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Artificial Intelligence in Multi-Messenger Astronomy

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Abstract

The arrival of multi-messenger astronomy has marked a breakthrough in astronomy thanks to the ability to simultaneously observe astrophysical events using electromagnetic waves, gravitational waves, neutrinos, and cosmic rays. The increasing sensitivity of modern observatories has produced an explosion in the amount and diversity of astronomical data, requiring novel solutions to cope with data analysis challenges in real time. Artificial intelligence (AI), which encompasses machine and deep learning as well as physics-informed approaches, has been demonstrated to be an enabling technology to tackle these issues. Nowadays, AI methods have become a central piece within the whole process of multi-messenger astronomy, involving the use of such methods in the different phases: from detecting the presence of a signal, filtering out the noise, classifying the type of event, estimating its parameters, localizing the source, to carrying out follow-up observations. This review presents an introduction to the application of AI for multi-messenger astronomy, showcasing current advances, applications, and main problems that can be found when dealing with this technology for data analysis purposes in multi-messenger astronomy.

Keywords

Multi-Messenger Astronomy, Artificial Intelligence, Machine Learning, Gravitational Waves, Astrophysical Data Analysis

1. Introduction

There have been a great many changes in the field of astronomy during the last century, which saw the transition of this discipline from simple astronomy using only electromagnetic radiation to multi-messenger astronomy, in which different types of waves such as electromagnetic waves, gravitational waves, neutrinos, and cosmic rays are used to study various astrophysical processes. In contrast to traditional astronomy in which all the physical processes were observed using only certain wavelengths of light, the use of multi-messenger approach allows getting more complete information about one and the same source by using data collected through different means of detecting radiation. The discovery of gravitational waves coming from binary neutron star merging event GW170817 along with electromagnetic waves in different wavelengths has been the first confirmation of the efficiency of this method [1] [2]. The success in multi-messenger astronomy is due to fast progress in building next generation observational facilities. Gravitational wave observatories on Earth, like Advanced LIGO, Virgo, and KAGRA work together with electromagnetic facilities covering the whole spectrum, whereas neutrino detectors, such as IceCube and KM3NeT, along with ultra-high-energy cosmic ray observatories keep track of all transient events happening in the Universe. Instead of working separately, these facilities nowadays constitute a global network, where data from different detectors are used in combination to enhance source localization and astrophysical modeling, and for rapid follow-up observations [1] [3]. Such an approach has broadened the research area of astronomy and provided unique opportunities for studies of merging compact objects, active galactic nuclei, supernovae, tidal disruption events, and many other phenomena in the Universe.

As the scientific capability of modern observatories advances, the computational challenges posed by the data produced have advanced with it. Modern astronomical observatories now produce data that is unprecedented in size, speed, and complexity. The Vera C. Rubin Observatory is expected to generate approximately 10 million transient alerts each night during the Legacy Survey of Space and Time (LSST), creating a major requirement for automated real-time classification and prioritization [4]. The survey is designed for rapid processing of newly acquired images and generation of transient alerts, requiring robust low-latency analysis pipelines [4] [5]. Similarly, data-intensive challenges are being posed by gravitational wave astronomy due to increasing sensitivity of the detectors that result in higher numbers of detections. Third-generation gravitational-wave observatories, including the Einstein Telescope and Cosmic Explorer, are expected to substantially increase the annual detection rate of compact-binary mergers, creating significant computational and data-analysis challenges [6]. The heterogeneity of the multi-messenger data set makes the problem more difficult as well. Images derived using electromagnetic radiation, time series from gravitational wave detectors, neutrino interaction events, and cosmic ray air showers vary considerably in terms of their temporal resolution, dimensionality, statistical behavior, and noise structure. Effective scientific use requires not only fast processing of the individual data streams, but also fast integration of the diverse information gathered at different geographical locations. Model-driven analysis processes have been very effective, but are often too costly for large scale parameter estimation, template matching, transient detection, and low latency alerts [3] [7] [8].

This has placed Artificial Intelligence (AI) in the role of an important technology underlying future astronomical science. In recent times, machine learning, deep learning, graph neural networks, transformers, and physics-guided learning techniques have shown impressive results in the areas of signal detection, denoising, anomaly detection, source classification, parameter estimation, and multimodal data fusion [4] [8] [9]. For the purpose of giving an overview, **Figure 1** describes the place of artificial intelligence in multi-messenger astronomy. This figure explains how heterogeneous signals obtained through electromagnetic, gravitational-wave, neutrino, and cosmic-ray detectors are combined using AI for deriving complementary physics to facilitate source localization and parameter estimation.

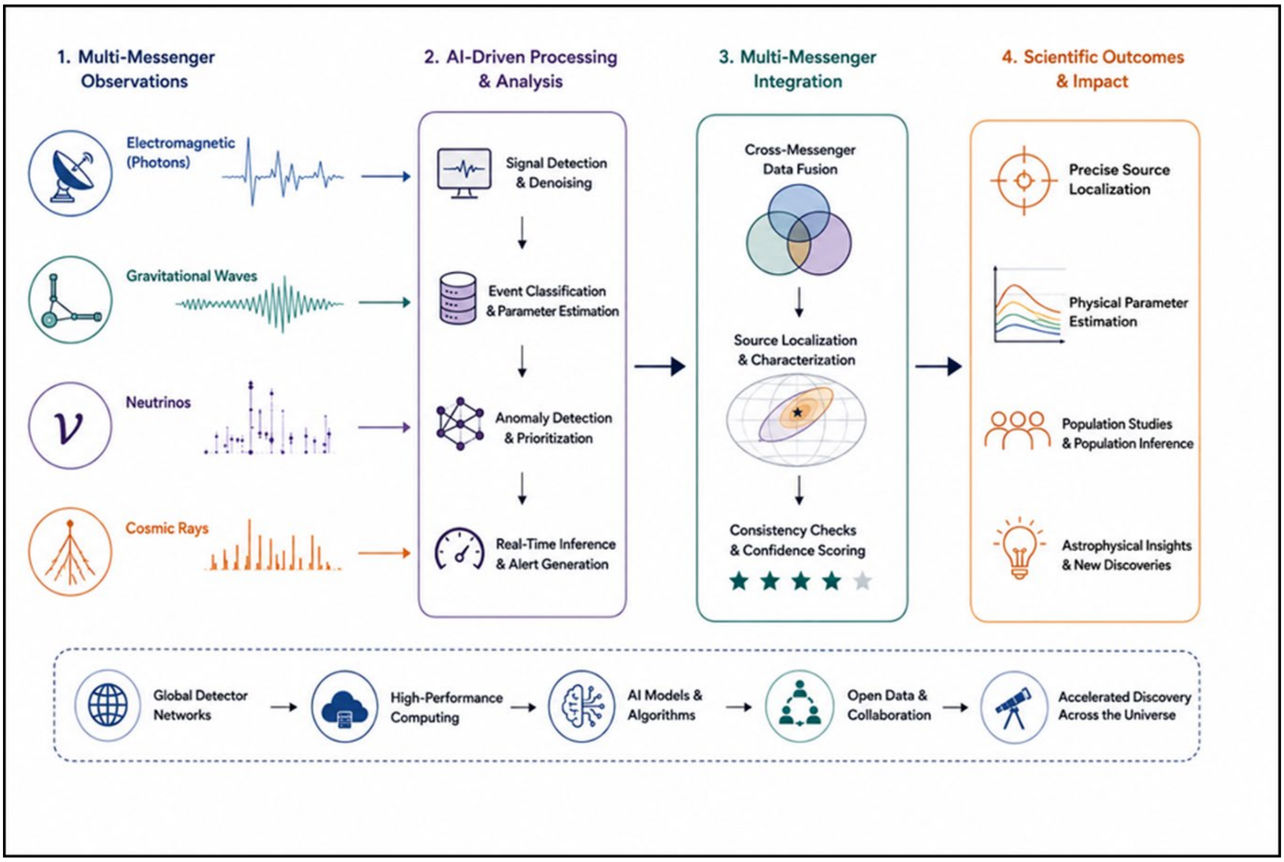

Figure 1. Overview of AI-assisted multi-messenger astronomy, illustrating the integration of heterogeneous astronomical observations for scientific discovery.

As opposed to conventional analytical approaches that depend on feature engineering and computationally expensive numerical approaches, AI algorithms allow for the automatic learning of complex nonlinear mappings using observed and simulated data in an efficient manner. This has led to an incorporation of AI at each step of multi-messenger analysis, including detector calibration and characterizations, event detection, source localization, follow-up scheduling, and scientific analysis, thereby increasing the efficiency and scientific productivity of current telescopes and detectors [4] [8] [9]. AI is anticipated to become even more important with the advent of petascale and exascale observations in astronomy. The coming generations of observatories such as the Rubin Observatory, Square Kilometre Array (SKA), Einstein Telescope, Cosmic Explorer, Laser Interferometer Space Antenna (LISA), and Cherenkov Telescope Array (CTA) will continuously produce multi-modal datasets whose complexities are beyond the reach of traditional approaches to their analysis [7] [9]. The union of data-driven astronomy and AI has caused many scientists to view multi-messenger astronomy as the perfect field of science where trustable physics-driven and multi-modal artificial intelligence can be developed [4]. This review has chosen the literature as an attempt to represent examples of well-established and proven applications of AI, important demonstration cases, and new trends in multi-messenger astronomy. In particular, a lot of attention was paid to papers that demonstrated the application of artificial intelligence techniques in real-life astronomical data analysis processes, such as signal detection, classification, parameter estimation, association, localization, and prioritization. The operational or quasi-operational astronomical pipelines were differentiated from research prototypes based on their ability to integrate with observational facilities or real-time data streams, while those that are simulated archived, or just proving some concepts were classified as new research approaches.

In this review, we provide a brief outline of the rapidly developing area where artificial intelligence meets multi-messenger astronomy. We start by describing the features of multi-messenger astronomy and computational difficulties that arise during such observations. Then, we describe AI approaches which are being used currently in astronomy. After that, we review the application of AI throughout the whole observational pipeline of multi-messenger astronomy, as well as notable scientific results that have been achieved through this approach. Finally, we address the challenges and possibilities for future developments.

2. Multi-Messenger Astronomy: Data and Challenges

Multi-messenger Astronomy (MMA) has revolutionized astrophysics observation by combining complementary information carried by different types of messengers in the universe such as electromagnetic, gravitational waves, neutrino, and cosmic rays. Different from traditional astronomy that uses mainly electromagnetic observation, MMA utilizes the combination of different physical probes originating from the same astrophysical phenomenon to give a better understanding of the underlying characteristics and emission mechanisms of these phenomena. Through this new approach of research, many phenomena like compact binary merger, active galactic nucleus, and core-collapse supernova have been better investigated [1] [2]. EM observations continue to form the basis of astronomical observations, ranging across radio waves to very-high-energy gamma rays, and providing high-resolution spatial, spectral, and temporal data. The Large Synoptic

Survey Telescope and the Square Kilometre Array are expected to deliver data sets in petabytes scale, while observatories like the James Webb Space Telescope and the Cherenkov Telescope Array will deliver valuable information from different wavelength and energy regimes [4] [10]. Alongside these EM observations, gravitational wave observatories like Advanced LIGO, Advanced Virgo, and KAGRA directly measure the disturbances of spacetime due to merger events of compact objects, and future observatories like the Einstein Telescope and the Cosmic Explorer are expected to achieve an order of magnitude increase in the detection rates [6] [11]. High-energy neutrino observatories, like IceCube and KM3NeT, provide a unique insight into hadronic particle acceleration in extreme astrophysical sources since neutrinos pass unhindered through matter and magnetic fields [12] [13]. Observatories for cosmic rays expand the range of observation by measuring ultra-high energy charged particles produced by some of the most powerful sources in the Universe. All these different messengers, together, give a multi-dimensional understanding of astrophysical phenomena, which is not possible with EM observations alone [2].

It is the variety of these types of observations that brings another key feature of MMA-heterogeneous data. Contrary to conventional astronomical survey, multi-messenger observations imply fundamentally different data types, which include high-resolution images, spectra, light curves with uneven sampling, gravitational wave strain signals, neutrino interactions, and air showers. Such datasets vary substantially by their spatial and temporal resolutions, signal-to-noise ratio, dimensionality, probability distributions, and other features. Additionally, datasets are gathered by geographically dispersed detectors with different sensitivities, detection thresholds, observational cadence, and calibration methods, thus creating a substantial computational problem of combining heterogeneous datasets [5] [9]. Parallel to the diversification of data types, astronomical observatories have entered an era where data sizes and velocities are unmatched. For instance, LSST at Rubin Observatory will be expected to produce up to 20 TB of raw imaging data every day, producing almost 60 PB of raw data in its decade-long surveying period, while also producing about 10 million transient alerts every day that need automatic detection and follow-ups [4]. Likewise, improvements in detector sensitivities are predicted to boost gravitational wave detections from tens of detected waves per observational cycle to tens of thousands of compact binary coalescences in annual rates with the help of next-generation interferometers [6] [9]. This trend of large data throughput along with the increasing event rates has transformed astronomy into a computation-limited field.

A yet another challenge that arises is associated with the ephemeral nature of many multi-messenger events. The electromagnetic counterpart to gravitational wave detection can last for several hours or days, whereas a high-energy neutrino trigger can be followed up only immediately to gain the most science from it. Thus, low-latency data analysis has become one of the crucial requirements in modern observational astronomy. Classical approaches to data analysis are very robust and physical in nature but are associated with the use of computationally expensive matched filters, Bayesian parameter estimations, and candidate validation, all of which become ever more complicated as the volume of observational data increases [5] [14]. The combination of these challenges clearly demonstrates that future developments in multi-messenger astronomy will be contingent not only upon improvements in detectors, but also upon equally important breakthroughs in computational techniques. Real-time analysis of heterogenous, high dimensional, and continuously arriving data sets is now a fundamental requirement of modern astronomy, thus creating the perfect conditions for the application of artificial intelligence techniques. Thus machine learning and deep learning techniques have become effective methods for speeding up data analysis, enhancing detection capabilities, and performing immediate scientific interpretation. The next section will provide an overview of some of the leading AI techniques used in this revolution.

3. AI Techniques in Astronomy

With the fast generation of astronomical data, astronomy has evolved into a data-driven science that requires methods for computational processing of large amounts of complex and diverse data to derive useful information. AI, especially machine learning (ML) and deep learning (DL), has become an important tool that augments physics-based methods in the analysis of astronomical data by allowing the recognition of patterns, detection of anomalies, classification of signals, and real-time decision-making. Rather than being a replacement for physics-based methods, AI is used as an efficient way of computation that helps to increase the speed of the analysis without losing detection accuracy [5] [7]. Machine learning consists of a large family of algorithms where statistical patterns are learned directly from the data without relying on predefined programming rules. In the context of astronomy, supervised machine learning algorithms have seen extensive use in the domain of source classification, transient detection, photometric redshift estimation, star parameter determination, and gravitational-wave candidate identification, using labeled datasets. Unsupervised machine learning techniques help in detecting new astronomical structures, rare objects, and anomalies in large survey data, whereas semi-supervised and self-supervised machine learning algorithms have emerged in recent times to make use of the large amounts of unlabeled data in astronomy [7] [8].

When it comes to AI techniques, Deep Learning has exhibited outstanding performance in handling large astronomical data through automatic learning of feature hierarchies from input data. CNNs are highly useful when dealing with astronomical image data because of their capacity to discover spatial structures that make them an excellent choice for classifying galaxies based on their morphology, identifying sources, gravitational lenses, and transients [9] [14]. Time series data including gravitational wave strains, pulsar signals, and variable star light curve data can be detected and classified at high speeds using deep neural networks with low computational delays as compared to traditional templates [5] [14]. Transformers have also contributed to the expansion of the use of AI technology in astronomy by their development. The Transformer model was initially created for natural language processing tasks, but its self-attention mechanism allows for capturing the long dependencies in the data sequence efficiently. The flexibility of the Transformer makes its use possible for various problems, including time-series analysis in astronomy, multimodal data analysis, and large-sky surveys in which the obtained observations at various wavelengths and messengers can be analyzed simultaneously [8].

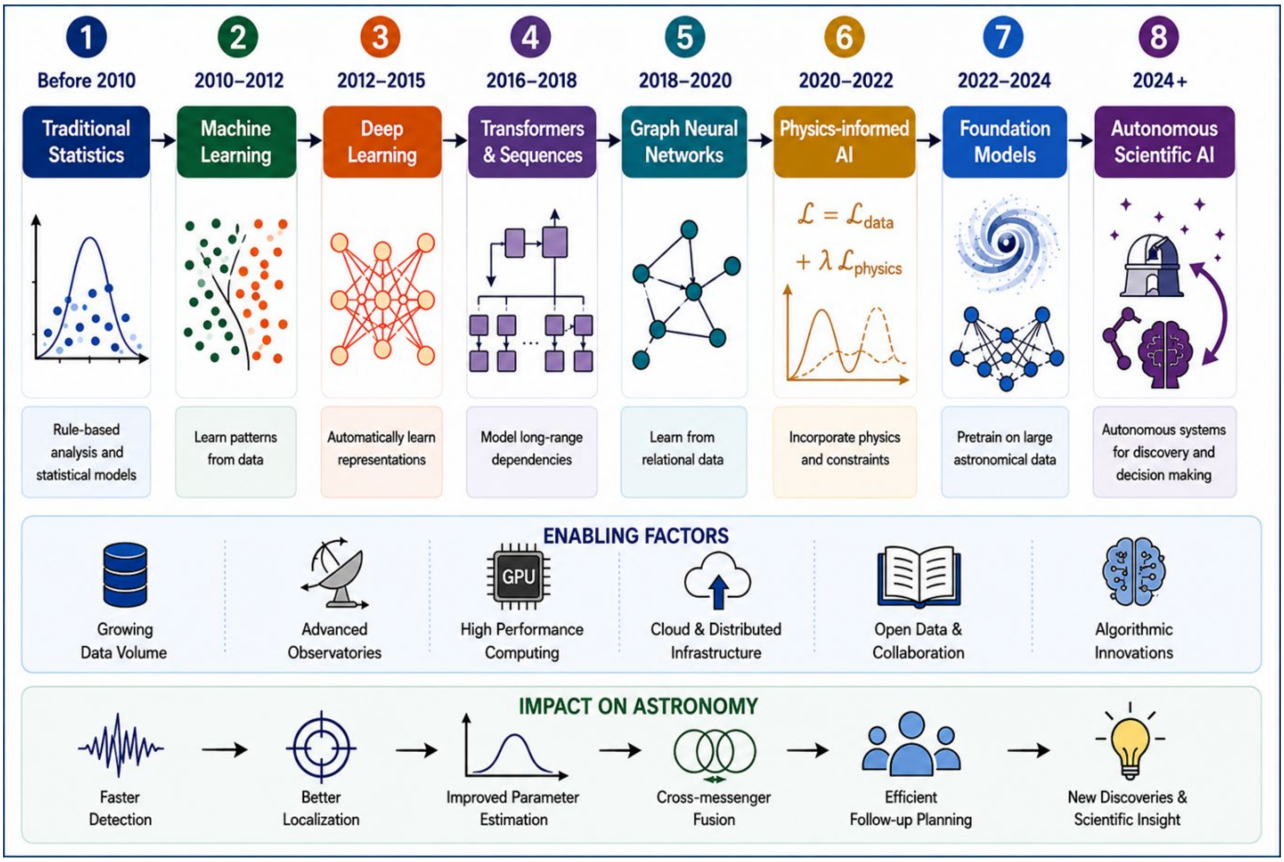

Figure 2. Evolution of AI in astronomy.

A further rapidly evolving domain is the use of Graph Neural Networks (GNNs), which are particularly adapted to analyzing relational and non-Euclidean data. In contrast to standard neural networks that are applied to structured grids, GNNs are inherently well-suited to representing astronomical systems as interconnected graphs, where the nodes can denote celestial objects or events from detectors, while the edges indicate relations. This has been found useful in the context of event association in multi-messenger astronomy, galaxy clustering, particle tracking in high-energy physics experiments, and optimizing detector networks, where many complex interactions between different observations need to be modeled [9] [15]. AI in astronomy has moved from classical statistical or machine learning techniques to more advanced deep learning, graph neural network, and physics-informed learning approaches. More recent advancements in AI include the use of foundation models and autonomous AI to analyze large-scale astronomical data with heterogeneous data types for scientific decision-making in real time. **Figure 2** illustrates the technological advances and key milestones in AI for astronomy.

However, even though data-driven models perform well with respect to prediction, they suffer from the problem of generalization outside of the probability distributions that they are trained upon. As a result, the notion of physics-informed artificial intelligence has emerged. It implies using known physical laws, conservation laws, differential equations, or other constraints as a part of the learning procedure. Physics-informed models yield physically meaningful predictions with limited dependence on large annotated datasets. They have become crucial in astronomy due to applications in gravitational wave waveform modelling, parameter estimation, numerical simulations, inverse problems, and surrogate modelling of expensive physical processes [16] [17].

Table 1. Overview of AI techniques, representative models, astronomical applications, and key advantages.

AI Technique	Representative Models	Typical Astronomical Applications	Advantages
Machine Learning	SVM, Random Forest, XGBoost	Classification, redshift estimation	Fast, interpretable
Deep Learning	CNN, RNN	Images, spectra, time series	Automatic feature extraction
Transformers	ViT, Time-series Transformers	Multimodal fusion, sequential data	Captures long-range dependencies
Graph Neural Networks	GCN, GAT	Detector networks, galaxy graphs	Models complex relationships
Physics-Informed AI	PINNs	Waveform modelling, inverse problems	Physically consistent predictions
Explainable AI	SHAP, LIME, Grad-CAM	Model interpretation	Improves scientific trust

With increasing adoption of AI into the process of discovery in science, transparency and accuracy of models have become crucial issues. The majority of deep learning models tend to be "black box" models in that it is impossible to determine the physics behind the model's predictions. As a result, Explainable Artificial Intelligence (XAI) became a growing field of research that seeks to increase model interpretability and scientific validity. Such methods as feature attribution, saliency maps, attention and uncertainty measures allow scientists to find the features of observations that cause certain decisions and verify their consistency with known astrophysics [18]. In the field of astronomy, where conclusions are based not only on predictions but also on physical interpretation of the data, explainability becomes especially important. Taken together, these approaches to AI form a very flexible computational toolbox for current-day astronomy. Machine learning provides an efficient approach to making statistical inferences; deep learning allows automated extraction of features from difficult observations; graph-based approaches and transformers allow combining different types of information into one dataset, and physics-based and explainable AI help increase the robustness and explain ability of scientific methods. These techniques are essential for analyzing heterogeneous astronomical datasets in the era of multi-messenger astronomy. A summary of some of the major AI methodologies used in astronomy can be presented in **Table 1**. The focus is on the main categories of algorithms, selected models, their respective applications in astronomy, and the primary benefits they offer. It is not meant to be an exhaustive list but only to highlight those methodologies which have proven to be impactful in astronomy.

4. AI across the Multi-Messenger Pipeline

In multi-messenger astrophysics, the science pipeline involves a series of interrelated steps that lead to the conversion of observed data into scientific insight. In contrast to traditional observational astrophysics, which usually involves data gathered from a single facility at one particular wavelength regime, multi-messenger astrophysics involves the combination of data acquired simultaneously using electromagnetic, gravitational waves, neutrino, and cosmic ray facilities. The combination of these varied observation channels allows for an examination of the varied physical mechanisms responsible for these astrophysical events and consequently provides additional insight into the origin and development of these extreme cosmic events. The ability to analyze such data successfully not only requires advanced observational capabilities but efficient computing as well [2] [5]. The growing sensitivity of modern observatories has brought about changes in the nature of astronomical data analysis which have been profound and fundamental. Modern observatories continually produce multi-dimensional images, spectra, time series, particle interactions, and detector telemetry, resulting in datasets which are vastly different in terms of their temporal sampling, geographic location, statistics, and even noise properties. Moreover, the occurrence of astrophysical transients such as neutron star collisions, gamma ray bursts, fast radio bursts, and high-energy neutrinos demands timely detection and coordinated observation in less than a minute. Traditional methods of analyzing such data may be physically well-founded and robust, but can become computationally intensive when faced with continuously incoming data [5] [9].

AI has been discovered as a game changing computational paradigm for tackling such problems. Instead of replacing traditional approaches of statistics and physics, AI enhances the existing analysis pipelines with its capabilities of performing fast calculations, discovering complicated structures in observations, and making decisions in real time. With the recent developments of machine learning, deep learning, graph neural networks, and transformer networks, automated discovery of signals, noise reduction, fast classification of events, estimation of parameters, multimodal data fusion, and intelligent scheduling of follow up observations became possible. As a result, AI has become an integral part of multi-messenger astronomy of today, providing significant reductions in analysis delays [5] [9] [14].

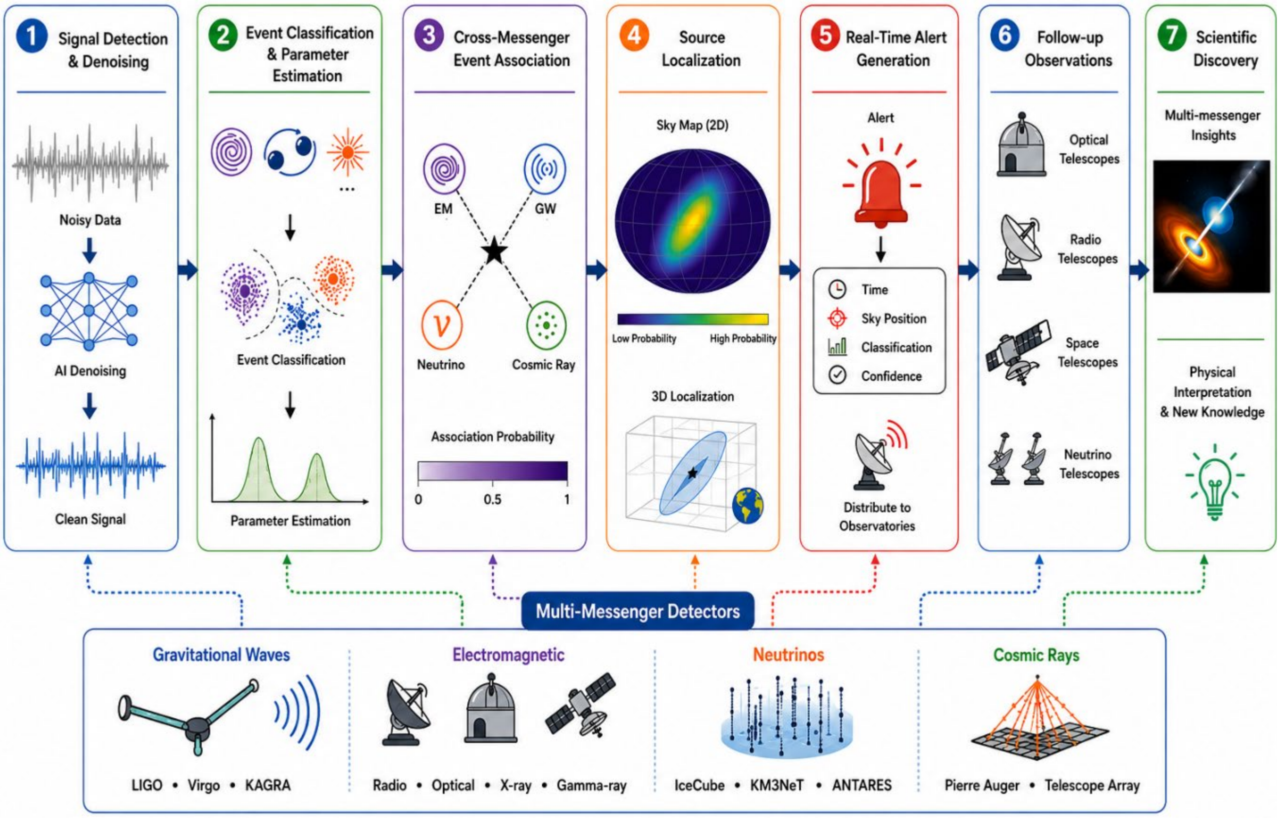

Figure 3. Schematic of the AI-enabled multi-messenger astronomy pipeline showing the major stages of data analysis and scientific discovery.

From a workflow standpoint, AI technology impacts almost all stages of the observational pipeline. At the detector stage, intelligent methods enhance data quality by performing denoising and noise modeling. After data acquisition, intelligent algorithms quickly separate real astrophysical signals from random noise and instrumental artifacts. When the events are detected, AI algorithms automatically identify the astrophysical source and estimate its physical parameters such as the type, mass, distance, luminosity, and confidence level. Multimodal learning algorithms analyze the information from various observatories to see if independent detections pertain to one and the same astrophysical event. Finally, intelligent decision systems produce alerts and schedule telescope follow-up observations. Figure 3 represents the flowchart of the AI-empowered multi-messenger astronomy pipeline. The figure depicts the processing of observations collected by gravitational wave, electromagnetic radiation, neutrino, and cosmic ray detectors through the subsequent stages of AI-empowered signal detection and denoising, event classification and physical parameter estimation, cross-messenger event association, source localization, and alerts generation in real time.

Prior to the extensive use of artificial intelligence, the task of detecting signals depended largely on well-defined and robust statistical algorithms for individual observatories. In gravitational-wave astronomy, matched filtering is the best method to detect the compact binary coalescence when there are precisely modeled waveforms, while Bayesian inference and coherent excess power search algorithms are utilized in the detection of weakly modeled and unmodeled transients [14] [15]. But this method involves correlation with hundreds of thousands of waveform templates that leads to an exponential increase in computation as a result of sensitivity improvements and increasing parameter space covered. Similar issues exist in electromagnetic surveys where transient detections depend on image differencing and statistical filtering to reduce false detections, and in neutrino observatories where likelihood-based reconstruction methods are employed to distinguish rare astrophysical signals from the strong background of atmospheric neutrinos [4] [16] [17]. Even though these algorithms are essential in astronomical data analysis, they fail to meet the requirement of being fast enough for multi-messenger detection.

4.1. Signal Detection and Denoising

The stages of signal detection and denoising belong to the very beginning of the pipeline of multi-messenger astronomy and lay the foundations for the reliability of all future analysis. Modern observatories constantly receive huge amounts of various types of data, which include not only actual astrophysical information but also instrument and environment noises, as well as statistical noise. With the increase in the sensitivity of detectors, the volume and diversity of observation data have also grown. In particular, Vera C. Rubin Observatory is forecasted to provide around 20 TB of images each night and about 10 million transients alerts each observing night, which cannot be checked manually [4] [19]. Furthermore, state-of-the-art gravitational wave detector systems constantly collect strain data sampled at a high rate from geographically distributed interferometers, whereas neutrinos and cosmic rays detectors constantly measure the interaction of billions of particles of which only a small percentage come from astrophysical origins [4] [12]. Therefore, the effective detection of signals and suppression of noises have become crucial for modern multi-messenger astronomy.

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AI technology has thus been seen as an auxiliary technology that greatly enhances the speed of signal detection without compromising on the statistical methods. Instead of substituting conventional methods, AI methods have been incorporated into the current detection process pipeline as means of quickly screening potential signals and artifacts, and performing noise modeling prior to the use of more computationally intensive methods. Such an approach helps in significantly cutting down computation time while maintaining the statistical reliability of conventional detection methods [21].

One of the earliest successes in this domain was demonstrated by George and Huerta [14] who constructed deep convolutional neural networks to detect compact binary merger signals directly from the noisy strain data from the LIGO observatory. Such a technique was able to achieve sensitivity similar to conventional matched filtering techniques but reduced inference time from the template-bank searches to just a few milliseconds, making it possible to perform real-time gravitational wave detection. Later developments in this direction have included the use of deeper neural networks, transfer learning, and attention mechanisms to make such networks more robust against non-Gaussian detector noise and glitches that are experienced during observing campaigns [5] [21]. Another important use case of AI in gravitational-wave astronomy is the suppression of noise. Noise in detectors is non-stationary in nature and also contains transient noise which is hard to model via traditional statistical methods alone. Methods such as deep denoising autoencoders, variational autoencoders, generative adversarial networks, and most recently diffusion models have been used to reconstruct astrophysical waveforms and retain their physical features [17] [22]. These have achieved success in the recovery of gravitational waves at low signal-to-noise ratio and thus increasing the detectability of compact binary mergers and other transient phenomena. While the use of diffusion models in operation is in the initial stages, recent studies suggest a lot of promise in waveform reconstruction under difficult observation conditions.

Consequences of the use of signal detection through AI technology go beyond gravitational wave astronomy. In optical time domain surveys like ZTF and LSST, which are carried out by the Vera C. Rubin Observatory, there is continuous monitoring of the dynamic universe and millions of transient candidates are produced. Where ZTF generates several hundreds of thousands of transient candidates per night, the anticipated number for LSST will be about 10 million per night, the great majority of which do not represent true astrophysical transients but either image artifacts, moving objects in the Solar System, or varying foreground objects [4] [23]. Machine-learning classifiers have thus become a must for "real-bogus" classification, classifying real astronomical events from false signals, with high precision, and significantly reducing the number of candidates that need human intervention [19] [24]. Comparable trends are observed in high-energy astrophysics. Only a tiny number of events at neutrino detectors like IceCube are of astrophysical origin, while most other events arise from atmospheric muons and neutrinos [12]. For this reason, machine learning has become an essential part of event selection and background rejection, utilizing the distribution of events recorded by photomultiplier arrays [25]. The same applies to the Cherenkov Telescope Array (CTA), where deep learning methods are used for separating gamma rays and hadrons, identifying particles, and reconstructing energy.

Table 2. Representative AI applications for signal detection and denoising in multi-messenger astronomy.

Observatory/ Facility	Data Type	AI Application	Representative Outcome	Ref.
LIGO-Virgo-KAGRA	Gravitational-wave strain	CNN-based signal detection	Millisecond-scale inference with sensitivity comparable to matched filtering	[14]
LIGO-Virgo-KAGRA	Gravitational-wave strain	Autoencoders, GANs, diffusion models	Improved denoising and recovery of weak signals	[22]
Zwicky Transient Facility (ZTF)	Optical survey images	Real-bogus classification	Automated filtering of hundreds of thousands of transient candidates per night	[19]
Vera C. Rubin Observatory (LSST)	Wide-field survey images	Automated transient detection	Processing of ~10 million alerts per night	[4]
IceCube	Neutrino events	Machine-learning event selection	Enhanced background rejection and event reconstruction	[25]
Cherenkov Telescope Array (CTA)	Gamma-ray events	Deep-learning reconstruction	Improved gamma-hadron separation and sensitivity	[23]

Although considerable progress has been made, there are still a few hurdles that need to be overcome in order for AI-based detection methods to be implemented in future observatories. The effectiveness of these approaches is highly dependent on the data they are trained with, thus being vulnerable to detector upgrades, variations in the noise environment, and novel astrophysical phenomena. Besides, issues related to the interpretability of certain deep learning architectures also bring about concerns about statistical significance and physical validity of the results obtained using these models. This has sparked research interests in hybrid systems that would use physics-based detectors along with machine learning and physics-informed neural networks where the governing physical laws would be embedded directly into the training process [17] [18]. Consequently, it can be stated that AI has made signal detection and noise reduction a computationally feasible task from what was a computationally very expensive process before. Through complementing existing statistical approaches to data analysis rather than substituting them, AI provides fast detection of various astrophysical signals from gravitational waves to cosmic rays, and in doing so provides an important starting point for further classification of those signals. **Table 2** presents representative applications of artificial intelligence across major astronomical observatories and facilities. It highlights the relationship between the underlying astronomical data, the AI techniques employed, and their demonstrated outcomes, providing an overview of how AI is being integrated into diverse observational and data-analysis workflows.

4.2. Event Classification and Parameter Estimation

Upon successful identification of a potential astrophysical signal, the next step within the multi-messenger pipeline is that of identifying the physical cause of the signal and determining the physical properties of the source responsible for the signal. Event classification serves the purpose of categorizing astrophysical events into different groups depending on the class of astrophysical phenomenon, such as binary black hole mergers, binary neutron star mergers, neutron star-black hole mergers, supernovae, tidal disruption events, active galactic nuclei, or high-energy neutrino sources. Following this step comes parameter estimation, where the intrinsic and extrinsic parameters of the source are determined, such as masses, spins, luminosity distances, inclination angles, sky locations, and any other relevant parameters needed to interpret the scientific significance of the astrophysical phenomenon. Historically, source characterization has been done using Bayesian inference and stochastic sampling methods such as Markov Chain Monte Carlo (MCMC) and Nested Sampling to obtain a statistically sound posterior distribution of the parameters of the sources. Such approaches are still considered state-of-the-art in gravitational wave parameter estimation due to their ability to provide an uncertainty quantification. Nevertheless, as dimensionality of the parameter space increases, the cost of Bayesian inference becomes prohibitive. The analysis of compact binary merger can take hours or even days to converge, thus preventing fast distribution of the information about the sources. Another area that promises significant speedup of the process is artificial intelligence. Instead of substituting Bayesian inference with machine learning approaches, it is now commonly used as an auxiliary tool providing fast initial estimates for further Bayesian inference [2] [5].

A groundbreaking experiment was conducted by George and Huerta, who presented the Deep Filtering model using deep convolutional neural networks to perform end-to-end processing of gravitational waves signals. The Deep Filtering method performed signal classification and source parameter estimation simultaneously and directly from noisy detector signals, obtaining detection results with the level of accuracy similar to matched filtering but performing inference much faster than traditional methods—in the range of milliseconds instead of hours. The study showed the potential of deep learning for estimating component masses of binary black holes directly from raw time-series data, enabling real-time follow-up observations in multi-messenger astronomy [5] [14]. Recent research in the field has developed even more efficient methods for AI-assisted parameter estimation using probabilistic machine-learning algorithms capable of producing Bayesian posteriors. Several machine-learning algorithms including deep neural networks, normalizing flows, Bayesian neural networks, and others were tested and shown to produce accurate parameter estimation results, substantially reducing computational cost compared with conventional Bayesian analysis and enabling low-latency inference. This is especially useful during gravitational wave observing runs since low-latency inference increases chances of finding counterparts of the source.

Besides being used for gravitational-wave astronomy, AI finds applications in modern optical time-domain surveys such as the Zwicky Transient Facility (ZTF) and the Vera C. Rubin Observatory Legacy Survey of Space and Time (LSST). The latter, for example, is anticipated to produce up to 10 million alerts per night. Fully automatic classification methods must be employed for separating transient sources of interest from variable stars, moving Solar System objects, and instrument noise. Therefore, machine-learning is implemented into the pipeline of optical surveys for transient event classification and target prioritization for spectroscopic observations and multiwavelength follow-up [2] [5]. Moreover, artificial intelligence has become an indispensable tool for high-energy astronomy as well. For instance, the IceCube Neutrino Observatory uses machine learning for classifying astrophysical neutrinos against an overwhelmingly large atmospheric background through making use of the information about spatial distribution, timing, and energy of events obtained by the detector. Machine learning is applied for similar purposes in gamma-ray astronomy as well, for improving the identification of particles, discrimination between gamma-ray and hadron events, and energy estimation in Imaging Atmospheric Cherenkov Telescopes.

However, several significant challenges continue to arise despite these advancements. The vast majority of the supervised learning techniques rely heavily on the quality of the training data sets used and may be unreliable in cases where the properties of detectors and populations of celestial objects differ from those used in training. Additionally, uncertainty quantification remains an open challenge since proper confidence intervals play a pivotal role in precision astrophysics. Hence, hybrid Bayesian-AI methods and physics-aware machine learning have been gaining popularity in recent years. All things considered, AI has enabled the transition of event classification and parameter estimation from time-consuming operations into fast and efficient parts of the multi-messenger astronomy workflow. As a result, the process of extracting scientifically valuable information about sources right after their discovery becomes very fast and contributes greatly to successful observational campaigns involving various types of signals [2] [5]. Additionally, the claimed advantages of the AI techniques can be measured by numerical quantities, such as inference time, computational costs, classification accuracy, and parameter estimation accuracy. Specifically, in case of gravitational wave analysis, the deep learning algorithms have proven themselves able to achieve signal detection and parameter estimation much faster than Bayesian inference techniques and, therefore, are adequate to low-latency requirements. In turn, transient classification systems in optical astronomy are specifically tailored to work on very large-scale alert streams, whereas event selection AI techniques in high-energy observatories allow for efficient detection of astrophysical signals out of a substantial background. The conclusion one may make is that the main advantage provided by AI techniques is not just better classification, but rather fast provision of scientifically meaningful results within a computationally feasible timeframe. **Table 3** summarizes representative AI-driven applications across major astronomical facilities, with emphasis on the specific computational tasks enabled by these approaches and their resulting scientific contributions. The examples demonstrate the role of AI in accelerating event characterization, improving parameter inference, prioritizing transient candidates, managing high-volume alerts, and enhancing the identification of astrophysical signals across different messenger channels.

Table 3. Representative AI applications for event classification and parameter estimation.

Observatory/Facility	AI Application	Scientific Outcome	Reference
LIGO-Virgo-KAGRA	Deep Filtering (CNNs)	Real-time binary merger classification and mass estimation	[14]
LIGO-Virgo-KAGRA	Deep probabilistic inference	Rapid parameter estimation with Bayesian-like accuracy	[5]
Zwicky Transient Facility (ZTF)	Automated transient classification	Prioritization of optical transients for follow-up	[19]
Vera C. Rubin Observatory (LSST)	Automated alert classification	Processing of ~10 million alerts per night	[4]
IceCube	Event classification	Improved astrophysical neutrino identification	[12]

4.3. Cross-Messenger Event Association and Data Fusion

The capability to study one and the same astrophysical phenomenon using a number of messengers, such as gravitational waves, electromagnetic radiation, neutrinos, and cosmic rays is among the major achievements in modern-day astrophysics. Given that each of the messengers studies distinct physical phenomena and locations in the source, a joint study of all the data offers much better insight into the studied phenomenon compared to a single observation. Thus, the success of the multi-messenger approach in astrophysics not only relies upon detecting individual events but also upon fast and accurate correlation of events observed by different geographically separated facilities. The power of multi-messenger studies has been exemplified in the case of the neutron star binary merger GW170817, which has been observed via gravitational waves using the LIGO-Virgo detector array, followed by the association with a short gamma-ray burst, GRB 170817A and optical kilonova from more than seventy observatories around the world. This set of data has opened up new windows to study neutron star mergers, r-process nucleosynthesis, jet formation, and measurement of the Hubble constant [1] [2]. Similarly, the association of the high-energy neutrino event IceCube-170922A with the flaring blazar TXS 0506+056 provided strong evidence for an astrophysical source of high-energy neutrinos, supported by the temporal and spatial coincidence and subsequent multi-wavelength observations [3].

Conventionally, the cross-messenger associations have been made via the coincidence analysis using temporal, spatial, and astrophysical consistencies. Events recorded in different observatories are analyzed in predefined time intervals and localizations, followed by likelihood or Bayesian statistics to calculate the probability of their origin from a common source of astrophysical nature. While this approach is statistically sound, its computational cost grows fast along with the increasing number of observatories and transient alerts. For example, the Vera C. Rubin Observatory is expected to generate approximately 10 million transient alerts per night, while future third-generation gravitational-wave observatories are expected to substantially increase the number of detectable compact-binary events [10] [12]. The use of artificial intelligence, however, has proven to be a powerful approach for the integration of heterogeneous datasets in astronomy. While previous coincidence methods analyzed individual messengers and correlated them statistically, AI is able to analyze the temporal evolution, spectral properties, localization errors, morphologies of sources and astrophysical context all at once. Machine-learning methods allow the detection of correlations in nonlinear form and in consequence, the detection of associations that would not have been detected by using classical techniques [6].

The recent development in the multimodal deep learning domain has opened up further possibilities in this direction. State-of-the-art neural network architectures are able to fuse heterogeneous inputs such as gravitational wave time series, optical images, spectra, neutrinos, and catalog data into one latent representation which can be used for source characterization. For instance, Graph Neural Networks (GNN) is an area that has received considerable interest due to the natural structure of graphs formed by astronomical observations relating to transient events, host galaxies, observatories and their follow-ups [7]. Another field where artificial intelligence has played an important role is the operation of the current astronomical alert brokers. Facilities like ANTARES, Lasair, ALeRCE, and Fink play a critical role in the modern system of transient discovery. These intelligent brokers continuously consume massive alert streams produced by wide-field surveys, cross match the detections against archive catalogues, obtain contextual information, use automatic machine learning to classify the alerts, and flag the scientifically interesting targets for follow-up observations. For instance, the ALeRCE broker uses real-time stamp classification combined with light curve classification to identify astrophysical transients among instrument artifacts, whereas ANTARES and Fink make use of scalable machine learning pipelines that can process millions of alerts at once with low latency [8]-[11]. Intelligent alert brokers would become an essential component during the era of the Rubin Observatory when the massive amount of alerts would need automation in decision making.

Artificial intelligence for cross-messenger astronomy is now moving forward from task-specific neural networks to multimodal foundation models that can learn joint representations across different types of astronomical data. Drawing motivation from recent developments in vision-language models and large language models, such architectures enable integration of images, spectra, light curves, time series, metadata, and even natural-language descriptions into a single embedding space. The use of such models enables conducting multiple tasks of interest such as event association, source classification, anomaly detection, parameter estimation, and follow-up scheduling without the need for separate models for each one of them. Initial research shows that transformer-based models and self-supervised pretraining can be efficiently used in order to take advantage of huge amounts of unlabeled astronomical data provided by future instruments. Combined with intelligent alerting brokers and robotic telescope systems, such technologies will enable increasingly autonomous observatories capable of conducting observations, choosing follow-up strategy, and making scientific discoveries in a fully automated way [26]-[29].

Nevertheless, there are a number of obstacles to overcome. Multimessenger events differ from each other in temporal cadence, spatial resolution, localization, sensitivity of detectors, and quality of measurements. In addition to this, the majority of astrophysical transients are inherently rare objects, which means a lack of labeled data for training supervised machine learning algorithms. Thus, domain adaptation, transfer learning, self-supervised learning, and federated learning can be considered promising directions for generalization of models and collaboration between geographically dispersed observatories without data exchange [6] [12]. The problem of interpretability of the results of machine learning and their statistical significance is another important problem to consider. Follow-up observations imply high costs and quick decisions. This is why astronomers need not only precise classification of events, but also reliable estimation of confidence levels. Therefore, increasing attention is paid to hybrid approaches based on machine learning and Bayesian inference, probabilistic graphical models, and explainable AI [6] [13]. Overall, AI has revolutionized the process of associating events across multiple messengers from a manual and statistically intensive process to an intelligent, efficient, and low-latency part of the multi-messenger astronomical pipeline. By combining different observations, ranking candidate events, and allowing fast dissemination of scientifically important alerts, AI provides a great deal of added value to joint observing campaigns using next-generation telescopes.

It is critical to draw a line between AI applications that have already been implemented in actual or almost actual astronomical pipelines and those which are still on the research and prototype stage. Among more developed AI applications are machine learning-based alert classification, transient filtering and prioritization, with multiple astronomical alert brokers showing their work on large datasets. On the other hand, multimodal foundation models, cross-messenger representation learning, and fully autonomous follow-up systems are still developing areas of research, which need further validation, quantification of uncertainties and robustness testing before actual implementation and integration with heterogeneous observatory infrastructure. For this reason, the applications presented in this review are discussed both in terms of their actual capabilities and future perspectives of multi-messenger astronomy. Table 4 provides examples of platforms and techniques that use artificial intelligence to carry out multi-messenger event correlation, alert filtering, and heterogeneous data fusion. These examples demonstrate how artificial intelligence can be utilized to facilitate the search for multi-messenger counterparts, real-time filtering and ranking of astronomical alerts, and the fusing of observations from various telescopes and messengers.

Table 4. Representative AI applications for cross-messenger event association and data fusion.

Observatory/ Platform	AI Application	Scientific Outcome	References
LIGO-Virgo + Multi-wavelength facilities	GW170817 counterpart association	Multi-messenger confirmation of binary neutron-star merger	[1] [3]
IceCube + Fermi + Optical observatories	Neutrino-EM association	Identification of TXS 0506+056 as a high-energy neutrino source	[12]
Rubin Observatory (LSST)	Alert stream processing	~10 million alerts processed nightly	[4]
ANTARES Broker	Machine-learning alert prioritization	Rapid transient filtering and distribution	[30]
Lasair Broker	Automated transient annotation	Real-time event characterization	[31]
ALeRCE Broker	Machine-learning transient classification	Prioritized follow-up observations	[32]
Fink Broker	AI-assisted alert filtering	Large-scale real-time transient selection	[33]
Graph Neural Networks	Multi-source data fusion	Improved association of heterogeneous observations	[34]

4.4. AI-Driven Source Localization and Sky Mapping

After astrophysical transients have been detected, classified, and connected through multiple messengers, the crucial task within the process of multi-messenger astronomy is the localization of the sources in the sky. Correct localization allows for prompt follow-up observations using electromagnetic waves, host-galaxy identification, and analysis of the surroundings of the sources. As many astrophysical transients change on timescales from seconds to days, localization has to be both fast and precise. Any delay in creating sky maps may lead to missing of the fading transient objects, thus, limiting the scientific output of multi-messenger observations [1] [3] [35]. The necessity for fast localization was made clear during the observation of the binary neutron star merger event called GW170817, during which the first detection of the gravitational waves was followed by a coordinated search using more than seventy different observatories on the ground and in space. The rapid gravitational-wave detection was followed by a coordinated electromagnetic search over a relatively large sky region, ultimately leading to the identification of the optical counterpart and its host galaxy NGC 4993 [1] [3] [35] [36].

The conventional localization techniques vary greatly between different messengers. In gravitational wave astronomy, the technique of localization consists of triangulation, in which the differences in arrival time, amplitude, and phase of the signal observed at different locations are used together with Bayesian inference to create a probability sky map. Fast localization pipelines such as BAYESTAR can rapidly generate probability sky maps following gravitational-wave detections, whereas more computationally intensive Bayesian parameter-estimation methods provide more detailed localization and source-parameter estimates at substantially higher computational cost [37]-[40]. Localization procedures differ for other types of messengers as well. Localization of high-energy neutrinos, for example, is done using the direction of trajectories of secondary particles created in the result of neutrino interactions within the detector volume in case of Ice Cube. The localization of sources of gamma-ray events is based on shower reconstruction, whereas the localization of optical transients is achieved via astrometric calibration and image differencing with sub-arcsecond accuracy. Despite the fact that each of the listed procedures turned out to be quite efficient independently, the fusion of localization data from various observatories is a computationally difficult task due to their heterogeneity [3] [13].

An important issue is posed by the high localization uncertainties often observed in gravitational-wave observations. During the early Advanced LIGO observing runs, the limited detector network often resulted in large gravitational-wave localization regions, increasing the observational resources required for electromagnetic follow-up. The addition of further detectors such as Advanced Virgo and later KAGRA has helped reduce these uncertainties substantially through better triangulation geometry. However, next-generation detectors will still produce localization uncertainties large enough to make intelligent selection of follow-up observations a necessity [37] [41]. AI has proved to be a suitable way out of these computational problems in that it learns the non-linear mapping between detector responses and source location directly from the observational data. Deep learning algorithms do not make use of the usual parameter estimation techniques of Bayesian inference since they do not involve repetitive sampling of high dimensional parameter spaces using computationally intensive likelihoods but rather achieve localization via one inference process after the training is completed.

Advancements in recent times have shown how useful Convolutional Neural Networks (CNNs), Temporal Convolutional Networks (TCNs), recurrent neural networks, and transformers are for gravitational-wave localization. The aforementioned models are capable of analysing strain data from detectors and learning the spatial relationships between different detectors without any need for explicit waveform template matching. This means that localization posteriors can now be created in milliseconds to seconds, which is orders-of-magnitude faster than conventional Bayesian sampling techniques [5] [21] [42]. The other significant advance in this area has been the use of normalizing flows and other methods of simulation-based inference for fast gravitational wave parameter estimation. Unlike traditional approaches that predict only a single sky location of a source, such methods learn the full posterior distribution of source parameters, comprising sky location, luminosity distance, inclination angle, and mass of a binary. This allows one to obtain uncertainty estimates similar to those obtained using Bayesian inference but at significantly lower computational costs [43].

AI technology is also being applied to localization beyond gravitational wave astronomy. Deep-learning systems are being used to perform image segmentation and centroid detection, as well as host galaxy classification, in optical sky surveys. Machine-learning techniques are used to aid beam forming and source extraction, as well as FRB localization, in radio astronomy, while high energy experiments are using AI methods for event reconstruction and direction estimation through detector response data. With the convergence of these trends in a number of observational fields, a unified localization framework is now emerging, where observations from different messengers can be brought together in a consistent probabilistic framework, greatly enhancing localization accuracy [3] [44]. Another exciting approach is the use of Graph Neural Networks (GNNs) for localization tasks that include distributed detector networks. As the observatories themselves can be thought of as spatially connected networks, such an approach will help to easily represent the connections between the detector locations, arrival times, localization errors, and the observations made. This way of representing relations will help in fast propagation of information within the network of detectors and also help to efficiently combine heterogenous localization data obtained through gravitational-wave detectors, neutrino detectors, optical telescopes, and gamma-ray observatories. The workflow involved in AI assisted source localization is briefly described in **Figure 4**. Observations coming from various messengers are combined through the use of advanced artificial intelligence techniques to create probabilistic sky maps for source localization and verification purposes.

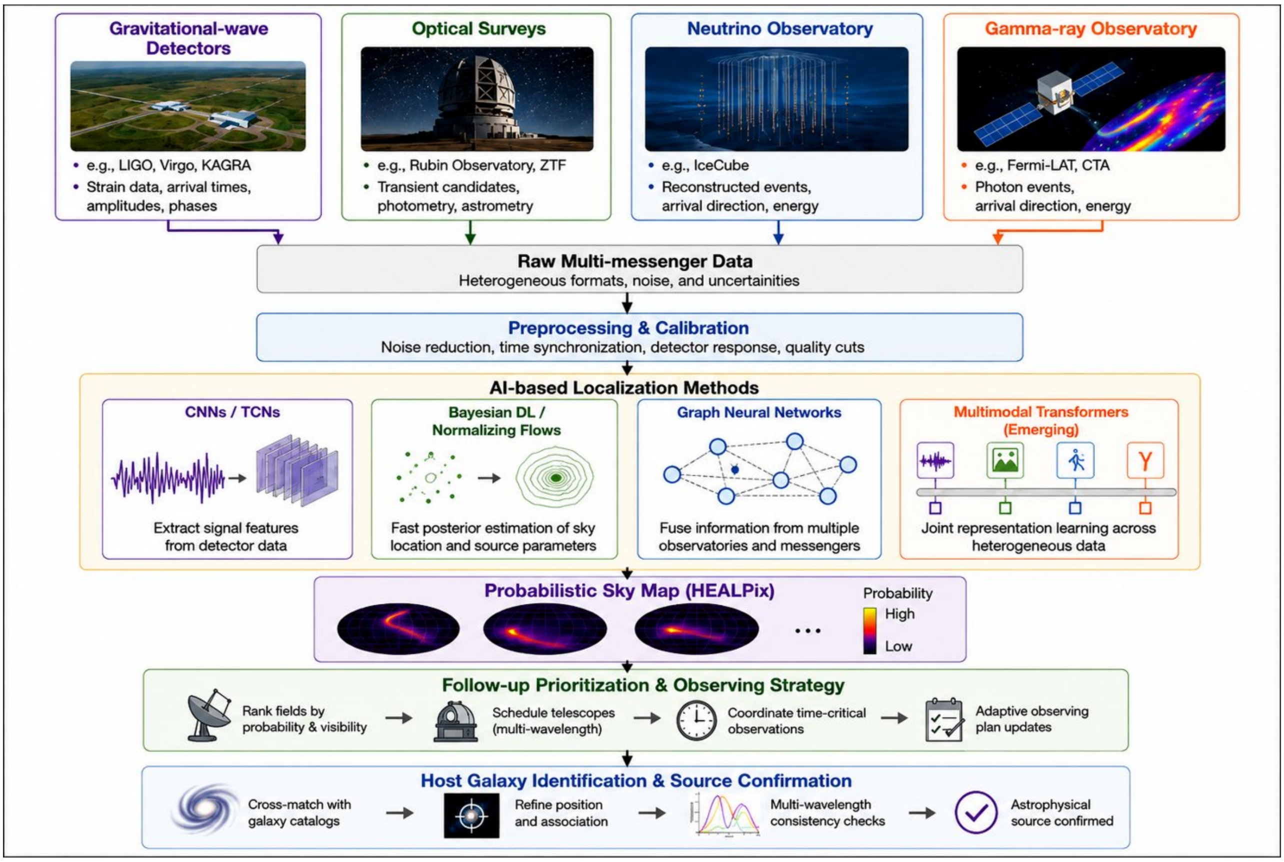

Figure 4. Schematic illustration of the AI-driven source localization pipeline in multi-messenger astronomy, from multi-observatory data acquisition to probabilistic sky mapping, follow-up prioritization, and source confirmation.

In summary, AI-based localization is one significant achievement of the multi-messenger astronomy pipeline in terms of computational speed and highly accurate localization. By employing deep learning, probabilistic inference, and graph-based data integration, AI technology achieves localization with great speed and improves collaboration among various observatories for their observations. Such ability becomes increasingly important because the number of transient events detected is growing due to new generations of telescopes being developed. After the rapid creation of source localization maps, the efficacy of AI-based source localization methods can be measured in terms of the following three major performance metrics: localization accuracy, computational latency, and scalability. Traditionally used Bayesian inference methods deliver highly accurate posterior probability distributions but suffer from high computational requirements since one needs to search through the whole parameter space by evaluating the likelihood multiple times. On the other hand, after training, deep learning models perform localization with only one step of forward inference, thereby saving multiple orders of magnitude in computational latency while delivering a similarly good performance of localization in a variety of astrophysical transient types. Recent investigations have shown that the use of AI-based localization systems enables the creation of probabilistic sky maps in milliseconds to seconds in comparison with minutes to hours that are required by traditional Bayesian parameter inference methods. Such achievements are especially useful for studying rapidly varying transients such as short gamma-ray bursts, kilonovae, and fast radio bursts, which offer valuable information about astrophysical processes at work [5] [14] [45] [46].

In addition to the speed of computation, AI systems offer advantages with regards to scheduling the use of telescopes and the efficient use of observational resources. Rather than surveying all of the fields within the localization region equally, AI algorithms sort candidate sky fields according to their probabilities of localization, based on galaxy catalogues, observability requirements, weather, and availability of telescopes. Such intelligent scheduling substantially reduces unnecessary observations and raises the chances of finding the actual astrophysical counterpart in the early stages of follow-ups. Similarly, robotized telescope networks are now using such intelligent optimizations to coordinate their work automatically [37] [47].

Nevertheless, AI-powered localization still faces several issues that need to be considered. First, the performance of supervised learning algorithms is highly dependent on the quality and representation of training data, whereas many astrophysical transients are rather rare in reality. As a result, simulated data sets play a key role in training algorithms and, thus, can lead to the problem of domain shift difference between simulation space and detector observations. Second, uncertainties associated with localization due to detector calibration problems, non-Gaussian instrumental noise, incomplete detector networks, and observational biases cannot be properly taken into account in deterministic deep-learning models. As a result, further improvement of uncertainty quantification methods is a promising field of research, with Bayesian deep learning, ensemble learning, simulation-based inference, and probabilistic neural networks among the most popular methods [44] [48].

Further, another crucial aspect in this regard relates to the interpretability and robustness of AI-generated predictions. Given that telescope scheduling is often connected with high costs and time limitations, astronomers need localization systems which are able to present transparency through the estimation of confidence as well as physical uncertainty regions. Therefore, explainable AI approaches, hybrid Bayesian-machine learning techniques and physics-informed neural networks attract growing interest as ways to enhance the reliability and interpretability of the proposed AI-assisted localization systems. It is believed that such an approach will help improve confidence in automated decision-making systems while maintaining rigorous statistical background typical for astronomy [48] [49]. The upcoming next-generation telescopes will emphasize the importance of intelligent localization algorithms even more. It is expected that both Einstein Telescope and Cosmic Explorer will produce significantly larger number of gravitational wave events with better localization precision, while the Vera C. Rubin Observatory, Square Kilometre Array, Cherenkov Telescope Array Observatory, IceCube-Gen2 and future space missions will produce unprecedented amounts of heterogeneous data. The integration of these sources of data into a single AI system will become possible by implementing increasingly advanced AI architectures that can handle various messengers, perform probabilistic source localization, coordinate telescope scheduling and update localization maps continuously [37] [50].

Table 5. Representative AI techniques for source localization in multi-messenger astronomy.

AI Technique	Primary Application	Major Advantages	References
Convolutional Neural Networks (CNNs)	Gravitational-wave sky localization, image-based transient localization	Fast feature extraction, low-latency inference, high localization accuracy	[5] [14] [45]
Temporal Convolutional Networks (TCNs)	Time-series analysis of detector strain data	Captures long temporal dependencies with efficient computation	[14] [45]
Recurrent Neural Networks (RNNs/LSTMs)	Sequential detector signal analysis	Effective for temporal correlations and transient signal evolution	[5] [14] [45]
Transformer-based Models	Multi-detector signal fusion and multimodal localization	Captures long-range dependencies and heterogeneous observations	[5]
Normalizing Flows / Simulation-Based Inference	Probabilistic sky localization and parameter estimation	Rapid posterior estimation with uncertainty quantification comparable to Bayesian inference	[46]
Bayesian Deep Learning	Localization uncertainty estimation	Provides probabilistic confidence intervals for follow-up prioritization	[46]
Graph Neural Networks (GNNs)	Distributed detector-network localization and data fusion	Efficient integration of heterogeneous observatory data and spatial relationships	[51]
Deep Learning for Optical Surveys	Image segmentation, centroid estimation, host-galaxy association	Accelerates transient localization and counterpart identification	[44]
AI for Radio and High-Energy Observatories	FRB localization, beam-forming optimization, event reconstruction	Improves localization efficiency and source identification across multiple messengers	[13] [44]

Moving forward, the fusion of multimodal deep learning, graph neural network, transformers, simulation-based inference, and foundation models is anticipated to revolutionize source localization by making it a self-sufficient scientific exercise. In addition to being localized through a single algorithmic approach, future AI will work as intelligent frameworks that can integrate heterogenous data, determine uncertainty, make follow-up observations, and assist astronomers throughout the entire multi-messenger discovery process. Such advancements are an essential step towards fully automated telescopes that can respond to transients with little human involvement but maximum scientific benefit of multi-messenger astronomy. Table 5 shows the most prominent AI methods used for source localization, signal analysis, parameter estimation, and multi-messenger data fusion. The table describes the main features and potential uses of the most important deep learning and probabilistic algorithms and illustrates how the use of these methods can increase the efficiency and precision of multi-messenger events detection.

5. Representative Applications of Artificial Intelligence in Multi-Messenger Astronomy

The use of artificial intelligence has progressed to such an extent that this technology is no longer considered auxiliary but rather a vital part of modern astronomical studies. The previous sections detailed the importance of artificial intelligence in detection, classification, localization, and fusion of data. These advancements have now led to the development of tools that can result in new major discoveries in numerous observational fields. Artificial intelligence tools are used to analyze vast quantities of observational data and detect events; furthermore, they help in planning observations and organizing follow-up observations. Instead of attempting a comprehensive overview of every astronomical facility currently being used, the following section provides a few specific examples of the use of artificial intelligence that will show the impact this technology has on four main scientific areas—gravitational waves detection, time-domain optical astronomy, neutrinos event reconstruction, and multimessenger discoveries.

5.1. Gravitational-Wave Detection

The discovery of gravitational waves made by the LIGO Scientific Collaboration in 2015 not only launched the field of gravitational-wave astronomy but also highlighted the significance of advanced computational techniques in processing weak signals present in detector noise [3]. Standard searches are based on the matched filtering approach where the data are correlated with a large set of waveform templates that represent different configurations of compact binary systems. The use of this technique is optimal when it comes to modelling of the signals but its computational complexity grows rapidly with increasing number of templates in the template bank especially for analyses involving low latency searches required for multi-messenger follow-ups [40]. However, artificial intelligence proved to be an efficient alternative since it learns the correspondence between the data from the detectors and the signals of astrophysical origin from training datasets. One of the first demonstrations of this approach was Deep Filtering where convolutional neural networks (CNNs) were used for detecting signals produced during the merger of binary black holes and estimating the properties of the sources in real time. After training, the neural network infers the results in a single forward pass thus dramatically reducing computation times down to milliseconds with the same sensitivity of detection compared to standard matched-filter searches at different signal-to-noise ratios [14] [21].

Moreover, AI has considerably helped characterize detectors. There are many instrumental and environmental perturbations, known as glitches, affecting gravitational-wave interferometers, which could simulate real astrophysical signals and decrease the sensitivity of the searches. Gravity Spy uses a combination of citizen-science classifications and deep-learning image recognition algorithms to classify such transient noise artifacts. Through the classification of glitches from real gravitational-wave signals, this approach contributes to the improvement of detector performance and accuracy of gravitational-wave detection pipelines [52]. In recent years, machine-learning algorithms have also been utilized for quick parameter estimation and localization, resulting in nearly instantaneous generation of probabilistic sky maps used for follow-up observations [37] [38]. As a consequence of all the advancements discussed above, AI has become an indispensable tool for analyzing data within the LIGO-Virgo-KAGRA framework. Rather than substituting Bayesian inference, machine-learning models have been employed in conjunction with conventional methods, providing rapid first-stage analyses to be further refined by time-consuming algorithms of parameter estimation. This sort of strategy is predicted to grow in importance due to an increased number of events detected at next-generation observatories [38] [50].

5.2. Time-Domain Optical Astronomy

State-of-the-art optical surveys of the sky are constantly observing the evolving Universe and detecting supernovae, variable stars, tidal disruption events, active galactic nuclei, and other transient phenomena. The growing sensitivity and field of view of wide-field telescopes resulted in the exponential increase of data volume, and the visual screening of transient candidates became impossible. For instance, the Zwicky Transient Facility provides hundreds of thousands of alerts each night, and the Vera C. Rubin Observatory is expected to produce almost 10 million alerts each night when conducting full-scale science operations [4] [53]. Thus, the effective usage of this wealth of data requires automated analysis pipelines based on AI techniques. Modern machine-learning techniques are often used to classify transients using the photometric light curves, the morphology of images, the evolution of colors and the additional data from the astronomical catalogues. Different supervised learning techniques such as random forests, convolutional, recurrent neural networks, and transformer models show extremely good results in recognizing supernovae, variable stars, active galactic nuclei and instrument artifacts. This approach significantly decreases the number of false positives and allows to quickly identifying interesting events that require further spectroscopic study and observations at multiple wavelengths [32] [54] [55].

The other equally important advancement in recent years has been the development of broker systems that use artificial intelligence algorithms such as ALeRCE, Fink, and ANTARES. Such platforms are capable of ingesting alert streams, cross-matching new discoveries against existing catalogues, extracting contextual information, classifying objects using machine-learning, and delivering priority alerts to the astronomy community minutes after discovery. They allow astronomers to allocate their observational facilities on promising transients while keeping human interventions to a minimum [30] [33] [56]. ALeRCE, for instance, uses a combination of imaging classification and light curves to differentiate between astrophysical transients and instrumental artefacts while Fink uses scalable machine learning pipelines in conjunction with distributed computing to efficiently process Rubin-scale alert streams. Apart from classification, AI is helping with photometric redshift estimation, host galaxy identification, image segmentation, and anomaly detection. Through deep-learning algorithms, rare or novel types of transient events are being identified by recognizing unusual patterns that cannot be classified by rule-based classification schemes. As a result, it is expected that artificial intelligence will be playing an increasing role in maximising science from future time-domain surveys where data rates will be too large to be handled through conventional means of analysis [4] [55].

5.3. Neutrino Event Reconstruction

Neutrino astronomy at high energies offers a special tool to study one of the highest energy regions in the universe, such as active galaxies, gamma-ray bursts, and core collapse supernovae. Neutrinos have a very low probability of interaction both with the matter and magnetic fields, making them ideal probes of the distant universe, where they can carry directional information about the origin of the neutrino events. Nevertheless, due to the weak cross-sections, their detection is quite difficult and requires kilometre-scale detectors like IceCube that can register a tiny amount of astrophysical neutrinos against the huge background of atmospheric muons and neutrinos [13]. The use of artificial intelligence in neutrino reconstructions helped to learn the complicated dependence between the signal and particle parameters and resulted in an increasing number of deep neural networks used to estimate the direction, energy, and topology of neutrino events from the recorded Cherenkov light images. As compared to conventional likelihood-based methods, machine learning algorithms not only allow for faster inference but also offer better performance in terms of angular resolution and energy estimations for different event categories [57] [58]. It allows for more robust identification of neutrino signals from astrophysical sources.

Machine learning methods have also advanced the field of background rejection in order to separate true neutrino interactions from the background noise and atmospheric events. In recent years, efforts have been made to use graph neural networks and geometric deep learning to take advantage of the non-uniform geometry of large neutrino detector setups, thus making it possible to extract spatial and temporal data from photomultiplier data. This is becoming increasingly relevant for future projects like IceCube-Gen2, where the amount of volume and data increases greatly [59] [60].

5.4. Multi-Messenger Discoveries

The scientific significance of AI within the field of multi-messenger astronomy may best be illustrated by separating out landmark discoveries from the AI methods that were applied during their follow-up and analysis. The detection of the electromagnetic counterparts of GW170817 was a discovery made possible by the initial detection of the gravitational waves by the LIGO-Virgo Collaboration, and the subsequent detection of GRB 170817A and AT2017gfo in follow-up observations. This was not an achievement of the AI; rather, AI algorithms have aided in the detection, classification, and follow-up of other such signals. Likewise, the association of IceCube-170922A with the flaring blazar TXS 0506+056 was based on the detection of neutrinos, their association, and multi-messenger observations. Although AI algorithms are a significant part of modern neutrino analysis, they should not be regarded as the cause of the historic discovery of multi-messenger associations [1] [36] [61] [62].

The association of IceCube-170922A with the flaring blazar TXS 0506+056 provided strong evidence linking high-energy neutrino emission to an active galactic nucleus, although the interpretation is based on statistical association and should not be regarded as definitive proof from a single event. Event reconstruction with machine learning algorithms, quick-latency alerts, and multi-wavelength observations with gamma-ray, X-ray, optical, and radio telescopes allowed for thorough examination of the source and established strong links between the activity of active galactic nuclei and high energy neutrino emission [12] [63]. This research stressed the necessity of intelligent selection and follow-ups for efficient scientific results from transients. In the future, with the emergence of new observatories including Einstein Telescope, Cosmic Explorer, Vera C. Rubin Observatory, Square Kilometre Array, Cherenkov Telescope Array Observatory, and IceCube-Gen2, the amount and complexity of observation data will drastically grow. That is why artificial intelligence will play a key role in creation of autonomous observatories that will be able to perform real-time detection, localization, intelligent scheduling and coordination of multi-messenger observations with minimum human participation [4] [6] [50] [60]. In summary, these examples of representative applications show that artificial intelligence has progressed from being just a computing tool to being a foundational science infrastructure for astronomy in the modern world. The fast processing of different kinds of data, increased efficiency of observations, and the ability to make discoveries using various types of messengers are changing the nature of astronomical observations through the integration of AI into the observation process. The importance of the use of AI in future astronomical facilities will be crucial in the years to come. Even though there have been various forms of AI that have been designed to address particular issues in astronomy, most of them are similar and are used together in multi-messenger data analysis. Figure 5 below shows how different forms of AI are connected in relation to their representative applications in science. Table 6 shows the main areas of applications of AI in multi-messenger astronomy by listing the AI approaches used, their main scientific contributions, and the facilities where the approaches are being used. The table gives an overview of how AI is aiding gravitational wave detection, time domain optical surveying, neutrino event reconstruction, and multi-messenger observations.

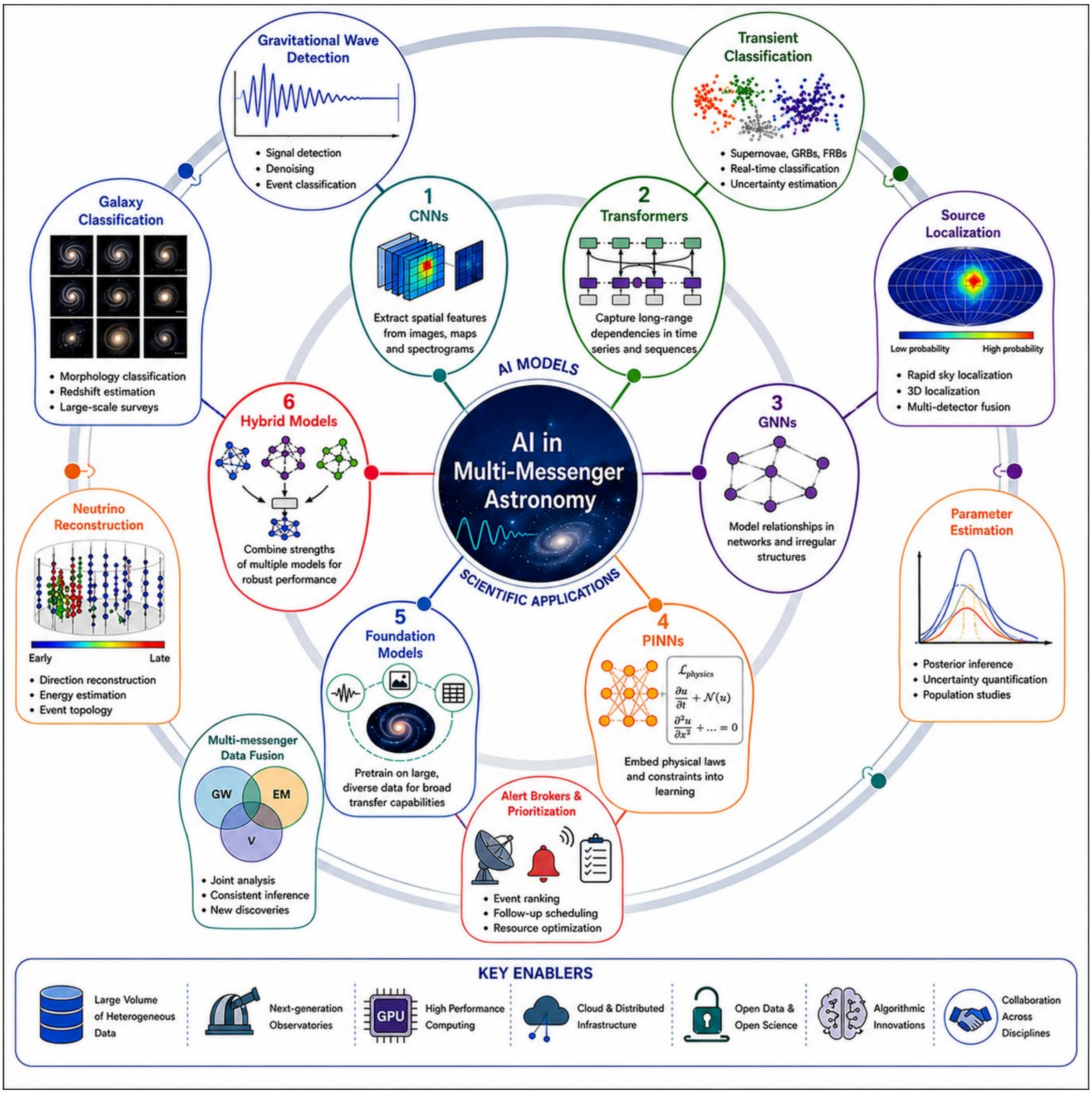

Figure 5. Major artificial intelligence models and their representative applications in multi-messenger astronomy, together with the key technological enablers driving AI-assisted astronomical discovery.

Table 6. Representative applications of AI in multi-messenger astronomy, their primary scientific contributions, and the associated observational facilities and missions.

Application Area	Representative AI Techniques	Major Scientific Contribution	Key Facilities /Missions	References
Gravitational-wave detection	CNNs, Deep Filtering, Bayesian neural networks	Real-time signal detection, parameter estimation, glitch classification	LIGO, Virgo, KAGRA	[3] [14] [21] [37] [38] [40] [50] [52]
Time-domain optical astronomy	CNNs, Random Forests, Alert Brokers, Transformers	Automated transient classification and rapid follow-up prioritization	ZTF, Rubin Observatory, ALeRCE, Fink	[10] [30] [32] [53]-[56]
Neutrino event reconstruction	Deep Neural Networks, Graph Neural Networks	Direction reconstruction, energy estimation, background rejection	IceCube, IceCube-Gen2	[13] [57]-[60]
Multi-messenger discoveries	Bayesian inference, Deep learning, Intelligent alert systems	Rapid localization and coordinated follow-up of transient events	LIGO-Virgo, IceCube, Swift, Fermi, Global telescope network	[1] [6] [12] [36] [61]-[63]

6. Challenges and Opportunities

Despite the tremendous success of artificial intelligence in multi-messenger astronomy that shows how well AI can speed up the process of analyzing the data and classifying events, there are still some essential challenges that have to be solved before making artificial intelligence a trusted and independent element of astronomy studies. Contrary to commercial machine-learning projects, astronomical data is frequently sparse, transient events are rare, instruments and measurements are heterogeneous and have high uncertainties. Therefore, besides improving predictions, creating reliable AI systems also requires making them interpretable, robust, and physically consistent.

6.1. Limited Labeled Datasets

Supervised machine learning techniques require huge amounts of training data labeled correctly. However, in multi-messenger astronomy, validated astrophysical events are scarce, especially in the cases of gravitational waves, high-energy neutrinos, fast radio bursts, and electromagnetic counterparts of transient phenomena. Despite huge volumes of observational data that are produced every day by modern observatories, only a relatively small part of it is associated with well-defined sources that can be used for supervised learning. Such an unevenness hinders generalizability of deep-learning architectures and poses risks of overfitting to particular observational regimes [64]-[66].

One of the possible solutions to this problem is the use of simulated data sets obtained with physically based numerical simulations. Simulations allow for obtaining huge samples of training data, but they may not reflect the complete diversity of detector noise, instrument systematic effects, and even unknown astrophysical objects. As a result, machine learning algorithms trained on simulations tend to demonstrate subpar performance when dealing with observational data. Self-supervised learning, semi-supervised learning, active learning, and transfer learning offer alternative methods which reduce dependence on manually labeled data and allow the AI to make use of huge amounts of unlabeled astronomical data [28] [67]-[69].

6.2. Explainability and Uncertainty Quantification

In many cases, current advanced AI methods are sophisticated nonlinear systems, whose reasoning processes are hard to explain. Despite the high predictive power of deep neural networks, understanding of the process underlying a certain prediction is challenging. In astronomy, where results of observations can affect theoretical models and require expensive follow-up observations, confidence in the science necessitates not only the prediction accuracy but also transparent reasoning and estimation of the uncertainties [70] [71]. In recent times, a new focus in the research is put on the explainable artificial intelligence (XAI), which allows finding the observational features contributing to specific classification or parameter determination. Feature attribution, saliency maps, SHAP values, and attention visualization are some of the techniques providing useful insights into the model behavior and helping to confirm that AI systems use physically relevant features, not the artifacts of observations [17]. Another equally important aspect is the uncertainty estimation by means of Bayesian neural networks, Monte Carlo dropout, deep ensembles, and probabilistic machine-learning algorithms. The latter gives an opportunity to assess the confidence level of every prediction and make better decisions concerning the observation priorities and candidate's selection.

6.3. Domain Adaptation and Generalization

Datasets in astronomy are inherently heterogeneous as data come from different telescopes with various wavelengths, sensitivities, spatial resolutions, and noise properties. Models trained on data from one telescope often perform worse when used on data from another instrument due to different detector behavior, different observation strategies, or other reasons. This issue, known as domain shift, is the main obstacle for generalized AI deployment in various astronomical surveys [64] [72]. One way of solving domain shift problems is to transfer knowledge between different observational domains without having to train the model on a new dataset. Transfer learning, adversarial domain adaptation, and representation learning have already shown great results allowing models trained on some survey to be generalized to observations taken with other telescopes [68] [72]. These techniques will be even more useful as observations from the Vera C. Rubin Observatory, Einstein Telescope, Square Kilometre Array, and IceCube-Gen2 start being used in future multi-messenger networks [4] [59]. Instrument-independent AI models that can perform well on heterogenous data are one of the biggest challenges for the next decade.

6.4. Computational Cost and Scalable Infrastructure

The enormous data rates expected to be produced by the next-generation telescopes impose serious computational burdens on traditional approaches to data analysis and even contemporary AI approaches. In order to train large deep-learning models, one needs powerful computational resources, including fast GPUs, distributed computation systems, and effective storage solutions. Moreover, operational pipelines often need real-time inference with latency restrictions, especially for transients which need to be observed immediately [4] [59] [64]. Recent developments in cloud computing, distributed learning, specialized AI hardware, and high-performance computing made large-scale applications of AI in astronomy much more feasible. Techniques such as model compression, knowledge distillation, quantization, and effective parallel computation also provide a promising way to make AI solutions less computationally expensive while preserving predictive performance. Collaboration between astronomers, computer scientists, and engineers is needed to develop effective AI infrastructures to process data rates from future astronomical facilities [4] [59] [65].

6.5. Reliability in Scientific Discovery

Perhaps one of the most difficult obstacles to overcome in AI-based astronomy is building trust that such discoveries will be scientifically valid and not just statistically correct. In some cases, machine learning algorithms may use some underlying biases, instrument artifacts, or spurious correlations that are physically meaningless. Such methods can result in either false positives or false scientific conclusions based on predictions that have not been independently verified [64] [70]. The next generation of astronomical AI tools should include physical considerations right from the beginning. Physics-informed neural networks, physics-bayesian and physics-machine learning models, and physics foundation models incorporating both observational data and physics principles are some promising trends in increasing reliability and interpretability [17]. No less crucial is developing standardized test datasets, reproducible benchmarks, and open-source software and methods for uncertainty estimation to allow for independent verification of AI models among different research groups [17] [64] [65]. It seems unlikely that AI will replace existing scientific approaches and become a replacement for theoretical and numerical modeling and observational data interpretation; instead, it will remain a scientific companion.

In summary, it will be through tackling the aforementioned challenges that will define the influence that artificial intelligence will have on the future of multi-messenger astronomy. Further advancements in explainable AI, uncertainty-driven learning, scaling computing power, domain adaptation, and physics-informed machine learning provide an outstanding chance of developing robust, interpretable, and autonomous scientific systems able to analyze the large amount of data generated by future observatories [17] [64] [65].

7. Future Perspectives

AI is anticipated to be one of the essential components of future multi-messenger astronomy. Though current AI algorithms primarily automate some specific procedures such as signal detection, event classification, and source localization, further research will pay more attention to creating integrated intelligent systems that will be able to work with the entire scientific process. The combination of foundation models, multimodal learning, physics-informed AI, autonomous observatories, and AI-assisted scientific discovery can significantly change the way astronomical observations are conducted, analyzed, and understood [64]-[66]. One of the promising ways is the creation of foundation models in astronomy. Based on the success in large-scale machine learning, such models can be pre-trained on massive data consisting of various astronomical images, spectra, light curves, gravitational wave signals, neutrino events, and simulations in order to acquire representations of astrophysical phenomena. After being trained, foundation models can be used for different tasks using small datasets containing labeled information [64] [65].

The advancement of science in the future will depend heavily on multimodal artificial intelligence, where heterogeneous data from different messengers are analyzed in one computation framework at the same time. The use of multimodal artificial intelligence that will analyze information obtained from electromagnetic observations, gravitational waves, neutrinos, and numerical simulations will help with improving the identification of sources, estimation of their parameters, event association, and gaining a more comprehensive understanding of transient astrophysical phenomena. The development of such learning frameworks will be especially important due to coordinated observation data obtained from next-generation observatories [26] [65] [66]. The inclusion of physics in the machine-learning model will also be crucial for achieving better results. Physics-informed learning includes governing equations, conservation laws, and observational constraints within the neural network architecture. Such models will provide better interpretability and generalization compared to data-driven learning models and, thus, is more scientifically reliable [17].

The large amounts of data that will be gathered through the Vera C. Rubin Observatory, Einstein Telescope, Square Kilometre Array, Cherenkov Telescope Array Observatory, and IceCube-Gen2 will also foster progress in the creation of autonomous observatories able to schedule their observations intelligently, detect events in real time, adapt their observational strategy, and perform follow-up observations with little to no human input [4] [6] [59]. Finally, one would expect AI to move past being a computational tool to becoming an active participant in scientific discoveries. The future AI tools may help researchers uncover unknown astrophysical phenomena, discover correlations hidden in heterogeneous data sets, formulate scientifically relevant hypotheses and suggest what future observations should look like. However, it will still be essential for AI predictions to have clear explanations, accurate uncertainty estimates, replicability, and to be firmly grounded in well-established physical theories. Far from taking over astronomers' work, AI is more likely to complement their skills and knowledge [17] [64] [73]. In summary, the future of multi-messenger astrophysics will depend on AI systems that are intelligent, interpretable, and physically informed enough to process the massive and complex data sets from future telescopes. Cooperation between physicists, astronomers, and computer scientists will continue to be crucial in exploiting the full capabilities of such technology.

The future of multi-messenger astronomy will depend more and more on a tightly connected artificial intelligence infrastructure that bridges heterogeneous observatories, scalable data infrastructure, and automated scientific workflows. Instead of being standalone analytics, the foundation models, physics-informed learning, and decision support systems will be part of an ecosystem that would enable real-time discoveries and joint scientific endeavors of humans and artificial intelligence. This AI ecosystem for multi-messenger astronomy is shown in **Figure 6**.

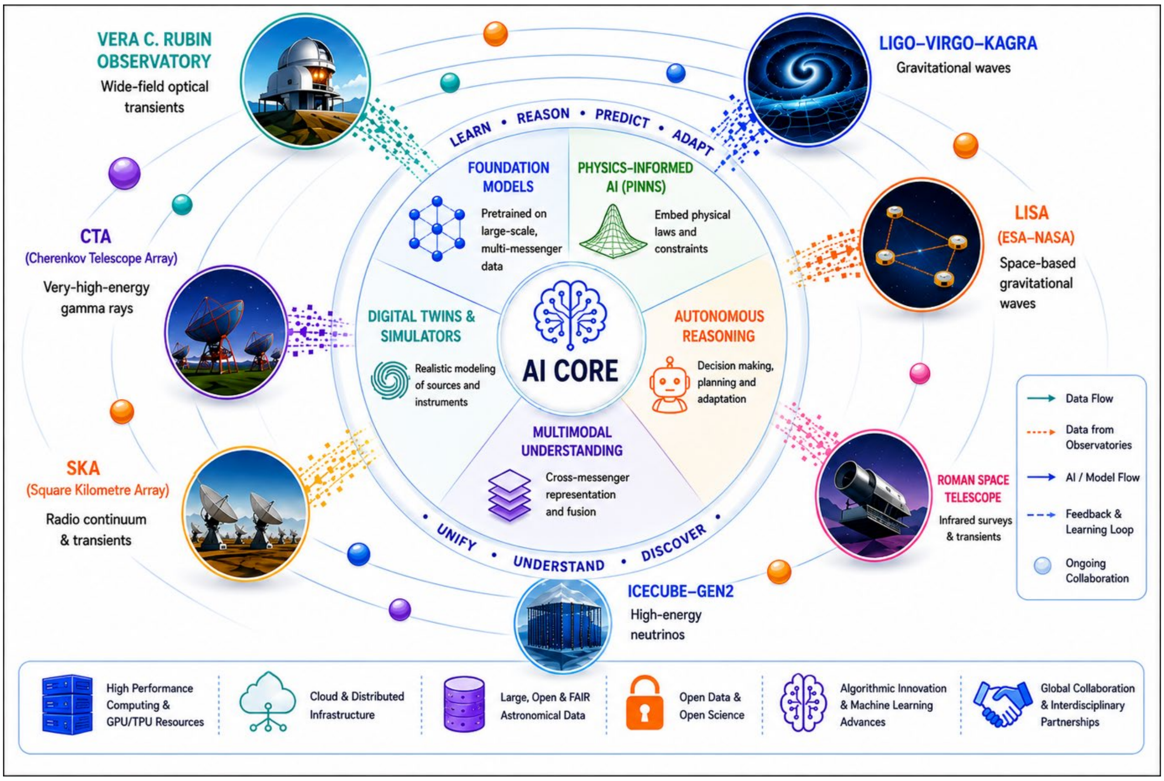

Figure 6. Conceptual illustration of the future AI ecosystem for multi-messenger astronomy, highlighting the integration of next-generation observatories, advanced AI capabilities, and collaborative scientific workflows to enable intelligent, real-time astronomical discovery.

8. Conclusions

The multi-messenger approach has revolutionized modern astrophysics through the integration of electromagnetic observations, gravitational waves, neutrinos, and cosmic rays in order to study some of the most energetic processes in the Universe. The huge amounts of different and complex data gathered in this manner, however, have also introduced a number of challenges for computations, which cannot be effectively solved using only traditional analysis methods. In addition, artificial intelligence became an essential technological tool that can complement the physics-based approach in order to provide fast and scalable solutions to various problems of analysis of astronomical data. In this review, the use of artificial intelligence in the field of multi-messenger astronomy has been extensively analyzed. The discussion started with the description of the computational problems introduced by the heterogeneous nature of astronomical data and went through machine-learning methods, their application in detection, denoising, classification, estimation, data fusion, localization, and discovery of events in multi-messenger astronomy. Some examples of the use of AI in gravitational-wave astronomy, optical surveys, and observations of high-energy neutrinos show how AI has helped to significantly increase efficiency and enable real-time scientific decision making.

Nonetheless, there are still many unresolved issues that prevent the AI from becoming a full-fledged scientific collaborator. Lack of labeled data sets, the domain adaptation of the learning algorithms to diverse instruments, uncertainty quantification, explainability, scaling of the computational resources, and rigorous validation of the results are all open questions for the future. Resolving them will involve closer connections between machine learning and well-known physical laws and probabilistic inference techniques. In the future, the development of new approaches such as foundation models, multimodal learning, physics-informed artificial intelligence, and autonomous observatories is set to reshape the field of astronomy. Instead of replacing traditional modeling with AI algorithms, the latter will be used alongside theoretical models and numerical simulations in order to speed up the analysis of complex observations without compromising the scientific validity of the results. With new generation observatories, such as Vera C. Rubin Observatory, Einstein Telescope, Square Kilometre Array, Cherenkov Telescope Array Observatory, LISA, and IceCube-Gen2, coming online, AI will become an integral part of scientific exploration, turning multi-messenger astronomy into an efficient scientific enterprise.

Author Contributions

Rashi Pandey: Conceptualization, investigation, literature review, visualization, and writing of the original draft. Sananjay Biswas: Conceptualization, supervision, validation, and review and editing of the manuscript. Both authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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