Astronomy and Computing 51 (2025) 100921

Contents lists available at ScienceDirect

Astronomy and Computing

journal homepage: www.elsevier.com/locate/ascom

Bridging gaps with computer vision: AI in (bio)medical imaging and astronomy

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ARTICLE INFO

Keywords:
Deep learning
MRI
Radio interferometry
Object detection
Segmentation
Generative models
Anomaly detection
Reinforcement learning

ABSTRACT

This paper explores how artificial intelligence (AI) techniques can address common challenges in astronomy and (bio)medical imaging. It focuses on applying convolutional neural networks (CNNs) and other AI methods to tasks such as image reconstruction, object detection, anomaly detection, and generative modeling. Drawing parallels between domains like MRI and radio astronomy, the paper highlights the critical role of AI in producing high-quality image reconstructions and reducing artifacts. Generative models are examined as versatile tools for tackling challenges such as data scarcity and privacy concerns in medicine, as well as managing the vast and complex datasets found in astrophysics. Anomaly detection is also discussed, with an emphasis on unsupervised learning approaches that address the difficulties of working with large, unlabeled datasets. Furthermore, the paper explores the use of reinforcement learning to enhance CNN performance through automated hyperparameter optimization and adaptive decision-making in dynamic environments. The focus of this paper remains strictly on AI applications, without addressing the synergies between measurement techniques or the core algorithms specific to each field.

1. Introduction

Artificial intelligence (AI) has revolutionized numerous scientific fields, playing a pivotal role in advancing our understanding across diverse disciplines. From climate science to genomics, AI-driven techniques have enabled researchers to tackle complex problems, analyze vast amounts of data, and generate new insights at an unprecedented pace. One of the most transformative impacts of AI has been in the realm of data science, where machine learning algorithms and advanced computational methods have become integral tools for researchers.

In both astronomy and medical imaging, AI and data science are essential, revealing notable similarities in their methodologies and challenges. Though seemingly disparate, these fields share a common reliance on sophisticated data analysis techniques to interpret complex datasets and uncover hidden patterns. As we delve into the vastness of the universe and the intricacies of the human body, we observe common techniques driven by a shared quest for knowledge and understanding.

Both fields grapple with the task of managing extensive datasets. In astronomy, researchers process immense celestial data from next-generation telescopes like the Large Synoptic Survey Telescope (LSST) and the Square Kilometre Array (SKA). For example, the LSST is expected to detect and catalog approximately 20 billion galaxies, producing around 10 terabytes of data each night and up to 60 petabytes over its 10-year survey period. Similarly, the SKA data center will receive around 600 GB/s of data during a typical 6-hour observation, amounting to several petabytes. After near-real-time processing, including cleaning, calibration, and averaging, the data is reduced to about 100 TB, which is then stored for further analysis (Wang et al., 2020).

Similarly, medical and biomedical imaging face the challenge of handling large-scale, high-resolution datasets. Medical imaging technologies such as Magnetic Resonance Imaging (MRI), Computed To-

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https://doi.org/10.1016/j.ascom.2024.100921
Received 4 April 2024; Received in revised form 25 November 2024; Accepted 9 December 2024
Available online 18 December 2024

mography (CT) scans, and Positron Emission Tomography (PET) scans generate massive volumes of data. For instance, a single full-body MRI scan can produce up to 1 gigabyte of data, and with thousands of scans conducted daily worldwide, the aggregate data volume quickly becomes enormous. Biomedical projects like the Human Connectome Project (Van Essen et al., 2012) have already generated over 1 petabyte of imaging data mapping the brain's neural networks. Future initiatives like the UK Biobank aim to scan 100,000 participants, further contributing to the data deluge.

The challenges in medical imaging extend beyond sheer data volume. High-resolution images require precise and rapid analysis to assist in diagnosis and treatment planning. The complexity of human anatomy and the need to detect subtle anomalies make manual analysis time-consuming and prone to error. AI and machine learning offer powerful solutions by automating image analysis, enhancing accuracy, and speeding up diagnosis. Techniques such as convolutional neural networks (CNNs) are particularly effective in identifying patterns and abnormalities in medical images, aiding in the early detection of diseases like cancer, neurological disorders, and cardiovascular conditions.

This review delves into the synergies between astronomy and (bio)medical imaging, emphasizing their shared reliance on data science and machine learning. The focus is on elucidating the profound similarities in the challenges, algorithms, and methodologies within both domains, with particular attention given to CNN applications. These powerful neural networks have found remarkable utility in both astronomy and medical imaging, serving as a common thread that underscores the harmonious integration of advanced technologies in disparate scientific disciplines. In astronomy, CNNs have been pivotal in handling diverse celestial datasets. For instance, they play a crucial role in the automated classification of celestial objects, facilitating the identification of variable stars, galaxies, and exoplanets in large-scale surveys. Similarly, in medical imaging, CNNs contribute significantly to the automated analysis of intricate scans, aiding in detecting anomalies and segmenting relevant structures. The commonality in using CNNs illustrates a shared commitment to leveraging cutting-edge technologies for pattern recognition in complex datasets.

In astronomy and medical imaging, applying AI and data science is not just a convenience but a necessity. The ability to process and interpret vast amounts of data efficiently and accurately is crucial for advancing our understanding of the universe and improving human health outcomes. This paper aims to extract valuable lessons from these parallels for researchers in both fields. By scrutinizing the applications of CNNs, we illuminate the potential for cross-disciplinary collaboration, urging scientists to draw insights from each other's methodologies and experiences. The intersection of astronomy and medical imaging, as evidenced by the shared challenges and solutions involving CNNs, serves as a rich ground for collaborative endeavors, fostering enhanced research achievements. By illuminating these parallels and offering tangible examples, this paper strives to underscore the interconnectedness between astronomy and medical imaging and inspire collaboration among researchers. The fusion of knowledge from these distinct yet converging fields can drive advancements in data science, machine learning, and ultimately, the broader understanding of our universe and the intricacies of human health.

This paper is structured as follows: it begins with a subsection in the introduction that provides an overview of CNNs, explaining their architecture and fundamental principles. The paper then explores the similarities between MRI and radio interferometry, highlighting their shared reliance on advanced imaging techniques. Next, it addresses the comparable challenges of object detection in astronomy and cell segmentation algorithms in biomedical imaging. The discussion then moves to comparing the literature on generative models and anomaly detection algorithms, identifying common challenges across both fields. By drawing these parallels, the research underscores the adaptability and versatility of CNNs as indispensable tools in overcoming shared obstacles. The paper concludes by discussing future paths for interdisciplinary collaborations between astronomers and biomedical scientists, emphasizing the potential for mutual advancements through shared knowledge and techniques.

1.1. Convolutional Neural Networks (CNNs)

CNNs are a class of deep learning algorithms that excel at processing structured grid data, such as images, by capturing and representing intricate patterns and structures. This capability has made CNNs indispensable across various applications, including image and video recognition, medical image analysis, and astronomical data interpretation. Their robustness and versatility highlight their significance as powerful tools in both scientific research and practical applications. The architecture of CNNs comprises convolutional layers, pooling layers, and fully connected layers, which work together to enable the network to automatically and adaptively learn spatial hierarchies of features from input images. In the following, we provide more details on these layers. In Fig. 1, we provide an overview of the CNN main layers and their functionality.

Convolution Layer: A convolutional layer is a fundamental building block of CNNs designed to process and extract features from input data, particularly images. It operates by applying a set of learnable filters, kernels, across the input data in a sliding window fashion. See Fig. 1 for a graphical representation of convolution layer. Kernels are typically smaller than the input dimensions, move across the input data with a defined stride, and padding (adding extra pixels around the input image or feature map to maintain spatial dimensions) can be added to maintain the spatial dimensions.

Max Pooling: A Max Pooling (maximum pooling) layer is typically positioned after convolutional layers in a CNN to perform dimensionality reduction and feature extraction. The operation of a max pooling layer involves within the sliding a window, over the feature map and selecting the maximum value within each window. This process effectively downsamples the input representation, reducing its dimensions while retaining the most significant features. By doing so, max pooling reduces the computational load of the network, making it more efficient and faster. Additionally, it enhances the robustness of the network by maintaining the most activated features, which are usually the most important for distinguishing patterns in the data.

Dense Layer: Also known as a fully connected layer, it is a critical component in neural network architectures. Its name derives from the fact that each neuron in the layer is connected to every neuron in the preceding layer, facilitating the combination of features extracted from earlier layers. Dense layers are primarily used to transition from spatial feature maps to a final classification or regression output, making them essential for learning complex mappings between inputs and outputs in neural networks. Typically, dense layers are followed by activation functions, which introduces non-linearity into the network, enabling it to model intricate relationships between inputs and outputs. The choice of activation function is crucial as it influences the network's training dynamics and overall performance. Readers are encouraged to refer to Sharma et al. (2017) for a more in-depth exploration of activation functions.

2. MRI and radio interferometry imaging

Magnetic Resonance Imaging (MRI) plays a crucial role in medical imaging by providing detailed anatomical information essential for accurate diagnosis and treatment planning. However, MRI can be slow due to the need for high-resolution images and precise signal sampling. To address this issue, significant advancements such as Parallel Imaging (PI) and Compressed Sensing (CS) have been made. PI utilizes arrays of receiver coils to acquire multiple signals simultaneously, preserving image quality while accelerating imaging by exploiting spatial sensitivity information. On the other hand, Compressed Sensing leverages the

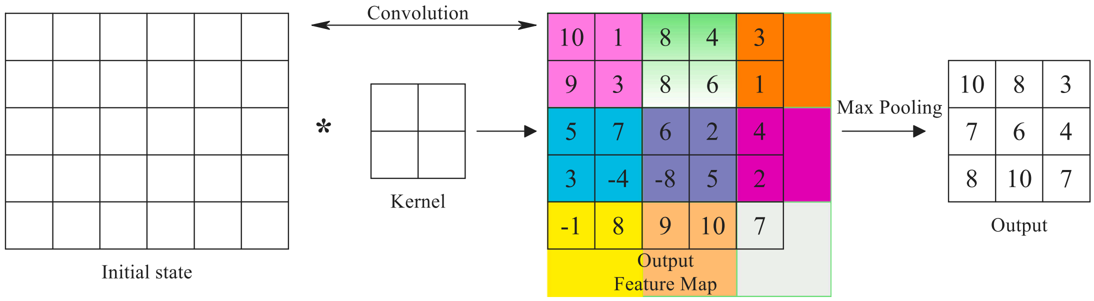

Fig. 1. This figure represents the functionality of CNNs considering the convolution and maxpooling layers.

Table 1
A comprehensive examination of MRI and Radio Astronomy perspectives across different aspects.

Aspect	MRI	Radio astronomy
Purpose	Medical imaging for diagnosis and research	Studying celestial objects and phenomena in the universe
Imaging Target	Internal structures of the human body	Distant astronomical objects and celestial bodies
Frequency Range	Radio frequencies	Radio wavelengths (typically longer than those used in MRI)
Instrumentation	MRI scanner	Radio telescopes
Signal Source	Hydrogen nuclei in the body	Electromagnetic radiation from celestial sources
Detection Mechanism	Measurement of RF signals emitted by excited nuclei	Capture and analysis of radio waves emitted by celestial objects
Spatial Resolution	High spatial resolution, often sub-millimeter	Spatial resolution vary based on the size and design of the radio telescope
Temporal Resolution	High temporal resolution, capturing dynamic processes	Temporal resolution depends on observation duration and instrument capabilities
Applications	Medical diagnosis, soft tissue imaging, functional studies	Studying galaxies, pulsars, quasars, cosmic microwave background, etc.
Technological Challenges	Minimizing artifacts, optimizing signal-to-noise ratio	Managing interference, achieving high sensitivity, and mitigating atmospheric effects
Examples of Discoveries	Visualization of internal organs, detection of abnormalities	Discovery of pulsars, mapping cosmic microwave background, identification of distant galaxies
Usage in Different Fields	Mainly in medicine and biological research	Astronomy, astrophysics, and cosmology
Data Analysis Techniques	Image reconstruction, signal processing for clinical interpretation	Spectroscopy, interferometry, data processing for astronomical interpretation
Impact on Society	Significant impact on medical diagnostics and healthcare	Deepening our understanding of the universe, contributing to astrophysical knowledge
Collaboration Opportunities	Collaboration with medical professionals and biologists	Collaboration with astrophysicists, astronomers, and cosmologists
Key Technologies	Superconducting magnets, RF coils, advanced image processing algorithms	Large radio dishes, interferometers, sophisticated data analysis software

sparsity of MRI signals, enabling rapid data acquisition and reconstruction from undersampled k-space data (k-space, often referred to as the measurement space, is a conceptual space representing spatial frequencies.). By exploiting redundancy in the image domain, CS algorithms accurately reconstruct high-quality images from fewer measurements, substantially reducing scan times. With the advent of AI, new CS algorithms leverage deep learning and CNNs to achieve this from even fewer measurements, enhancing efficiency and reconstruction quality further.

Simultaneously, in radio astronomy, the impracticality of constructing a single massive telescope — necessary to achieve the high resolution needed to observe fine details in distant celestial objects — led to the adoption of interferometry. By combining signals from multiple smaller telescopes, interferometry effectively simulates a much larger aperture, providing the desired resolution. This approach involves collecting signals in k-space (Fourier space), a conceptual space representing spatial frequencies, similar to MRI. The complexities of signal correlation and reconstruction in k-space necessitate advanced computational methods to achieve precise images of the cosmos. Interferometric arrays, such as the Very Large Array (VLA) and the Atacama Large Millimeter/submillimeter Array (ALMA), collect vast amounts of data in k-space that require sophisticated algorithms for accurate image reconstruction. These methods must account for factors such as signal noise, atmospheric distortion, and the relative positions of the telescopes, making the reconstruction process highly complex and demanding.

Table 1 represents an overview of the comparison between radio astronomy and MRI, two fields that utilize radio frequencies for distinct purposes. In MRI, radio frequencies are employed to interact with hydrogen nuclei (protons) present in the human body. These hydrogen nuclei possess a property called spin, which makes them behave like tiny magnets when subjected to a magnetic field, such as the one generated by the MRI scanner. On the other hand, radio astronomy harnesses radio frequencies to capture and interpret electromagnetic radiation from celestial sources, contributing to our understanding of the Universe. Table 1 underscores the unique applications and technological innovations in both MRI and radio astronomy, showcasing their pivotal roles in advancing scientific knowledge and technology. In the following, we offer foundational insights into radio astronomy and MRI. Readers interested in delving deeper into MRI signal acquisition and image reconstruction are encouraged to consult (Ramzi, 2022), while (van der Veen et al., 2019) offers additional insights into imaging within radio interferometry.

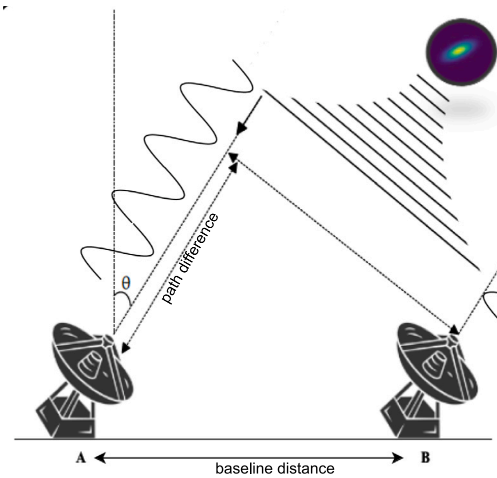

Fig. 2. Radio Interferometry enhances astronomical observations by combining signals from multiple radio receivers, optimizing resolution and sensitivity. In-phase combination and varying baseline lengths contribute to constructive interference, allowing for versatile imaging of celestial structures.

2.1. Fundamentals of radio interferometry

Radio interferometry measures the sky brightness distribution using aperture synthesis technique. Aperture synthesis, also known as interferometry, is a method in radio astronomy that allows for high-resolution imaging of celestial objects without needing a single, extremely large telescope. This technique involves multiple radio telescopes spread over a large area, working together as an array to collect radio signals from astronomical sources (Thompson et al., 2017). One key concept in aperture synthesis is the u-v plane, also known as the visibility plane, which is a mathematical representation of the spatial frequency domain (u and v). It is related to the baseline length (B), the angle between the baseline and the source in the sky θ, and the wavelength of the observed radiation λ. Fig. 2 illustrates the principles of radio interferometry, where astronomical observations are enhanced by combining signals from multiple radio receivers. By aligning the signals in-phase, the system maximizes constructive interference, thereby improving the resolution and sensitivity of the observations. The varying lengths of baselines — the distances between different receivers — allow the interferometer to capture a wide range of spatial frequencies. This versatility enables detailed imaging of celestial structures across various scales, from small, compact sources to expansive, diffuse regions in space. The spatial frequencies for two orthogonal directions are given by:

$$u = Bsin(\theta)/\lambda, v = Bcos(\theta)/\lambda$$

Visibility data of spatial frequencies u, v can be expressed as follows:

$$V(u,v,w) = \iiint I(l,m,\nu)\, e^{-2\pi i(ul+vm+w(\sqrt{1-l^2-m^2}-1))}\, dl\, dm\, d\nu \tag{1}$$

It is a function of sky brightness distribution $I(l,m,\nu)$ or I^{obs}, angular coordinates l, m and frequency ν. Eq. (1) represents the complete forward problem in which we relate the visibility data to the surface brightness distribution of the sky. However, due to a limited number of baselines, sparse sampling of the $u-v$ plane occurs, leading to gaps and incomplete information on certain angular scales. Here, we show the imposed sampling by the function $S(u,v)S(w)$, which affects the observed visibilities by Eq. (2). In practice, the distribution of baselines, telescope locations, and observation strategy collectively determine the sampling function. The goal is to sample the u-v plane adequately to ensure proper coverage of spatial frequencies.

$$V'(u,v,w) = V(u,v,w) \cdot S(u,v)S(w) \tag{2}$$

To make the image of the sky observed by radio waves, we need to solve the inverse imaging problem given sampled $V'(u,v,w)$ to get an approximation of $V(u,v,w)$ and therefore $I(l,m,\nu)$. The inverse Fourier transform to get an estimation of the sky surface brightness distribution is as follows:

$$I'(l,m,\nu) = \iiint V'(u,v,w)\, e^{-2\pi i(ul+vm+w(\sqrt{1-l^2-m^2}-1))}\, du\, dv\, dw \tag{3}$$

In summary, the fundamentals of radio astronomy, particularly the aperture synthesis and interferometry equations, showcase the intricate processes involved in capturing and reconstructing high-resolution images of celestial objects. Remarkably, these methods share significant similarities with the principles underlying MRI in the medical field, which will be discussed in the next section. Both disciplines rely on capturing raw data in a conceptual space (uv-space in radio astronomy and k-space in MRI). This data must then undergo complex post-processing steps to transform it into meaningful images. The sophisticated algorithms used in both fields, whether to correct for signal noise, atmospheric distortion, or to exploit data sparsity, underscore a shared reliance on advanced computational techniques. These parallels highlight a fascinating intersection between the two domains, emphasizing the universal challenges and innovative solutions in signal acquisition and image reconstruction, demonstrating how both fields utilize the same foundational backbone to achieve their goals.

2.2. Fundamentals of MRI imaging

Magnetic Resonance Imaging (MRI) is a medical imaging technique that uses strong magnetic fields and radio waves to generate detailed images of the internal structures of the body. It serves as a pivotal imaging modality in medicine, demonstrating extensive applications crucial for diverse medical purposes. For instance, in the diagnosis and management of epilepsy (Bernasconi et al., 2019), brain activity assessment (Zhao et al., 2016), brain tumors detection (Kalpathy-Cramer et al., 2014) and segmentation (Neve et al., 2022), liver superior contrast imaging providing both morphologic and physiologic information (Vu et al., 2018), cancer diagnosis (Andraş et al., 2021), etc. Advanced MRI techniques such as perfusion MRI are sensitive to microvasculature and are beneficial in tumor classification (Zacharaki et al., 2009), stroke region identification, and characterizing various diseases.

Similar to Radio Interfrometry Imaging (Section 2.1), fundamental principles of MRI are particularly rooted in the mathematical concept of Fourier transforms (Greengard and Lee, 2004). The magnetic field gradients are applied in different directions during the MRI scan. These gradients cause variations in the resonance frequency across space, leading to different frequencies in the acquired signals. The mathematical operation decomposes functions of time or space into constituent frequencies, facilitating the conversion of raw MRI data into meaningful images. The following equation exemplifies the mathematical operations:

$$V(k_l) = \iiint \rho(r) e^{-i2\pi k_l r}\, d^3 r \tag{4}$$

In Eq. (4), $V(k_l)$ represents the MRI signal acquired at a specific frequency k_l along the k_l axis in k-space. $\rho(r)$ shows the spatial distribution of nuclear spin density within the imaged object, where r is a three-dimensional vector representing spatial coordinates. It describes how the MRI signal in k-space is obtained through the Fourier transform of the spatial distribution of nuclear spin density within the imaged object.

Collecting all the signals in MRI is hindered by several practical and physical constraints such as time constraints, patient comfort and compliance, susceptibility to motion artifacts, safety concerns, data storage and processing challenges. Sampling in Fourier space is an effective solution to shorten the examination time. Considering the sampling function of $S(k_l)$, we have:

$$V'(k_l) = V(k_l) \cdot S(k_l) \tag{5}$$

and

$$\rho'(r) = \iiint V'(k_l) e^{-i2\pi k_l r} \, d^3 k_l \tag{6}$$

Eq. (6) illustrates the inverse Fourier Transform operation applied to the sampled $V'(k_l)$ to reconstruct the MR image. In the subsequent section, we elaborate on the utilization of artificial intelligence techniques to reconstruct $\rho'(r)$ in a manner that closely resembles $\rho(r)$.

2.3. MRI and RI similarities

MRI and radio astronomy share fundamental similarities in the necessity for careful sampling strategies and the subsequent challenges associated with collecting sampled data. In MRI, the process of collecting signals involves spatial encoding through k-space sampling, where inadequate sampling can result in aliasing artifacts and compromise image quality. Similarly, in radio astronomy, the u-v plane serves as the Fourier conjugate of the sky brightness distribution, and proper sampling is vital for accurate image reconstruction. The challenge lies in optimizing sampling density while considering time constraints and minimizing artifacts. While more emphasized in radio astronomy, both fields contend with the trade-offs between spatial and temporal resolution, aiming to achieve a balance that guarantees the reliability of the acquired data. A few studies in the literature have already mentioned these similarities in an interdisciplinary manner (Monnier et al., 2022; Terris et al., 2023; Farrens et al., 2020; Putzky and Welling, 2019).

In MRI, the limited number of radio frequency coils or sensors, akin to the limited antenna pairs in RI, poses a challenge regarding the number of signals that can be simultaneously acquired. Advanced sampling techniques, such as parallel imaging and compressed sensing (CS), aim to overcome this limitation. Parallel imaging utilizes multiple coils to acquire signals, simultaneously reducing the total acquisition time (for example (Hamilton et al., 2017)). In radio astronomy, parallelization concepts analogous to parallel imaging find expression in beamforming or phased array processing techniques. Unlike the traditional use of parallel imaging in MRI, RI leverages the synergy of multiple antennas to capture signals from celestial sources. Through beamforming, these individual signals are intelligently combined to enhance the sensitivity and resolution of the array. Beamforming effectively synthesizes a "virtual" antenna or beam that is steered electronically towards a specific point or region in the sky. It enables a broader field of view, facilitating simultaneous observations of multiple sky regions. The benefits extend to rapid surveying, allowing astronomers to cover expansive areas efficiently and dynamic tracking of celestial phenomena such as moving sources or transient events (Chen et al., 2021). While not a direct transplant of parallel imaging, the parallelization strategies employed in radio astronomy, particularly through beamforming, contribute significantly to radio telescope arrays' effectiveness, versatility, and innovative potential.

Conversely, compressed sensing exploits the sparsity of information to recover the complete image from undersampled data efficiently. The utilization of compressed sensing in both radio astronomy (Wenger et al., 2010; Wiaux et al., 2009; McEwen and Wiaux, 2011) and MRI (Jaspan et al., 2015; Lustig et al., 2008, 2007) exhibits intriguing parallels. In both contexts, CS promises to significantly accelerate data acquisition, offering a common advantage of reduced measurement requirements. In radio astronomy, this translates to more efficient observations, particularly in wide-field surveys, where the sparsity of celestial sources enables the reconstruction of detailed images from a sparse set of measurements. Similarly, in MRI, the potential for substantial reductions in data acquisition time is a key benefit, contributing to enhanced patient comfort and minimizing the impact of motion artifacts during scanning. Deploying CS in radio astronomy and MRI presents researchers with common challenges. One shared concern lies in the delicate balance between data reduction and image quality. The computational complexity of CS algorithms poses another shared challenge, requiring careful consideration to ensure the timely processing of data in both fields. As radio astronomy and MRI researchers navigate these shared challenges, collaborative efforts may foster cross-disciplinary insights, ultimately advancing the efficient use of compressed sensing across the broader spectrum of imaging sciences.

Other comparable challenges in both MRI and radio astronomy arise from various sources of noise that can compromise the quality of acquired signals and subsequently impact image fidelity. Common noise types, such as thermal noise originating from electronic components, atmospheric influences, and radio frequency interference, pose challenges in maintaining signal integrity. In MRI, factors like patient motion and susceptibility-induced artifacts contribute to noise, while RI contends with calibration errors and ionospheric effects. These shared challenges manifest in reduced signal-to-noise ratios, decreased spatial and temporal resolution, and potential artifacts. Addressing these noise-related issues through advanced signal processing techniques and meticulous system calibration is essential for optimizing the quality and reliability of imaging outcomes in both domains.

In conclusion, the common challenges encountered in optimizing sampling strategies in MRI and radio astronomy underscore the interdisciplinary nature of imaging sciences. Both fields grapple with the critical importance of precise signal acquisition, recognizing that inaccuracies in capturing phase-encoded signals can lead to undesirable truncation artifacts. Additionally, shared obstacles related to noise, including inherent thermal noise and external interference, further emphasize the collective endeavor to maintain signal fidelity amidst environmental complexities. Nonetheless, there is promise in innovative methodologies such as parallel imaging and compressed sensing. These approaches offer potential solutions to expedite data acquisition and reduce measurement requirements. However, their implementation necessitates careful consideration of the delicate balance between data reduction and preserving image quality. Moreover, the computational demands of these techniques pose additional challenges that must be navigated.

2.4. AI role to overcome the challenges

AI algorithms, particularly CNNs, have emerged as valuable tools for addressing noise and sampled data challenges in both MRI and RI. In the context of MRI, adaptive sampling techniques have been introduced to optimize data acquisition strategically. For instance, recent studies have explored the combination of under-sampling pattern optimization with content-based reconstruction networks, leveraging a pixel attention mechanism to extract multi-scale features (Yu et al., 2023; Yang et al., 2023). Additionally, CNNs can mitigate motion artifacts during MRI data acquisition by predicting and correcting distortions caused by involuntary movements (Ben Yedder et al., 2021). Conversely, in RI, where fixed antenna positions restrict sampling strategies, CNNs are utilized for quality control in observed images (Radford et al., 2023). CNNs also excel in denoising applications, effectively distinguishing astronomical signals from unwanted noise components. Studies such as (Rezaei et al., 2022; Vafaei Sadr et al., 2019) exemplify using CNNs to differentiate noise from genuine signals emitted by radio sources.

The following section delves into the comparative landscape of utilizing CNNs for image reconstruction in MRI and RI building upon the shared attributes outlined in Section 2.3. It explores the disparity in research attention between the two fields, highlighting the dominance of CNN-based algorithms in MRI reconstruction methodologies contrasted with their relatively underexplored application in RI.

2.4.1. Image reconstruction with CNNs

The literature underscores a notable discrepancy in using CNN-based algorithms for converting signals from the Fourier domain (k-space) to the image domain between MRI and radio astronomy. MRI demonstrates a greater emphasis and research activity in this area compared to radio astronomy. This variation can be attributed to several factors, including the historical dominance and clinical relevance of MRI in medical imaging, prompting extensive research to enhance its reconstruction techniques. Conversely, despite its fundamental role in astrophysics, radio astronomy encounters fewer studies employing CNN-based algorithms for k-space to image domain conversion, possibly due to the distinct challenges of radio interferometry data and the evolving nature of the field. This difference highlights the importance of exploring and adapting advanced CNN-based approaches in radio astronomy to capitalize on the benefits observed in the MRI domain. In the following, we delve into key research contributions for image reconstruction in both fields. Table 2 provides a comparative overview of state-of-the-art algorithms for image reconstruction in both MRI and RI. Please note that this table provides only an overview of a handful of algorithms. There are many researches in the literature such as those discussed in Montalt-Tordera et al. (2021) that explore advanced image reconstruction techniques from k-space in MRI. This includes the development and application of methods such as compressed sensing, deep learning-based algorithms, and iterative reconstruction techniques that aim to improve image quality, reduce scan times, and enhance diagnostic accuracy. Another example is presented in Pezzotti et al. (2020), which effectively addresses the challenge of undersampling k-sampled data by accurately reconstructing high-resolution images while minimizing common issues such as noise and blurring. Notably, this model was evaluated in the context of the "FastMRI" challenge, a collaborative competition sponsored by Facebook AI Research and NYU Langone Health, which aimed to advance the state-of-the-art in MRI image reconstruction (Zbontar et al., 2018).

The application of AI specifically for reconstructing RI images in the Fourier domain remains a relatively untapped area, suggesting significant potential for breakthroughs in the field. Although there are some examples in the literature, such as (Rezaei et al., 2022; Chiche et al., 2023; Terris et al., 2023; Connor et al., 2022), that explore image reconstruction within the image-domain, the use of AI in reconstructing RI images from the Fourier domain has been limited. This is partly because traditional RI image reconstruction has largely focused on image-domain techniques like deconvolution methods. The challenges of reconstructing images from interferometric data have led to the development of sophisticated algorithms like WSClean (Offringa et al., 2014). WSClean utilizes techniques such as "w-stacking" to correct for the Earth's curvature, ensuring accurate sky images by dividing data into layers based on their "w" coordinate — a third dimension in the u-v-w coordinate system used in interferometry — and combining them to produce a clearer image. While radio astronomy must account for Earth's curvature to produce accurate images, MRI instead focuses on challenges like noise reduction and resolution enhancement. Before the advent of deep learning, MRI image reconstruction primarily depended on classical signal processing and mathematical techniques like the inverse Fourier transform and compressed sensing algorithms. However, CNNs and deep learning algorithms have increasingly surpassed these traditional methods, offering superior and faster results for tasks akin to deconvolution, though in MRI, these processes are typically referred to as "denoising".

The transition to utilizing AI in this context represents a paradigm shift, requiring novel algorithmic developments and computational frameworks tailored to the unique characteristics of Fourier-transformed RI data. Several avenues for improvement can be pursued to enhance the current state of research in this area. One approach involves refining AI architectures better to accommodate the complex frequency-domain data inherent in RI imaging. This may entail the development of specialized neural network architectures capable of effectively processing Fourier-transformed data while preserving relevant spatial information. Moreover, collaborative efforts with scientists from other domains, such as MRI, can contribute to advancing the field of RI image reconstruction. MRI researchers have expertise working with Fourier-transformed data and have developed sophisticated reconstruction techniques tailored to MRI imaging modalities. By integrating perspectives from multiple disciplines, including computer science, medical imaging, and signal processing, collaborative efforts can drive the development of comprehensive and versatile solutions capable of addressing the complex challenges inherent in RI image reconstruction. A great example of such interdisciplinary work is Farrens et al. (2020) in which the authors have developed an open source image processing package, namely PySAP for various fields including MRI and RI. It offers fast wavelet transforms, sparse image transforms and modular optimization tools.

3. Segmentation and object detection

Segmentation models in computer vision are essential tools for classifying individual pixels within an image, producing segmentation masks that assign each pixel to a predicted class. Unlike object detection, which relies on bounding boxes to identify objects and their locations, segmentation operates at the pixel level and provides detailed contour and region information. This information is important for follow-up morphological and texture analysis of the segmented objects and brings many biological-related insights. The encoder–decoder architecture is predominantly studied and applied in biomedical segmentation. In biomedical imaging, cell segmentation is critical in identifying and separating individual cells within an image. We will use cell segmentation as an example to explore the development of deep learning models solving segmentation problems. Accurate cell segmentation is particularly vital in cancer studies, where it aids in quantifying tumor cells and offers insights into growth patterns and treatment responses (Ranjbarzadeh et al., 2023). Similarly, cell segmentation contributes to the exploration of neural networks in neurology, deepening our understanding of brain function and facilitating personalized medicine through tailored treatment plans based on individual cell characteristics (Das et al., 2022). Furthermore, in infectious disease research, cell segmentation assists in uncovering the dynamics of pathogens within host cells.

Object detection techniques, on the other hand, have revolutionized astronomical research by automating the identification and analysis of celestial objects across vast datasets. Examples include asteroid detection and tracking (Du et al., 2024) and transient detection (Liu et al., 2023), which identifies temporary astronomical phenomena. Likewise, in medical and biomedical imaging, object detection is applied in tasks such as tumor detection (Saeedi et al., 2023) and breast cancer detection (Mahmood et al., 2020). The parallels between object detection in astronomy and cell segmentation in biomedical imaging underscore the universal applicability and transformative potential of CNNs. Table 3 offers an overview of the selected studies exploring the applications of object detection and segmentation algorithms. Highlighted within are notable examples of CNN-based algorithms widely utilized across both astronomical and (bio)medical fields. Fig. 3 presents an example illustrating the application of object detection and segmentation algorithms in both astronomy and (bio)medicine. This figure emphasizes the similarities between the data in these two fields and highlights the potential challenges and problems they share. On the left, Amgad et al. (2022), focus on generating accurate annotations for cell nuclei to generate a dataset for segmenting cell nuclei in breast cancer histology. Similarly, in He et al. (2021), the authors use object detection algorithms to study celestial objects by classifying them into quasars, stars, and galaxies.

3.1. Object detection

CNNs and their variations have become powerful tools, providing robust solutions for object detection tasks in both astronomy and medical science. In the following section, we focus on object detection algorithms in these fields. However, given the close relationship between object detection and instance segmentation algorithms, we

Table 2
A comparative study of the image reconstruction techniques being used in MRI and Radio Interferometry (RI) from Fourier (k-space) domain.

Study	Year	Field	Main contribution	Challenges
Farrens et al. (2020)	2020	MRI & RI	An open source package for image reconstruction, fast wavelet transforms and optimization algorithms applicable to diverse imaging domains.	GPU implementations, a wider range of optimization algorithms and incorporating AI algorithms are missing
Li et al. (2024)	2024	MRI	Encoding Enhanced (EN2) CNN for highly undersampled data reconstruction. Utilizing convolution along either the frequency or phase-encoding direction, resembling the mechanisms of k-space sampling.	limited validation: only on lung MRI with Cartesian undersampling.
Yang et al. (2023)	2023	MRI	Optimizing k-space under-sampling pattern	only applicable on single-coil data, potential biases from synthesis network, and achieving robustness in different imaging scenarios.
Zibetti et al. (2022)	2022	MRI	The joint learning of sampling patterns and variational network parameters aims to improve MRI reconstruction by acquiring information from selective sample positions in k-space and eliminating undersampling artifacts.	Algorithm Complexity and sensitivity of the hyper-parameters in optimization.
Bahadir et al. (2020)	2020	MRI	LOUPE: an end-to-End learning framework that can determine where to sample in k-space and reconstructing under-sampled scans simultaneously	consideration of physical implementation costs, extension to non-Cartesian settings, and refining the optimization process in relaxation of thresholding operation.
Geyer et al. (2023)	2023	RI	CNN is being used totally in k-space. The input is sampled k-space radio data while the output is fully sampled. GAN has been used to simulate real looking radio galaxies.	only perfectly calibrated data is being used.
Taran et al. (2023)	2023	RI	Conducting source localization directly from sampled k-space data. Closely located sources have also been considered. High completeness has been reported in noisy data.	Generalization of the algorithm is not tested and the real data validation is missing.
Schmidt et al. (2022)	2022	RI	inspired by super-resolution models, reconstructs k-space (amplitude and phase) data	assumption on galaxy morphology might be simplistic.

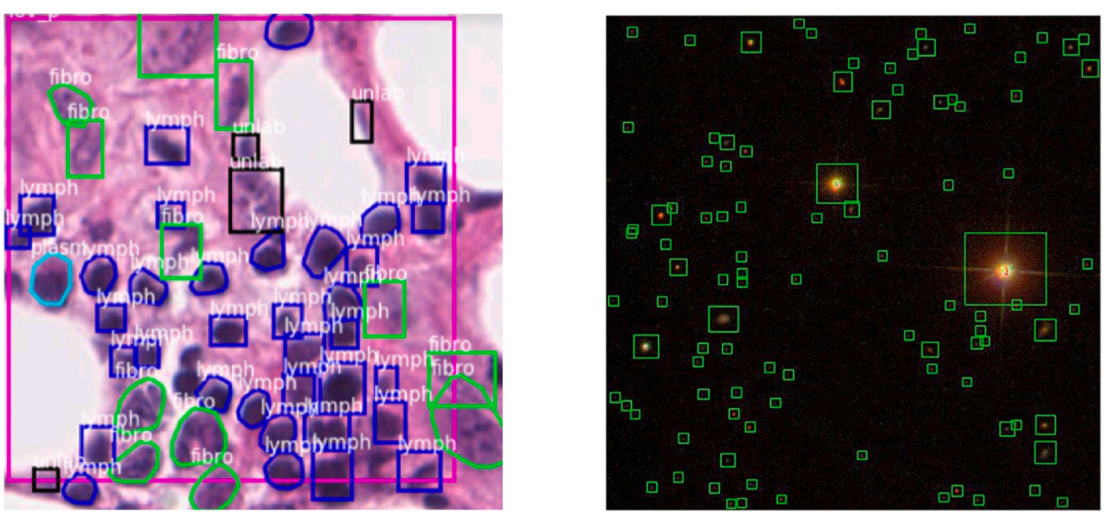

Fig. 3. This figure highlighting the similarities between the datasets in the astronomical and (bio)medical fields and the common challenges they face. The left panel (Amgad et al., 2022) is an annotation effort for cell nuclei in breast cancer histology. While on the right, He et al. (2021) employs object detection algorithms to classify celestial objects into categories such as quasars, stars, and galaxies.

also highlight the applications of these methods across both disciplines. Mask R-CNN (He et al., 2017), Faster R-CNN (Ren et al., 2016), and YOLO (You Only Look Once) are among the popular object detection and instance segmentation algorithms that have been used in both fields.

Mask R-CNN is a versatile framework that delivers multiple outputs for object detection and segmentation tasks. It classifies objects by determining the object class within each bounding box and enhances the accuracy of the bounding box coordinates. Moreover, Mask R-CNN creates segmentation masks that accurately delineate an object's shape at the pixel level, providing a detailed representation of its contours. In biomedicine, an example of Mask R-CNN's application is its use as a nucleus segmentation model citeLee2022. In astronomy, Mask R-CNN has been employed in various applications, including the classification, localization, and segmentation of galaxies based on their morphology (Farias et al., 2020), offering pixel-level segmentation for precise analysis.

Faster R-CNN operates through a two-stage process. Initially, it employs a region proposal network (RPN) to generate region proposals efficiently (stage one), followed by a classifier trained to predict object classes and refine bounding box coordinates (stage two). Its efficiency in medical imaging is evident in tasks like tumor detection (Mahmood

Table 3
This table presents an overview of a few studies on object detection and segmentation in both astronomy and biomedicine applications. YOLO, Fast R-CNN, UNet and its variations are among the most popular algorithms in both fields.

Study	Year	Field	Main contribution	Challenges
Cornu et al. (2024)	2024	Astronomy, Object Detection	efficient in crowded fields and detecting small blended objects, by introducing custom elements and adaptations to the YOLO framework.	Real-time computation load for astronomical image viewers and services.
He et al. (2023)	2023	Astronomy, Object Detection	Using multi-scale feature fusion modules and transformers.	Generalizability to different types of celestial bodies and imaging conditions, hyperparameter optimization.
Rezaei et al. (2022)	2022	Astronomy, Segmentation	addressing both detection and characterization of celestial sources, improving detection performance and purity of detected objects.	segmenting low SNR objects, handling complex source structures and generalizability to various astronomical images.
Vafaei Sadr et al. (2019)	2019	Astronomy, Object Detection	Enhances SNR of sources in the original map. Then uses dynamic blob detection to detect sources.	Generalizability to the location and size of the region noise estimation, hyperparameter optimization.
Oktay et al. (2018)	2018	Biomedicine, Segmentation	Attention Unet introduces attention gates to highlight important features to select the regions of interest.	The experiments with residual connections do not provide a significant performance improvement.
Chen et al. (2021)	2021	Biomedicine, Segmentation	Transformers provide stronger encoders. TransUNet has superior performance in medical segmentation.	High computational requirements and long training time
Stringer et al. (2020)	2020	Biomedicine, Segmentation	Cellpose is a generalized model for cell segmentation without requiring model retraining and parameter optimization.	Further improvement to segment irregularly shaped cells.
Schmidt et al. (2018)	2018	Biomedicine, Segmentation	StarDist is designed for accurate dense cell segmentation and has fewer parameters to train.	a parametric shape model can also result in only segment nuclei with reasonable complete shape.

et al., 2020), where its precision and accuracy are particularly beneficial. Similarly, in astronomical imaging, Faster R-CNN showcases its versatility by accurately detecting galaxies (Cao et al., 2023) and various other celestial objects (Jia et al., 2020). The robust performance and adaptability of Faster R-CNN make it an indispensable asset in both medical and astronomical research endeavors.

In contrast, YOLO employs a single-stage process, dividing the input image into a grid and directly predicting bounding boxes and class probabilities from each grid cell. Despite its simplicity compared to Faster R-CNN, YOLO has found applications in medical and biomedical imaging, such as breast cancer detection (Quan et al., 2023), brain tumor detection (Safdar et al., 2020). In the field of astronomy, YOLO has been utilized to identify and classify celestial objects (He et al., 2023; Grishin et al., 2023).

Although numerous object detection algorithms exist beyond Mask R-CNN, Faster R-CNN and YOLO, these two are highlighted here due to their widespread adoption and notable successes in both medical and astronomical applications. Their effectiveness underscores the importance of tailored algorithms capable of addressing the unique challenges posed by these domains.

3.2. Segmentation

Segmentation of cells and nuclei is a crucial step in many biological applications, aiding in the understanding of diverse phenomena within biological systems. Deep learning models have significantly enhanced the accuracy and efficiency of cell segmentation. Similarly, in astronomy, segmentation is essential for analyzing and interpreting vast and complex datasets. It enables researchers to isolate and examine specific structures within cosmic images, facilitating the identification and segmentation of large-scale cosmic structures, the delineation of stellar and galactic features, and the detection of celestial objects amidst noisy backgrounds. The precision and efficiency provided by segmentation are vital for advancing our knowledge of both biological systems and the universe, supporting discoveries in various fields, from stellar formations to the dynamics of galaxies.

U-Net and its variants have been extensively studied and used in both field. In Fig. 4, we present schematic diagrams of U-Net and its variants, which are discussed in the following. U-Net was originally introduced by Ronneberger et al. (2015) to improve cell segmentation and tracking performance in 2015. Its encoder–decoder structure is able to extract useful context and map it back to the output segmentation mask. Several well-known U-Net based variants were proposed subsequently to improve the segmentation performance and efficiency further. U-Net++ (Zhou et al., 2018) enhanced the connection between encoder and decoder networks using nested and dense skip pathways. In this manner, the model bridges the semantic gap between encoder and decoder feature maps. It incorporates deep supervision to enable model pruning and dense skip connections to improve gradient flow during training.

U-Net++ has been used to segment Bacillus subtilis cells from microscope images with low contrast and fuzzy edge information (Kong et al., 2023). Similarly, U-Net and its variants have made significant contributions to astronomy. For instance, U-Net has been employed to segment large-scale structures in cosmic simulations (Aragon-Calvo, 2019), while U-Net++ has been particularly effective in segmenting filamentary structures within the interstellar medium (Zavagno et al., 2023). Filamentary structures in astronomy refer to the thread-like formation of gas and dust within the interstellar medium, which are often associated with star formation regions.

Attention U-Net (Oktay et al., 2018) is another influential variant from U-Net. It has been instrumental in addressing the segmentation challenges posed by overlapping nuclei. Stacked U-Nets (SUNets) (Kong et al., 2020) employ a two-stage learning framework to segment both nuclei regions and the overlapping areas between them, merging the results to achieve precise instance segmentation in histological images. Similarly, Attention U-Net, combined with a graph-based random walk (Zhang et al., 2020), has been effectively utilized to extract instances from heavily overlapped cell clumps. Researchers have further explored integrating attention mechanisms with other U-Net variants, such as combining attention gates with U-Net++ to segment cells of varying sizes in multi-modal high-resolution microscope images (Yang and Chen, 2023).

We observed that the development of U-Net variants tightly follows the advancements in computer vision. Google's Inception architecture was integrated with U-Net to help automatically choose the convolution

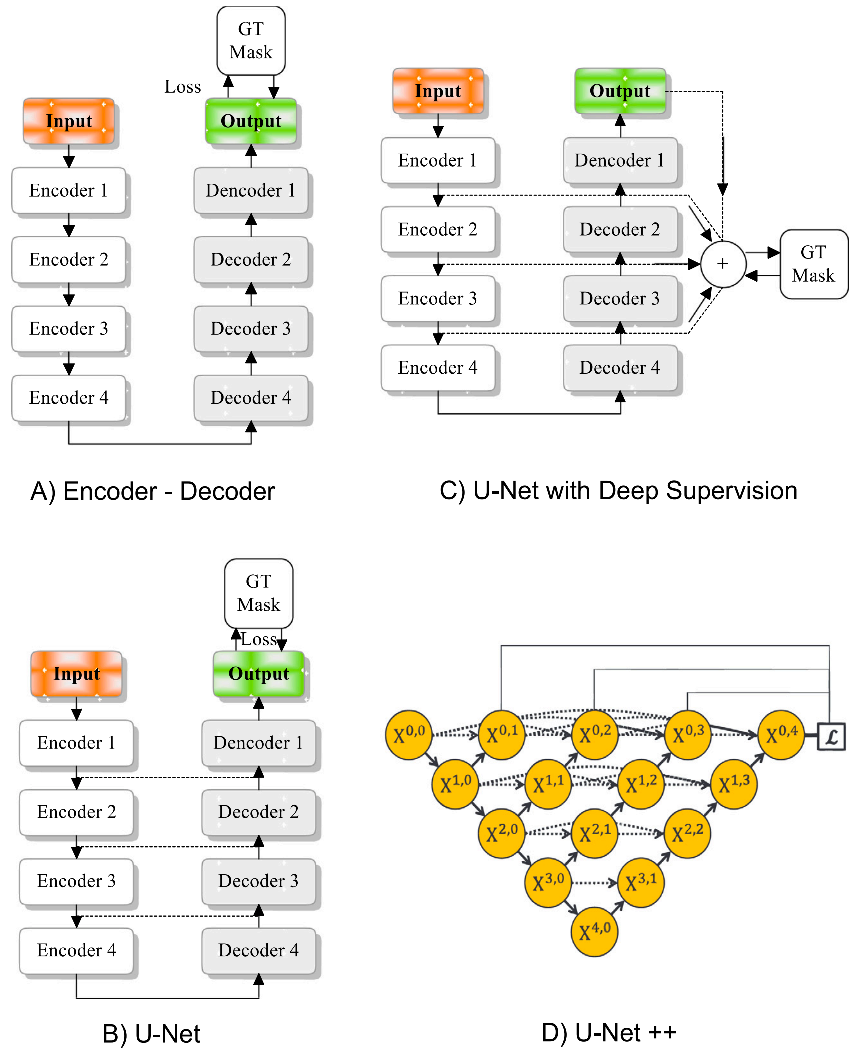

Fig. 4. This figure illustrates several prominent segmentation algorithms used in astronomy and (bio)medical imaging. The Encoder-Decoder model compresses and reconstructs images to segment detailed features. U-Net improves upon this by adding skip connections to retain high-resolution details, making it highly effective for biomedical tasks. U-Net with Deep Supervision adds intermediate layer supervision to enhance accuracy. U-Net++ further refines this with nested skip pathways and additional supervision for improved feature fusion and segmentation performance. Each architecture addresses specific challenges in both fields, showcasing their versatility.

layers in the deep network (Punn and Agarwal, 2020). U-Net was modified to employ dense blocks to deepen the network architecture (Cai et al., 2020). Dense downsampling and upsampling paths help reuse the features and provide a better localization in the output image. In Chen et al. (2021), TransUNet was introduced specifically for medical image segmentation such as multi-organ segmentation and cardiac segmentation. It is based on incorporating transformers into U-Net architecture. A two-branch architecture including U-net and TransUNet, was designed to segment overlapping nuclei (Tran et al., 2022). With this combination, the model can extract both local and global features for more robust segmentation.

In astronomy, these advanced segmentation techniques have also found significant applications as well. TransUNet, which merges the attention capabilities of transformers with the U-Net architecture, excels at capturing long-range dependencies and contextual information within images. This makes it particularly adept at segmenting complex and diverse structures, such as small impact craters on the Moon with high precision (Jia et al., 2021). On the other hand, Swin-UNet integrates the Swin Transformer with U-Net, providing a hierarchical approach to image processing. Renowned for their efficiency in handling multi-scale images, Swin Transformers are crucial for accurately segmenting astronomical objects of varying sizes and structures. Swin-UNet has demonstrated its efficacy in segmenting clouds from remote sensing images (Gong et al., 2023) and detecting astronomical targets in multi-color photometry surveys (Jia et al., 2023), showcasing its versatility and adaptability across different resolutions and complexities in astronomical applications.

4. Generative models

Generative models are machine learning algorithms that allow computers to generate data that mirrors real-world observations. They have been instrumental in fields such as computer vision, signal and natural language processing, and robotics. The underlying principle of generative models is to learn the distribution and covariance of the training set where the input consists of a random noise vector. There are several types of generative models, including but not limited to, Gaussian Mixture Models (GMM) (Liang et al., 2022), Hidden Markov Models (HMM) (Lane, 1999), and more recently, Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs) (Doersch, 2016; Girin et al., 2020; Pan et al., 2019; Saxena and Cao, 2021; Creswell et al., 2018), and diffusion models (Gottwald et al., 2024; Croitoru et al., 2023; Cao et al., 2024; Takagi and Nishimoto, 2023).

GANs usually consist of two deep learning models contesting in a zero-sum game framework (Goodfellow et al., 2020). A generator network G that generates new data instances and a discriminator

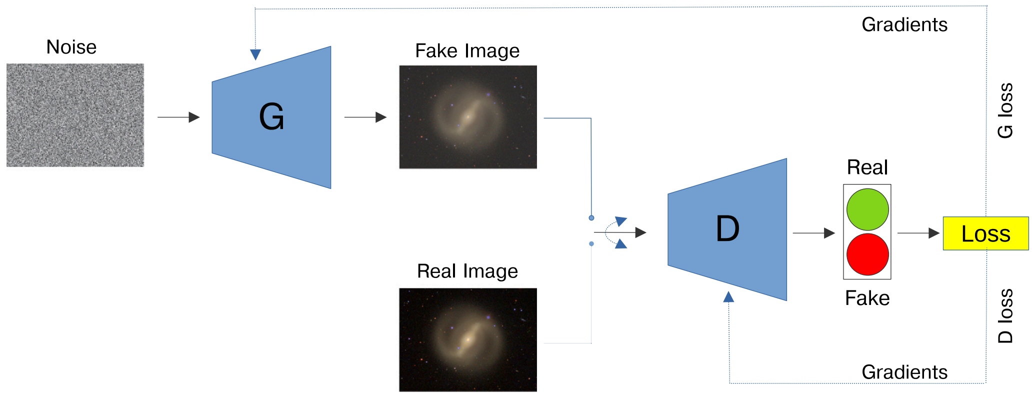

Fig. 5. Primary elements of Generative Adversarial Networks.

network D that evaluates them (see Fig. 5). The generator network inputs a random noise vector and outputs a data instance. The discriminator network takes a data instance as input (real or generated by G) and predicts the probability that the data instance was drawn from the real data distribution. The generator is trained to maximize the likelihood of the discriminator's misjudgment. Each GAN configuration is a minimax two-player game, and the networks are trained together in an adversarial manner using back-propagation.

Diffusion Models are also a more recent class of generative models that have gained significant popularity in recent years. They work by progressively adding Gaussian noise to a dataset and then learning to reverse this process (Song et al., 2020; Nichol et al., 2021). This approach enables them to create remarkably accurate and detailed outputs. In more refined terms, a Diffusion Model is a specific kind of latent variable model that utilizes a stable Markov chain to establish connections to the latent space (Song et al., 2020). This sequence subtly infuses noise into the data, aiming to derive an estimated posterior of the latent variables that match the dimensionality of the actual data. A notable advantage of Diffusion Models is their independence from adversarial training. The challenges associated with adversarial training are widely recognized (Shafahi et al., 2019). Therefore, when there are non-adversarial options available that offer similar performance and training efficiency, they are typically the preferred choice.

4.1. Applications in medicine

Generative models have shown immense potential in medicine. They are used for medical imaging, drug discovery, disease diagnosis, and personalized treatment planning. By learning from large datasets of patient information and medical images, these models can generate new synthetic data, augment existing datasets, and even predict future medical outcomes. In the following, we will explain the applications of generative models in three key areas: medical imaging, synthetic patient data, and drug discovery.

4.1.1. Medical imaging

Medical imaging benefits from generative models in different ways such as image synthesis and augmentation, image-to-image translation, and super-resolution. The models have been used to synthesize medical images and augment existing datasets, addressing privacy challenges and dealing with rare diseases, where the available data is limited. By generating synthetic images that mimic the characteristics of real patient data, these models can significantly increase the size and diversity of datasets, improving the performance of diagnostic algorithms (Rashid et al., 2019; Frid-Adar et al., 2018; Sandfort et al., 2019).

The second application of generative models in medical imaging is image-to-image translation, which involves converting one type of medical image into another. For instance, GANs have converted CT scans into "pseudo" MRI scans and vice versa. This can be particularly useful in situations where a certain type of scan is not available or is too risky for a patient (Zhang et al., 2018; Jabbarpour et al., 2022; Chen et al., 2024).

Generative models have also been used to enhance the resolution of medical images, a process known as super-resolution. High-resolution images can provide more detailed and accurate information, which is crucial for diagnosis and treatment planning (Kaji and Kida, 2019).

4.1.2. Synthetic patient data

Generating synthetic patient data is another application of Generative models. It can address key challenges related to patient data privacy and scarcity. For instance, researchers can leverage these models to generate synthetic electronic health records (EHRs) that maintain the statistical properties of real EHRs without containing any identifiable patient information (Jadon and Kumar, 2023; Yale et al., 2020). A significant use case of this method involves creating artificial datasets for cancer studies, leveraging the publicly accessible cancer registry data provided by the Surveillance Epidemiology and End Results (SEER) program. This research scrutinized three distinct methodologies for creating synthetic data: models based on probability theory, imputation models rooted in classification, and generative adversarial neural networks. The synthetic datasets, which included over 360,000 individual cases, demonstrated the potential of generative models in medical research (Goncalves et al., 2020). An alternate study underscored the value of synthetic data in the healthcare sector, pinpointing seven applications: research in simulation and forecasting, hypothesis generation, testing of methods and algorithms, research in epidemiology and public health, advancement of health IT, educational programs and training, public distribution of data sets, and strategies for data linkage. The study provided evidence that synthetic data are helpful in different aspects of healthcare and research (Gonzales et al., 2023).

4.1.3. Drug discovery

Drug discovery is a complex and time-consuming process to identify novel compounds with therapeutic potential. Traditionally, this involves extensive experimental screening of large chemical libraries. Generative models have emerged as powerful tools to accelerate this process by predicting promising drug candidates, refining molecular structures, and analyzing vast datasets (Blanco-Gonzalez et al., 2023; Gupta et al., 2021). Their application has led to the discovery of novel molecular structures with potential therapeutic properties (Bilodeau et al., 2022; Abbasi et al., 2022).

In a remarkable demonstration of the power of artificial intelligence, scientists employed the protein folding prediction model, AlphaFold, to identify a new CDK20 small molecule inhibitor, achieving this breakthrough in a mere 30 days (Ren et al., 2023). This unprecedented speed was made possible by AlphaFold's ability to accurately predict protein structures, which is a critical step in drug discovery.

Cyclin-dependent kinase 20 (CDK20) is an enzyme that plays a role in cell cycle regulation and has been implicated in the progression of certain cancers. By understanding the three-dimensional structure of CDK20, researchers could design a molecule that would specifically bind to and inhibit its function.

In a parallel development, Evotec, a German biotech company, declared the initiation of a phase 1 clinical trial for an innovative anticancer compound, a product of their collaboration with Exscientia. This firm, based in Oxford, harnesses the power of AI for the discovery of small-molecule drugs. Utilizing Exscientia's AI design platform, Centaur Chemist, they were able to pinpoint the drug candidate in a span of just 8 months (Savage, 2021). Centaur Chemist likely employs a combination of machine learning algorithms and cheminformatics techniques to generate and evaluate potential drug molecules rapidly. This significantly accelerated drug discovery process is a testament to the potential of AI in this field.

To put things into perspective, the conventional drug discovery process typically spans four to five years. Another instance is exemplified by Insilico Medicine. This firm announced that, through a structure-based generative chemistry approach, they had identified a potent, selective, and orally bioavailable small molecule inhibitor of CDK8, a promising candidate for cancer treatment. Li et al. (2023). Structure-based drug design leverages the knowledge of a target protein's structure to create molecules that precisely fit and interact with it. By employing generative models, Insilico Medicine could efficiently explore the chemical space to discover a suitable inhibitor for Cyclin-dependent kinase 8 (CDK8). CDK8 is a regulatory kinase that is part of the mediator complex, playing a key role in the regulation of gene transcription and having implications in cancer progression.

4.2. Applications in astrophysics and cosmology

Generative models have found significant applications in Astrophysics and Cosmology, providing novel ways to simulate and understand complex cosmic phenomena. In the following subsections, we will explore the applications of generative models in three key areas: galaxy formation, universe simulation, and the simulation of events like gravitational waves and Radio Frequency Interference (RFI) for better detection.

4.2.1. Galaxy formation

Generative models can generate synthetic galaxies that closely resemble real ones observed in the universe. They learn from large datasets of galaxy images and use this knowledge to generate new galaxies with varying characteristics such as size, shape, and color. This has been particularly useful in understanding the underlying physics of galaxy formation and evolution. For instance, GANs have been used to generate realistic images of galaxies at different stages of their evolution, providing insights into the processes that drive galaxy formation and transformation (Fussell and Moews, 2019; Lanusse et al., 2021).

4.2.2. Universe simulation

On the large scales, often in three dimensions, Generative models have also been used to simulate the structure formation of the universe. These models are adept at producing new, physically plausible representations of the cosmic web, the grand-scale architecture of the universe. Employing these simulations led to the creation of a very comprehensive and precise virtual depiction of the universe. These simulations reconstruct the entire cosmic evolution, from the inception at the Big Bang to the current state, providing researchers with a dynamic platform to explore various cosmological theories and parameters. For instance, GANs have been used to generate fast and accurate dark matter simulations, providing a valuable tool for cosmological studies (Rodriguez et al., 2018; Perraudin et al., 2019; Ullmo et al., 2021).

4.2.3. Other simulations

Generative models have also been used to simulate time-dependent events like Gravitational Waves and Radio Frequency Interference (RFI) for better detection. These models can efficiently constrain numerical gravitational-wave population models at a previously intractable complexity (Wong et al., 2020; McGinn et al., 2021). Within the scope of RFI, generative models have been instrumental in autonomously segregating spectrogram (a visual way of representing the signal strength) observations affected by RFI. This process effectively distinguishes between the signals of interest and the RFI components (Vos et al., 2019).

4.3. Similarities and differences

Generative models have revolutionized both medicine and astrophysics by augmenting data and simulating complex phenomena. Despite differences in application context, data characteristics, and goals, these models demonstrate versatility across domains. Both fields leverage generative models for data augmentation, simulation, and uncertainty quantification, but differ in data dimensionality, privacy, and model complexity. Interdisciplinary innovations have emerged, including physics-informed GANs (Yang et al., 2019, 2020) and conditional VAEs (Won et al., 2022), with astrophysics inspiring new medical imaging techniques. GANs are widely used in both fields, while VAEs are more commonly used in medicine for dimensionality reduction. Diffusion models are gaining popularity in astrophysics for simulating complex cosmic events (Cuesta-Lazaro and Mishra-Sharma, 2024). Future directions include interdisciplinary research, transfer learning, and addressing common challenges such as robustness and interpretability. Physics-informed deep learning, which integrates physical laws into neural networks, shows promise in both fields. Although more established in astrophysics, where physical laws are well defined, researchers actively explore its application in medicine, particularly in medical imaging and personalized treatment planning.

5. Anomaly detection

Anomaly Detection (AD), also known as outlier detection, involves identifying data samples that exhibit significant deviations from the overall data distribution (Fernando et al., 2021; Chalapathy and Chawla, 2019). Therefore, it is essential to clearly define the concept of 'overall data distribution' and establish specific criteria for identifying what constitutes a 'significant deviation.' The notion of overall data distribution is rooted in normal data patterns, while significant deviation pertains to abnormal data. These distinctions can be made by the user through manual labeling of data into normal and abnormal categories in a supervised algorithm, or they can be automatically detected by the machine during training on the entire dataset in an unsupervised manner (Ruff et al., 2020).

The emergence of deep learning algorithms has initiated a revolutionary epoch in AD. For example, one of the most significant advantages of deep learning is its ability to model non-linearity and automatically learn features. The capability to precisely capture underlying data distributions allows deep learning models to effectively detect deviations from learned patterns (Thudumu et al., 2020). Deep Anomaly Detection (DAD) has found numerous applications across a wide range of domains, particularly in biomedical and astronomy fields. Investigating the similarities and differences in DAD approaches, can lead to significant improvements in DAD algorithms for both areas in the future. By focusing on these similarities and differences, we aim to bridge the gap in applying DAD algorithms between the biomedical and astronomy domains. Below, we provide a summary of current DAD algorithms, categorizing them based on their training objectives and whether they require labels for normal or abnormal data during training.

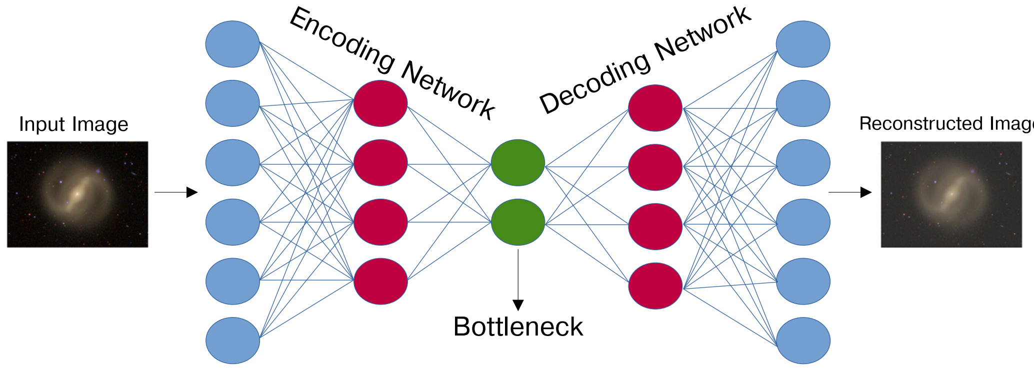

Fig. 6. Demonstration of the key elements of an Auto Encoder.

5.1. Unsupervised deep anomaly detection

Unsupervised anomaly detection does not rely on supervision data to determine if a sample is normal or abnormal during training. This makes unsupervised algorithms attractive to the DL community because they do not require labeled datasets (Baur et al., 2020; Thudumu et al., 2020). Two popular unsupervised DL architectures are Auto Encoders (AEs) (Tschannen et al., 2018) and Generative Adversarial Networks (GANs) (see Section 4 and Fig. 5). AE networks are a type of unsupervised neural network algorithm where the target data array is set to be the same as the input data array. As showed in Fig. 6, an AE consists of three parts: an encoder, which learns patterns in the input data; a bottleneck that creates a compressed representation; and a decoder that reconstructs the input from this compressed representation. This model is trained to minimize the reconstruction loss which is a distance function between the reconstructed data array and input one (Yang et al., 2021; Dong et al., 2018). There are multiple variations of AEs including sparse AEs (Wen et al., 2019), De-Noising AEs (Vincent et al., 2008) and Variational AEs (Kingma and Welling, 2019). In the following, we will explore the application of ADD techniques across two distinct but conceptually similar domains: biomedical signals and spectroscopic astronomy. Both fields involve complex time-series data that, despite their different origins, share common data processing challenges. For example, we will compare datasets from biomedical fields, such as ECG and EEG, with astronomical data, including gravitational waves and radio pulsars. We will investigate how techniques like VAEs and GANs are used to detect abnormalities in biomedical imaging modalities such as X-ray, CT, and MRI scans, and how these methods are similarly applied in astronomical photometry to identify anomalous sources in large-scale datasets.

5.1.1. Electrical biomedical signals and spectroscopic astronomy

Electrical biomedical signals are a diverse data set that play a crucial role in monitoring and diagnosing various health conditions. These signals can be broadly categorized into three main types: Electrocardiogram (ECG), Electroencephalogram (EEG), and Magnetoencephalography (MEG) (Rangayyan and Krishnan, 2024). ECG measures the electrical activity of the heart and is widely used to detect heart conditions. EEG captures the electrical activity of the brain, which is essential for diagnosing neurological disorders like epilepsy and MEG records the magnetic fields produced by neural activity in the brain, providing highly detailed information about brain function. A similar data type in astronomy is spectroscopic data. It provides us the light intensity across different wavelengths, which is recorded as flux in each frequency bin or pixel. It provides critical insights into the physical properties of celestial objects, such as their composition, temperature, velocity, and more (Xiong et al., 2010; Leung and Bovy, 2018).

In essence, while biomedical signals focus on monitoring the internal workings of the human body, spectroscopic data in astronomy gives a window into the physical characteristics of distant celestial bodies. Understanding and analyzing these distinct data types are crucial for advancing knowledge and making discoveries in their respective fields. In the following, we provide examples of ECG/gravitational wave and EEG/radio pulsar data are not meant to be comprehensive, but rather illustrative of the similarities between biomedical signals and astronomical spectroscopic data. The key objective is to showcase the potential for applying analogous deep learning techniques across these fields, with the aim of inspiring cross-disciplinary knowledge transfer and the exploration of novel data analysis approaches.

ECG and Gravitational Wave data: ECG data captures the polarization changes in heart cells, reflecting the electrical impulses that drive the heartbeat. By analyzing the timing and amplitude of this electrical activity, it is possible to differentiate between normal and abnormal heartbeats, which is essential for diagnosing various cardiac conditions (Ebrahimi et al., 2020; Pabitha et al., 2023; Rawi et al., 2022; van der Valk et al., 2023). In the field of astronomy, one type of spectroscopic data comes from Gravitational Waves (GW), which are ripples in spacetime caused by massive astronomical events, such as the merging of compact binary objects like black holes or neutron stars (Rawi et al., 2022; Abbott et al., 2019). A notable example of GW data is the detection of GW150914, one of the first gravitational waves ever observed, which resulted from the merger of two black holes. This groundbreaking detection was made by the LIGO and Virgo Collaboration (The Ligo Scientific Collaboration and The Virgo Collaboration, 2016).

In Fig. 7, we provide a comparison between ECG and GW data, highlighting their similarities in terms of data type and Pre-processing requirements. Despite originating from vastly different sources — one from the human heart and the other from cosmic events — both data types share common characteristics that make them amenable to similar DAD approaches. This similarity suggests that techniques used to analyze ECG data could be effectively adapted for use with GW data, and vice versa.

The most commonly used architectures for analyzing time-series data, such as ECG and gravitational wave data, are 1D CNNs and Recurrent Neural Networks (RNNs). These architectures are particularly effective when integrated into AEs and GANs for anomaly detection tasks. In Dutta et al. (2021), the authors introduced a recurrent AE model called MED-NET, which successfully identified ECG anomalies, achieving an impressive accuracy of 97.93%. A similar recurrent AE model was used in detecting GW signals by Moreno et al. (2021). Although these two studies address different types of problems, they utilize similar data types and machine learning architectures, highlighting the versatility of these approaches.

In another study (Qin et al., 2023), the authors employed a Bidirectional Long Short-Term Memory (LSTM) layer within a GAN architecture to detect abnormalities in ECG signals. This technique could be adapted for GW data to improve the accuracy of anomaly detection in this area as well. Further examples in the literature illustrate the successful application of these architectures. For instance, Refs. Jang

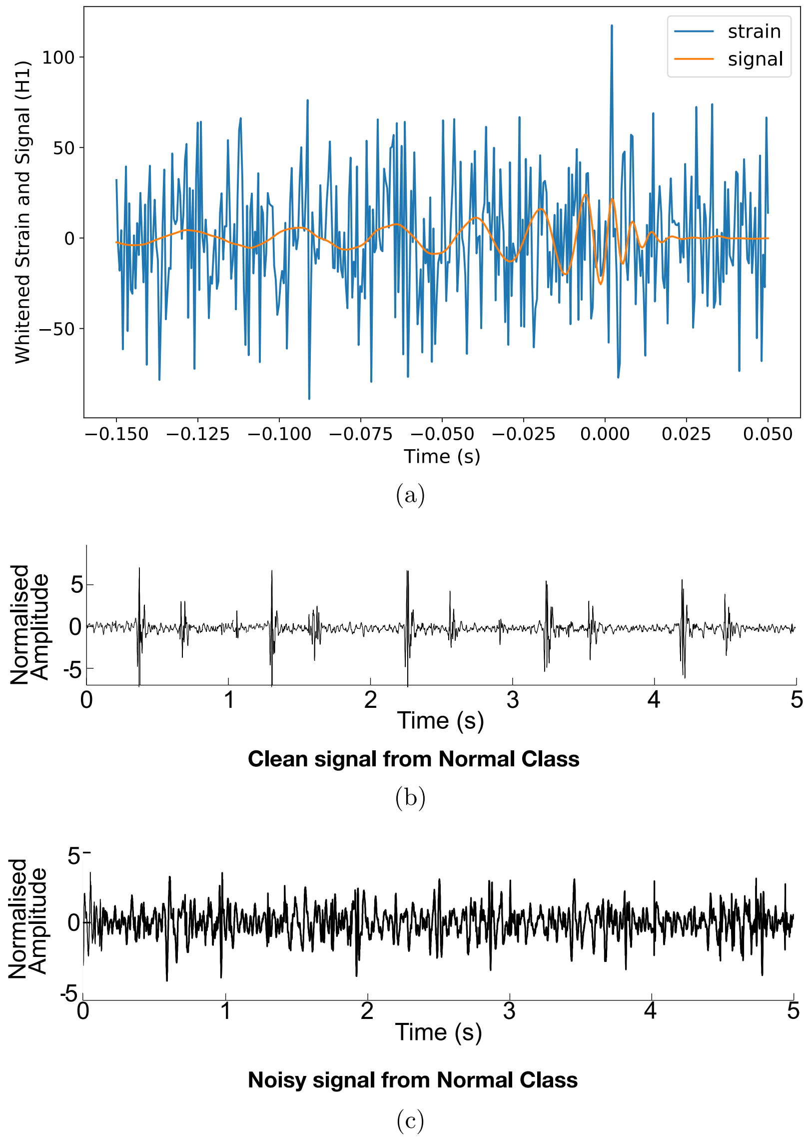

Fig. 7. In (a) we show an instance of simulated gravitational wave strain (Xia et al., 2020) and two typical examples from the PhysioNet CinC 2016 heart sound dataset (Clifford et al., 2016), with the clean signal in (b) and affected by noise in (c) are shown.

et al. (2021), Pereira and Silveira (2019), Zhu et al. (2019) focus on using these methods for ECG data, while Refs. Corizzo et al. (2020), Raikman et al. (2023), Benedetto et al. (2023) explore their application in GW data. These studies provide valuable insights and could inspire further advancements in both fields by leveraging the strengths of these machine learning techniques.

EEG and Radio Pulsar data: EEG is commonly used to record electrical brain activities and study sleep patterns, psychological disorders, and epilepsy. It is a convenient way to monitor and diagnose epileptic seizures, as epilepsy often causes abnormal brain activities (da Silva, 1998). A similar datatype to EEG in astronomy is a radio pulsar. It is a rapidly spinning, highly magnetized neutron star emitting powerful electromagnetic radiation beams from its magnetic poles (Philippov et al., 2020). Pulsar discoveries have significantly advanced our understanding of astronomy and cosmology, particularly in the areas of exoplanet detection and testing the fundamental principles of general relativity (Voisin et al., 2020). In the following, we provide examples from the literature that have used similar DL models as anomaly detectors on these similar datasets.

In Truong et al. (2019) a GAN architecture is trained with two primary objectives. The generator aims to create realistic-looking Short-term Fourier Transform (STFT) images derived from EEG signals. The discriminator's role is to distinguish between real and generated STFT images accurately. Following generator training for seizure prediction, the authors repurpose the discriminator by appending two fully-connected layers. This repurposed network transitions from differentiating real and fake data to classifying brain activity as normal or abnormal. Following a similar GAN-based strategy in Balakrishnan et al. (2020) applied the approach to radio pulsar data, including frequency-phase and time-phase information, to successfully detect new pulsars. Both EEG and pulsar radio data pre-processing approaches involve normalization to standardize the data, dimensionality reduction to simplify complex data structures, and segmentation into uniform units (super-frames or bins) for consistency. Feature extraction is key in both cases, with EEG data transformed into Mel Spectrograms and pulsar data into various plots (e.g., Pulse Profile, Frequency-Phase Plot). Further examples are provided in the Refs. Shoeibi et al. (2021), Wen and Zhang (2018) for EEG, and Liu et al. (2024), Yin et al. (2022) for radio pulsars.

5.1.2. Biomedical imaging and photometric astronomy

Biomedical imaging relies on various data types, with X-ray radiography, Computed Tomography (CT) scans, and MRI as primary tools.

These imaging techniques provide detailed visual information crucial for diagnosing and monitoring various medical conditions. In contrast, photometric astronomy uses telescopes to measure the amount and color of light emitted by celestial objects, revealing important details about their temperature, distance, and composition. While photometric data provides valuable insights, spectroscopic data is often preferred in deep anomaly detection models, such as Autoencoders (AEs), for identifying anomalous samples. Spectroscopic data offers more detailed information about the physical properties of celestial objects, making it more effective for detecting anomalies.

In biomedical imaging, it is more common to apply machine learning architectures directly to the image data, given that this field primarily deals with visual data. Unlike astronomy, where diverse data types are commonly integrated, biomedical imaging has traditionally focused on analyzing images alone. However, there is a growing interest in combining imaging data with other types of patient data, such as tabular data from medical records. This integrative approach could benefit from techniques used in astronomy, where multiple data types are already routinely combined. By leveraging diverse data sources, the effectiveness of anomaly detection in biomedical imaging could be significantly enhanced.

There is a wide range of DAD architectures available for analyzing biomedical images. In Chatterjee et al. (2022), the authors employ VAEs, while in Kascenas et al. (2022), they utilize denoising AEs to detect anomalies in brain MRIs. In Nakao et al. (2021), GANs architecture is utilized to detect abnormal samples in chest X-ray images, while Esmaeili et al. (2023) offers a detailed examination of the application of GANs for identifying anomalous samples in seven medical imaging datasets encompassing diverse modalities and organs/tissues. Similar examples in astronomy includes (D'Addona et al., 2021) the authors use AEs to find unexpected sources, and Storey-Fisher et al. (2021) where GANs are used to identify anomalous galaxy images.

5.2. Supervised deep anomaly detection

A supervised algorithm can be used for anomaly detection by training it on a labeled dataset where normal and abnormal (anomalous) instances are clearly identified. During training, the algorithm learns to distinguish between the features of normal and abnormal data. Once trained, the model can be applied to new, unseen data to classify instances as either normal or abnormal. However, supervised learning methods are inherently biased towards expected anomaly distributions and are limited in their ability to detect pathologies beyond those they are specifically designed for. This constraint has important consequences as it restricts the range of detectable pathologies and ignores a wide variety of potential anomalies in the context of image data from astronomy and (bio)medical imaging.

Supervised anomaly detection transforms into classification problems in biomedical imaging and astronomy. In this approach, training data are labeled before the training process, and depending on the number of labels, this classification problem can become a multi-classification problem. For example (Varma et al., 2019) has used CNNs on X-ray images of the foot, knee, ankle and hip to find anomalous samples. A similar CNN network is used in Becker et al. (2021) for the morphological classification of radio sources in astronomy. In the study by Guida et al. (2021), three-dimensional (3D) CNNs are employed on knee MR images for knee osteoarthritis classification. The findings suggest that training a 3D-CNN model on 3D MR images holds more promise in enhancing the diagnostic accuracy for knee osteoarthritis in clinical settings compared to the prevalent use of 2D-CNNs on 2D X-ray images. On the other hand, a comparable situation arises in astronomy, as discussed in Chegeni et al. (2023), where the authors introduced a method called 'Clusternets' that relies on 3D-CNNs to differentiate scenario involving dark energy in the field of astronomy. The results indicate that training a 3D-CNN model on 3D simulation snapshots shows greater potential for improving classification accuracy in distinguishing dark energy compared to the common practice of using 2D-CNNs on 2D power spectra derived from these 3D snapshots. Another example would be the detection of rare galaxies in the form of a classification problem in Rezaei et al. (2022).

In astronomy and biomedical imaging, the application of CNNs for classification typically follows a structured hierarchy. This process involves selecting the appropriate number and types of layers and fine-tuning architectural parameters to suit the specific problem. Conversely, in both domains, utilizing these CNNs often involves a touch of creativity. For example, in the study by Xu et al. (2018), a hierarchical 2D-CNNs architecture was developed for detecting anomalies in chest X-ray images. As shown in Fig. 8, this approach involved a two-step process: first, a 2D-CNN named 'CXNet-m1' was designed to classify chest X-ray images as normal or abnormal. Subsequently, the abnormal images were labeled as both multi-label and single-label to train a second classifier, 'CXNet-m2'. The results of the paper demonstrate that this approach is more effective than fine-tuning the architecture of multi-labeled classification CNNs. As illustrated in Fig. 9, This approach can potentially be applied to astronomy classification problems, such as galaxy morphology classification. More examples can be found in references for classification of Alzheimer's disease (Nawaz et al., 2020) and brain tumor (Rai and Chatterjee, 2021) using MRI data. On the other hand in astronomy, we can found references for morphological classification of galaxies (Cavanagh et al., 2021) and supernova classification (Qu et al., 2021), which could inspire the use of these structures to enhance both literary works.

5.3. Other deep anomaly detection approaches

In the field of anomaly detection, various alternative approaches have been utilized, with self-supervised and active learning being among the most significant. In the following, we introduce these approaches and provide examples from astronomy and (bio)medicine that could inspire using these architectures to enhance research in both domains.

5.3.1. Self-supervised learning

Self-supervised learning (SSL) represents an innovative approach with significant potential to address challenges in anomaly detection (AD) tasks. Unlike traditional supervised learning, which depends on large amounts of labeled data, SSL operates without explicit labels. Instead, it trains models using a pretext task where labels are generated automatically from the input data itself. This process involves creating tasks such as predicting parts of the data or reconstructing corrupted inputs, which allows the model to learn meaningful and robust features of the data. These learned representations are then transferable to downstream tasks, including anomaly detection. For instance, SSL techniques often involve preliminary tasks such as context feature engineering (Noroozi et al., 2018), where the model learns to predict missing parts of an image based on its surrounding context; image inpainting (Pathak et al., 2016), which involves filling in missing regions of an image; and context prediction (Doersch et al., 2016), where the model predicts the spatial arrangement of image patches. These methods help the model develop a deeper understanding of the data structure, enabling it to better identify anomalies in various applications. By leveraging these self-generated tasks, SSL can effectively enhance the performance of AD systems, especially in scenarios where labeled data is scarce or expensive to obtain.

Recent studies have explored the use of SSL in AD within biomedical and astronomical images. For instance, in Tian et al. (2023) the authors recommend an approach 'PMSACL' which is a unique optimization technique that distinguishes a regular image category from several artificially created abnormal image categories by ensuring that each category forms a compact cluster in the feature space. They demonstrate that the PMSACL pre-training enhances the precision of state-of-the-art unsupervised AD methods on various medical image

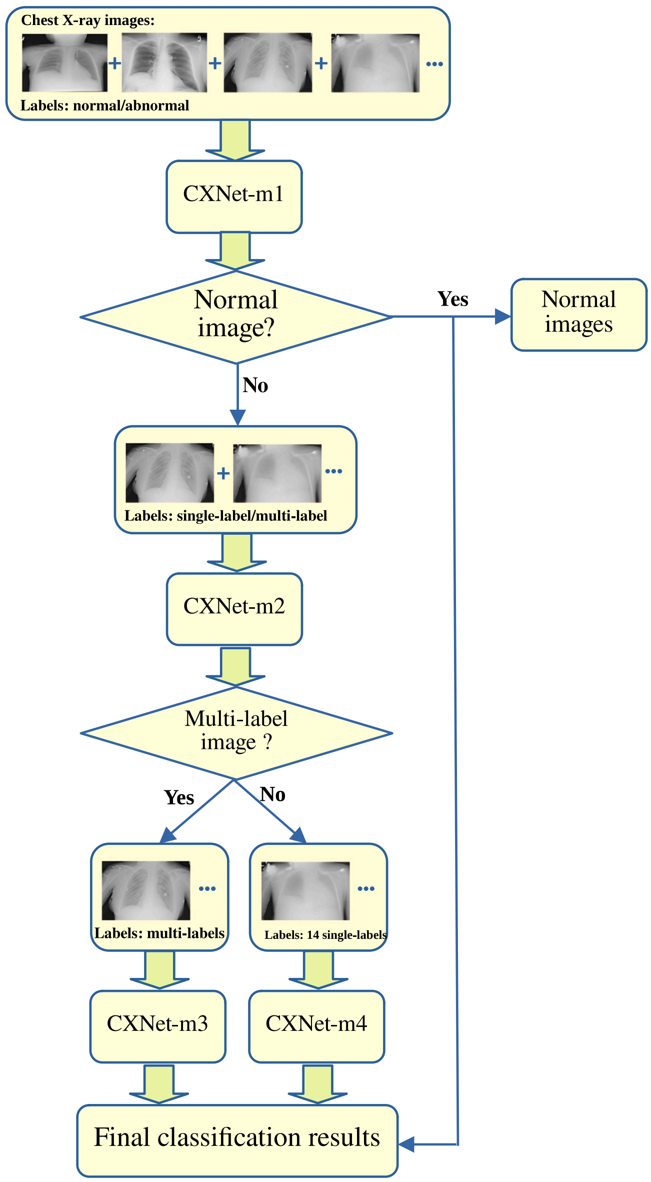

Fig. 8. Hierarchical CNNs structure (Xu et al., 2018) to find anomalous samples in chest X-ray.

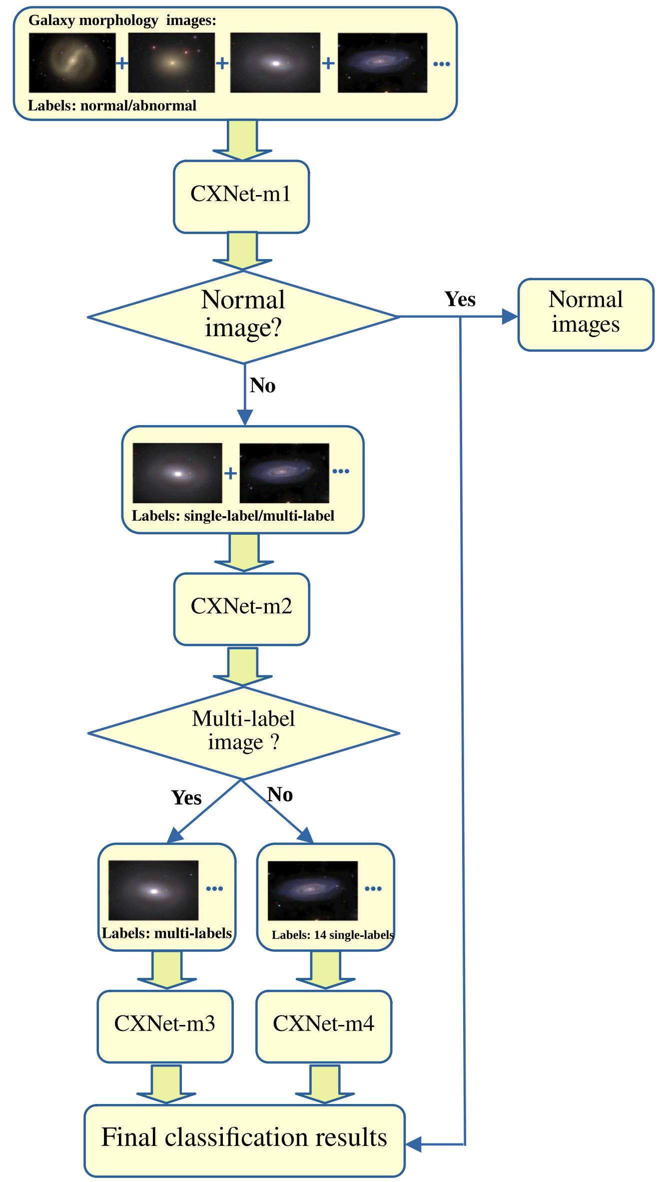

Fig. 9. Suggested proposal to apply the hierarchical CNN structure on galaxy morphology classification.

analysis benchmarks, including colonoscopy and Covid-19 Chest X-ray datasets. In the field of astronomy, for example in Hayat et al. (2021), the authors have utilized SSL to extract meaningful representations from sky survey images that are beneficial for a range of scientific purposes. These representations can be employed as features to surpass supervised methods that are trained solely on labeled data. The achieved results show that the classification accuracy with this method is equal to the supervised models while requiring 2–4 times fewer labels for training.

5.3.2. Active learning

Active Learning (AL) is a strategy where an algorithm actively interacts with a human or an oracle to obtain labels for data points it finds uncertain or ambiguous. Instead of randomly selecting instances for labeling, the algorithm identifies and queries the most informative or uncertain data points. This targeted approach aims to improve the learning model's performance efficiently while minimizing the number of data points that need to be labeled. This makes AL particularly valuable in scenarios where labeling is expensive or time-consuming, as it optimizes the process of acquiring essential labels and accelerates the development of high-performing models.

In Lochner and Bassett (2021), the authors employ a method called 'Astronomaly' to identify rare and significant astrophysical events within astronomy survey data. They leverage active learning to efficiently distinguish between noteworthy anomalies and irrelevant data, such as instrument artifacts or rare astronomical phenomena that might not be of immediate interest to researchers. This approach helps focus efforts on truly significant discoveries while minimizing the distraction of less relevant data. Similarly, in Iglesias et al. (2011), the authors address the challenge of identifying organs in CT scans, which traditionally requires a large volume of manually annotated 3D images. To overcome this, they integrate active learning into their training procedure, which smartly selects a minimal yet representative subset of images for labeling. This approach allows for accurate anatomical segmentation while reducing the need for extensive manual annotations, thereby streamlining the process and making it more cost-effective.

Both studies illustrate the effective use of active learning (AL) in diverse fields — astronomy and medical imaging — to improve data analysis and lower the costs associated with manual labeling. In astronomy, AL aids in distinguishing significant astrophysical events from noisy data, while in medical imaging, it refines the labeling process for accurate anatomical segmentation. However, it is important to note that SSL and AL have yet to make substantial advances in the realm of anomaly detection within these fields. There remains significant potential to enhance the efficiency of both supervised and unsupervised learning models by leveraging pretext tasks, such as medical and astronomical image segmentation. By incorporating SSL techniques and AL strategies, it may be possible to improve anomaly detection outcomes and streamline data processing in these areas.

6. Common ML challenges in astronomy and medicine

Like other solutions, machine learning algorithms present specific challenges that warrant careful consideration before implementation. These challenges encompass scalability issues, potential biases in the data, imbalances within datasets, the existence of non-labeled data, and the necessity to mitigate noise within the provided dataset. Effectively addressing these challenges requires interdisciplinary collaboration among domain experts, data scientists, and machine learning specialists. Additionally, continuous research and advancements in machine learning methodologies are crucial in refining solutions and tackling evolving challenges within the dynamic fields of astronomy and medical imaging.

1. Scalability Issues

1.1. Astronomy : Astronomy deals with massive datasets generated by ground-based and space-based surveys. Traditional computing resources may struggle to handle the scale and complexity of these datasets. As a solution, astronomers employ distributed computing frameworks (e.g., Apache Spark) and parallel processing techniques to process and analyze large volumes of observational data efficiently. Cloud computing resources are often leveraged for scalable and on-demand computational power.

1.2. Medicine: Medical imaging datasets, especially high-resolution scans, can be enormous and computationally intensive. Similar to astronomy, cloud computing and parallel processing are utilized to address scalability issues. High-performance computing (HPC) clusters are employed to handle the computational demands of processing and analyzing large medical imaging datasets.

2. Biased Data

2.1. Astronomy: Bias in astronomical datasets can arise from observational constraints or selection biases in survey designs, potentially leading to skewed model outcomes. Calibration processes are implemented to correct for observational biases. Statistical methods and data Pre-processing techniques help identify and mitigate biases, ensuring that machine learning models are trained on more representative datasets.

2.2. Medicine: Bias in medical datasets may result from demographic disparities in patient populations or healthcare access. Strategies include oversampling minority groups, adjusting class weights during training, and employing techniques to ensure fair representation of diverse patient cohorts. Ethical considerations play a role in addressing bias to avoid perpetuating healthcare disparities.

3. Imbalanced Data

3.1. Astronomy: Certain classes of celestial objects may be underrepresented in astronomical datasets, leading to imbalances. Techniques like oversampling, undersampling, or using advanced algorithms designed for handling imbalanced datasets are among the existing solutions. These methods ensure that machine learning models can effectively learn from both majority and minority classes.

3.2. Medicine : Imbalances may exist in medical datasets, especially when dealing with (rare) diseases or conditions. Similar to astronomy, oversampling, undersampling, and the use of specialized algorithms are employed to address imbalanced medical datasets. Algorithms designed to handle skewed distributions, such as those based on ensemble learning, can be beneficial.

4. Non-labeled Datasets

4.1. Astronomy: In astronomy, a large volume of unlabeled data exists primarily due to the vast scale and complexity of astronomical surveys. The sheer amount of data generated by telescopes and other instruments exceeds the capacity of human experts to label comprehensively. Additionally, the diversity of celestial objects and phenomena requires specialized knowledge to accurately annotate the data, which is often impractical given the resources available. As a result, much of the data remains unlabeled, posing challenges for supervised learning approaches in the field.

4.2. Medicine: Obtaining comprehensive and accurate labels for data is often a significant challenge due to the complexity and volume of medical images, as well as the expertise required to annotate them correctly. To address this issue, unsupervised learning methods, such as clustering algorithms and self-supervised learning, are increasingly employed to analyze and extract useful patterns from non-labeled medical datasets.

5. Noise in Datasets

5.1. Astronomy: Astronomical datasets can be affected by various noise sources, such as atmospheric conditions and instrumental errors. Preprocessing techniques, including data cleaning and filtering, are crucial to reduce noise impact. Signal processing methods, such as Fourier analysis, are applied to enhance the signal-to-noise ratio in astronomical observations.

5.2. Medicine: Medical images may contain noise due to factors like patient movement or equipment limitations. Image denoising techniques are employed, ranging from traditional filters to deep learning-based approaches. Quality control processes, including motion correction and artifact removal, are integral to ensuring the accuracy of medical image analysis.

7. Enhancing CNN's performance with RL

CNNs have several advantages in object detection and segmentation tasks such as the ability to learn hierarchical features from input data, capture spatial hierarchies, perform end-to-end learning, and use transfer learning. However, they often require large amounts of labeled data for effective training, which can be challenging to acquire in both (bio)medical imaging and astronomy. Training deep CNNs is computationally intensive and requires powerful hardware resources. The complex nature of deep neural networks, including CNNs, often results in a lack of interpretability. They can also be prone to overfitting, particularly when the training dataset is limited. There are several challenges in object detection and segmentation algorithms such as generalizability (see Section 3 for more details). For example, in (bio)medical imaging, the variations in tumor appearance, size, location, and imaging artifacts leads to generating numerous research efforts, each dedicated to a specific problems space. One solution to generalizability is to benefit from reinforcement learning (RL) technique in architecture search, and automatic hyper-parameter estimation. In this section, we delve deeper into the algorithmic aspects of a few articles in the context of multi-object detection, and discuss the impact of RL to improve the decision-making process in algorithm development.

Algorithm 1 demonstrates the general processing steps in using CNNs in object detection and classification tasks. This algorithm takes a

Algorithm 1 CNN pseudo-code for object detection

Input: Input Image I, Training Data (X, Y)
Output: Tumor Classification
Initialize CNN parameters:
Filter size: f, Stride: s, Padding: p
Number of filters: n_f, Learning rate: α
Initialize Weights and Biases:
W_1, b_1 for Convolutional Layer 1
W_2, b_2 for Fully Connected Layer
Forward Propagation:
Convolution Layer 1: $Z_1 = W_1 * I + b_1$, Activation: $A_1 = \mathrm{ReLU}(Z_1)$
Fully Connected Layer: $Z_2 = W_2 \cdot \mathrm{Flatten}(A_1) + b_2$, Activation: $A_2 = \mathrm{Softmax}(Z_2)$
Compute Loss:
Cross-Entropy Loss: $L = -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{c} Y_{ij} \cdot \log(A_{2ij})$
Backward Propagation:
Compute Gradients: $\frac{\partial L}{\partial W_2}, \frac{\partial L}{\partial b_2}, \frac{\partial L}{\partial W_1}, \frac{\partial L}{\partial b_1}$
Update Weights and Biases:
$W_1 = W_1 - \alpha \cdot \frac{\partial L}{\partial W_1}$, $b_1 = b_1 - \alpha \cdot \frac{\partial L}{\partial b_1}$
$W_2 = W_2 - \alpha \cdot \frac{\partial L}{\partial W_2}$, $b_2 = b_2 - \alpha \cdot \frac{\partial L}{\partial b_2}$
Training Loop:
for each epoch **do**
    Shuffle and batch the training data
    for each batch $(X_{\text{batch}}, Y_{\text{batch}})$ **do**
        Perform Forward Propagation
        Compute Loss
        Perform Backward Propagation
        Update Weights and Biases
    end for
end for
Classification:
Use the trained CNN to classify the original I

Algorithm 2 Integrating RL into CNN-based Images

Input: Labeled medical imaging dataset $\mathcal{D}$, CNN model CNN
Initialize: RL agent RL_Agent, CNN parameters Θ_{CNN}, RL hyperparameters
for each training iteration **do**
    1. Active Learning with RL:
        - Select informative samples for annotation using RL_Agent: $\mathcal{S}_{\text{annot}} \leftarrow \text{RL\_Agent}(\mathcal{D})$
    2. Dynamic Hyperparameter Tuning:
        - Adjust CNN hyperparameters using RL-guided strategy: $\Theta_{\text{CNN}} \leftarrow \text{RL\_Agent}(\Theta_{\text{CNN}})$
    3. CNN Training:
        - Train CNN on the labeled dataset: $\text{CNN}(\mathcal{D}, \Theta_{\text{CNN}})$
    4. Automatic Segmentation Refinement:
        - Refine CNN's segmentation using RL: Refined_Segmentation ← RL_Agent(CNN, Segmentation)
    5. Transfer Learning with RL:
        - Apply RL for efficient transfer learning between datasets: $\Theta_{\text{CNN\_new}} \leftarrow \text{RL\_Agent}(\Theta_{\text{CNN}}, \mathcal{D}_{\text{new}})$
    6. Adaptive Image Acquisition:
        - RL-guided selection of informative images for training: $\mathcal{S}_{\text{train}} \leftarrow \text{RL\_Agent}(\mathcal{D})$
    7. Interactive Segmentation with RL:
        - RL-guided interaction with human annotator for real-time refinement: Refined_Segmentation ← RL_Agent(CNN, Human_Feedback)
    8. Handling Data Imbalance:
        - Use RL to adjust sample weights during training: Weights ← RL_Agent($\mathcal{D}$)
    9. Optimizing Evaluation Metrics:
        - Dynamically optimize evaluation metrics using RL: Optimized_Metrics ← RL_Agent(Metrics)
end for
Output: Trained CNN model for brain tumor segmentation

labeled image dataset and a CNN model as input. The CNN parameters are initialized along with other hyperparameters. Images undergo Pre-processing steps, and the dataset is split into training and validation sets. Then, the algorithm iterates through each training epoch, and the CNN processes the input images using its current parameters to produce predictions. The cross-entropy loss is computed based on the predicted and true labels in the training set. The gradients of the loss to the CNN parameters are computed through backpropagation, and the CNN parameters are updated using gradient descent. Finally, the trained CNN model is evaluated on the validation set to monitor its generalization performance.

RL brings significant benefits in machine learning tasks through its versatile capabilities. By actively selecting the most informative samples for annotation, RL guides CNN models to prioritize critical areas within images, such as regions of interest like tumors, galaxies, etc. thereby significantly enhancing accuracy. This targeted focus ensures that the model learns from the most relevant information, leading to more precise and reliable outcomes. Moreover, RL's adaptive nature is pivotal in real-time adjustment of hyperparameters during training. This agility allows the model to continually adapt and optimize its performance as data distributions evolve, ensuring that it remains effective and robust across varying conditions and datasets. Furthermore, RL optimizes image acquisition strategies by intelligently selecting relevant imaging modalities or parameters. By doing so, it not only enhances the quality and relevance of the final results but also contributes to reducing unnecessary data acquisition costs and processing time. Additionally, RL's interactive capabilities foster seamless collaboration between human experts and automated systems. This collaborative approach enables real-time segmentation refinement based on user feedback, leveraging the strengths of both human expertise and machine learning algorithms to achieve superior results. By dynamically addressing data imbalance and optimizing evaluation metrics, RL ensures that the CNN models deliver robust and clinically relevant performance across various medical imaging applications. This adaptability and efficacy make RL a versatile and indispensable tool in the imaging domain.

We discuss the use of RL in optimizing CNN models performance by providing the pseudo-code in Algorithm 2. Similar to Algorithm 1, it gets labeled imaging dataset as input but it also imports a pre-existing CNN model. The RL agent is initialized along with the CNN parameters. Pre-processing steps are applied to prepare the data for integration with the CNN. The algorithm enters a training loop and utilizes RL to select informative samples, adjust hyperparameters, refine segmentation, facilitate transfer learning, guide image acquisition, and interact with a human annotator. RL is also employed to handle data imbalance and optimize evaluation metrics. The output is a trained CNN model with optimized parameters and potentially enhanced by RL-guided strategies.

Algorithm 3 presents an improved algorithm that takes into account RL. The process of using reinforcement learning for tumor detection involves several steps. First is Initialization, which sets up the initial conditions for the reinforcement learning algorithm. Next, comes pre-processing and Model Initialization, where the input MRI image is prepared by applying pre-processing steps, converting it into a feature vector for RL state representation, and initializing the CNN for feature extraction. Additionally, the tumor classifier is also initialized in this step. The Main RL Training Loop is where the RL agent interacts with the environment. Features are extracted from the modified image, combined with the state, and an action is selected based on the ϵ-greedy policy. The image is modified, and the agent receives a reward from the tumor classifier. Q-values are updated based on the reward, and the exploration rate is adjusted. Therefore, classification is performed after RL training. The original image is classified using tumor classifier to provide the final tumor classification.

Algorithm 3 Reinforcement Learning for Brain Tumor Detection

```
Input: MRI Image I, RL Parameters
Output: Object Classification
Initialize Q-table Q with random values
Set learning rate α, discount factor γ, exploration rate ϵ
Preprocess I (e.g., normalization, resizing)
Convert I to feature vector S for RL state representation
Initialize CNN for feature extraction (e.g., pre-trained on ImageNet)
Initialize tumor classifier
Train CNN and classifier on labeled data
while not converged do
    Extract features F using CNN from preprocessed I
    Combine S and F to form RL state S_RL
    Select action A using ϵ-greedy policy based on Q(S_RL, A)
    Apply A to modify I (e.g., focus on certain regions)
    Obtain reward R from tumor classifier based on modified I
    Preprocess modified I and update state S_RL
    Update Q-value: Q(S_RL, A) ← (1 − α) · Q(S_RL, A) + α · (R + γ · max_a′ Q(S_RL, a′))
    Update ϵ (exploration rate decay)
end while
Classification:
Use the trained CNN and classifier to classify the original I
```

8. Conclusion and future direction

This paper has highlighted the synergies between astronomy and biomedical imaging, particularly emphasizing the utilization of artificial intelligence, notably convolutional neural networks, to tackle shared challenges. We started by building upon previous literature discussing parallels in imaging processes between MRI and radio astronomy. We then elaborated on these similarities, emphasizing the crucial need for precise signal acquisition to prevent aliasing artifacts and ensure accurate image reconstruction in both domains. Innovations such as parallel imaging and compressed sensing have emerged as promising strategies to overcome these challenges, enabling efficient data acquisition and offering benefits in terms of reduced measurement requirements and enhanced imaging efficiency. Both fields face common challenges including the need to balance data reduction with image quality and the computational complexity of algorithms. Collaborative endeavors between MRI and radio astronomy researchers hold potential to drive advancements in image reconstruction, and signal processing techniques across disciplines.

Moreover, this study has underscored a shared challenge in object detection and segmentation between (bio)medical and astronomical fields. We have highlighted common technologies employed in both domains to identify and segment objects of interest in images, introducing representative deep-learning models. By focusing on cell segmentation as an example, we have observed the evolution of deep learning segmentation models, such as U-net and its variants, within biomedical studies. Given the diverse sample preparation procedures, cell lines, and microscopy modalities, there exists a pressing need to develop generalized models for cell segmentation. This underscores the importance of continued interdisciplinary collaboration to address shared challenges and drive innovation in both astronomy and biomedical imaging.

One way to introduce generalizability is to integrate Reinforcement Learning in the object detection or segmentation tasks. RL-enabled object detectors can facilitate adaptive decision-making processes, enabling object detectors to iteratively refine their predictions and adapt to varying environmental conditions. By leveraging RL's capacity to adaptively learn from diverse data sources and environments, there is promising potential to mitigate this challenge. Through interdisciplinary collaboration and the application of shared methodologies, such as RL, researchers can foster innovative solutions that transcend disciplinary boundaries, leading to enhanced object detection capabilities and deeper insights across biomedical sciences and astronomy.

Our research extends to study generative models, a class of machine learning algorithms adept at creating synthetic data that mimics real-world observations in both fields. In medicine, they address data scarcity and privacy concerns, allowing researchers to develop new diagnostic tools, personalize treatment plans, and even discover novel drug candidates. For instance, generative models can create synthetic patient data that preserves statistical properties while safeguarding privacy. In astrophysics, generative models grapple with the vastness and complexity of the cosmos. Here, they are instrumental in simulating galaxies, the large-scale structure of the universe, and even cosmic phenomena like gravitational waves. These simulations offer valuable insights into galaxy formation, dark matter distribution, and the evolution of the universe itself. Despite these domain-specific applications, both medicine and astrophysics leverage generative models to augment data, create simulations of complex phenomena, and ultimately push the boundaries of scientific discovery.

Moreover, we studied deep anomaly detection approaches in both (bio)medical and astronomy imaging. Unsupervised deep anomaly detection has gained more attention recently due to its ability to work without labeled data. The two main architectures commonly used in unsupervised deep anomaly detection are Autoencoders and Generative Adversarial Networks. By exploring the similarities and differences in applying deep anomaly detection approaches in these fields, we can enhance the algorithms for both biomedical and astronomy. This paper compares these approaches using similar datasets in astronomy and biomedical imaging, such as Electrocardiogram and gravitational wave data. Furthermore, techniques like hierarchical Convolutional Neural Networks within the supervised learning context in biomedical imaging can be adapted for astronomy applications, such as galaxy morphology classification. Alternative approaches like self-supervised learning and active learning show significant potential to improve the efficiency of both supervised and unsupervised deep anomaly detection methods.

In light of this research, there are several avenues for future exploration and collaboration between researchers in biomedical imaging and astronomy. Integrating Reinforcement Learning (RL) into object detection and segmentation tasks can enhance adaptability and generalizability, particularly in addressing diverse sample preparations and microscopy modalities in biomedical studies. Furthermore, extending research into generative models offers promising prospects for overcoming data scarcity and privacy concerns and simulating complex phenomena in both fields. Collaborative efforts to adapt and refine deep anomaly detection approaches, such as Autoencoders and Generative Adversarial Networks, can lead to more robust algorithms benefiting both biomedical and astronomical imaging tasks. By leveraging shared methodologies and datasets, interdisciplinary collaboration is key to unlocking innovative solutions that transcend disciplinary boundaries and advance scientific discovery in both domains. Also, we plan to explore the implementation and empirical evaluation of the proposed RL-CNN integration to validate the algorithmic concepts discussed. This will involve conducting performance tests and comparative studies to measure the effectiveness of RL in enhancing CNN performance, particularly in the context of tumor detection and other complex object detection tasks. Additionally, we intend to investigate how different RL strategies can be fine-tuned for various CNN architectures to address challenges such as data imbalance, computational requirements, and generalizability.

CRediT authorship contribution statement

S. Rezaei: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization. **A. Chegeni:** Writing – review & editing, Validation, Resources, Methodology, Formal analysis, Data curation. **A. Javadpour:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Data curation, Conceptualization. **A. VafaeiSadr:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Data curation. **L. Cao:** Writing – review & editing, Writing – original draft, Supervision, Investigation. **H. Röttgering:** Writing – review & editing, Writing – original draft, Supervision. **M. Staring:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

SR acknowledges the Kiem grant from Leiden University, which supports the development of new interdisciplinary research collaborations across disciplines. AC was supported by the MUR PRIN2022 project 20222JBEKN with title "LaScaLa" - funded by the European Union - NextGenerationEU.

Data availability

No data was used for the research described in the article.

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