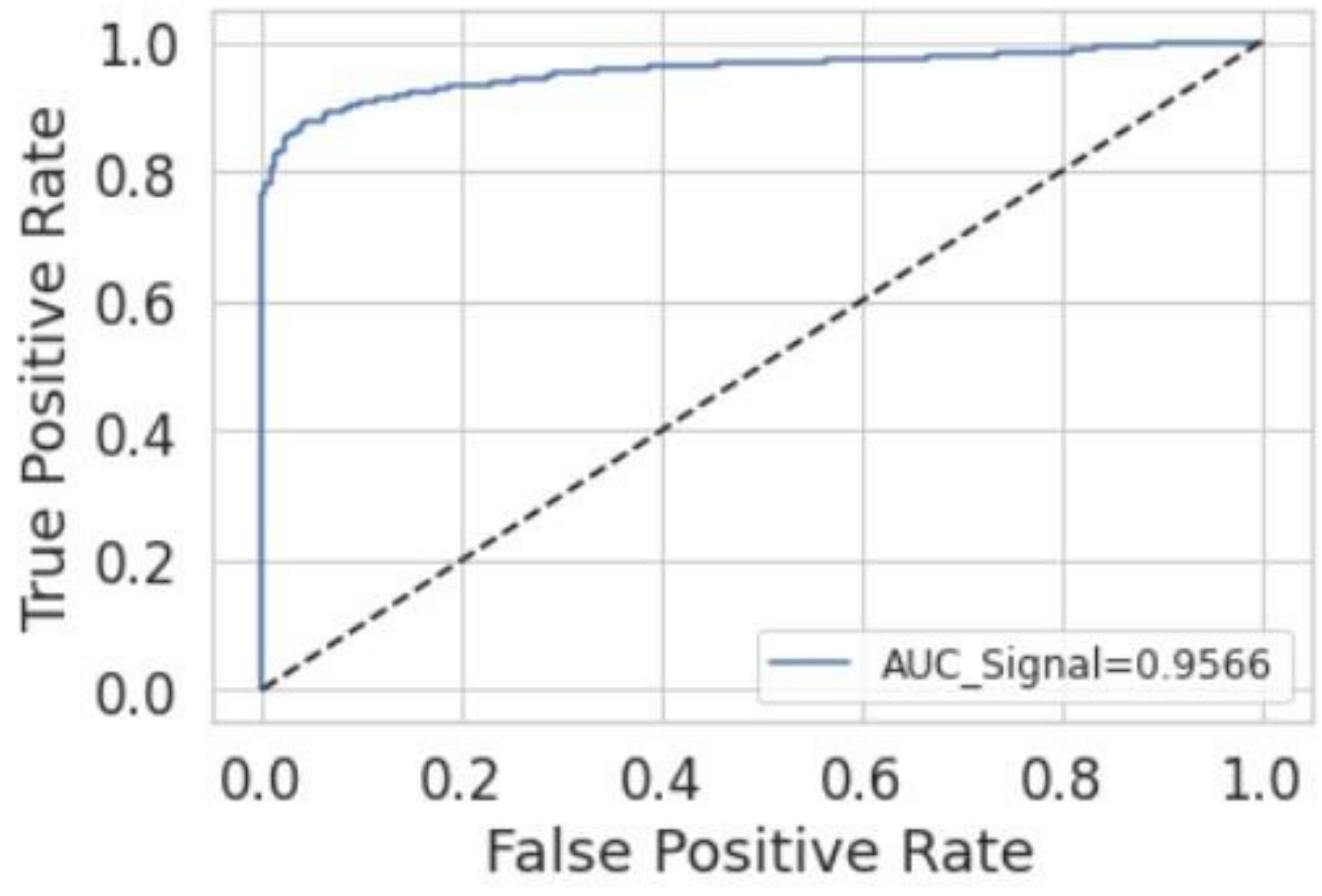
This data is split into batches and the training loss is measured after each batch. Through training, we are able to assess how well the data fits the CNN model. This is done by assessing the error through each epoch. Similarly, the validation accuracy is calculated for the validation data set and gives us an idea of how well the model performs.





The model is able to distinguish between noise and signal well, but also between signal types. For binary classification, high performance for one class is desired. This is summarized in the ROC curve below. Ideally, we want a maximum area under the curve (AUC) value which indicates higher true positive rates for a small false positive rate.

Testing Accuracy	**91.17%**
Noise Accuracy	94.17%
Signal Accuracy	88.17%
NR Accuracy	87.5%
SR Accuracy	87%
FR Accuracy	90%



References

[1] Einstein, A., & Rosen, N. (1937). On gravitational waves. Journal of the Franklin Institute, 223(1), 43-54.

[2] M. V. Gubin, "Using Convolutional Neural Networks to Classify Audio Signal in Noisy Sound Scenes," *2018 Global Smart Industry Conference (GloSIC)*, 2018, pp. 1-6, doi: 10.1109/GloSIC.2018.8570117.