We present results on the search for the coalescence of compact binary mergers using convolutional neural networks and the LIGO/Virgo data, corresponding to the O2 observation period. Two-dimensional images in time and frequency are used as input, and two sets of neural networks are trained separately for low mass (0.2 - 2.0 M⊙) and high mass (25 - 100 M⊙) compact binary coalescence events. We explored neural networks trained with input information from a single or a pair of interferometers, indicating that the use of information from pairs leads to an improved performance. A scan over the full O2 data set using the convolutional neural networks for detection demonstrates that the performance is compatible with that from canonical pipelines using matched filtering techniques. No additional events with significant signal-to-noise ratio are found in the O2 data.

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I. INTRODUCTION

Since the detection of a gravitational wave (GW) in 2015 [1] a new era of gravitational wave astronomy has opened. This was confirmed with the detection of up to 11 events at the end of the second observation run (O2) [2]. Additional 39 events were recently reported corresponding to the first part of the third observation run (O3), for a total of 50 events [3]. All the detected events to date are compatible with being originated by compact binary coalescence (CBC) of black holes (BH) or neutron stars (NS). The LIGO and Virgo Collaborations use matched-filtering techniques to extract the events from the much larger background (for a comprehensive review of the experimental techniques see Ref. [4]). The presence of a distinct chirp-like shape in the CBC events, when represented in spectrograms showing the signal in frequency-time domain, makes the use of a convolutional neural network (CNN) a valid alternative suitable for GW detection.

A machine learning approach for GW astronomy has been studied severely along the years [5-7]. In particular, different CNNs have been previously studied for the detection of GW events [8-11] and in distinguishing between families of glitches [12-14]. In this paper, we focus on the detection of CBC events with either very low (0.2 - 2.0 M⊙) or very high (25 - 100 M⊙) mass ranges, and explore a CNN based on a ResNet50 architecture [15] that has shown to give good results in image classification.

II. DATA PREPARATION

The study uses the O2 open data [16] from LIGO-Livingston (L1), LIGO-Hanford (H1) and Virgo (V1) interferometers with 4096 Hz sampling rate. After applying quality requirements, the samples have a total duration of 154.0, 157.8, and 20.8 days for L1, H1 and V1, respectively. A fraction of the data, 7.4 days in each interferometer, is used for constructing background and background plus injected signal images for the purposes of the CNN training. The resulting total number of images are enough for an adequate training of the network. It constitutes a small fraction (about 5%) of the L1 and H1 data set but it amounts to 36% of the V1 data. Special precaution was taken in the preparation of the background images to avoid including any of the identified GWs events in O2, as collected in the O2 catalog.

Waveforms for GW signals are generated using the IMRPhenomPv2 [17] model and combined with data segments from the different interferometers, after taking into account the proper relative orientations, times of arrival and antenna factors. In the case of the low mass CBC regime, masses in the range between 0.2 - 2.0 M⊙ are considered for the two compact objects in the binary system, and the corresponding luminosity distance DL is limited to nearby events in the range 1 - 50 Mpcs. In the case of high mass regime, signals with masses in the range between 25 and 100 M⊙ and DL in the range between 100 and 1000 Mpcs are considered. Other parameters related to the position in the sky and orientation of the source are taken as homogeneously distributed. This finally results in a signal grid with O(250000) different signals. The injected signals are limited to a fixed maximum duration of five seconds. The five-seconds window is computed backward from the merger time to remove low-amplitude monochromatic-like parts of the waveform and avoid confusing the network during training. A low fre-
frequency threshold of 80 Hz (20 Hz) is applied for the low-mass (high-mass) signal grid, in order to control the duration of the injected signal. Finally, the signals are randomly placed within the five-seconds window.

Once the GW signals are injected in the different L1, H1 and V1 background data segments, the data are processed. First, the data are whitened following the same prescription as in Ref. [4]. Two-dimensional arrays holding spectrogram data are then produced using Q-transforms [18], in order to arrive to the desired images in terms of amplitude vs time vs frequency, with 400 bins in time and 100 bins in frequency. Figure 1 presents an example of a spectrogram for a GW signal with BH masses of 51 M⊙ and 53 M⊙, and D_L = 664 Mpcs, for which the GW signal is clearly observed.

![Spectrogram Image](image)

**FIG. 1:** Example of a spectrogram as a two-dimensional image in time versus frequency corresponding to a CBC injected signal in the L1 interferometer with BH masses of 51 M⊙ and 53 M⊙, and D_L = 664 Mpcs.

In the low mass regime, and after taking into account the distance and the antenna factors for the detection, the strength of the GW signal is such that it often becomes invisible in the images and constitutes a challenge for the CNN training. Hence, to avoid a potential bias, we limit the signal injections to those events for which the effective distance D_{eff}, defined as

\[ D_{eff} = \frac{D_L}{\sqrt{(1 + \cos^2(l))^2 F_+^2/4 + \cos^2(l) F_x^2}} , \]

is smaller than 60 Mpcs, where l denotes the inclination angle, and F_+ and F_x are the antenna factors for the interferometer corresponding to the two GW polarizations. When the CNN receives pairs of signals from two different detectors as input (see section III), we require that at least one of them fulfills the D_{eff} < 60 Mpcs requirement. In the case of high mass range, signals are loud enough and no requirements on D_{eff} are applied.

III. NEURAL NETWORK DEFINITION AND TRAINING

We adopted, as nominal, a deep CNN ResNet-50 with a 50-layer architecture, as described in Ref. [15], which demonstrates a good performance for image recognition. Alternatively, we explored the implementation of a CNN similar to that used in Ref. [12] for the detection and classification of noise in GW detectors. The latter did not show a better performance. As already mentioned in Sec. III, two-dimensional images from different interferometers are input to the different CNNs, for which real data from LIGO/Virgo O2 observation period is employed to build the background and signal+background images. A total of 128000 images per interferometer are used, evenly divided into background-only and background+signal. About 63% of the sample is devoted for training, whereas a 7% and a 30% are used for validation and testing, respectively. Two separate CNNs are trained for the low-mass and the high-mass ranges. In the course of the CNN training, it was observed that the presence of glitches in the data was not completely suppressed by the whitening process. This translates into large variations, image-by-image, in the amplitude that in turn results into instabilities related to the batch normalization layers [19]. This was solved after renormalizing the contents in each image by its average in such a way that the contents in an image have an average equal to zero and a variance equal to one.

We first explored training three separate CNNs for L1, H1 an V1 data. For a number of epochs greater than five, the three CNNs reach stability. In the low-mass range and for the case of L1 and H1, a validation accuracy of the order of 88% is obtained. The V1 accuracy is smaller and a value around 75% is reached. Similarly, the validation loss ranges from 0.2 in the case of L1 and 0.4 in the case of H1, up to 0.7 in the case of V1. In the high mass range, the CNNs present a better performance, to large extent attributed to the larger signal strain. The CNNs for L1, H1 and V1 show a validation accuracy of about 96%, 92%, and 82%, and validation losses of 0.23, 0.03 and 0.60, respectively. Altogether, these variations reflect the differences in sensitivity across interferometers. This is also clearly observed in Figure 2 top, showing the receiver operating characteristic (ROC) curves for the separate CNNs, representing the true positive (TP) versus the false positive (FP) rates, where the differences in sensitivity between L1, H1 and V1 become evident.

The performance of the CNNs can be improved by including the information of pairs of interferometers during the training process. In this way, the CNN learns about the correlations between images in two different channels when the signal is present. Given the limited duration of the V1 O2 data, the simultaneous use of the three interferometers as input was outside the scope of this study, but remains a natural extension of the work towards O3 and O4 observations runs. As expected, the
Figure 2: ROC curves for the CNNs using (top) single and (bottom) pairs of interferometer inputs for (left) low mass and (right) high mass ranges.

Inclusion of the V1 information in O2 did not translate into a significant improvement, whereas the L1-H1 combination leads to a slightly better performance of the CNN (see the ROC curves in Figure 2 (bottom)), with an accuracy of 91% (97%) and a loss below 0.1 (0.3) for the low (high) mass range.

Figures 3 and 4 present the final CNN output used for background and signal discrimination for the L1, H1 and V1, and the H1-L1 CNNs, respectively, as determined from the test samples, for both low mass and high mass ranges. The discriminant for the rest of the CNNs show similar features. A clear discrimination is obtained between signal and background samples. The ROC curves and the anticipated fake event rates are finally used as guidance in determining the final CNN threshold for classifying signal and background images. The CNN thresholds are adjusted such that the number of false positives in each case is limited to about 25 events per day. In Table 1 the information about the thresholds used in each case and the corresponding performance in terms of true positive and false positive rates is collected.

IV. INJECTION TESTS

In order to determine the performance of the CNNs, injection studies of GW signals with given signal-to-noise ratios ($\rho$) are performed. The study is carried out separately for low and high mass ranges, in which masses and distances are injected following a homogeneous probability distribution. For each GW signal, the value for $\rho$ is computed following the prescription in Ref. 8 solving
the integral
\[ \rho^2 = \int_{f_{\text{min}}}^{f_{\text{max}}} df \frac{|h(f)|}{S_n(f)}, \]
(2)
in the frequency domain \( f \), where \( |h(f)|/S_n(f) \) denotes the signal and \( S_n(f) \) is the power spectral density of the background. In the case of the background, a fixed period of time of 4096 seconds is used, whereas for the signal we employed the five-seconds window covered by the image. A Tukey window with \( \alpha = 1/9 \) is considered for the Fourier transformation. The signal templates are then re-scaled to targeted values \( \rho^T \) by multiplying the amplitude of the signal by the ratio \( \rho^T/\rho \). Figure 5 shows the fraction of GW signals identified by the CNNs as a function of \( \rho^T \) in the case of inputs from single and pairs of interferometers, and for low- and high-mass ranges, respectively. As expected, the efficiency for signal detection increases rapidly with \( \rho^T \), becoming more efficient for large \( \rho^T \) values. In the case of the high mass range, the L1-H1 CNN provides the best results with an efficiency for selection of about 80\% for \( \rho^T = 6 \), becoming fully efficient for \( \rho^T = 8 \). The other CNNs involving Virgo performed differently but also become fully efficient around \( \rho^T = 8 \). In the case of the low mass range, the differences among CNNs become more evident, with L1-H1 still providing the best performance with a 80\% efficiency for \( \rho^T = 12 \), becoming fully efficient for \( \rho^T = 16 \). Table II collects, separately for single interferometer and pair of interferometers based CNNs, the values of \( \rho^T \) for given signal detection efficiencies.

### V. RESULTS

The low mass and high mass CNNs were used to search for candidate events in the O2 data. As shown in the previous sections, the performance of the CNNs that use information from pairs of interferometers is slightly better than that from the CNNs relying on single detections, and therefore are used to obtain the final results.

| L1 – H1 | 99/96 | 70/92 | 0.05/0.06 |
| L1 – V1 | 98/99 | 65/84 | 0.04/0.03 |
| H1 – V1 | 99.7/97 | 69/93 | 0.03/0.04 |

| L1 – H1 | 99/96 | 74/95 | 0.06/0.09 |
| L1 – V1 | 99/97 | 66/88 | 0.03/0.05 |

TABLE I: Value of the CNN selection discriminant in the low mass and high mass ranges, together with the anticipated true positive (TP) and false positive (FP) rates.

| L1 – H1 | 11/9/0.65 | 13/7.5/23 | 0.95 |
| L1 – V1 | 13.5/6.5 | 15/7.5/25 | 0.95 |
| H1 – V1 | 17/6.0 | 23/7.5 | >25/20 |

| L1 – H1 | 11/0.5 | 12/6.0 | 19/0.7 |
| L1 – V1 | 13/5.5 | 15/6.5 | 24/8.0 |
| H1 – V1 | 13.5/5.0 | 17/6.0 | 23/7.5 |

TABLE II: Values of \( \rho^T \) at given detection efficiencies for the different CNNs using a single detector or detector pairs.

We first applied the CNNs discrimination to the data segments corresponding to the events included in the O1+O2 LIGO-Virgo catalog. The results are collected in Table III A majority of the events were properly identified by at least one of the CNNs. In particular, the GW170817 event, corresponding to the NS-NS event, was identified by the low-mass CNN, whereas the rest of the events in the catalog that were identified, corresponding to BH-BH events, triggered the high mass CNN. All the rest of the events, for which none of the CNNs detected the signal, correspond to events with masses outside the ranges considered for the training.

We then performed a scan of the full O2 data set, for which a slicing window of five seconds duration was used in steps of 2.5 seconds (leading to a 50\% overlap between

![Figure 5: Efficiency vs \( \rho^T \) for the different CNNs in the (top) low mass and (bottom) high mass mass ranges.](image)
TABLE III: Summary of the CNN response to the O1+O2 catalog events.

| Event       | CNN Detected value (Y/N) | CNN Detected value (Y/N) |
|-------------|--------------------------|--------------------------|
| GW170104    | 0.001 N                  | 1.0 Y                    |
| GW170608    | 0.02 N                   | 0.008 N                  |
| GW170729    | 0.1 N                    | 1.0 Y                    |
| GW170809    | 0.15 N                   | 1.0 Y                    |
| GW170814    | 0.01 N                   | 1.0 Y                    |
| GW170817    | 1.0 Y                    | 0.04 N                   |
| GW170818    | 0.003 N                  | 1.0 Y                    |
| GW170823    | 0.05 N                   | 1.0 Y                    |
| GW150914 (O1) | 0.24 N                 | 1.0 Y                    |
| GW151012 (O1) | 0.06 N                 | 0.95 N                   |
| GW151226 (O1) | 0.29 N                 | 0.08 N                   |

TABLE IV: Results of the low mas and high mass scans over the full O2 data for the different CNNs considered. The number of images processed and detected are reported together with the corresponding daily detection rate.

| CNN    | Images | Detected Events/day | Detected Events/day |
|--------|--------|---------------------|---------------------|
| L1-H1  | 4977233 | 5496                | 47                  |
| H1-V1  | 584993  | 439                 | 26                  |
| L1-V1  | 601877  | 3078                | 178                 |

VI. SUMMARY

We have presented the result of studies using convoluted neural networks based on the ResNet50 architecture to search for compact binary coalescence of black holes in the LIGO-Virgo data from the O2 observation run. Two separate CNNs are trained specifically for low mass (0.2 − 2M⊙) and high mass (25 − 100M⊙) black holes, and the training process explores the simultaneous use of pairs of interferometers as input. The simultaneous use of the three interferometers in the CNN was not allowed by the limited size of the Virgo O2 data. A performance comparable to that of the first detection steps of the dedicated pipelines is reported for the CNNs in terms of efficiency and purity in selecting signal events. A scan over the full O2 data set is carried out demonstrating that the CNN response is similar to that obtained in matched-filtering based pipelines. All the O1+O2 catalog events, with masses compatible with the training parameters, are identified by the CNNs, and no new events are detected with a significant signal-to-noise ratio. This study shows the viability of CNN-based pipelines and could be regarded as a step towards an online implementation, in preparation for the future LIGO-Virgo-KAGRA combined observation runs. Future studies will extend the...
CNN training towards the simultaneous use of multiple interferometers relevant for O3 and O4 observation runs.

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