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# AI in Gravitational Wave Analysis, an Overview

**Vincenzo Benedetto [1,2,*,†], Francesco Gissi [1,2,*,†], Gioele Ciaparrone [2] and Luigi Troiano [3]**

1 Department of Engineering (DING), University of Sannio, 82100 Benevento, Italy
2 Kebula s.r.l., 84084 Fisciano, Italy; gioele.ciaparrone@kebula.it
3 Department of Management & Innovation Systems (DISA-MIS), University of Salerno, 84084 Fisciano, Italy; ltroiano@unisa.it
* Correspondence: vincenzo.benedetto@unisannio.it (V.B.); francesco.gissi@unisannio.it (F.G.)
† These authors contributed equally to this work.

**Abstract:** Gravitational wave research presents a range of intriguing challenges, each of which has driven significant progress in the field. Key research problems include glitch classification, glitch cancellation, gravitational wave denoising, binary black hole signal detection, gravitational wave bursts, and minor issues that contribute to the overall understanding of gravitational wave phenomena. This paper explores the applications of artificial intelligence, deep learning, and machine learning techniques in addressing these challenges. The main goal of the paper is to provide an effective view of AI and deep learning usage for gravitational wave analysis. Thanks to the advancements in artificial intelligence and machine learning techniques, aided by GPUs and specialized software frameworks, these techniques have played a key role over the last decade in the identification, classification, and cancellation of gravitational wave signals, as presented in our results. This paper provides a comprehensive exploration of the adoption rate of these techniques, with reference to the software and hardware involved, their effectiveness, and potential limitations, offering insights into the advancements in the analysis of gravitational wave data.

**Keywords:** gravitational waves; AI; deep learning; machine learning; GPU computing

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## 1. Introduction

Gravitational waves have presented researchers with a multitude of intriguing challenges, each of which has led to significant advancements in the field. In particular, several key research problems have emerged, including glitch classification, glitch cancellation, gravitational wave denoising, binary black hole signal detection, gravitational wave bursts, and various minor problems that contribute to the overall understanding of gravitational wave phenomena.

Within the domain of gravitational wave astronomy, a "glitch" denotes an abrupt and transient perturbation observed in the data emanating from pulsars or neutron stars. Pulsars, characterized as rapidly rotating neutron stars emitting regular electromagnetic pulses, are indispensable tools for investigating various astrophysical phenomena, including gravitational waves [1]. However, the unparalleled stability of pulsar signals can occasionally be disrupted by these so-called "glitches". Glitches are sudden enhancements in a pulsar's rotation rate, resulting in a temporary alteration of its observed frequency, otherwise referred to as the spin frequency [2]. These anomalies stem from intricate processes within the pulsar, such as the interaction between its superfluid interior and solid crust, leading to an exchange of angular momentum [3].

The consequences of glitches extend deeply into the domain of gravitational wave analysis, particularly concerning continuous gravitational wave sources. These sources, driven by persistent emission of gravitational waves, frequently arise from non-axisymmetric deformations or instabilities in neutron stars [4]. Monitoring pulsar rotations and detecting glitches furnish researchers with invaluable insights into the internal dynamics and fundamental characteristics of neutron stars [5]. However, the presence of glitches introduces complexities into gravitational wave searches. The abrupt alteration in a pulsar's spin frequency momentarily affects the precision of predictions for its timing behavior, potentially confounding the distinction between gravitational wave signals and glitches during data analysis [6].

Glitch classification is a fundamental and essential task in gravitational wave research. It revolves around the identification and categorization of unexpected noise or anomalies present in the data collected by gravitational wave detectors [7]. Precise classification of glitches holds immense importance as it enables the differentiation of genuine gravitational wave signals from various noise sources. Early research efforts in glitch classification focused on techniques, such as principal component analysis (PCA) [8,9] and multi-layer perceptron (MLP) [10], which demonstrated some success in automating the classification process. Building upon these foundations, subsequent studies explored the application of Gaussian clustering, Bayesian models, and wavelet detection filters, pushing the boundaries of glitch classification even further. Nonetheless, recent advancements in deep learning have showcased the remarkable potential of convolutional neural networks (CNNs) [11] for glitch classification [12]. By employing the time–frequency image analysis, CNNs have proven to be effective tools for automating and improving glitch classification accuracy. Other classes of numerical models for glitch analysis attempt to disentangle glitches into their speculated elementary constituents, ref. [13].

Other pressing challenges in gravitational wave studies are glitch cancellation and denoising of gravitational wave signals [14]. The primary objective here is to differentiate genuine signals from unwanted noise and eliminate identified glitches, thereby achieving high-precision measurements of gravitational waves. Noise in gravitational wave signals can originate from a variety of sources, including seismic activity, thermal fluctuations, and electronic noise. However, dealing with noise becomes particularly challenging when it exhibits non-stationary characteristics and possesses a variable probability distribution. Researchers have dedicated extensive efforts to overcome these challenges by developing advanced algorithms and techniques. Through the application of adaptive filters, time–frequency analyses, and sophisticated machine learning methods, scientists have made significant progress in denoising gravitational wave signals and enhancing the accuracy of measurements [15,16] .

The detection and analysis of binary black hole signals are a compelling area of research within gravitational wave studies. Binary black holes serve as captivating astrophysical objects, and the identification of their gravitational wave signals provides valuable insights into the nature, formation, and evolution of these enigmatic entities. Detecting these signals amidst the background noise presents a significant challenge as binary black hole signals are orders of magnitude weaker than the characteristic amplitude of the noise. Researchers have leveraged various data analysis methods, including matched filtering and template matching techniques, to identify and extract these elusive signals from the data captured by gravitational wave detectors [17]. This research has not only contributed to a better understanding of binary black holes but has also enriched our knowledge of the larger cosmic landscape.

Gravitational wave bursts constitute another intriguing research area. These transient events, characterized by short-duration bursts of gravitational waves, can arise from cataclysmic phenomena, such as supernovae or compact object mergers. Detecting and characterizing these bursts provide crucial information about the underlying astrophysical processes and the sources responsible for their generation. Researchers have developed specialized algorithms and signal processing techniques, including time–frequency analyses and deep learning approaches, to identify and study gravitational wave bursts like in [18]. The study of these events not only broadens our understanding of the cosmos but also provides insights into the dynamics and behaviors of cataclysmic astrophysical events.

In addition to the aforementioned core research problems, several minor issues contribute to the comprehensive analysis of gravitational wave data. These include issues such as data preprocessing, noise characterization, modeling, signal parameter estimation, event localization, and data visualization. Addressing these minor challenges collectively enhances the overall accuracy, efficiency, and interpretability of the gravitational wave data analysis process.

Overcoming these research problems and challenges would not have been possible without the remarkable advancements in artificial intelligence, deep learning, and machine learning techniques. These technologies have played a pivotal role in enabling the identification of weak signals buried within noise, the accurate classification of various signal types, and the cancellation of unwanted noise sources [19]. The graphics processing unit (GPU) has emerged as a critical hardware component in accelerating the computations required for deep learning and machine learning models. Furthermore, dedicated software frameworks and libraries, such as TensorFlow, PyTorch, and Keras, have been explicitly developed for the analysis of gravitational wave data, facilitating efficient and effective implementation of these advanced techniques.

This paper aims to comprehensively explore the applications, technical implementations and hardware acceleration, of artificial intelligence, with a key focus on deep learning, in addressing the main research problems associated with gravitational wave astronomy. It will delve into the methodologies and algorithms employed in glitch classification, glitch cancellation, binary black hole signal detection, gravitational wave bursts, and other minor challenges. By examining the effectiveness of these techniques, highlighting potential limitations and describing the application of software frameworks and graphical accelerators, this paper seeks to provide an understanding of how advances in AI and deep learning have and are significantly contributing to the development of gravitational wave research over the last decade. This trend is clearly growing in terms of both adoption and complexity of AI-based methods and techniques, and reflects an increasing focus on the use of AI in this field of research, as evidenced by the importance given to these techniques and methodologies for projects, such as Gravity Spy [20] and other recent works, like in [21].

The following part of this work is structured as follows: Section 2 discusses works and achievements in glitch classification; Section 3 focuses on glitch cancellation and GW data denoising; Section 4 explores the detection of binary black hole signals; Section 5 presents works related to gravitational wave burst detection and analysis; Section 6 provides an overview of other challenges and issues encountered in gravitational wave analysis using data-centric approaches; Section 7 offers a quantitative discussion on research efforts, areas of interest, and employed technologies; Section 8 concludes the work with our summary and findings.

## 2. Glitch Classification

Glitch classification on gravitational waves is the process of identifying and categorizing unexpected noise or anomalies in the data collected by gravitational wave detectors. Glitches can arise from various sources, such as instrumental artifacts, environmental factors, or even cosmic events. Classifying these glitches is crucial in order to distinguish them from actual gravitational wave signals, which can provide valuable insights into the nature of the universe. The process of glitch classification involves analyzing the time–frequency patterns of the signal and comparing them to a database of known glitches.

Machine learning algorithms are often used to automate this process and to improve the accuracy and efficiency of glitch classification. Through glitch classification, scientists hope to enhance the sensitivity and reliability of gravitational wave detectors and unlock new discoveries in the field of astrophysics. Before the breakthrough of AI models, gravitational waves and glitches were mainly analyzed with analytical models, as presented in [22], using a method based on triangular norms. Then, machine learning (ML) and deep learning (DL) models have been used to classify the glitch that occurred on a gravitational waveform to better address the method for its mitigation or deletion. Some of the first attempts in glitch classification research were conducted in [10,23]. Both research groups developed signal artifact classification models based on machine learning. Ref. [10] defined an approach based on principal component analysis (PCA), multi-layer perceptron (MLP), and self-organizing maps (SOMs); this approach detected and classified glitches in gravitational waveforms into two categories: bursts and glitches. Ref. [23] tested support vector machines and random forest on the same task. The second phase of research development in the glitch classification area is mainly conditioned by the application of models with deeper statistical underpinnings, such as Gaussian clustering and Bayesian models. Ref. [9] firstly performed a formulation of these models for glitch classification with simulated data and then [24] applied such models to real data. They represents works in this area with three different approaches: PCA with Gaussian mixture model (GMM); Bayesian models; wavelet detection filters with machine learning-based classification.

Since 2017, a new class of approaches has taken hold, involving the time–frequency image analysis of glitch events, opening up the area of deep learning for gravitational wave analysis. This perspective enabled the implementation of convolutional neural networks (CNNs), which are particularly suitable for image classification and image analysis tasks. Ref. [20] presents one of the earliest applications of a CNN model for glitch classification on LIGO detector data, cited in ref. [25]. Then several improvements in classification performances have been achieved with CNN multi-view and parallel view, as introduced in ref. [26]. The multi-view technique consists of data pre-processing to merge images of glitches of different durations into a single image, combining the characteristics of different glitches. The parallel view technique is a more sophisticated algorithm that uses a group of parallel CNNs to extract relevant features from different images; these features are used to feed the last CNN that combines features from previous networks.

CNNs have been compared with the classical machine learning approach, such as the support vector machine, as cited in ref. [12], with CNNs demonstrating better cross-class classification performance. Within the glitch classification area, ref. [27] proposed a method to predict whether a glitch is likely to appear at a given time based on gravitational wave detector auxiliary channels; see ref. [1]. This method is based on elastic-net-based machine learning for understanding (EMU).

## 3. Glitch Cancellation/GW Denoising

The secondary reference problem in our review consists of glitch cancellation tasks and gravitational wave signal denoising. The main goals are to differentiate the signal from noise and remove the identified glitches, avoiding systematic errors in the signal detection and parameter estimation of the GW. Noise in the signal can come from a variety of sources, including seismic activity, thermal fluctuations, and electronic noise in the detectors themselves.

The task might be very complex due to the nature of noise: it could be stationary and additive with uniform temporal behavior or non-stationary, exhibiting a mutable probability distribution. The non-stationary case is obviously more difficult to identify and remove. The literature offers numerous works employing supervised learning for gravitational wave denoising. In the case of non-stationary noise distribution, accurately estimating probability distribution parameters is crucial to better estimate the profile of disturbing signals. Ref. [28] first applied deep neural networks, specifically recurrent neural networks based on gated recurrent units (GRUs) [29], and then turned to machine learning algorithms, obtaining better results. Regarding the analysis and approach of the problem as a single block, ref. [30] used 1D convolutional neural networks fed by signals from different input channels; the model outputs the prediction of the noise. In this case, the approach to the denoising problem does not consider the repartition into the statistical characterization of noise, but it involves the analysis of the signal as a whole to identify noise interference. Numerous studies have incorporated CNNs into their pipelines, outperforming other denoising models, as seen in ref. [16]. The research shows that the dilated causal convolutions pipeline outperforms existing pipelines, even those based on classic convolution, and provides reliable results in real time. The paper also demonstrates the potential of deep learning in improving the sensitivity of gravitational wave detectors, which can enable the detection of weaker signals from distant sources.

Also, ref. [14] employed CNN, but the scope was quite different; the authors focused on the reconstruction of the signal combined with simulated noise data.

A common problem for, roughly, most research areas, is the availability of high-quality data; this issue forced artificial intelligence research teams to adopt unsupervised or semi-supervised learning algorithms. Ref. [15] proposed an unsupervised learning model based on denoising autoencoders with RNNs. The use of recurrent autoencoders allows the network to capture temporal dependencies in the signal, further improving the denoising performance. The results were evaluated based on the mean squared error and overlap, as referenced in ref. [31]. Some works focused on defined signal frequency bands, e.g., ref. [32] used CNN to potentially mitigate the angular noise in aLIGO [33,34], which is the limiting noise source of the current sensitivity in the 30 Hz band.

## 4. Binary Black Hole Signal Detection

Binary black holes are some of the most fascinating objects in the universe, and detecting their gravitational waves can provide crucial insights into the nature of black holes, their formation, and the evolution of galaxies. In recent years, the detection and analysis of gravitational waves from binary black holes have significantly enhanced with the application of deep learning techniques.

The following papers have proposed various machine learning and deep learning models to enhance the detection and analysis of gravitational waves. Ref. [17] proposed a deep learning model for the real-time detection and parameter estimation of binary black hole mergers. The model is based on a convolutional neural network (CNN) and extends an algorithm formulated in their previous work [35], including an analysis of real LIGO data. Furthermore, they propose a deep neural network-based system that can enable real-time multi-messenger astrophysics by combining gravitational wave detection with other forms of astrophysical observations. The model uses classical feedforward networks and is proposed as an attempt to define a single pipeline that is capable of solving problems, like identifying the presence or absence of GW signals, classifying noise transients, and reconstructing the astrophysical properties of detected GW sources.

A different model was exploited in ref. [36] in order to explore the use of deep networks to match the matched-filter model sensitivity, ref. [37], in face of lower latency in gravitational wave signals from binary black hole detection. ref. [36] used a CNN architecture and demonstrated that it could significantly reduce the computational cost of matched filtering. A more traditional way of using AI was conducted in ref. [38]; the authors defined a machine learning-based approach to rank the candidate signals detected by gravitational wave detectors. They used a gradient boosting machine and achieved help in identifying the most significant signals and reducing the false alarm rate. Similarly, ref. [39] proposed a machine learning-based classifier to identify inspiral signals in non-ideal single-detector data. The model is based on a random forest approach and can help improve the detection of gravitational waves from binary black holes using single detectors.

A newer approach was proposed in ref. [40], which uses a convolutional transformer-based architecture to detect gravitational waves from binary black holes. The model architecture is built on a transformer, employs self-attention mechanisms, can significantly reduce computational costs, and improve detection accuracy with respect to purely convolutional-based architectures. An interesting deep learning-based approach to detect gravitational waves from binary black holes using multiple detectors was proposed in ref. [41]. They exploit the benefits of already-known squeeze-and-excitation networks (SENets) from ref. [42], in combination with a soft-thresholding shrinkage function in order to define a new classification model that can significantly improve the signal-to-noise ratio and reduce false alarms with slight computational costs compared to classical CNNs. The authors of [43] focused on the inference phase of gravitational wave detection models. They integrated a modified version of the WaveNet model [44], optimized for inference, with high-performance computing (HPC) to improve the speed of gravitational wave detection, allowing for automatic and real-time detection of gravitational wave signals. The proposed model is trained on a large dataset of simulated signals to improve its accuracy and reliability. The authors demonstrate the effectiveness of their approach by achieving higher detection rates with lower false positives compared to existing methods. Overall, this paper presents an innovative application of deep learning and HPC for advancing the field of gravitational wave astronomy.

Differently, in ref. [45], the authors propose a hybrid machine learning/deep learning approach to identify strongly lensed gravitational wave events. The model is based on the combination of multiple deep pre-trained DenseNet201 networks with two XGBoost classifiers; it can help distinguish between lensed and non-lensed events and provide insights into the lensing properties of the universe. Finally, in ref. [46], the authors propose a recurrent autoencoder (AE) approach to detect gravitational waves from binary black holes without prior knowledge of the source parameters. The work shows a comparison between two types of recurrent AEs (LSTM-AE and GRU-AE) and a non-recurrent one (convolutional AE), showing the trade-off between accuracy and generalization when using an unsupervised strategy rather than a supervised approach. The results also show an improvement in the detection of weak and unknown signals and provide insights into the population of binary black holes.

## 5. Gravitational Wave Bursts

Gravitational wave bursts encompass a diverse array of transient events that can be categorized as unmodeled signals, exhibiting sudden and intense releases of gravitational wave energies over short time periods [47]. These bursts—searched for with unmodeled searchers—may originate from a variety of astrophysical phenomena, including core-collapse supernovae, cosmic string cusps, and other cataclysmic events that defy precise parameterization [48,49]. The exploration of unmodeled burst searches presents unique challenges and requires sophisticated data analysis techniques that are capable of identifying and characterizing these transient, impulsive signals [50]. This distinction between modeled and unmodeled searches enriches the understanding of gravitational wave detection strategies and underscores the necessity of tailored approaches for each category.

To analyze gravitational wave bursts, scientists employ sophisticated data analysis techniques, including time–frequency analysis methods, machine learning, and deep learning algorithms. These approaches help identify and characterize bursts amidst background noise and extract valuable information about their origin, energy, and other relevant parameters. In more detail, a novel approach using artificial neural networks (ANNs) is presented in ref. [51] to identify GW signals produced with short gamma-ray bursts (SGRBs). The authors demonstrate that ANNs can improve the sensitivity of detecting these GW signals by reducing noise in the data. In more detail, they used a multi-layer perceptron (MLP) model, which shows superior performance to traditional statistical detection methods when applied to data from advanced LIGO and Virgo detectors.

Different works have exploited the use of CNNs and compared their results with other techniques, such as in ref. [18,52]. They both focused on using CNNs to detect and classify gravitational wave signals from core-collapse supernovae. The first work compared two convolutional neural networks (CNNs), one-dimensional and two-dimensional architectures, in order to analyze data from the advanced LIGO and Virgo detectors; the authors demonstrated that their approach can achieve high levels of accuracy ($\geq$95%) in detecting and classifying signals. Similarly, the latter used a CNN-based architecture; the authors demonstrated the effectiveness of their approach by comparing the performance of their CNN model with traditional matched-filtering techniques. In both cases, the results show that deep learning approaches achieve higher detection rates with lower false alarms compared to traditional methods. A more in-depth analysis was performed in ref. [53]; the authors investigated the use of deep learning algorithms for detecting gravitational wave signals from core-collapse supernovae. The authors used three different reduced CNN architectures from the SoA models: ResNet, Inception v4, and Inception-ResNet v1. The models were reduced by minimizing the number of parameters, using, for example, minimal amounts of pooling layers and skip connections, in order to achieve better efficiency and inference times, demonstrating the feasibility of designing new, low-latency detection pipelines for CCSN.

## 6. Minor Problems and Tasks

In addition to classical problems, as detailed in previous sections, there are smaller classes of gravitational wave problems and tasks that have proved particularly suitable for analysis with artificial intelligence models. This area includes compact binary coalescence, data generation for glitch identification and classification, and the study of source populations to discriminate the generative sources of gravitational waves.

The modeling of gravitational wave bursts is suitable for generative models, like GANs. In fact, ref. [54] introduces generative adversarial networks (GANs) to generate generalized gravitational wave bursts. The paper presents an approach based on latent space exploration to combine characteristics from five classes of waveforms to generate new hybrid waveforms. Thanks to adversarial patterns, the GAN learns to generate realistic and diverse gravitational wave burst signals. Other works, such as [55], employed machine learning techniques to rapidly generate waveform templates for LISA data analysis. Specific algorithms, such as order-reduction, have been used to approximate and interpolate the complex dynamics of extreme mass ratio inspiral (EMRI) waveforms, allowing for efficient waveform generation. Ref. [56] leverages deep generative models, specifically conditional autoencoders, to model gravitational waveforms. Using the generative capabilities of autoencoders and conditional autoencoders, authors can generate synthetic waveforms based on desired conditions. Generating a waveform could be similar to modeling a natural language phrase, as ref. [57] demonstrates using deep seq2seq models, to analyze and understand the merging and ring-down phases of binary black hole coalescences. This class of models, mostly used for natural language processing, can generate waveforms as sequences of tokens.

Machine learning and deep learning techniques offer promising solutions for improving data quality in glitch detection/classification. These methods enable the automatic extraction of relevant features from data, allowing for the accurate identification and classification of glitches. Supervised learning algorithms can be trained on labeled glitch data to create robust models that distinguish between different types of glitches. Unsupervised learning approaches can discover underlying patterns in unlabeled data, aiding in the identification of novel or unknown glitches. By leveraging machine learning and deep learning, researchers can enhance the accuracy and efficiency of glitch detection/classification, leading to improved data quality and more reliable scientific measurements. Refs. [20,58] present projects focused on the study of gravitational wave noise. These works utilize machine learning algorithms in combination with citizen science participation to improve the performance of gravitational wave detectors. Machine learning models assist in identifying and classifying gravitational wave signals, while citizen scientists contribute to data validation and labeling, collectively enhancing the detector's sensitivity and efficiency. In order to increase data variability, GANs have been used to generate new synthetic glitches; ref. [59] employs GANs to generate synthetic transient noise artifacts in gravitational wave detector data. GANs are trained on real data to learn the statistical properties of noise artifacts and generate realistic synthetic samples. This allows researchers to study and develop strategies to mitigate the impact of transient noise on gravitational wave analyses. Ref. [60] presents an unsupervised learning architecture for classifying transient noise in interferometric gravitational wave detectors. Through an unsupervised approach, the model can learn patterns and features in the noise data, enabling the identification and categorization of different types of noise sources without requiring labeled training data. The specific approach is based on variational autoencoders (VAEs) and CNNs to extract features and classify time–frequency spectrogram 2D images.

The task of population studies in gravitational wave analysis involves investigating and characterizing the population of astrophysical sources that produce gravitational wave signals. It aims to gain insight into the distribution, properties, and behaviors of these sources in the universe. The detection of gravitational wave sources, such as mixed binaries or low-mass black holes, as reported in ref. [61], has been performed using Bayesian inference processes.

## 7. Discussion

Over the past decade, there has been an increasing trend of research papers focusing on the application of artificial intelligence (AI) in the study of gravitational waves.

According to the retrieved data from the IEEE, Elsevier, and ACM sources, there has been a substantial increase in the number of papers published each year on the topic, with a total of 300 papers published from 2013 to 2022 (Table 1). The year 2017 marked a significant turning point in the trend, as the number of papers doubled from the previous year. Elsevier showed the highest number of papers, with a total of 245 published between 2013 and 2022, followed by IEEE (with 26) and ACM (with 29). The rise in interest in the application of AI to gravitational wave research is likely due to the increasing availability of data, the development of more advanced AI algorithms, and the growing interest in multi-messenger astronomy. This trend is expected to continue in the future, with AI playing an increasingly important role in the analysis and interpretation of gravitational wave data.

**Table 1.** Number of papers grouped by source and year of publication.

| | Source | | |
|---|---|---|---|
| **Year** | **IEEE** | **Elsevier** | **ACM** |
| 2013 | 0 | 1 | 0 |
| 2014 | 1 | 1 | 2 |
| 2015 | 0 | 7 | 1 |
| 2016 | 1 | 16 | 1 |
| 2017 | 2 | 26 | 5 |
| 2018 | 2 | 16 | 4 |
| 2019 | 1 | 37 | 4 |
| 2020 | 1 | 40 | 4 |
| 2021 | 10 | 47 | 5 |
| 2022 | 8 | 54 | 3 |
| Total | 26 | 245 | 29 |

Following this brief introduction of research efforts (in terms of published papers in gravitational waves area with artificial intelligence involvement), we conducted an analysis of a set of 49 papers, 2 of them were general reviews of gravitational waves studies, and the remaining 47 dealt with specific works that used at least one AI-based approach for achieving results.

Table 2 shows the number of papers and corresponding percentages published in major research areas related to gravitational waves analysis.

**Table 2.** Number and percentage of papers grouped by resolved problem.

| Resolved Problem | Number of Papers | Percentage |
|---|---|---|
| Glitch Classification | 10 | 21% |
| Gravitational Wave Bursts | 4 | 9% |
| Glitch cancellation/GW denoising | 6 | 13% |
| Signal Detection (BBHs) | 10 | 21% |
| Population Studies | 3 | 6% |
| Data search and query | 1 | 2% |

**Table 2.** *Cont.*

| Resolved Problem | Number of Papers | Percentage |
|---|---|---|
| Continuous wave search | 1 | 2% |
| Parameter estimation | 3 | 6% |
| CBC—Waveform modeling | 4 | 9% |
| Stochastic gravitational wave background | 1 | 2% |
| GW in cosmology | 1 | 2% |
| Improving data quality | 3 | 6% |

The table indicates that "Glitch Classification" and "Signal Detection (BBHs)" are two of the most studied areas, each accounting for 21% of the total papers published. "Glitch cancellation/GW denosing" and "CBC—Waveform modeling" are the next most popular areas, each accounting for 13% and 9% of the papers, respectively. The remaining areas, such as "Gravitational Wave Bursts", "Population Studies", and "Parameter Estimation", account for smaller percentages of the total papers published; "Improving data quality" accounts for 6.1% of the analyzed papers.

By analyzing the different works, we found that deep learning, despite being the most recent and advanced approach, is the most widely used, with 31 out of 49 papers employing it. It is followed by machine learning (with only 23 papers). For 13 papers, classical statistical methods were used either in combination with or for comparison to AI techniques. Interestingly, there were seven papers that combined deep learning and machine learning techniques.

The use of GPUs is not prevalent, with only 15 papers mentioning their use, and 4 of those utilizing multi-GPU techniques to speed up computations. It is worth noting that no other GPU architectures, apart from NVIDIA, were mentioned in the analyzed papers. Table 3 shows the distribution of different NVIDIA GPU architectures mentioned in the analyzed papers, along with their release year, and the overall percentage of mentions. The oldest architecture mentioned was NVIDIA Kepler (released in 2012), while the most recent was NVIDIA A100 (released in 2020). There was no mention of Ada Lovelace architecture GPUs being released in 2022, likely due to the sharp increase in hardware costs in recent times.

**Table 3.** Percentage of GPU architecture mentions in papers.

| Architecture | Release Year | Percentage |
|---|---|---|
| Tesla | 2007 | 25.0% |
| Fermi | 2010 | 0.0% |
| Kepler | 2012 | 12.5% |
| Maxwell | 2014 | 6.3% |
| Pascal | 2016 | 25.0% |
| Volta | 2017 | 18.8% |
| Turing | 2018 | 6.3% |
| Ampere | 2020 | 6.3% |
| Ada Lovelace | 2022 | 0.0% |

The use of specific frameworks is also noteworthy, with TensorFlow [62] and scikit-learn [63] being the most commonly used, followed by PyTorch [64] and Theano [65]. TensorFlow is an open-source machine learning framework developed by Google, which is widely used in deep learning research and industry applications. Moreover, scikit-learn is a Python library that provides simple and efficient tools for data mining and data analysis, with built-in algorithms for classification, regression, and clustering tasks. PyTorch is a popular open-source machine learning library based on the Torch library; it is known for its dynamic computational graphs and ease of use. Theano is a Python library that allows for efficient mathematical expression evaluation and it supports CPU and GPU computations.

## 8. Summary and Conclusions

The statistics presented in this analysis indicate a growing interest in utilizing deep learning and machine learning techniques for gravitational wave analysis. These techniques have proven to be useful in detecting and characterizing gravitational waves, resulting in an increasingly intensive use of techniques and algorithms based on AI.

The use of GPUs and specialized frameworks has played a significant role in facilitating research in this field. GPUs have been instrumental in speeding up the computations and accelerating the analysis process. Specialized frameworks, on the other hand, have made it easier for researchers to develop and implement complex deep learning and machine learning models for gravitational wave analysis.

Moreover, the increasing interest in deep learning and machine learning techniques in gravitational wave analysis signifies the potential of these techniques in advancing our understanding of the universe. The ability to detect and analyze gravitational waves has opened up new avenues for studying black holes, neutron stars, and other astrophysical phenomena.

In conclusion, the statistics presented demonstrate the crucial role of deep learning and machine learning techniques in gravitational wave analysis and the significance of using GPUs and specialized frameworks in accelerating research in this field. This area of research is likely to continue to grow and evolve in the future, contributing to our understanding of the universe and its mysterious phenomena.

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