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Advances on the morphological classification of radio galaxies: A review[☆,☆☆]

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ABSTRACT

Modern radio telescopes will generate, on a daily basis, data sets on the scale of exabytes for systems like the Square Kilometre Array (SKA). Massive data sets are a source of unknown and rare astrophysical phenomena that lead to discoveries. Nonetheless, this is only plausible with the exploitation of machine learning to complement human-aided and traditional statistical techniques. Recently, there has been a surge in scientific publications focusing on the use of machine/deep learning in radio astronomy, addressing challenges such as source extraction, morphological classification, and anomaly detection. This study provides a comprehensive and concise overview of the use of machine learning techniques for the morphological classification of radio galaxies. It summarizes the recent literature on this topic, highlighting the main challenges, achievements, state-of-the-art methods, and the future research directions in the field. The application of machine learning in radio astronomy has led to a new paradigm shift and a revolution in the automation of complex data processes. However, the optimal exploitation of machine/deep learning in radio astronomy, calls for continued collaborative efforts in the creation of high-resolution annotated data sets. This is especially true in the case of modern telescopes like MeerKAT and the LOw-Frequency ARray (LOFAR). Additionally, it is important to consider the potential benefits of utilizing multi-channel data cubes and algorithms that can leverage massive datasets without relying solely on annotated datasets for radio galaxy classification.

1. Introduction

Radio astronomy has seen an accelerated and exponential data eruption in the last two decades. Future radio telescopes like the Square Kilometre Array (SKA) will generate data sets on the scale of Exabytes. This will be one of the largest known big data projects in the world (Farnes et al., 2018). The low-frequency instrument SKA-LOW will be located in Australia while the mid-frequency instrument SKA-MID will be located in South Africa. SKA-LOW will have a peak real-time data rate of 10 TB/s (Labate et al., 2022), while SKA-MID will have a peak real-time data rate of 19 TB/s (Swart et al., 2022). Other similar projects currently contributing to data-intensive research in astronomy that form the baseline/pathfinder to SKA include MeerKAT,[1] which generates raw data at 2.2 TB/s (Booth and Jonas, 2012), the Murchison Widefield Array (MWA)[2] with a data rate of ∼300 GB/s (Lonsdale et al., 2009) and the LOw-Frequency ARray (LOFAR) generating raw data at the rate of 13 TB/s (van Haarlem et al., 2013). Astronomy has thus become a very data-intensive field with multi-wavelength and multi-messenger capabilities (An, 2019).

With the Evolutionary Map of the Universe (EMU) generating up to ∼70 million radio sources (Norris et al., 2011) and with the SKA expected to discover more than 500 million radio sources (Norris et al., 2014), computer-aided applications are unavoidable. Since the first publication on using deep learning for classifying radio sources by Aniyan and Thorat (2017), various machine/deep learning techniques have been explored and applied in many scientific publications. Hence, there is a need to take stock of published papers to get an up-to-date snapshot of the progress achieved and the current state-of-the-art in this field. This survey provides a comprehensive review of the existing approaches for radio galaxy classification, identifies the key

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[1] https://www.sarao.ac.za/gallery/meerkat/.
[2] https://www.mwatelescope.org.

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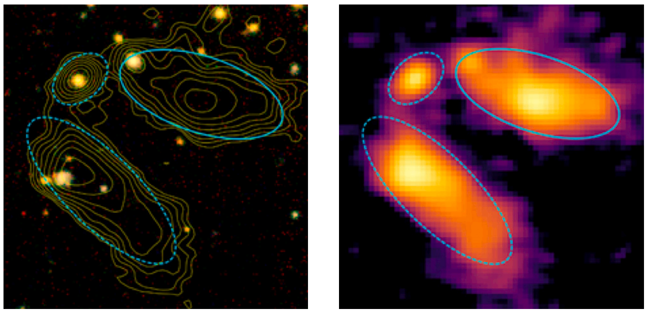


Fig. 1. An astronomical image as obtained from an optical and a radio telescope: (a) the Legacy telescope (optical) *R*-band intensity, and (b) the LoTSS-DR2 stokes *I* intensity. Source: Public LOFAR Galaxy Zoo: LOFAR. This is a typical example of a bent type galaxy.

challenges, and suggests future research directions (research gaps) in this rapidly evolving field.

Morphological classification is a crucial aspect of radio astronomy, as it allows scientists to understand the physical properties and characteristics of celestial objects based on their form and structure. Additionally, automated morphological analysis of large radio images can be a source of rare astrophysical phenomena, leading to serendipitous discoveries (Ray, 2016). Moreover, radio astronomy has played a very fundamental role in stimulating and spurring discoveries in the fields of cosmology, astrophysics, and telecommunications (Burke et al., 2019). Radio astronomy allows us to study celestial objects and phenomena at wavelengths that are not visible in the optical spectrum, providing unique insights into the Universe. For instance, radio image cubes are supplemented by data obtained from other portions of the electromagnetic spectrum for cross-identification to help tackle fundamental scientific challenges. Fig. 1, obtained from the public LOFAR Galaxy Zoo: LOFAR project,[3] illustrates this cross-identification process on an optical and a radio image of the same celestial object. These studies can help us better understand the physical processes at work in the Universe and the diverse objects it contains (Burke et al., 2019).

1.1. Key challenges in radio astronomy

In recent years, artificial intelligence has been extensively applied to automate daunting manual and challenging tasks in radio astronomy. Some of the main areas that have experienced revolution and notable progress are telescope performance monitoring and the processing/transformation of visibility and image cube data. In modern telescopes, the demand for high-resolution observations and efficiency is very high, hence, the necessity of real-time system health checks. To achieve this, machine learning algorithms are exploited (Hu et al., 2020). In Mesarcik et al. (2020), machine learning algorithms have demonstrated the capability to reliably detect, flag, and report system issues with above 95% accuracy. This substantially mitigates the risk of failures while at the same time maintaining the peak performance of the telescopes. During the data curation stage in the visibility domain, machine learning techniques are used to automate the process of detection and correction of errors occurring in recorded data, while simultaneously removing outliers in the data sets (Yatawatta and Avruch, 2021). Furthermore, they are applied in the identification and removal of radio frequency interference (RFI) - unwanted (noise) signals - which are produced by telecommunication technologies and other man-made equipment (Kerrigan et al., 2019; Vafaei Sadr et al., 2020; Sun et al., 2022). These kinds of signals and errors would degrade the quality of the data if not flagged.

In the image domain, the process of calibration relies heavily on the optimal fine-tuning of calibration parameters in the raw data processing pipelines. Reinforcement learning is applied to automate the process of selecting and updating calibration parameters (Yatawatta and Avruch, 2021). This process is a tedious task due to the high number of calibration parameters that must be tuned for telescopes with large fields of view (Wijnholds et al., 2010). Moreover, astronomy has experienced a proliferation in the application of machine/deep learning in astronomical radio images to explore and address fundamental scientific challenges. The major areas of research in radio astronomy include: extraction and finding of radio sources such as point-like sources and extended sources (Pino et al., 2021); classification of the celestial objects based on their morphological features (Lukic et al., 2018; Wu et al., 2018); the study and detection of rare celestial objects and phenomena such as pulsars, supernovas, quasars, Fast Radio Bursts, the 21 cm cosmological signal, and galaxies with unique and extraordinary morphologies (Bethapudi and Desai, 2018; Agarwal et al., 2020; Galvin et al., 2020; Mangena et al., 2020; Mostert et al., 2021; Bianco et al., 2021; Ni et al., 2022; Hartley et al., 2023); and the retrieval of galaxies with similar morphological characteristics (Abd El Aziz et al., 2017; Ndung'u et al., 2023).

Generally, computer-aided systems have resulted in a paradigm shift in the capacity, capability, and rate at which immense and complex astronomical data is exploited relative to traditional methods. This has been further boosted by high computing, software, and hardware improvements — playing a critical role in the automation of the research processes in modern astronomy. Big data, however, still presents challenges due to its complexity, and the computational resources and execution times that are required by such data sets.

The rest of the paper is structured as follows: Section 2, provides a brief background on radio astronomy. Section 3 presents the approach followed to retrieve the relevant papers for this review. Section 4 provides a detailed review of the adoption of machine/deep learning algorithms in morphological classification. Section 5 highlights the opportunities, challenges and future trends foreseen in the field of radio astronomy and finally, Section 6 presents a summary of the paper, highlighting the major insights from the review paper.

2. Background

2.1. Radio telescopes

Radio telescopes are specialized astronomical instruments that detect and receive very weak radio emissions radiated by extraterrestrial sources, for example, galaxies, planets, nebula, stars, and quasars. Radio telescopes can either be single parabolic dishes, such as the Five hundred meter Aperture Spherical Telescope (FAST) in China or a number of inter-connected telescopes/antennas; of which the Giant Metrewave Radio Telescope (GMRT) and LOFAR are prime examples (Table 1 and Fig. 2).

Angular resolution and sensitivity are fundamental aspects to consider in a telescope. While angular resolution refers to the ability of a telescope to clearly differentiate radio sources observed in the sky, sensitivity is the measure of the weakest radio source emissions detected over the random background noise (the flux density of celestial objects). Sensitivity is a product of several factors, namely signal coherence and processing efficiency, collecting aperture/dish area, along with receiver noise levels (Swart et al., 2022). With high resolution and sensitivity, astronomers are able to clearly resolve between celestial

[3] https://www.zooniverse.org/projects/chrismrp/radio-galaxy-zoo-lofar.

Table 1
Type and major radio telescopes of both the parabolic dishes and aperture arrays.

Type	Description	Major telescopes
Parabolic dishes	Single dish radio telescopes which have a parabolic reflector that receives incoming radio waves and focuses them onto a central radio antenna. The antenna receives and amplifies signals to generate radio images.	FAST Effelsberg Green Bank
Aperture/ Interferometric arrays	Large numbers of small connected antennas (radio wave receivers) on the ground in a certain order so as to capture multiple beams and a wide field of view of the sky. Interferometry principles are used to synthesize all signals from every antenna in the array and produce radio images with the same resolution as an image that was produced by a single dish. The interferometric array produces the same resolution as a single-dish instrument with the same size as the longest baseline in the aforementioned array.	LOFAR MWA
	Interferometry array or telescopes have a similar configuration to the aperture array telescope configuration. These are a series of connected parabolic dish telescopes. Radio interferometry principles are used to synthesize all the signals from all the constituent telescopes in the array.	MeerKAT GMRT VLA

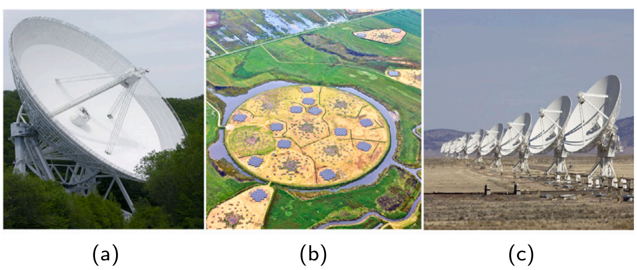


Fig. 2. Radio telescopes: (a) Effelsberg radio telescope single parabolic dish, (b) LOFAR antennas, and (c) the Karl G. Jansky Very Large Array (VLA) telescope array.

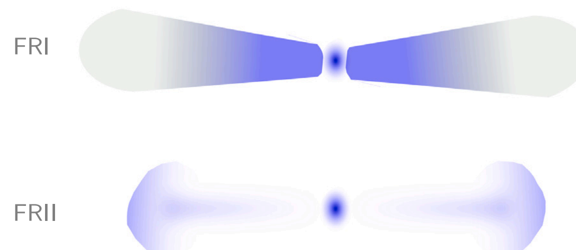


Fig. 3. A typical Fanaroff Riley I & II classification of radio galaxies.

objects and in doing so reveal more details of far faint stars and galaxies. The high angular resolution and sensitivity of radio telescopes have greatly boosted the acquisition of high resolution images through the next generation of wide-field radio surveys. For instance, LOFAR achieves a sensitivity of ∼100 μJy/beam and a resolution of ∼6″ which enables it to detect sources that are faint and have small angular scales with a high resolution (Shimwell et al., 2022a).

2.2. Radio galaxies

Radio galaxies are extensive astrophysical objects of radio emissions created by active supermassive black holes which form extended structures called jets and lobes. Fanaroff and Riley (1974) proposed to classify radio galaxies into two major families characterized by the distribution of luminosity of their extended radio emission. The first family is composed of centre-brightened (bright core) with one or two lobes. They have brightened cores extending to the lobes; exuding a decaying luminosity from the core. They are called Fanaroff & Riley I (FRI) galaxies. The second family is composed of edge-brightened lobes separated by a core at the center (the luminosity of the lobes decays as you move towards the center). They are referred to as Fanaroff & Riley II (FRII) galaxies (Fig. 3). Further examination of the morphological characteristics of FRI and FRII galaxies resulted in the identification of the narrow-angled tail (NAT) and wide-angled tail (WAT) (Rudnick and Owen, 1976) radio source populations with bent jets. In recent years, Fanaroff & Riley 0 (FR0) galaxies, which are compact point-like sources, were added to the radio galaxy classification (Baldi et al., 2015). They are approximately five times as numerous as the total number of FRI and FRII sources and therefore constitute the largest population of radio galaxies (Baldi et al., 2018). Other rare and minority classes of sources include Ring-shape, X-shape, W-shape, S-shape or Z-shape, Double Double, Tri-axial, and other Hybrid morphologies (Proctor, 2011).

2.3. Data management

In data-centric fields such as astronomy, data management standards of the archived data are essential in conduit of knowledge discovery and innovation. They increase the rate of adoption of scientific discovery, knowledge integration and reuse in the wider community of researchers. The data management practices adopted must by design and implementation follow the FAIR (Findable, Accessible, Interoperable and Reusable) principles (Wilkinson et al., 2016). The system should allow easy data access, search, tagging, retrieval, and replication in an efficient and transparent way. This leads to seamless integration and will allow global collaborations with other projects with similar data programs/systems.

Large radio astronomy facilities in the world store their data in either raw, calibrated/intermediate (for instance, VLA and LOFAR) or science-ready archives (for instance, ASKAP[4] and MeerKAT) (Louys et al., 2022). Some projects share their visibility data publicly via project-specific web interfaces.[5] Additionally, over the last few years, commendable progress in implementing FAIR principles in the field of astronomy has occurred due to the International Virtual Observatory Alliance (IVOA). It has been at the forefront of coordinating the integration of all the world's astronomy data into a federated system and has developed a standard set of protocols and specifications to be followed in astronomical data management (Louys et al., 2022). IVOA enhances data interoperability across global astronomical data providers. Moreover, a case study conducted by the Australian All-Sky Virtual Observatory demonstrated that the implementation of the recommended IVOA standards and protocols results in *almost* FAIR data (O'Toole and Tocknell, 2022).

[4] https://www.atnf.csiro.au/projects/askap/index.html.
[5] http://tdc-www.harvard.edu/astro.data.html.

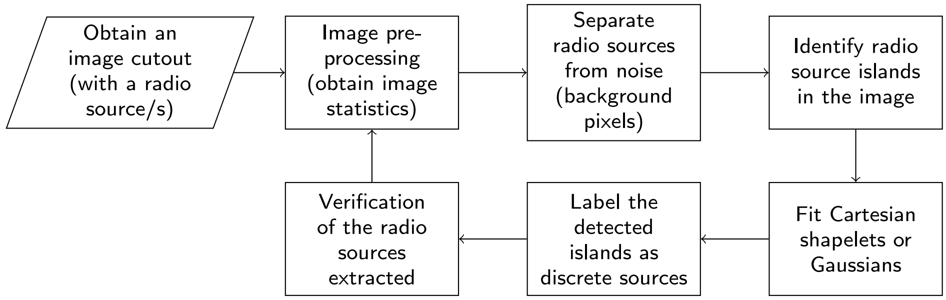
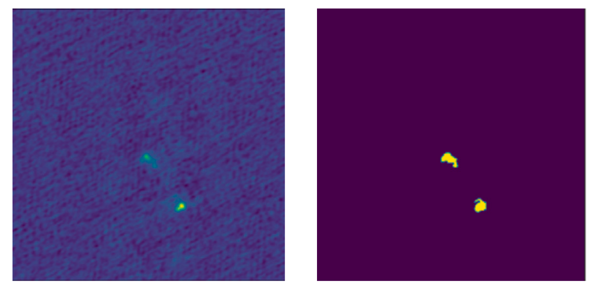


Fig. 4. The main steps illustrating the process of characterization and source extraction using PyBDSF.

2.3.1. Source extraction

Finding, extracting or characterizing whether radio sources are galaxies containing AGN or whether they are star-forming galaxies form the basis of the exploitation of radio surveys for scientific purposes. The data annotation mainly entails recovering the radio sources' delineation, position, estimated size, peak surface luminosity brightness, and providing labels and descriptions as per their morphological structure. The most reliable and accurate approach to annotating radio sources is a manual visual inspection of the images by radio astronomers. However, manual inspection by astronomers is limited due to the number of experienced astronomers dedicated to this task and also considering the size of the data.

Inspecting and characterizing radio sources is a difficult, costly, and time-consuming process. This has led to extensive development of statistical rule-based algorithms and methodologies for source extraction which are based on Cartesian shapelets, computer vision, Bayesian, and Gaussian methods. It has resulted in tools such as the Python Blob Detector and Source-Finder (PyBDSF) (Mohan and Rafferty, 2015), BLOBCAT, Hales et al. (2012) and Aegean (Hancock et al., 2012). PyBDSF, for instance, is based on the following algorithm, which is summarized in Fig. 4: (i) perform image pre-processing procedures and obtain image statistics, (ii) determine a threshold value that separates the radio sources and the background noise pixels in the image, (iii) with the background root mean square and mean values of the images, neighboring islands of radio source emissions are identified, (iv) the identified islands are fitted with multiple Cartesian shapelets or Gaussians to check if they are acceptable, and finally (v) the Gaussians fitted within an identified/detected island are labeled and grouped into discrete sources. Additionally, Fig. 5 shows an example of a two-component extended source extracted using PyBDSF.



(a) (b)

Fig. 5. (a) Original input image (with sources to be extracted) and (b) two-component compact sources output as identified and extracted by the PyBDSF software.

The study in Hopkins et al. (2015) finds that while these source finders are excellent for detecting compact sources, they suffer from insufficient robustness in the extraction of extended or diffuse sources. Therefore, to address this challenge, researchers are exploring deep learning-based techniques for the detection and extraction of radio sources. COSMODEEP (Gheller et al., 2018), DEEPSOURCE (Vafaei Sadr et al., 2019), ConvoSource (Lukic et al., 2019a), Mask R-CNN (He et al., 2017) in Astro R-CNN, and Tiramisu (Pino et al., 2021) - recent semantic segmentation based on U-Net (Ronneberger et al., 2015) are some examples. These methods have shown that the use of deep learning methodologies in the automatic detection and extraction of radio sources is robust and achieves high accuracies of above 90%. They offer promising alternatives for the extraction of diffuse sources that are known to be difficult to extract.

2.3.2. Commonly used catalogs

The compilation of annotated data catalogs that are publicly available and accessible is an important contribution to the promotion of the development of research in morphological classification of radio galaxies. Catalogs were compiled with different objectives such as detailed exploration, comparison and examination of a given population of galaxies (Baldi et al., 2018; Miraghaei and Best, 2017), provision of large and comprehensive labeled data sets for mining radio galaxy morphologies (Gendre et al., 2010; Proctor, 2011; Griese et al., 2023) and the creation of representative and balanced catalogs encompassing different classes of radio galaxies (Aniyan and Thorat, 2017; Ma et al., 2019a). Owing to the varied aims and different procedures of sample selection in developing the catalogs, the number of radio morphological classes per data set is different. For example, some catalogs contain a single class (Baldi et al., 2018; Capetti et al., 2017a; Capetti et al., 2017b), two classes (Best and Heckman, 2012; Gendre and Wall, 2008; Gendre et al., 2010), or more (Miraghaei and Best, 2017; Ma et al., 2019a; Proctor, 2011). Additionally, the catalogs are derived from various radio telescope surveys with different levels of luminosity. Table 2 summarizes the commonly used data sets in machine/deep learning applications of radio astronomy.

2.4. Anomaly detection

Besides the classification of known radio galaxies, recent studies aim to discover and characterize galaxies with unexpected properties (anomalies) (Giles and Walkowicz, 2018; Lochner and Bassett, 2021; Lochner et al., 2023; Mesarcik et al., 2023). With large data sets generated by radio telescopes, such as the EMU generating ∼70 million radio sources (Norris et al., 2011), the SKA1 All-Sky continuum survey (SASS1), which is expected to generate ∼500 million radio sources, or the SKA2 All-Sky continuum Survey (SASS2), which is expected to increase to ∼3500 million radio sources (Norris et al., 2014), the odds of discovering unknown unique objects are beyond doubt.

Anomaly detection is mainly an unsupervised task where no labeled data is required. In radio astronomy, there are few anomaly detection

Table 2
Commonly used data sets for morphological and anomaly detection. Abbreviations are defined in Table A.5 in the Appendix.

Dataset description	Galaxy groups	Year	Reference	Cited in
FRGMRC (n = 960) comprises 1. FR0CAT catalog 2. FRICAT catalog 3. FRIICAT catalog 4. Proctor catalog 5. CoNFIG 1–4 catalog	Compact, FRI, FRII, Bent	2023	Brand et al. (2023)	Brand et al. (2023)
FIRST radio galaxy data set: Samples selected from FIRST survey, 1995	Compact, FRI, FRII, Bent	2023	Griese et al. (2023)	
LoTSS (DR1 & DR2)	S, C and M	2019, 2022	Shimwell et al. (2019, 2022b)	Ntwaetsile and Geach (2021), Mingo et al. (2019), Lukic et al. (2019b) and Mostert et al. (2021)
LRG catalog (n = 1442) comprises 1. FR0CAT catalog 2. FRICAT catalog 3. FRIICAT catalog 4. Cheung catalog 5. Proctor catalog 6. CoNFIG 1–4 catalog	FR0, FRI, FRII, BT, XRG, RRG	2019	Baldi et al. (2018), Capetti et al. (2017a), Capetti et al. (2017b), Proctor (2011), Cheung (2007), Gendre et al. (2010) and Ma et al. (2019a)	Becker et al. (2021) and Ma et al. (2019a)
The unLRG catalog (14 245 samples): Samples selected from Best and Heckman samples (BH12)			Ma et al. (2019a)	Becker et al. (2021) and Ma et al. (2019a)
FR0CAT: Compact sources were extracted from BH12 sample	FR0	2018	Baldi et al. (2018)	Aniyan and Thorat (2017), Alhassan et al. (2018) and Rustige et al. (2023)
MiraBest (n = 1256) comprises 1. SDSS-DR7 2. FIRST survey, 1995 3. NVSS survey, 1998	FRI, FRII, Double–double, Head–tail, Wide-angle-tailed, Hybrid, Unclassified	2017	Miraghaei and Best (2017)	Scaife and Porter (2021), Sadeghi et al. (2021) and Slijepcevic et al. (2022)
FRICAT: Composed from 1. SDSS-DR7 2. FIRST survey, 1995 3. NVSS survey, 1998	FRI		Capetti et al. (2017a)	Aniyan and Thorat (2017), Alhassan et al. (2018), Samudre et al. (2022) and Maslej-Krešňáková et al. (2021)
FRIICAT: Composed from 1. SDSS-DR7 2. FIRST survey, 1995 3. NVSS survey, 1998	FRII		Capetti et al. (2017b)	Aniyan and Thorat (2017), Alhassan et al. (2018), Samudre et al. (2022) and Maslej-Krešňáková et al. (2021)
Radio Galaxy Zoo: Composed from 1. FIRST data release of 2004. 2. ATLAS-DR3. 3. WISE 2012 data release. 4. Spitzer Space Telescope data	S, C and M	2015	Banfield et al. (2015)	Tang et al. (2022), Wu et al. (2018), Ralph et al. (2019) and Lukic et al. (2018)
BH12: Composed from 1. SDSS-DR7 2. FIRST survey, 1995 3. NVSS survey, 1998	LERG, HERG	2012	Best and Heckman (2012)	Baldi et al. (2018) and Ma et al. (2019a)
Proctor catalog: Composed from the FIRST survey released in 2003.	X-shape, W-shape, Ring-shape, S-shape or Z-shape, Double Double, Wide-angle tail, Narrow-angle tail, Giant radio sources, Hybrid morphology, Tri-axial morphology	2011	Proctor (2011)	Ma et al. (2019b), Rustige et al. (2023), Maslej-Krešňáková et al. (2021) and Samudre et al. (2022)
CoNFIG 1–4: Composed from, 1. FIRST survey, 1995 2. NVSS survey, 1998	FRI, FRII	2008, 2010	Gendre and Wall (2008) and Gendre et al. (2010)	Aniyan and Thorat (2017), Alhassan et al. (2018) and Rustige et al. (2023)

applications that can be referenced. Galvin et al. (2019a), Galvin et al. (2020), and Mostert et al. (2021) investigated self-organizing maps to identify categories of radio galaxies using the Radio Galaxy Zoo Citizen project, Faint Images of the Radio-Sky at Twenty centimeters (FIRST) and Wide-field Infrared Survey Explorer (WISE) surveys, and LoTSS data, respectively. The identified objects that did not fall in any category of the known galaxies were annotated as outliers. In addition, Lochner and Bassett (2021) developed an active anomaly detection algorithm[6] that uses isolation forest and local outlier factor algorithms. In their paper, the anomaly detector is coupled with user feedback (based on interest). The algorithm detects and flags

[6] Active anomaly detection is an anomaly detection approach based on active learning. Active learning involves leveraging the expertise of a domain expert and the computational power of machine learning to improve the efficiency and effectiveness of the learning process.

outliers and the user scores the results, which are then used to suppress dissimilar objects and display similar ones.

Anomaly detection is challenging mainly because some identified anomalies may be artifacts introduced during data recording, calibration, and reduction procedures. Further to Lochner and Bassett (2021), some flagged anomalies may not be of interest to the research objectives of the astronomer. Therefore, the identified anomalies largely depend on the focus area of the astronomer and hence the relevance of the anomalies to a study may not be easily captured by machine/deep learning algorithms. Despite the progress achieved in the exploitation of machine intelligence, anomaly detection remains a challenging field of research.

3. Survey methodology

As already mentioned, the motivation of this survey paper is to give an account of the recent progress of computer intelligence in morphological classification in radio image data, with a focus on the last seven years that have seen substantial progress in deep learning paradigms.

Web of Science (WoS)[7] and NASA's Astrophysics Data System (NASA/ADS)[8] databases were used to retrieve relevant literature papers for the study. These databases offer advanced search capabilities and comprehensive coverage of high-quality journal articles across various disciplines, particularly in the areas of Computer Science and Astronomy, which are the focus of our research. Also, WoS indexes only published papers, while NASA/ADS indexes a wider pool of articles from conference announcements, pre-publication platforms (such as arXiv), along with published papers.

We sought to obtain a fair and representative sample of papers from the large pool of pre-published papers[9] and peer-reviewed articles written over the last seven years (2017–2023). The search strategy protocol illustrating the inclusion and exclusion criteria adopted is shown in Fig. 6 We conducted a literature search using the queries shown in Table 3 and retrieved $(173+52=)$ 225 papers. We then applied an exclusion criterion to filter out papers that were not relevant to our review topic. Specifically, we excluded papers dealing with solar, quasar, stellar, and spectrometry research, as these research topics are beyond the scope of our review. This filtering process reduced the number of papers to 75.

Out of the 75 papers retrieved from the two databases, 32 were duplicates or conference announcements, which we omitted, leaving us with 43 unique papers. After carefully reviewing these remaining 43 papers, we identified 25 that fit within the scope of our review. The 18 papers excluded during this last phase had various reasons: some covered data catalogs, source extraction and the like; some focused on the classification of data in other wavelengths such as γ-rays; some were about RFI detection, while others concentrated on other noteworthy celestial objects and phenomenon within the field of radio astronomy like pulsars, the 21 cm cosmological signal and Fast Radio Bursts. We did not include keywords such as *'rfi'* and *'pulsar'* in the exclusion criteria in Table 3, even though they were not relevant to our review. This is because including the keywords caused a significant drop in the number of relevant papers within our scope.

Additionally, based on recommendations from our peers, we included seven recently published papers that were deemed relevant and useful for our topic. Consequently, our final set of papers for the literature review consists of 32 articles. Notably, from the final

[7] https://www.webofscience.com/.

[8] https://ui.adsabs.harvard.edu/.

[9] These papers include journal, conference, and pre-print papers.

Table 3
Search queries used in Web of Science and NASA ADS for the retrieval of relevant review papers. TS = Topic sentence and PY = Publication year. Quotation marks are used for exact matching. The text in italics indicates the exclusion criteria in both queries.

Database	Query
WOS	TS = ("radio galax*" AND "classif*" AND ("*learning" OR "convolutional neural network*" OR "features")) *NOT TS = ("quasar*" OR "spect*" OR "blaza*" OR "redshift*" OR "burst" OR "stell*" OR "solar" OR "x-ray")* AND PY = (2017–2023)
NASA/ADS	("radio galax*" AND "classif*" AND ("learning" OR "convolutional neural network" OR "features")) *NOT ("quasar*" OR "spect*" OR "blaza*" OR "redshift" OR "burst" OR "stell*" OR "solar" OR "x-ray")* AND year:2017–2023

selection of papers extracted, there was no review paper covering the scope of radio astronomy thus reinforcing the need for this work. The few available review papers that we identified were in the wider field of astronomy, assessing the adoption and maturity of machine learning and deep learning in the field (Fluke and Jacobs, 2020; Wang et al., 2018).

Table 4 presents a high-level summary of the surveyed papers. The papers provide a wide range of machine/deep learning-based methods applied in the field of radio astronomy. In the Coxcomb chart (similar to a pie chart) shown in Fig. 7, the radius of each circle segment is proportional to the number of papers it represents. Therefore, the radius is determined by the frequency of the methodology in the papers surveyed. It can be observed that the majority of the methodologies used are based on shallow and deep convolutional neural networks (CNNs). Radio astronomy has indeed adopted and adapted the latest innovative and novel methodologies such as deep CNNs and Transformers from the larger science community. This has consequently led to the development of massive data-driven intelligent pipelines, which have automated the rather inefficient historically manual process.

4. Adoption of computer intelligence in radio astronomy

The adoption of machine/deep learning in radio astronomy has led to a plethora of machine and deep learning applications in classification and segmentation tasks. This can to a large extent be attributed to the resurgence of machine/deep learning, resulting in the development of innovative and novel deep learning architectures such as CNNs (also known as ConvNets) due to the exploitation of high-resolution images. ConvNets are to some extent inspired by the biological functionality of the human visual cortex. They have become the de facto choice for many computer vision tasks.

A simple ConvNet is generally composed of a set of convolutional (multiple building blocks), and subsampling (pooling) layers followed by a fully connected layer as shown in Fig. 8. In addition, various linear and non-linear mapping functions and regulatory units are embedded in the structure (e.g activation functions, batch normalization, and dropout) to optimize its performance. CNN models are designed to automatically and adaptively learn spatial features during training. The convolution and subsampling layers are focused on feature extraction while the fully connected layer maps the extracted features onto outputs. In the early layers of a CNN, simple features like edges are identified. Then, as the data progresses through the layers, more sophisticated features are determined. Notably, ConvNets classify images based on learned weights in the form of convolutional kernels obtained through the training process.

In the next section, we delve into a synthesis of the papers listed in Table 4.

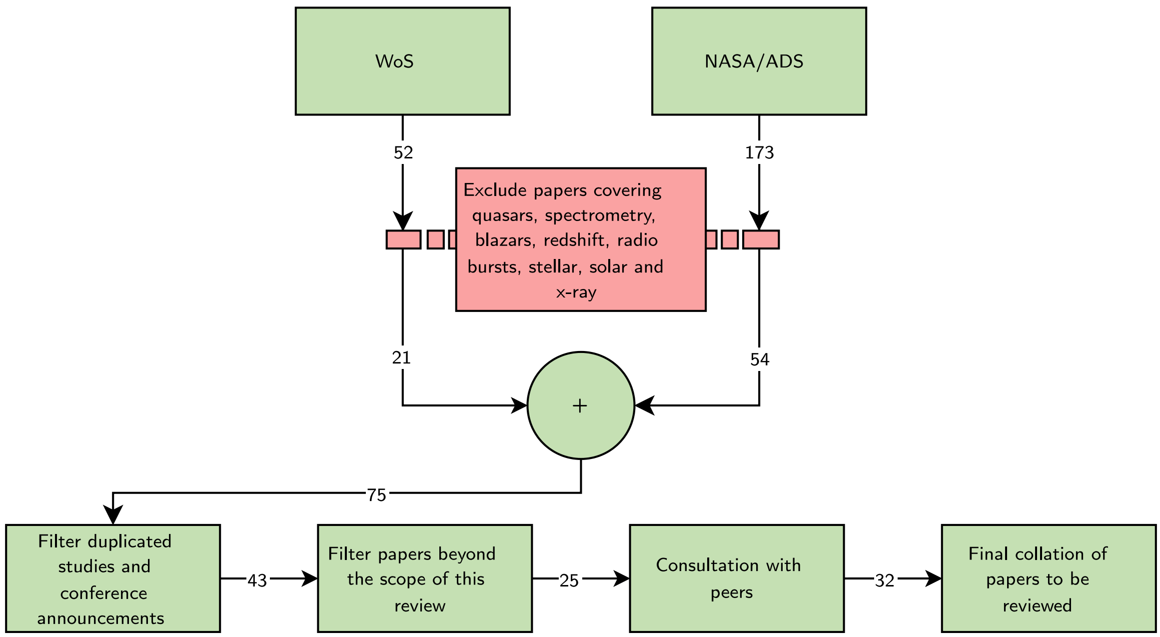


Fig. 6. A schematic study design process of exclusion and inclusion criteria adopted for the retrieval of the relevant articles considered in this survey. The flowchart shows the number of papers based on the query executed on 04/09/2023.

Table 4
Summary of the literature reviewed in this paper with a focus on classification problems. Abbreviations are defined in Table A.5 in the Appendix.

Number	Method name	Learning strategy	Catalog/Dataset	Data Aug.	Year	Citation
1	WSSS	SU	ASKAP & EMU	✓	2023	Gupta et al. (2023)
2	CNN	SU	ASKAP, Radio Galaxy Zoo & ATCA	✓		Sortino et al. (2023)
3	SSGEC	SSL	VLA FIRST survey & MiraBest	✓		Hossain et al. (2023)
4	Gradient Boost	SU	Best and Heckman sample	×		Darya et al. (2023)
5	CNN	SU	FRGMRC	✓		Brand et al. (2023)
6	BYOL	SSL	MiraBest & Radio Galaxy Zoo-DR1	✓		Slijepcevic et al. (2023)
7	wGAN	SU	FROCAT, FRICAT, FRIICAT, CoNFIG I & II, MiraBest, Proctor	✓		Rustige et al. (2023)
8	HeTu-v2	SU	VLA FIRST, 1995	✓		Lao et al. (2023)
9	CAESAR-MRCNN	SU	ASKAP & EMU	✓		Riggi et al. (2023)
10	FixMatch	SSL	Radio Galaxy Zoo	✓	2022	Slijepcevic et al. (2022)
11	CNN	SU	Radio Galaxy Zoo	✓		Tang et al. (2022)
12	YOLO	SU	FR0CAT, FRICAT, & FRIICAT	✓		Zhang et al. (2022)
13	FSL/DCNN	SU	FRICAT, FRIICAT, CoNFIG, Proctor	✓		Samudre et al. (2022)
14	CNN	SU	FRICAT, FRIICAT, CoNFIG & Proctor	✓	2021	Maslej-Krešňáková et al. (2021)
15	YOLO	SU	FRICAT & FRIICAT	✓		Wang et al. (2021)
16	E2CNN	SU	MiraBest	✓		Scaife and Porter (2021)
17	CONVXPRESS	SU	LRG & URG	✓		Becker et al. (2021)
18	HDBSCAN	US	LoTSS-DR1	×		Ntwaetsile and Geach (2021)
19	SVM and TWSVM	SU	MiraBest	×		Sadeghi et al. (2021)
20	CNN		Simulated SKA-like data	×	2020	Bonaldi et al. (2020)
21	Attention Gate CNN	SU	MiraBest & FR-DEEP	✓		Bowles et al. (2021)
22	CML	SU	Toothless Data	×	2019	Becker and Grobler (2019)
23	SOM & CAE	US	Radio Galaxy Zoo	✓		Ralph et al. (2019)
24	SOM	US	Radio Galaxy Zoo	×		Galvin et al. (2019b)
25	CNN	SSL	FRICAT, FRIICAT, Proctor	✓		Ma et al. (2019b)
26	DCNN	SU	CoNFIG, FRICAT, 2MASS, NVSS 1998 & FIRST 1995	✓		Tang et al. (2019)
27	SIMPLENET	SU	LoTSS DR1	✓		Lukic et al. (2019b)
28	PINK	US	Radio Galaxy Zoo	✓		Galvin et al. (2019a)
29	MCRGNet	SU	Best and Heckman sample	✓		Ma et al. (2019a)
30	FIRST Classifier	SU	CoNFIG, FRICAT, FRIICAT Proctor	✓	2018	Alhassan et al. (2018)
31	CLARAN	S	Radio Galaxy Zoo	×	2018	Wu et al. (2018)
32	Toothless	SU	CoNFIG, FRICAT, FRIICAT & Proctor	✓	2017	Aniyan and Thorat (2017)

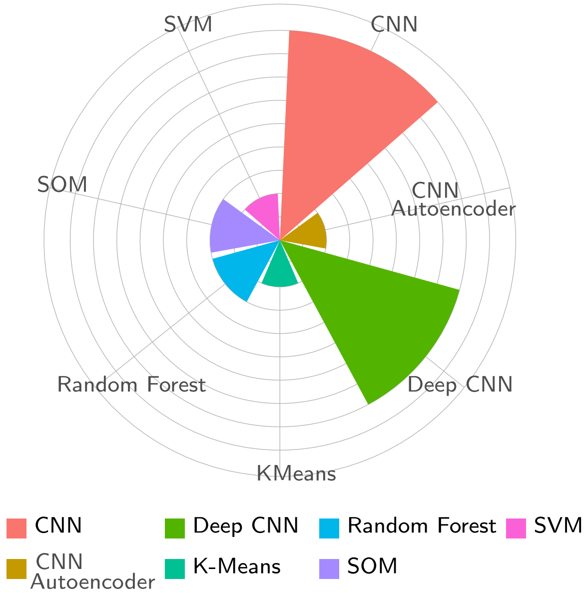


Fig. 7. A Coxcomb chart illustrating the top seven most commonly used machine learning methodologies in radio astronomy in recent years. The quantity of papers belonging to each of the seven categories is equal to the number of concentric circles that overlap the respective segment.

4.1. Morphological classification

The generation of science-ready survey catalogs requires the classification of processed calibrated radio images into various physical source categories such as galactic, extragalactic, AGN, and SF galaxies. The process of identifying and annotating such phenomena is very crucial in the preparation and release of science-ready products to the public for further scientific exploitation. Additionally, the process helps scientists to have a better comprehension of the Universe through exploring the fundamental laws of physics. Therefore, automating the process of visualization and the labeling of sources based on their morphological features is, therefore, critical in astronomy.

Broadly, morphological classification in radio astronomy entails grouping populations of Fanaroff–Riley (FR) radio galaxies into compact (point-like) and extended sources (FRI, FRII, WAT, NAT, XRG — X-shaped radio galaxies, RRG — ringlike radio galaxies, along with others); the extended sources contain complex morphological structures with two or more components in a galaxy. The developed FR classification approaches utilize either unsupervised, semi-supervised or supervised machine learning. Fig. 9 illustrates the general taxonomical categorization of classification methods reviewed.

Using supervised learning, Aniyan and Thorat (2017) developed the first ConvNet model based on Alexnet CNN architecture (Toothless[10]). Their model was evaluated on the Toothless[11] data set achieving accuracies of 95%, 91% and 75% for Bent-tailed, FRI and FRII, respectively. Their work provided a baseline that clearly demonstrates the potential of deep learning in classifying radio galaxies. Moreover, the VGG-16 architecture (Liu and Deng, 2015)*[12] was used in a semi-supervised way to classify radio galaxies and as such it leverages the large unlabeled data sets that are available (Ma et al., 2019b).

Unsupervised learning using methodologies like self-organizing maps were used by Galvin et al. (2019a), to construct radio morphologies based on similar/dissimilar characteristics of the Radio Galaxy Zoo project data (Banfield et al., 2015). The authors proposed the Parallelized rotation and flipping INvariant Kohonen maps (PINK) approach, which does not require training data labels, and hence avoids any potential bias by inexperienced practitioners in the Radio Galaxy Zoo project (Banfield et al., 2015). It only required human inspection and profiling of the resulting prototypes into known FR galaxy categories.

While deep learning methodologies are seen to be dominant in the classification task as seen in Table 4, conventional machine learning techniques have also been explored in the classification of FR galaxies. Becker and Grobler (2019) compared the following methodologies: Nearest Neighbors (Peterson, 2009)*, Support Vector Machine (SVM) (Cortes and Vapnik, 1995)*, Radial Basis Function SVM (Ding et al., 2021)*, Gaussian Process Regression (Banerjee et al., 2013)*, AdaBoosted Decision Tree (Freund and Schapire, 1997)*, Random Forest (Breiman, 2001)*, Naive Bayes (Rish et al., 2001)*, Multi-layered Perceptron (Piramuthu et al., 1994)* and Quadratic Discriminant Analysis (Bose et al., 2015)* in the classification of Fanaroff–Riley Radio Galaxies. Becker and Grobler (2019) used the Toothless data set excluding the bent-tailed radio sources in their implementation. A comparative analysis was performed between different conventional machine-learning algorithms on radio images. The Random Forest classifier was found to have the highest performance with an accuracy of 94.66% (Becker and Grobler, 2019). The study demonstrated that the derived morphological features from radio images are distinct and unique to radio galaxy classes. Additionally, Darya et al. (2023) demonstrated that gradient boosting methods (Friedman, 2002), such as XGBoost (Chen and Guestrin, 2016), LightGBM (Ke et al., 2017), and CatBoost (Dorogush et al., 2018), could perform competitively to CNN-based models.

In order to comprehensively discuss the papers under review, we consider data processing pipelines and model architectures used in the research papers. Specifically, the methodological applications covered in this review are categorized into three major groups: model-centric approaches, data-centric approaches, and weakly supervised approaches.

4.2. Model-centric approach

Research in computer intelligence predominantly dedicates resources and time to improving and optimizing machine learning algorithms. The development of novel model architectures has been witnessed in the space of deep learning. This has gradually been transferred to the field of radio astronomy given it is a data-driven field.

4.2.1. CNN architectures

Model architectures have been shown to play a significant role in improving and increasing the generalization of deep learning algorithms in classification problems. Therefore, we have seen progressive breakthroughs and applications of more complex architectures such as AlexNet (Krizhevsky et al., 2017)*(Aniyan and Thorat, 2017), VGG-16 (Ma et al., 2019b; Wu et al., 2018), and DenseNet (Huang et al., 2017)* (Samudre et al., 2022) in radio astronomy. The depth of the CNN architecture models are varied across different applications, depending on the required complexity. For instance, Lukic et al. (2019b) constructed four-layer (CONVNET4) and eight-layer (CONVNET8) convolutional networks, Becker et al. (2021) constructed eleven layers, Aniyan and Thorat (2017) constructed twelve layers, and Tang et al. (2019) constructed thirteen layers for classification of

[10] https://github.com/ratt-ru/toothless.

[11] Toothless is a three-class radio galaxy data set composed of selected well-resolved FRI (178 samples), FRII (284 samples), and Bent-tailed (254 samples) sources.

[12] The symbol * is used on citations that are not part of the papers under review.

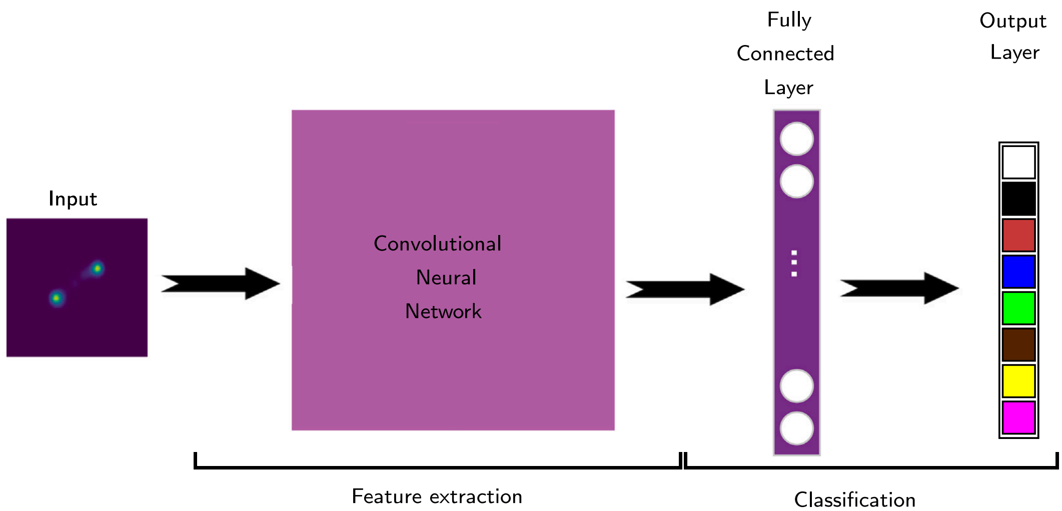


Fig. 8. The fundamental building blocks of a standard ConvNet.

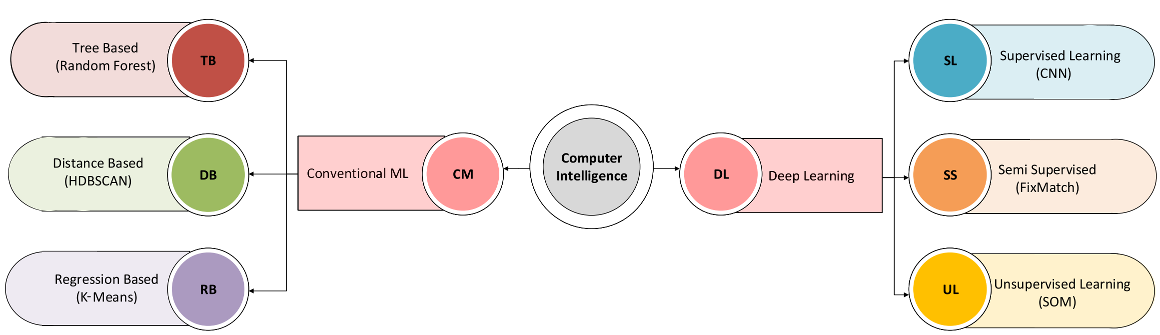


Fig. 9. Computer intelligence methodologies applied in the classification of radio galaxies.

radio galaxies. According to a comparative analysis done with a capsule network, CONVNET4 and CONVNET8 on the LoTSS DR1 data set, it was observed that CONVNET8 outperformed CONVNET4 and a capsule network, though with a marginal difference (Lukic et al., 2019b). The eight- and four-layer CNNs and the capsule network attained average precision scores of 94.3%, 93.3% and 89.7%, respectively. The secret behind the increase in depth of the convolutional layers is that it augments the number of nonlinear functions and introduces additional feature hierarchies that optimize the classification function. Consequently, the deep networks tend to achieve higher performance compared to more shallow networks (Tang et al., 2019).

4.2.2. Regularization techniques

Overfitting has been one of the central challenges affecting the robustness of radio galaxy classification models. The availability of small labeled astronomical data sets for building the models remains to be a major contributor to the challenge. To address this, researchers have adopted regularization techniques during model building. This is aimed at allowing the models to maximally learn from the limited training data and achieve better generalization. One technique used is the random dropping out of weakly connected units (neurons) of CNN connections during training (Tang et al., 2019, 2022). This approach is commonly referred to as dropout. Dropout helps to reduce parameter saturation during the training process preventing excessive co-adapting of the units. Moreover, to reduce covariance shift in the input data, the batch normalization technique is applied during model training (Tang et al., 2019, 2022). This involves standardizing the feature maps such that the values are transformed to follow a Gaussian distribution (regularize the network). These regularization approaches reduce the chances that the network will succumb to the vanishing gradient problem and reduce the time that the network requires to converge.

4.2.3. Specialized convolutional blocks

The key thrust in the performance of ConvNets compared to other models is the continued construction and integration of innovative processing units and the embedding of newly designed novel convolutional blocks. In radio astronomy, there are several novel research efforts in this direction.

Attention gates are convolutional blocks, that are analogous to the visual system of humans, that efficiently prioritize localized salient features in an object in order to contextualize and identify it. Bowles et al. (2021) implemented novel convolutional filters that localize salient features while suppressing irrelevant information on the provided images, thus, resulting in predictions obtained directly from pertinent and contextualized feature maps. The attention-gate layers are integrated in the CNN architectural backbone. This approach was found to reduce the CNN model training parameters by 50% and improves the interpretability of CNN models. It promotes explainable deep learning by using attention maps that can be investigated to trace the root cause of misclassification in a model. Despite the notable reduction in training parameters, the performance of the CNN architecture developed was equivalent to the state-of-the-art CNN applications in the literature.

Group equivariant Convolutional Neural Networks (G-CNNs) are convolution kernel filters that are embedded in a conventional CNN (Cohen and Welling, 2016)*. G-CNNs are aimed at supporting equivariance translation for a wider set of isometries (for example rotation and reflections) on the training data. By design, CNNs are constructed to be translation-equivariant of their feature maps, but this does not apply to other isometries such as rotation. This implies that G-CNNs allow preservation of group equivariance on augmented data - a common data-centric approach in deep learning model building. Thus, the increased data samples via rotational augmentations result in the same kernel (weight sharing) as they pass through the convolutional layers. This approach has been demonstrated to improve CNN architecture performance in the galaxy classification task using the MiraBest data set (Scaife and Porter, 2021).

Another innovative idea introduced to the standard convolutional architectures in radio astronomy is that of multidomain multibranch CNNs, which allow the models to take multiple data inputs as opposed to single source images (Tang et al., 2022).

4.3. Data-centric approaches

The quality and robustness of machine and deep learning algorithms are highly dependent on the quality of data. Quality entails the consistency, accuracy, completeness, relevance, and timeliness of the data. Principally, in order to improve the performance of the algorithms, data-centered approaches are paramount. The data (radio images) must be free from RFI noise and artifacts before calibration and processing. The data should not be ambiguous and each sample should belong to a definite radio galaxy class. Ideally, data must be highly curated.

In addition, to circumvent overfitting and simultaneously achieve high generalization accuracies, adequate data diversity on the training data set is a prerequisite. This aids in avoiding poor model performance when tested with real-world out-of-distribution data or covariate-shifted data.

4.3.1. Data augmentation

Data augmentation aims to increase the size and diversity of the training set. It is applied on the assumption that additional important information can be extracted from the insufficient data set available via augmentations. It has been widely espoused in radio galaxy classification to mitigate overfitting (Aniyan and Thorat, 2017; Alhassan et al., 2018; Lukic et al., 2018), to improve the performance of machine and deep learning models (Maslej-Krešňáková et al., 2021; Rustige et al., 2023; Lukic et al., 2018), to address rotational invariance (Becker et al., 2021), to increase the size and the diversity of the training data (Aniyan and Thorat, 2017; Alhassan et al., 2018; Becker et al., 2021; Ma et al., 2019a; Hossain et al., 2023), and to address the class imbalance, especially for the minority classes among the radio galaxy population groups in the training data (Lukic et al., 2018). There are different kinds of augmentation strategies. Two of these strategies are positional augmentation and color augmentation. Examples of the former include scaling, flipping, rotation, and affine transformation. Examples of the latter include brightness, contrast, and saturation (Best and Heckman, 2012; Becker et al., 2021; Scaife and Porter, 2021; Slijepcevic et al., 2022). Other augmentation approaches include upsampling or oversampling of the minority class and the utilization of generative adversarial networks (GANs) to generate new class instances (Rustige et al., 2023). The literature attests to the fact that data augmentation is a data-centered strategy that can significantly improve model performance and result in models with improved generalization ability (Maslej-Krešňáková et al., 2021).

Maslej-Krešňáková et al. (2021) found that improvement of model performance and capacity to generalize on out-of-distribution data was highly dependent on the augmentation strategy that was employed. They found that brightness increase, vertical or horizontal flips, and rotations led to better performance while zoom, shifts, and decrease in the brightness of the images degraded model performance. Therefore, the process of finding an optimal data augmentation strategy in a project is non-trivial. A downside of data augmentation is that any inherent bias or data errors will be inherited by the augmented data. Nevertheless, this does not rule out the fact that data augmentation is an important data-centric approach for both increasing minority data classes and improving model performance in the computer vision paradigm.

4.3.2. Rotation-invariance

Radio galaxies display diverse observational morphological shapes contingent upon the orientation of their jets relative to the line-of-sight of the telescope. Models must be robust enough to classify a test image even when presented in a different orientation, assigning it to the correct class. However, this is not always the case, resulting in low generalization of models in radio galaxy classification. Several methods can be used to deal with the problem of varying rotations in radio sources. One method, as already discussed, is to apply G-CNNs, which are specially designed to encode the orientation information of input galaxy images (Scaife and Porter, 2021). Another way is to augment the training data by adding rotations to the samples, enabling the CNNs to learn different orientations of the classes (Becker et al., 2021). Additionally, a pre-processing step can be done to standardize the rotation of all radio sources. This can be done by using principal component analysis (PCA) to align the principal components of the galaxies with the axes of the coordinate system, effectively normalizing their orientations (Brand et al., 2023). Similarly, Polsterer et al. (2019), perform a pre-processing step on the images by aligning them with the principal axis of their main component using a rotation and flipping invariant similarity measure. Therefore, in the pre-processing step, all images are adjusted through centering and scaling to ensure their invariance against this type of variation.

4.3.3. Feature engineering

Feature engineering is aimed at improving model accuracy in machine learning. It involves the process of careful selection based on domain knowledge, feature extraction, creation, manipulation, and transformation of the training data. The engineered features are targeted at providing the 'precise physical properties' of the image data for model development. In radio galaxy morphological classification, example morphological features include peak brightness, lobe size, and number of lobes (Becker and Grobler, 2019). Moreover, feature descriptors that represent the texture of radio images via Haralick features[13] (Ntwaetsile and Geach, 2021) and the use of Radial Zernike polynomials to extract image moments such as translation, rotation, that are scale-invariant are more examples of features that can be utilized (Sadeghi et al., 2021). In some cases, the principal component analysis (PCA) method is used to extract and reduce features from the images. PCA finds the components with the most variance in the data, which helps to reduce the data size and memory usage during training (Darya et al., 2023; Brand et al., 2023).

Machine learning algorithms are applied on the features engineered (compact representations of the radio images) for classification of radio galaxies. In this case, either supervised or unsupervised approaches are used, for example, Hierarchical Density Based Spatial Clustering of Applications with Noise (HDBSCAN) (Ntwaetsile and Geach, 2021), Random Forest (RF) (Becker and Grobler, 2019), gradient boosting methods (Darya et al., 2023) and SVM (Sadeghi et al., 2021). Feature engineering has been shown to provide machine learning algorithms with features of high importance resulting in high recognition performance, with accuracies above 95% (Sadeghi et al., 2021). However, the main drawback is that it requires domain expertise to design feature descriptors. Therefore, they may be unable to capture all the relevant information in the data.

[13] Haralick features are a set of thirteen non-parametric measures which are derived from the radio images based on the Grey Level Co-occurrence Matrix.

4.4. Weak supervision approaches

In radio astronomy, most publicly available catalogs contain 10^3 radio galaxies. Moreover, the cost of labeling sufficiently large (in deep learning terms) radio astronomical data sets is very high. On the contrary, unlabeled catalogs consist of Petabytes of data (from a single survey). Hence, the essence of exploring algorithms and strategies with the capacity of leveraging the massive unlabeled public catalogs and/or exploiting the small annotated data sets available are paramount.

Three weakly supervised methods, namely transfer learning, semi-supervised learning, and N-shot learning are discussed.

4.4.1. Transfer learning

Transfer learning is a paradigm that reuses knowledge gained from pre-trained models on massive data sets to fine-tune them on other tasks, making it effective if the training set is small. In the context of classification of radio galaxies, transfer learning has been investigated and has contributed to improved accuracies compared to other methods, such as few-shot learning (Samudre et al., 2022). The pre-trained model's weights and biases provide the generic feature representations essential to the model for identifying low-level features (i.e, shapes and edges) of the objects. Then, the complementary complex features specific to the classification task at hand are learned by fine-tuning the last layers of the model using the available small labeled data set. The study by Tang et al. (2019) investigated whether it was possible to develop robust cross-survey identification machine learning algorithms that made use of the transfer learning paradigm. In their research, they used FIRST and NVSS survey data, which are characterized by high- and low-resolution images, respectively. They found that models pre-trained on high-resolution surveys (FIRST) can be effectively transferred with high accuracies of about 94% (a case of 2 classes: FRI and FRII), to lower-resolution surveys (NVSS). However, the converse was observed not to be true.

Similarly, transfer learning on radio galaxy classification has been shown to achieve high performance even after extending the number of classes to more than two: FRI and FRII. Lukic et al. (2019b) used Inception ResNet model v2 (Szegedy et al., 2017) to classify three classes (FRI, FRII, and Unresolved) from the LoTSS-DR1 data. Inception ResNet model v2 achieved an average accuracy of 96.8%; the best performance compared to ConvNet-4, ConvNet-8 and Capsule Networks model architectures that they experimented with on the same data set. Additionally, a transfer learning method based on the Densenet architecture (Huang et al., 2017)* was tested by Samudre et al. (2022). They obtained a precision of 91.9%, a recall of 91.8% and an F_1 score of 91.8% for the classification of compact, FRI, FRII, and Bent radio galaxies with less than 3000 test samples (Samudre et al., 2022). Notably, transfer learning was observed to converge faster compared to conventional CNN architectures. For instance, the model converged faster (10 fewer epochs on average) than other models such as ConvNet-4 (Lukic et al., 2019b).

4.4.2. Semi-supervised learning

Semi-supervised learning (SSL) involves self-supervised learning followed by supervised fine-tuning. Thus, it utilizes both annotated data samples and a large amount of unannotated data during training. Employing semi-supervised techniques for the radio galaxy morphological classification task has recently been gaining traction within the literature. The reason for this can be ascribed to the fact that there are large publicly available unannotated data sets that are available for use within the field of radio astronomy.

Concerted efforts have been dedicated to investigating the possibility of exploiting these algorithms and conducting a comparative analysis of the performance with supervised machine learning (Ma et al., 2019b,a; Slijepcevic et al., 2022). Ma et al. (2019b) trained a semi-supervised model where they constructed a radio galaxy morphology classifier (autoencoder) from the VGG-16 architecture. The autoencoder was pre-trained on a large unannotated data set of 18,000 radio galaxies from the BH12 catalog (Best and Heckman, 2012). The pre-training of the modified VGG-16 architecture was aimed at updating its weight and bias parameters — allowing the model to learn the low-level morphological features of the radio galaxies (such as shapes and outlines). The pre-trained model was then fine-tuned with a small annotated data set of about 600 radio galaxies only. It was observed that the SSL strategy achieved high average precision and recall (of 91% and 90%, respectively). Similarly, the MCRGNet classifier (SSL model) was pre-trained on the unLRG (unlabeled radio galaxy) (14,245 samples) and fine-tuned on the LRG (labeled radio galaxy) (1442 samples) data sets (Ma et al., 2019a). The MCRGNet's average classification precision was 93%. This was a better precision compared to the competing methods at the time. Hossain et al. (2023) and Slijepcevic et al. (2023) use self-supervised methods BYOL (Bootstrap Your Own Latent) model (Grill et al., 2020)* and SimCLR (A Simple Framework for Contrastive Learning of Visual Representations) (Chen et al., 2020)* and later fine-tune the model for classification and achieve competitive results compared to classical supervised learning. For instance, Hossain et al. (2023) achieve a classification accuracy of 97.12% using a fine-tuned BYOL encoder, surpassing the state-of-the-art performance of 94.80% which was achieved by a supervised approach on the same dataset.

Another methodological approach used in SSL for radio galaxy classification is presented by Slijepcevic et al. (2022), which used the FixMatch algorithm (Sohn et al., 2020)*. In the FixMatch framework, a weakly augmented (for instance, shift or flip data augmentation methods) unannotated image is first fed into a model and then used to generate a pseudo-label. Then, in a concurrent fashion, the same unannotated image under strong augmentations (for instance, brightness, translation, or contrast) is fed into a model to generate a prediction. Thirdly, using cross-entropy or a distance measure, such as Fréchet inception distance, the model is trained to make the best prediction by matching the predictions of the pseudo-label[14] with the ones generated under the strongly augmented image (Sohn et al., 2020; Slijepcevic et al., 2022). Slijepcevic et al. (2022) used Tang's architecture classifier, in an SSL manner. They used MiraBest data (labeled) and the Radio Galaxy Zoo data release 1 (unlabeled). It was shown that the SSL strategy was able to extract knowledge from the unlabeled data thus achieving higher accuracy compared to the classifier based on Tang's architecture when applied to the MiraBest data (baseline).

4.4.3. N-shot learning

N-shot learning algorithms are designed to leverage the limited supervised information that is available (labeled data set) to make accurate predictions while avoiding overfitting challenges. There are different types of N-shot learning, namely Few-Shot Learning (FSL), One-Shot Learning (OSL), and Zero-Shot Learning (ZSL). Samudre et al. (2022) applied an FSL approach based on a Siamese neural network (Koch et al., 2015)*. The twin network model achieved an average precision of 74.2%, a recall of 74.0%, and an F_1 score of 74.1% for the classification of compact, FRI, FRII, and Bent radio galaxies (Samudre et al., 2022). In their experiment, a sample size of 2708 radio galaxies was used. The samples were composed of selections from the FRICAT, FRIICAT, CoNFIG, and Proctor data catalogs. While this approach has shown excellent performance on standard benchmark data sets, the twin network was found to yield relatively poor performance in comparison to state-of-the-art supervised machine learning approaches applied to real datasets.

[14] A pseudo-label is a label that is generated by a model's prediction rather than being manually assigned by a human annotator.

4.5. Beyond classification

In this section, we focus on a new emerging paradigm of galaxy detection, which goes beyond classification. Galaxy detection models not only classify the galaxies but also localize them. This is an innovative approach that addresses the limitations of traditional classification methods by incorporating an additional spatial component similar to source extraction (Section 2.3.1). Thus, the models can determine the precise locations and class labels of the detected galaxies. The first work on galaxy detection was conducted by Wu et al. (2018) using the Faster Region-based Convolutional Neural Networks (Faster R-CNN) method. They called their approach Classifying Radio sources Automatically with Neural networks (CLARAN). They trained CLARAN on the Radio Galaxy Zoo dataset to automatically detect and label diverse radio galaxies (galaxies with multiple components and peaks) into separate classes. This approach achieved an empirical plausibility accuracy of above 90% and a mean average precision (mAP) of 83.6%. Similarly, Wang et al. (2021) and Zhang et al. (2022) used YOLOv5[15] (Redmon et al., 2016)* for localization and recognition of radio galaxies. Both papers introduced novelty to the original YOLOv5 model. Wang et al. (2021) introduced a customized loss function and added an attention mechanism, the SKnet module (Li et al., 2019)*, to the architecture with the intention of making the model focus more on the salient radio source features in radio images. On the other hand, Zhang et al. (2022) introduced an attention mechanism dubbed SE Net (Hu et al., 2018)* to achieve the same end goal. The best YOLOv5 model achieved an mAP of 89.4% to locate FRI, FRII, and Compact radio galaxies. Alternatively, radio galaxy detection can be achieved by first performing segmentation and then classification (Lao et al., 2023). Lao et al. (2023) used Mask R-CNN achieving an mAP of 77.8% to locate Compact, FRI, FRII, Core-Jet (CJ), and Head-Tail (HT) sources. Similarly, Riggi et al. (2023) used Mask R-CNN, but this approach is noted to perform poorly on diffuse sources.

Gupta et al. (2023) proposed a weakly-supervised semantic segmentation approach for source segmentation and classification. Their method uses image-level class labels for training. They train the model to extract class activation maps (CAMs) and use them as pseudo labels to learn how to segment diffuse galaxies (with multiple components). Importantly, an inter-pixel relations network (IRNet) (Ahn et al., 2019)* is used to improve the CAMs and obtain instance segmentation masks over radio galaxies. Using ASKAP and EMU survey data their model achieved mAP_{50} of 67.5% for the radio masks across multiple classes[16]. Overall, Sortino et al. (2023), provides a comparison of notable semantic segmentation models in regards to how well they can perform source extraction, detection, localization and classification. Their findings show that Tiramisu (Pino et al., 2021) achieves the best performance without sacrificing much computational speed.

Additionally, novel deep learning approaches have been proposed for denoising and extracting complex faint radio emission from astronomical images (Gheller and Vazza, 2021) and to perform source localization directly in the visibility domain (Taran et al., 2023).

The Square Kilometre Array Observatory, through the Science Data Challenge series (1 and 2) (Bonaldi et al., 2020; Hartley et al., 2023), is also promoting the development of efficient and accurate analysis methods in the radio astronomy and scientific community. For instance, the Science Data Challenge 1 focused on source characterization, detection and classification methods. These methods were to be applied on simulated data (SKA-like data). Bonaldi et al. (2020) discusses the main challenges of source detection, classification, and characterization on simulated SKA continuum images: the high spatial density of the sources, the complex source morphologies, and the large data size. The paper also emphasizes the importance of applying multiple pipelines to the data to capture the diversity and complexity of the sources.

4.6. Strengths and weaknesses of morphological classification algorithms proposed

Machine and deep learning algorithms have automation capabilities that significantly reduce the reliance on astronomers as astronomical data increase exponentially. These algorithms generally excel at uncovering intricate salient patterns and hidden features within vast amounts of data, surpassing the limitations of human perception. Novel algorithms have been proposed for radio galaxy classification, significantly contributing to the automation and improvement of accuracy, robustness, and efficiency in classification models. For instance, models that are robust to rotations have been developed (e.g G-CNNs), ensuring accurate classification regardless of galaxy orientation. Moreover, researchers are exploring ways to achieve generalization inspite of the availability of limited annotated datasets (e.g., via Transfer Learning). Also, conventional machine learning algorithms, such as gradient boosting, which require less computational resources and are easier to interpret, have shown similar performance to deep learning algorithms. These advancements not only enhance model performance but also provide valuable insights for further research and development in the field, paving the way for discoveries and breakthroughs in our understanding of the Universe.

While machine learning and deep learning algorithms offer powerful capabilities, it is important to acknowledge their limitations and challenges. Firstly, these algorithms often demand significant computational resources and time to train and test, making them computationally expensive. Secondly, they can be susceptible to overfitting or underfitting if the dataset used for training is unrepresentative or imbalanced. Thirdly, the performance of these algorithms can be influenced by the choice of hyperparameters, architectures, and optimization methods, requiring careful tuning. Lastly, the main drawback of deep learning algorithms is the lack of interpretability or explainability of their results and decision-making process, which can hinder the understanding of how and why certain predictions are made. Recognizing these limitations encourages ongoing research and development to address these challenges and further enhance the applicability and reliability of machine learning and deep learning algorithms.

5. Opportunities, challenges, and outlook

Computer intelligence is having a remarkable impact on radio astronomy. A plethora of new insightful scientific work is published every year, resulting in even better and more accurate models that generalize well. As a result, it seems likely that robust models are soon to be developed that are capable of generating predictions across surveys from different yet related next-generation telescopes (such as LOFAR, MeerKAT, and SKA). Furthermore, these models would require slight to no modification once a new data release is made available. This highlights the potential for further scientific progress in utilizing raw radio image cubes generated by modern telescopes, through the incorporation of computer intelligence.

Despite the prevalence of massive high-resolution data sets from modern telescopes, only small sample-size annotated datasets have been catalogued over the past two decades. The limited size of the data can be attributed to the high cost of the labeling thereof. Also,

[15] YOLO stands for You Only Look Once: Unified, Real-Time Object Detection.

[16] 328 FR-I, 128 FR-II, 110 FR-X, and 196 R radio sources (Gupta et al., 2023).

the limited data available is subject to selection bias, since only well-resolved radio sources are hand-picked when creating the catalogs. This challenge, of limited data sets, hinders the ability to fully utilize and exploit the potential of machine/deep learning in the classification of radio galaxies in this data-rich field. While there are strategies (such as data augmentation, semi-supervised learning and weakly supervised approaches) leveraging small data samples (Tang et al., 2019; Slijepcevic et al., 2022), such techniques cannot match the diverse and unique astrophysical phenomena embedded in massive radio surveys. Therefore, this calls for continued collaborative efforts in the generation of annotated machine/deep learning-ready data sets.

It is evident that the current machine/deep learning models struggle to achieve satisfactory performance when applied to the latest high-resolution images from radio telescopes, such as LOFAR and MeerKAT (Tang et al., 2019). This limitation primarily arises from the fact that the training and testing datasets are drawn from different underlying distributions. As clearly seen in Table 2, most existing models are trained on radio galaxy images from surveys conducted two decades ago, such as the FIRST survey in 1995 and NVSS survey in 1998. These older images have lower resolution and higher noise levels compared to the recently surveyed data sets. Consequently, the models trained on such images fail to generalize to the new data sets from modern telescopes, resulting in the inaccurate detection and classification of radio sources.

The original images of radio galaxies are in 3D data cubes, but they are reduced to 2D data images for classification purposes using conventional algorithms. Data cubes (3D) contain additional information on the polarization of radio waves and are also provided at different radio frequencies/wavelengths which reveal different aspects of astronomical sources. The reduction of 3D data cubes to 2D images at the selected frequency results in the loss of important information that would be critical in training robust machine/learning models.

Radio astronomy is a data-rich and compute-intensive field, hence exploitation of scalable platforms and software is paramount. In order to train a model using techniques such as SOM (Galvin et al., 2019b), SVM (Sadeghi et al., 2021) and DCNN (Tang et al., 2019), a significant amount of computing resources are required. For instance, DCNNs typically require large amounts of images in order to learn over a million model parameters. Therefore, as the available data in astronomy increases exponentially, and more specialized machine/deep learning algorithms are developed, the demand for highly scalable computing performance is inevitable. High-performance computing (HPC), graphical processing units (GPUs) and distributed computing are often used to run such algorithms. In particular, big data (radio astronomical data) requires sophisticated methodologies to efficiently query and process large volumes of data. Despite the availability of numerous studies, as discussed in this review paper, there is still a wide gap in the utilization of scalable pipelines that allow for more efficient parallel and distributed machine/deep learning computations. Pipelines that would take advantage of some of the storage formats of the radio astronomical survey data. For instance, LOFAR uses H5parm, a Hierarchical Data Format version 5 (HDF5) compliant file format, which provides an excellent basis for applying Apache Spark,[17] a Big data processing ecosystem.

Radio sources are complex objects that consist of multiple spatially separated components. When these components are correctly grouped, they can be classified into respective galaxy groups; this process is referred to as radio source-component association. One of the promising directions for advancing research on machine/deep learning models for radio astronomy is to develop a multi-domain and multi-task model that can perform localization, radio source-component association, and classification in a given image. This multi-purpose model would thus encompass source extraction, which is a crucial step for data annotation. This would be beneficial for astronomers and researchers who need to create catalogs of massive datasets from radio surveys that will utilize reliable models (for instance, source extraction and classification models). Importantly, to make the models robust and reliable, especially in the case of diffuse emission, high-resolution data cubes at various wavelengths will have to be employed.

The inclusion of uncertainty quantification techniques in deep learning models is useful for enhancing the interpretability and generalization of radio galaxy classification models (Mohan et al., 2022). Uncertainty estimation plays a crucial role in understanding the reliability and confidence of the model's predictions, while also helping to identify sources of uncertainty such as noise, outliers, augmentation, or data curation. By quantifying the degree of uncertainty in the predictions of deep learning models for radio galaxy classification, researchers can gain valuable insights into the limitations and potential errors associated with these models. This information enables them to make informed decisions about the reliability of classifications and take appropriate measures to address any identified uncertainties.

Indexing radio galaxies beyond classification is a critical area of research. Indexing of identified radio sources is a prerequisite for fast retrieval of radio galaxies of similar/dissimilar morphological attributes. However, as this topic is hardly addressed in the literature covered, it highlights the existing research gap in radio astronomy that needs to be filled. Image indexing and/or retrieval is the process of finding objects (images) that have similar characteristics with varied shapes and sizes. Having developed a database of known and unknown (anomalous) radio astronomical structures, it is of great importance to develop a system that would aid in the quick retrieval of galaxies with similar morphological characteristics (Abd El Aziz et al., 2017). Ideally, identified objects are indexed with a hashing function that minimizes the distances between perceptually similar objects and maximizes those of dissimilar objects. This is a paradigm that has seen a lot of progress in recent years with the development of deep hashing methods (Luo et al., 2020), a paradigm that to our knowledge is yet to be leveraged in radio astronomy.

6. Conclusion

Radio astronomy is in the era of Big Data, presenting ubiquitous opportunities that necessitate extensive automation of data processing, exploration, and scientific exploitation. This will unravel cosmology, if modern telescopes reach their scientific goals. In this regard, astronomers have taken advantage of the deep neural network revolution in computer vision with notable success.

In this survey paper, we have presented a detailed literature overview of the data and algorithmic advances in data curation pipelines, data preprocessing strategies, and cutting-edge machine intelligence methods. New scientific works that involve the development of robust and accurate novel models have emerged in the field of radio astronomy. These models can capture the diverse and unique astrophysical phenomena found in large radio images through the use of techniques like data augmentation, semi-supervised learning, and weakly supervised approaches. This has opened up the possibility of creating models that can accurately predict the labels of sources from surveys (like LOFAR and SKA). Moreover, these models would not have to be significantly modified once new data becomes available.

This survey highlights some important and promising areas of research for studying radio galaxy morphologies. These include developing multi-domain and multi-task classification models that can perform localization and radio source-component association on radio image

[17] https://spark.apache.org/.

cubes; utilizing and leveraging on the 3D multi-channel data cubes and algorithms to perform radio galaxy classification; and the investigation of image indexing and retrieval algorithms for use within radio astronomy.

CRediT authorship contribution statement

Steven Ndung'u: Conceptualization, Methodology. **Trienko Grobler:** Conceptualization, Methodology. **Stefan J. Wijnholds:** Conceptualization, Methodology. **Dimka Karastoyanova:** Conceptualization, Methodology. **George Azzopardi:** Conceptualization, Methodology.

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.

Data availability

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

Appendix

Table A.5
The abbreviations are categorized into three sections, with the top section representing algorithm keywords, the middle section representing galaxies, and the bottom section representing astronomical surveys.

Acronym	Description
CAE	Convolutional Autoencoder
CML	Conventional Machine Learning
CNN	Convolutional Neural Network
BYOL	Boostrap Your Own Latent
DCNN	Deep Convolutional Neural Network
FCNN	Fully connected neural networks
FSL	Few-shot learning
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
PINK	The Parallelized rotation and flipping INvariant Kohonen-maps
SOM	Self-organizing Maps
SU	Supervised Learning
SSGEC	Semi-Supervised Group Equivariant CNNs
SSL	Semi-supervised Learning
SSUL	Self-supervised learning
US	Unsupervised Learning
WSSS	Weakly-supervised semantic segmentation
FR0	Fanaroff–Riley Class 0
FRI	Fanaroff–Riley Class I
FRII	Fanaroff–Riley Class II
XRG	X Radio Galaxy
RRG	Ring Radio Galaxy
S	Isolated source which is fitted with a single Gaussian
C	Sources that are fitted by a single Gaussian but are within an island of emission that also contains other sources
M	Sources which are extended and fitted with multiple Gaussians
LERG	Low-excitation radio sources
HERG	High-excitation radio sources
LRG	Labeled radio galaxy
unLRG	Unlabeled radio galaxy
ATCA	The Australian Telescope Compact Array
ATLAS-DR3	Australia Telescope Large Area Survey Data Release 3
CoNFIG	Combined NVSS-FIRST Galaxies
FRGMRC	FIRST Radio Galaxy Morphology Reference Catalogue
NVSS	NRAO-VLA Sky Survey
SDSS-DR7	The Sloan Digital Sky Survey Data Release 7
WISE	Wide-field Infrared Survey Explorer

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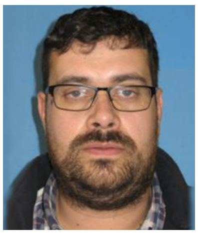

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