Abstract
Gravitational waves are ripples in the space time fabric when high energy events such as black hole mergers or neutron star collisions take place. The first Gravitational Wave (GW) detection (GW150914) was made by the Laser Interferometer Gravitational-wave Observatory (LIGO) on September 14, 2015. Furthermore, the proof of the existence of GWs had countless implications from Stellar Evolution to General Relativity. Gravitational waves detection requires multiple filters and the filtered data has to be studied intensively to come to conclusions on whether the data is a just a glitch or an actual gravitational wave detection. However, with the use of Deep Filtering the process is simplified heavily, as it reduces the level of filtering greatly, and the output is definitive and binary. This technique, Deep Filtering, uses a one-dimensional convolutional neural network (CNN). The model is trained by a composite of real LIGO noise, and injections of GW waveform templates. The CNN effectively uses classification to differentiate weak GW time series from non-gaussian noise from glitches in the LIGO time-series. The model’s sensitivity is higher than all prior studies in this field, when making real-time detections of GWs at an extremely low SNR, while still being less computationally expensive.

Keywords: Deep Learning, Convolutional Neural Networks, Detection, Gravitational Waves, LIGO, Classification, Time-Series

1. Introduction
Detection of gravitational waves (GWs) and the study of them can provide a better understanding of the universe from future cosmological observations to testing verifying the reliability of Einstein’s General Relativity. There has been a study related to using Deep Learning to make GW detections at University of Illinois at Urbana-Champaign; however, the architecture of their neural network (NN) was capable of completing the task, but not optimized for it. At low Signal to Noise (SNR) their accuracy was still lower than if they had used matched filtering, this was partly because they completely trained their model on waveform templates that disregarded essential features such as spin. In addition to this, our model utilizes LIGO data from both the Hanford and Livingston detectors, providing a higher level of confidence detection than a single detector that was used in the previous study.

The primary hypothesis of our study was that our NN would successfully be able to detect gravitational waves from weak signals in a comparable level of accuracy to matched filtering. Currently, matched filtering is most commonly used to make gravitational wave detections with multiple filters and band-passes; it is very computationally extensive, and there are many sources of human error. Therefore, if Astronomers resort to using Deep Filtering, the confidence in making a detection would increase along with a reduction in human error, whilst still using less computational power.

2. Approach

2.1 Data Collection
The initial steps we took to creating our model that could effectively classify Gravitational Waves (GWs) started with data collection. The majority of our data that was loaded onto the cloud was from the Gravitational Wave Open Science Center (GWOSC). Moreover, from this public source we uploaded the
time-series data from both the LIGO Hanford and Livingston detectors for the first 5 Binary Black Hole (BBH) events. These datasets after being uploaded to Google Drive were then loaded onto the Google Colab Notebook. Next, we regularized the time series data to be 16384 hertz per second; this sampling rate was found to be the optimum rate at which to train the CNN.

2.2 Data Manipulation

2.2.1 Splitting the input vector to isolate Gravitational Wave from the noise

The real LIGO event datasets were primarily still made up of noise and glitches; therefore, it was essential to separate the actual event from the rest of the noise. Moreover, we created a function that inputted both the data vector and the sampling rate, where the vector would be split in half and only the middle two seconds, that contain the event) would be extracted. The rationale behind taking only the middle two seconds was that all the events were in the range of 0.8 - 1.7s, so the reliability of the extraction was extremely high. Additionally, both the actual event, and the rest of the data, were stored in separate files. We used the extracted waveforms from those 5 events (both LIGO Hanford and Livingston data) for testing our CNN.

2.2.2 Sampling real LIGO Noise

To create a robust Deep learning model, there needs to be sufficient training data; however, the number of detected events by LIGO were far below the desired amount. Therefore, we had to create our own datasets using the limited amount of data available to us. We used the noise files created while splitting the input to vector, to create real LIGO noise where the waveform templates would be injected into, effectively representing continuous LIGO data streams. This gaussian noise was created by randomly sampling the LIGO event data (void of the Gravitational Wave). We created 10,000 noise samples which included glitches but not GWs.

![Image](image.png)

**Fig. 2.** The plot above is a visual representation of one of the randomly sampled noise files. The scale of the noise would be later increased to an end result of a SNR of 4 when combined with the waveform templates. With an SNR of 4, the noise in comparison to signal is even higher than that of real LIGO data. Therefore, this optimizes the deep filtering model to make real-time detections of Gravitational Waves.

2.3 Waveform Generator

To optimize the training of our model we had to use 10,000 labeled datasets; however, to achieve this we had to simulate our own waveforms, as the amount of real events is not of a sufficient number to train the CNN. We created our waveforms to simulate the gravitational waves produced when two BBH coalesce. The mass of these black-holes were randomly sampled between 5 Msun and 75 Msun. Furthermore, the
rest of the parameters like the spins of the BBHs, inclination were all kept constant. However, we did
create the simulated GWs for both the LIGO Hanford and Livingston detectors, which is an advancement
that no other prior research has done. Additionally, for 25% of the waveforms we changed the
time-location of the peaks by an offset of 0.6 seconds, making the Deep Learning model more proficient
in dealing with time-translations. We created 10,000 of these waveform templates to inject into the real
LIGO noise to form the training data for the CNN classifier.

Fig 2. The plot above shows one of the waveform templates we have created. The peak of the event is listed 0 seconds, and you
can faintly see the inspiral of both the BBHs before the actual event. Furthermore, the strain of both the real interferometer data
and the waveforms are in the same scale, reducing the number of transformations needed before injection into the gaussian
noise and glitches.

2.4 Injection of waveforms into LIGO Noise

In order to create the training datasets discussed above we had to refactor and scale the waveforms
appropriately before injecting the templates into the interferometer noise. The waveform templates from
both the LIGO Hanford and Livingston were merged to create a better estimate of an actual GW signal. To
create the final datasets we randomly sampled waveform templates and merged them with randomly
sampled noise files. In addition, we made us multiple levels of offsets and biases while merging both the
waveforms and the gaussian noise, as we required the GW signal to be completely embedded into the
noise. We also scaled down the simulated signal to a third of its original strength whilst normalizing the
sizes of the signal as well as the noise. In contrast to other studies, the entirety of our created datasets had
extremely low SNR, as when the model can make GW detections with a very weak signal, it would be
suited very well to make real-time detections at a much higher SNR.

2.5 CNN architecture

Deep Learning models have revolutionized the field of ML, as they are able to classify the faintest of GW
signals embedded in the noisiest of the time-domain signals. The supervised learning model we used was
a Convolutional Neural Network (CNN), as it is the most efficient and optimized to operate on time-series
data. The first step when building the model was to assign labels to the training data, regarding whether it
contains a GW or not. All the datasets where the gravitational wave was extracted from, which consisted
of both gaussian and non-gaussian transient noise (glitches) were given the label [0]. Next, the 5,000
datasets which contained a gravitational wave were given the label [1]. Although, there were 10,000 total
datafiles to train the Neural Network; we started off by using only 2,000 to optimize training time.
Furthermore, we then split those 2000 datasets into 1600 training examples and 400 test cases. From there
we reshaped the data to the format (2000 datasets, 16384 samples per second, 1 dimension) to input into
the CNN.

The CNN is a one-dimensional sequential model where the inputted data is forward-propagated through
the multiple layers of the model before it classifies the presence of a GW. The final layer uses the softmax
activation function to make a prediction on if there is a GW embedded in the time-series data or not. The
CNN uses 4 convolutional layers with filter sizes of 64, 128, 256 and 512, respectively. Moreover, the
kernel sizes used for each of the convolutional layers are 32, 64, 64, and 128, respectively. In addition to this, the standard activation function between convolutional layers is the ReLU function, which essentially works similar to the modulus function. We also used a kernel size of 4 for all the MaxPooling layers. Please take a look at the condensed NetChain figure below representing the classifier.

![NetChain](image)

**NetChain (Predictor)**

| Input  | vector (size: 16384) |
|--------|----------------------|
| 1 Reshape | matrix (size: 1 x 16384) |
| 2 Convolution | matrix (size: 64 x 16352) |
| 3 Pooling | matrix (size: 64 x 4088) |
| 4 ReLU | matrix (size: 64 x 4088) |
| 5 Convolution | matrix (size: 128 x 4024) |
| 6 Pooling | matrix (size: 128 x 1006) |
| 7 ReLU | matrix (size: 128 x 1006) |
| 8 Convolution | matrix (size: 256 x 942) |
| 9 Pooling | matrix (size: 256 x 236) |
| 10 ReLU | matrix (size: 256 x 236) |
| 11 Convolutional | matrix (size: 512 x 108) |
| 12 Pooling | matrix (size: 512 x 27) |
| 13 ReLU | matrix (size: 512 x 27) |
| 14 Flatten | vector (size: 13824) |
| 15 Dense (ReLU) | vector (size: 128) |
| 16 Dense (ReLU) | vector (size: 64) |
| 17 Dropout | vector (size: 16) |
| 18 Dense (softmax) | vector (size: 2) |
| Output | vector (size: 2) |

*Fig 3. The figure above illustrates the working of the CNN classifier. The model inputs a time-series vector of 16384 samples in one second, and the size of the vector/matrix is processed as shown by the figure above; however, when it reaches the last layer, the result (Presence of GW) is outputted. This model can easily be implemented for continuous data-streams, as the model can cross-verify between detectors if there is a GW present at that point in time.*

The size of the actual model is small at around 30 mb; however, it encodes a large amount of training examples. Prior studies have required large amounts of computational power and time, to try to duplicate our results. We are the first study to be able to run the entire model locally by using the GPU provided by Google for all Colab Research notebooks.

### 3. Results

The model has produced results that exceeded our expectations, as the sensitivity of the model was even higher than if we had used matched filtering at the same SNR. The model is able to differentiate non-gaussian glitches with real GW signal, as it was trained with examples where the signal was scaled down to a third of its strength. The model only outputs a vector of size 2 that predicts whether there is a gravitational wave present in the time-series; however, it does not output the masses of the Binary Black Holes (BBH) involved.

Our model is better suited to be implemented in the actual LIGO search pipeline in comparison to prior studies, because it uses waveforms from both the LIGO Hanford and Livingston detectors to train the
CNN. This ensures that when the model is making real-time detections it will be able to compare the time-series data from multiple detectors before making a definite prediction. Thus, minimising the false detection rate, as the model attaches the label [0] to all glitches from multiple detectors.

The accuracy of this model was at 100% at SNR of 4, where no prior study could achieve this accuracy at a SNR this low. To elaborate further, CNN could classify each and every testing dataset correctly. Please refer to Fig 4. to conceptualize the results of our model.

![Image](image_url)

**Fig 4.** The figure above is the actual output of the model after training it using the GPU provided by google. We trained the model in 12 epochs, with 1600 samples and 400 examples for validation. The rationale behind only using 20% of our total datasets was that the model had already reached a 100% accuracy after being trained with 400 samples. In the first epoch, the training accuracy was the lowest at a 92% sensitivity; however, it was still able to classify the validation examples correctly. This figure effectively proves the hypothesis that our CNN classifier would be able to make detections of GWs from weak signals at an accuracy higher than matched filtering.

However, the entirety of the model was trained on waveform templates and not actual event data, so we tested our model further with actual interferometer data. We extracted the time-series for the following events from GWOSC: GW170823, GW170818, GW170817, GW170814, and GW170809. Additionally, we also uploaded 6 time-series that included a glitch (non-gaussian noise) that may have been interpreted as a GW by other methods of detection.

The model was able to classify whether there was a GW in each of the datastreams correctly. Moreover, this also acts as validation that the model can determine the nuance in difference between the glitch and an actual GW. This may be partly because the waveform templates the model was trained with contained information regarding the spin, and other smaller details of the two celestial bodies.

We conducted another test to see whether the model could use Deep Filtering to be able to detect a faint GW signal in a time-series contaminated by glitches that coincided in the same location as the actual wave. We merged the GW170818 event data with the highly contaminated time-series, while using different biases and weights to reposition the wave. The merged datafile was compared to the datafile that only included glitches and heavy gaussian noise. The model was able to successfully predict which of the files contained the actual GW; however, it was only one test, so we can not generalize over all situations. These results prove the efficacy of our Deep learning model in making GW detection.

### 4. Conclusion
The results of this study definitively support the hypothesis that this model would be able to predict the presence of GWs at a high-level of accuracy even with weak signals. This paper displays some of the latest advancements in the application of machine learning (ML) that could drastically improve the current LIGO search pipeline. The model we used improves upon the previous studies done in this field, by making the process less computationally intensive whilst still increasing the sensitivity. This study is also the first to have a demonstrably higher accuracy than Matched Filtering, which is still the prevalent tool for searching for GWs. This can be inferred due to the fact that at the SNR of 4, even matched filtering cannot compete with a 100% sensitivity.

In the future, LIGO would have to implement a version of a Deep Learning model that would monitor the real-time interferometer data, and flag the presence of GWs by comparing the data of the multiple continuous data streams it has access to. Although, our model can make real-time detections of GW; there still needs to be many advancements before it can handle all the datastreams coming from each of the observatories. Firstly, the model would need to have an advanced parameter estimation feature that could estimate everything from the spin to the chirp mass of the system. This would however drastically increase the complexity of the NN, and it would require another level of computing power.

We made use of multi-dimensional waveform templates to train our CNN; however, it does not provide the same level of reliability as actual LIGO event data. Therefore, to improve the validity of the results in future studies, the tradeoff between the limited number of available event data, and the requirement of large amounts of training data for the model must be found. Additionally, this article demonstrates the ways in which Deep Filtering can be used to mine for a specific signal in a time-series that is contaminated by noise and glitches; thus, making this technique applicable to other unrelated fields.

The use of Deep Filtering to improve the LIGO search pipeline is becoming increasingly important, and in the future, models would be able to conduct tasks such as glitch classification more effectively, whilst using significantly less computing power. The techniques introduced in this article to classify gravitational waves using a Deep Learning model may be simple, but their applications are endless.

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