



University of Birmingham
School of Physics and Astronomy

Anwasha Sahu
MSci Physics with Particle Physics and Cosmology
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Machine Learning Applications in Radio Astronomy

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Abstract

The applications of convolutional neural networks and computer vision for classification, object identification and big data problems in radio astronomy is studied in this project report. This project used images from the MeerKAT Galactic Plane Survey and VLA FIRST Survey for training and generating synthetic data, with the goal of identifying and classifying radio objects of interest in the MeerKAT Galactic Plane Survey. Using 8028 augmented images for training a generative adversarial network to produce synthetic images for use in a multiclass classification model trained with 6248 images, a validation accuracy of 80.7% for the multiclass classification model was obtained. The methods studied can be applied to automate object identification and classification as upcoming large scale astronomy projects currently face the key challenge of processing copious amounts of data.

Key words: Generative adversarial networks (GANs), convolutional neural networks (CNNs), radio astronomy, MeerKAT, VLA FIRST, SKA, TensorFlow, multiclass classification, machine learning, deep learning, computer vision, bent-tail sources

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1. Introduction

Radio astronomy plays a critical role in modern astrophysics. As radio wavelength observations complement observations with infrared, optical, x-ray and gamma ray telescopes, a complete view of more complex astronomical sources can be obtained [1]. Radio frequencies span from 10 MHz to 1THz. Majority of astronomical sources emit at these frequencies and these wavelengths can penetrate dust clouds and Compton-thick layers of neutral gas resulting in minimal obscuring. This allows not only galaxies, supernovae and active galactic nuclei (AGNs) to be observed but also the cosmic microwave background [2]. Due to its versatility, a number of radio telescope surveys have been conducted in the past with the most promising set of results to come with the upcoming Square Kilometer Array (SKA) and its precursors such as the MeerKAT Array. SKA will be approximately 100 times more sensitive than its precursors however with the high-resolution data, a change in the data processing techniques is inevitable. The next-generation of radio surveys will generate data volumes in such large amounts that to keep up with the incoming data, processing must be done in near-real-time. This demands automation [3].

The popularisation of big data and machine learning techniques coinciding with the launch of radio telescope arrays such as MeerKAT, the Australian SKA Pathfinder (ASKAP) and LOFAR in the Netherlands provides astronomy with the advantage of speedy image processing and classification [3]. The architecture used to implement this is referred to as convolutional neural networks (CNNs). Given the formidable data sizes of radio images from the MeerKAT array with each image being estimated to be approximately 11.12 TB, automated image processing, object identification and classification with machine learning is a necessity [3], [4]. Machine learning methods have been applied to several fields in astronomy including star-galaxy classification, red-shift estimation, optical transients' classification and galaxy morphologies. The most efficient models at present can classify stars and galaxies with over 99% accuracy as seen in Brunner et al. 2017 and redshifts have been estimated to accuracies over 92% [4].

The outputs of these models predict categories based on distinct features of the inputs. In the case of galaxy morphologies, a human would be able to visually allocate similar categories based on the features. In fact, Dieleman et al. assessed the CNNs performance by conducting a citizen science study where the public sorted galaxies according to their morphological type. CNNs were initially constructed to replicate how the human brain processes information in visual format hence this study was successful in demonstrating this as the CNN and human results matched to a great extent [5], [6].

This project aims to extrapolate this advantage of CNNs for expanding current data sets of radio astronomy objects to generate synthetic radio objects of interest and utilise these in another CNN which aims to identify such objects in images obtained from the MeerKAT array and classify them.

Radio galaxies and radio-loud AGNs comprise the majority of radio objects. These objects are characterised by their synchrotron emission often resulting in double-lobed radio jets, filaments, compact nuclei, and/or radio halos which can extend up to ~ 2 Mpc from the core. Understanding the morphologies of such objects is key as increasing evidence points towards AGN playing a fundamental role in galaxy formation. Due to their short lifespans of $10^6 - 10^8$ years, AGNs inject colossal amounts of energy into their surrounding through relativistic jets. Additionally, it was shown that black hole masses are related to the bulge mass and velocity dispersion as shown in Ferrarese and Merritt 2000 and Gebhardt et al. 2000 implying a correlation between AGN activity and galaxy formation [7].

By assessing radio galaxies of different classifications obtained from the VLA FIRST survey, synthetic radio galaxy images were produced with a CNN (generative adversarial network) and computer vision techniques. Using these along with synthetic images from sources extracted from the MeerKAT Galactic Plane Survey using the AEGEAN catalogue of detected objects, a multiclass classification algorithm was developed using Python and TensorFlow. In addition to radio galaxies and AGN, this study included objects such as non-thermal filaments, supernova remnants and bow-shocks in the CNN input.

2. Background

2.1 Machine Learning

2.1.1 Terminology

Machine learning algorithms are algorithms which operate through learning from data. For a computer, 'learning' is defined when a "program learns from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E," as defined in Mitchell 1997 [8], [9].

There are several types of machine learning algorithms. This project utilises neural networks and deep learning primarily. Neural networks imitate the method that the human brain applies to problem solving. It does so through interconnected units which learn and can decipher relations in the observed data. When there are multiple connected layers of such interconnected units, this network utilises the process of deep learning [10]. Computer vision – the field of machine learning which allows machines to read and analyse image and video data with artificial intelligence – is heavily reliant on deep learning [11]. Some more definitions of terms which will be referred to later in this report are below.

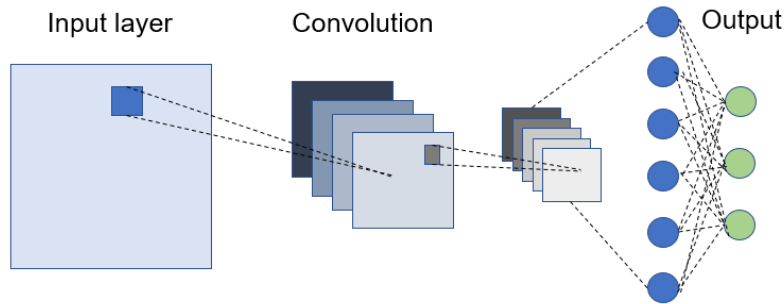


Figure 1: Schematic of a basic CNN. The convolutional layers in the second stage from the left are interconnected and have associated weights which contribute to subsequent layers and the output.

- i. **Data augmentation:** Artificially increasing a dataset by creating modified replicas of the original data. These could include geometric transformations, colour alterations, filter applications and noise addition [12].
- ii. **Activation Function:** This is a mathematical function which applies a weight to the input data, then transforms it and ultimately decides whether or not to activate a neuron in the CNN. A combination of linear and non-linear activation functions comprises the layers and form the backbone of the process of separating abstract features within the data [13]. The figure below shows the rectified linear unit (RELU) activation function which is the predominant activation function used in this study.

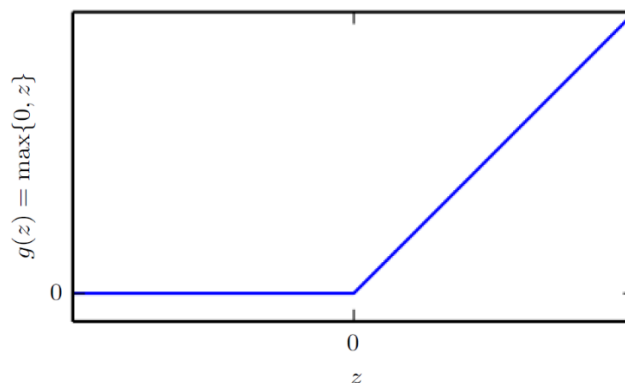


Figure 2: RELU activation function form [8].

- iii. **Training and validation set:** The training set is the dataset that the network learns from. The network learns the features of the training set as set by the user, then looks for such features in the validation set. The validation set is not seen by the algorithm during the learning process so its features are not used by the algorithm for training [14].
- iv. **Overfitting:** This occurs when the trained model provides extremely accurate result on the training set however performs poorly when provided with an unknown sample.
- v. **Training accuracy:** This is applicable in multiclass classification neural networks and is the proportion of correct class allocations of the training data during the learning process. The higher this value, the likelier it is for the model to perform better when supplied with validation data.
- vi. **Validation accuracy:** The validation accuracy is a measure of the proportion of correct class allocations in multiclass classification networks when the algorithm is applied to the validation set. If the validation accuracy is lower than the training accuracy, the model is likely to be overfitting [15].

2.1.2 Methods

This project utilises two CNNs primarily: a generative adversarial network (GAN) and a multiclass classification network (MCN), each of which are detailed below.

i. Generative Adversarial Networks (GANs)

This type of network consists of two neural networks which compete with each other and are trained simultaneously. One network is the generator and the other is the discriminator. The term 'adversarial' arises due to the two networks constantly conflicting with one another while training. When a training set of images is fed into the generator, it *generates* synthetic images similar to the training set – hence the name. The discriminator is trained with the training images simultaneously. It then attempts to determine whether the image fed into it from the generator is a real image or a synthetic image as it is unaware whether the image it was fed was from the training set or the generator. Both networks continually update their knowledge and instances of successes. Each instance of the generator generating a set of images and the discriminator analysing the images, is referred to as an epoch. At the end of each epoch, each network is assigned a score. If the generator successfully fools the discriminator, it receives a higher score. Else, the discriminator leads with the higher score. The number of epochs the program runs for should be determined by these scores. Ideally, the highest quality synthetic images are produced when the discriminator and generator have similar scores [16]. The architecture of a GAN is shown in Figure 3 below.

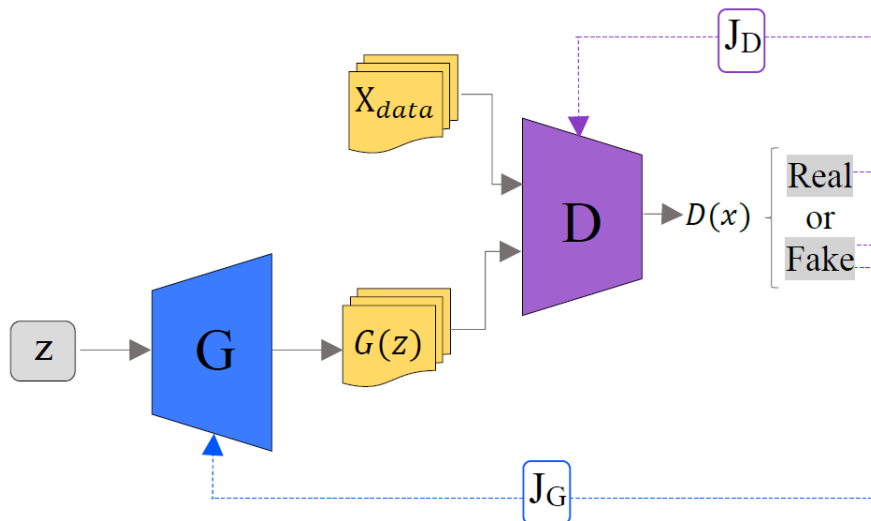


Figure 3: GAN architecture. J_G and J_D refer to the generator and discriminator loss functions respectively. The loss function is the penalty applied to each network for an incorrect prediction [16].

ii. Multiclass Classification Network

This network uses images allocated to different categories in the input. From these, generally 80% of the images are used for training and 20% for validation. At the end of each epoch, the validation

loss is obtained and the results of this epoch are fed back to the convolutional layers in a process called backpropagation. This is to improve the predictions of the network with each passing epoch. After all the epochs have run, new images can be input into the trained model and a class can be assigned [17].

2.2 Radio Astronomy

2.2.1 Object classes

Radio galaxies and radio-loud AGN are identified by their characteristic radio emissions and jets ranging from several pc to Mpc wide. This radiation is synchrotron emission and is indicative of magnetic fields and relativistic electron/positron jets [18]. The flux density versus frequency curves for typical radio galaxies is shown in Figure 4 below. There are several classes of such objects, some of which are discussed below.

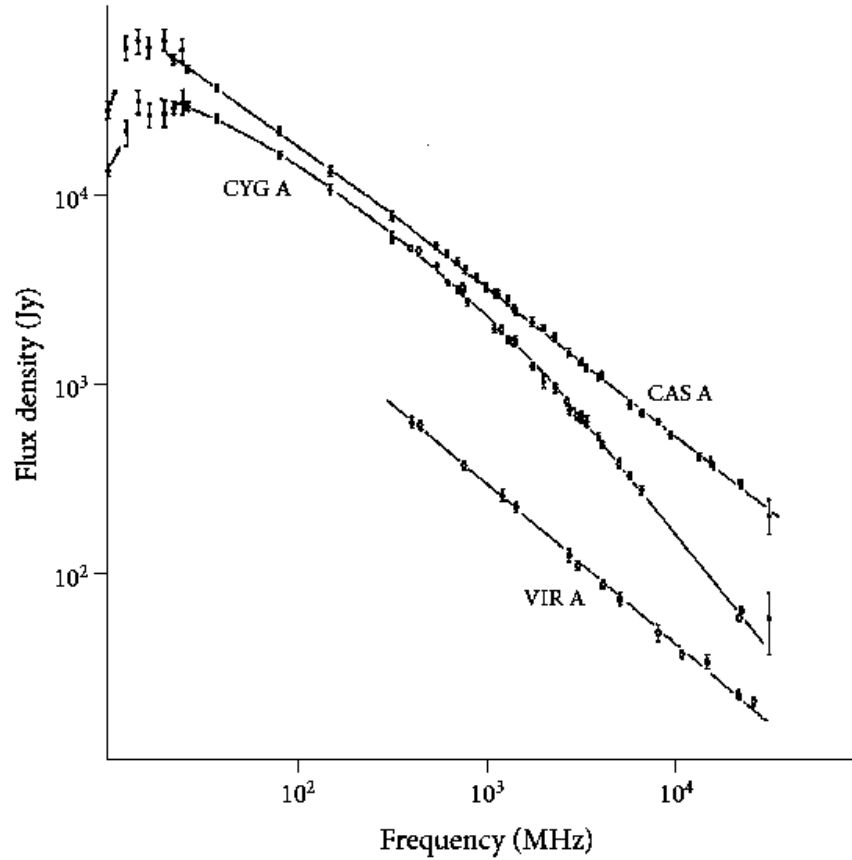


Figure 4: Radio spectrum for typical radio objects. This curve depicts the spectra for Cyg A, Cas A and Vir A from Baars et al. 1977 [2].

i. FR I, FR II and FR 0 AGN-powered Radio Galaxies

The Fanaroff-Riley (FR) classification system consists of two classes of extended radio galaxies: FR I and FR II. The classes are assigned depending on the ratio R of the distance between the brightest locations within the galaxy and the overall size of the galaxy. Galaxies with $R < 0.5$ are FR I and those with $R \geq 0.5$ are FR II. Typically, FR I objects have plume-like jets and cores. FR II objects have bright hotspots at the end of the lobes and fainter cores. FR I and FR II sources constitute the vast majority of radio galaxies. Some objects which do not have distinct FR I and FR II characteristics but rather a hybrid of both, are classified as FR 0 sources [19]. Figures 5a and 5b below provide an example of FR I and FR II objects.

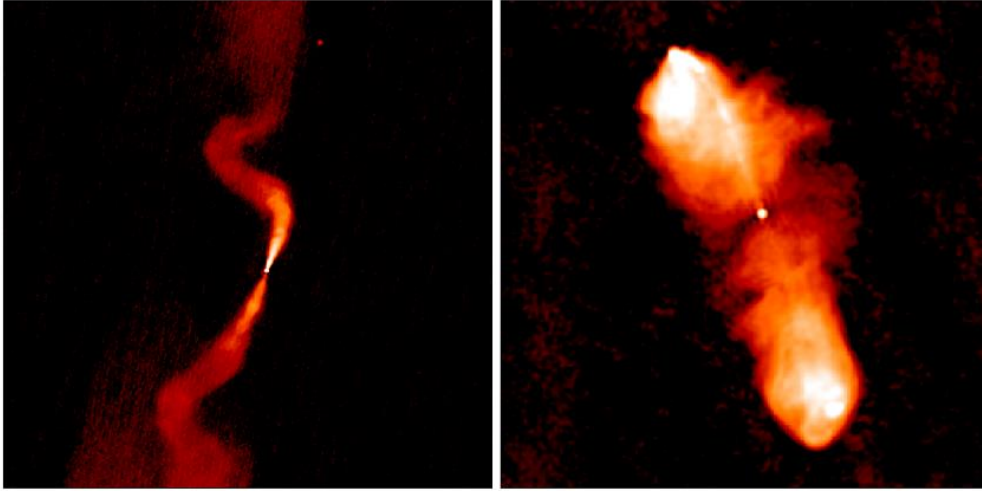


Figure 5a (*left*): FR I source 3C31. Note the brightest region is the core [18].
 Figure 5b (*right*): FR II source 3C98 with hotspots at the end of the lobe [18].

ii. Radio Filaments

Long radio filaments occur close to the Galactic Centre as high energy particle streams caused by interactions with strong magnetic fields from pulsar wind nebulae (PWN). As the PWN and interstellar winds reconnect, the pulsar wind particles escape, thus forming the long, thin filaments shown in Figure 6 below. Accelerated particles similar to PWN particles may also be emitted from supernovae [20].

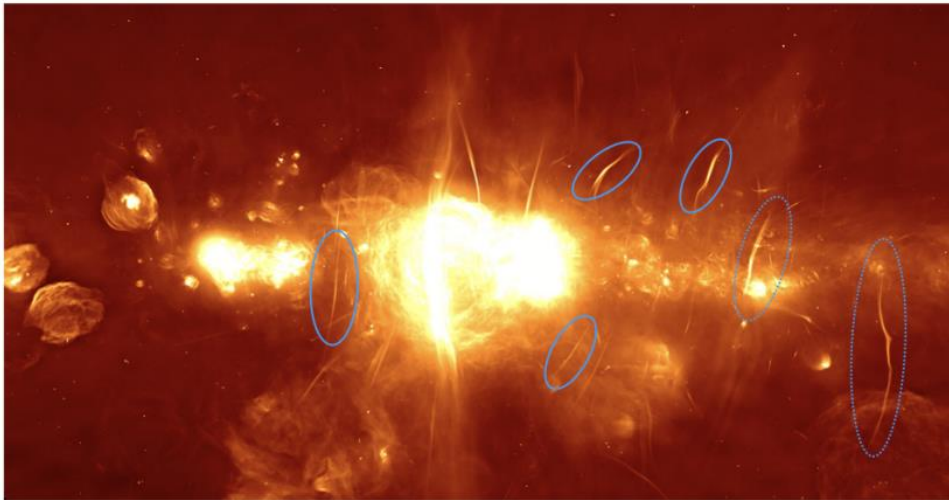


Figure 6: An image of the Galactic Center from MeerKAT with numerous filaments. Circled regions are 'orphan' filaments which are not connected to resolved sources [20].

iii. Odd Radio Circles (ORCs)

Compared to other radio objects, ORCs are relatively novel and poorly understood. These objects are faint, diffuse circular objects of radio emission with no emission at non-radio wavelengths. ORCs surround galaxies at moderate redshifts from 0.2 – 0.6, and some ORCs are known to have central galaxies. The circular structure may arise due to a spherical shockwave from the central galaxy due to a cataclysmic event such as a supermassive blackhole merger. Alternatively, it may appear to have a circular shape as it may be a double-lobed radio AGN viewed end-on. Lastly, the ORC may be a result of intergalactic interactions. A further ambitious theory hypothesises that ORCs may be the throat of the theoretically predicted wormholes. Figure 6 shows an image of the first-ever ORC to be observed, ORC1. The first image was obtained with ASKAP and MeerKAT performed a follow-up as seen in Figure 7 [21].

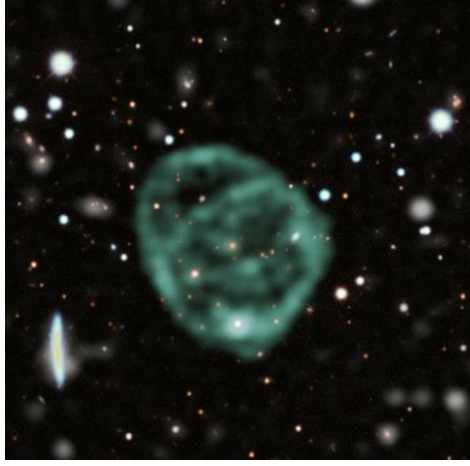


Figure 7: ORC1 as observed by MeerKAT Stokes-1, with increased contrast [21].

iv. **Wide Angled Tailed (WAT) and Narrow Angled Tailed (NAT) Sources**

WATs and NATs comprise the category of bent-tail sources. These objects have jets, or tails, which are bent at an angle away from the host galaxy. The extent of the angle determines whether the object is a WAT or a NAT. Some NATs may have the tail swept back to such a large extent resulting in the object appearing to have a head with a bright spot and a diffuse tail. Such sources may be referred to as Head-Tail or HT sources. The specific radio morphology is often linked to the environment of the galaxy cluster of the host galaxy. Hence, WATs and NATs may be used as tracers for such clusters. This is particularly insightful in cases where optical and X-ray band data is unavailable [19]. Figures 8a and 8b below depict an example of a WAT and NAT.

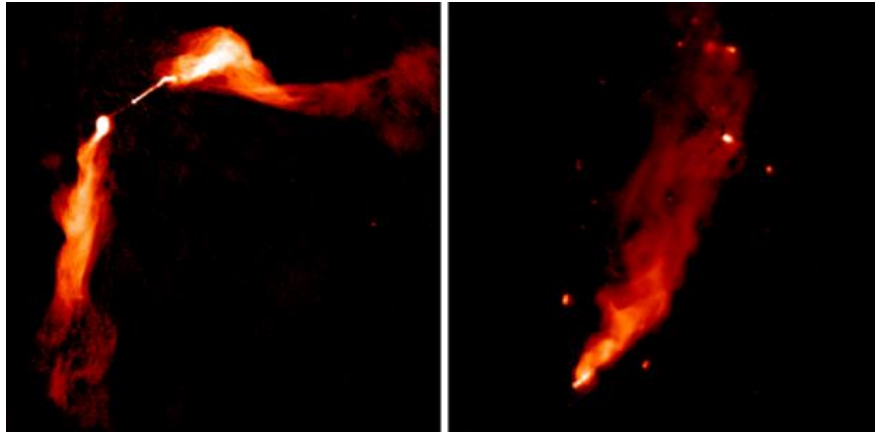


Figure 8a (*left*): WAT source 3C465. Note the wide angle between the tails [18].

Figure 8b (*right*): NAT source NGC6109. This source is also a HT object [18].

2.2.2 MeerKAT

The MeerKAT radio telescope array is the precursor for the Square Kilometer Array (SKA) being constructed in Australia and South Africa. Located in the Karoo National Park, South Africa, MeerKAT consists of 64 antennae each with a diameter of 13.5 m and a maximum baseline of 8 km. A single receiver is designed to cover a range of frequencies from 1.0 -1.74 GHz which may be changed to 0.9 – 1.67 GHz to allow deep HI surveys to probe to further redshifts. Currently, MeerKAT is the most sensitive centimetre wavelength in the Southern hemisphere [22].

3. Data

3.1 MeerKAT Galactic Plane Survey

i. Images

The project utilised objects detected in 30 image files in FITS format from the MeerKAT Galactic Plane Survey. This was provided in private communication with Dr Ian Stevens and will be presented in Goedhart et al. which is currently in preparation. Each image had a width of approximately 3° with flux in units of Jansky where 1 Jansky is $10^{-26} \text{ Wm}^{-2} \text{ Hz}^{-1}$ [23]. The imaging systems are sensitive to the order of tens of micro-Jansky with a spatial resolution of few arcseconds [23], [24]. The images underwent preliminary processing using the SAO Image DS9 Software [25]. A logarithmic scale was applied, and the colour scheme was altered to view distinct features as no features were visible on the linearly scaled images, as seen in the Figure 9 below.

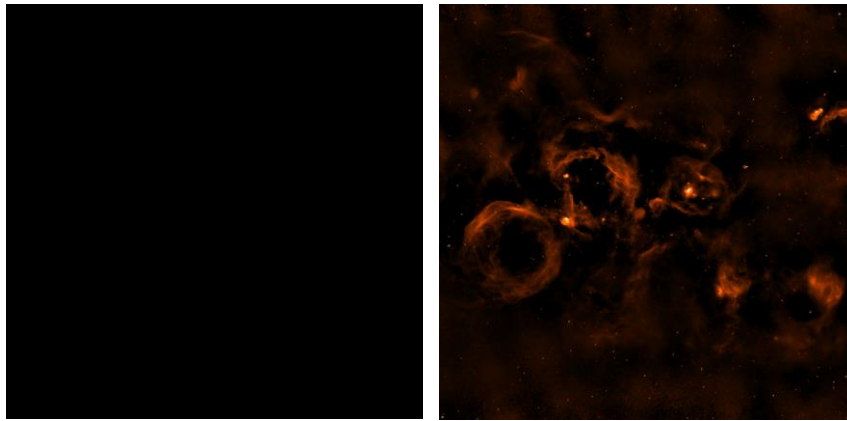


Figure 9: The left panel shows the region at galactic coordinates G053.5+0.0 with a linear scale and the right panel shows the same with a logarithmic scale applied. This uses SAO Image DS9.

ii. Extracting Cut-outs

Each MeerKAT GPS Image included a VOT table with data on coordinates of the brightest regions. A full source table was compiled by combining each individual source as specified with the Aegean compact source finder (see Acknowledgments). Aegean finds compact radio sources in images by locating ‘islands’ of pixels above a threshold value. It analyses the curvature of the image and determines the number of Gaussian components to be allocated to describe each such island. Along with intensity maps, spatial filters and convolutions with small point spread functions, Aegean can efficiently locate sources [26]. Islands with single sources were then eliminated and the mean coordinate for each multisource island was calculated. This was appended to a new source table with individual IDs for each multisource island. Each frame was individually imported and converted to galactic coordinates using a 2D cut-out routine. Each cut-out was 64×64 pixels and then normalised.

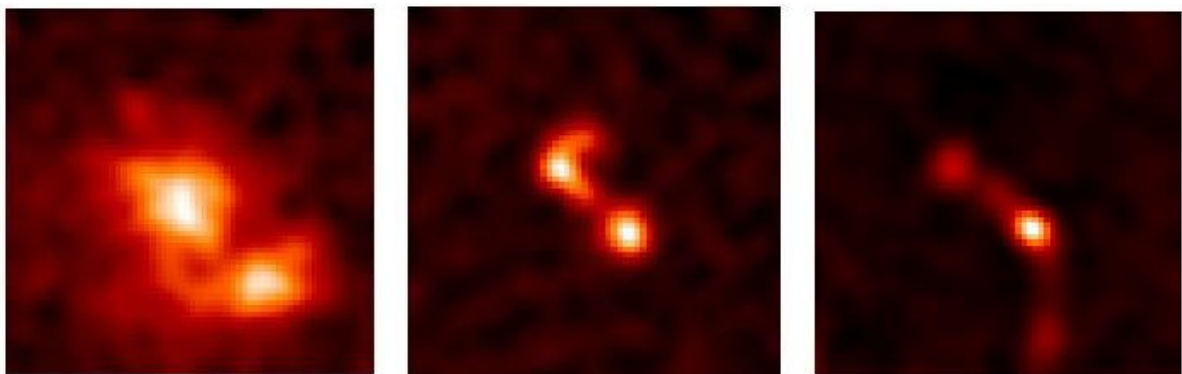


Figure 10: Examples of objects in MeerKAT GPS cut-outs.

3.2 VLA FIRST Survey Catalogue

The Faint Images of the Radio Sky at Twenty-cm (VLA) survey was conducted using the NRAO Very Large Array (VLA) spanning over 10,000 square degrees of the Northern and Southern Galactic Caps. The images have an rms of 0.15 mJy and a resolution of 5 arcseconds [27]. The GAN was trained with cut-outs from this survey to generate synthetic WATs and NATs.

The sources were obtained from the catalogue of radio galaxies provided in Sasmal et al. 2022. Sasmal et al. examined 95,243 sources and a catalogue of NATs and WATs was compiled. Of the 717 select sources, 287 were NATs with opening angles less than 90° and 430 were WATs [28]. The histogram of the opening angle distribution of NATs and WATs utilised in this study are shown in Figure 12 below.

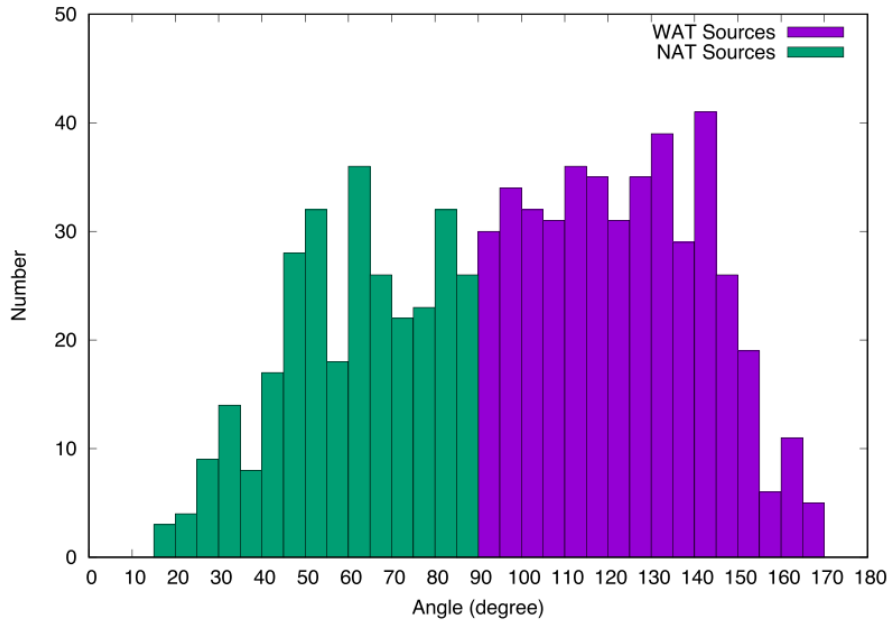


Figure 11: Angle distribution for NATs and WATs from VLA FIRST Survey [28].

Figures 12a and 12b depict an example of a NAT and a WAT from the catalogue.

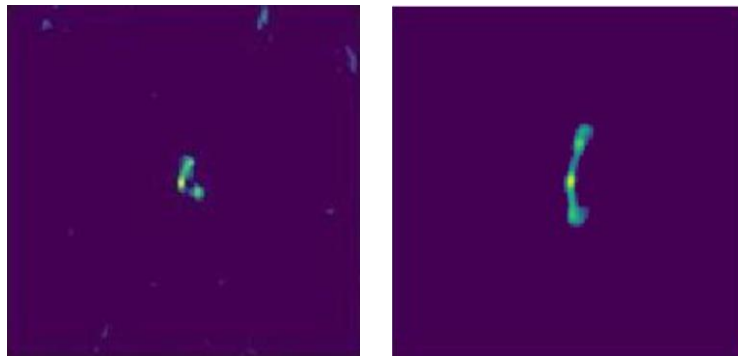


Figure 11a (*left*): NAT from VLA FIRST. Note the acute opening angle [27].
 Figure 11b (*right*): WAT from VLA FIRST. Note the obtuse opening angle [27].

4. Methods

This project utilised three different CNNs. These correspond to the GAN, Detecto – a Python package for object detection, and a multiclass classification model. The following sub-sections detail the architecture of each network. The structure of the three programs and their inter-connections are shown in Appendix A.

4.1 Generating Synthetic Images

The GAN was used to generate synthetic images of radio sources to increase the training set that would be used for multiclass classification at a later stage. The algorithm was run for three different sets of input data: NATs from FIRST, WATs from FIRST and cut-outs from the MeerKAT Galactic Plane Survey, as shown in Figure 13 below.

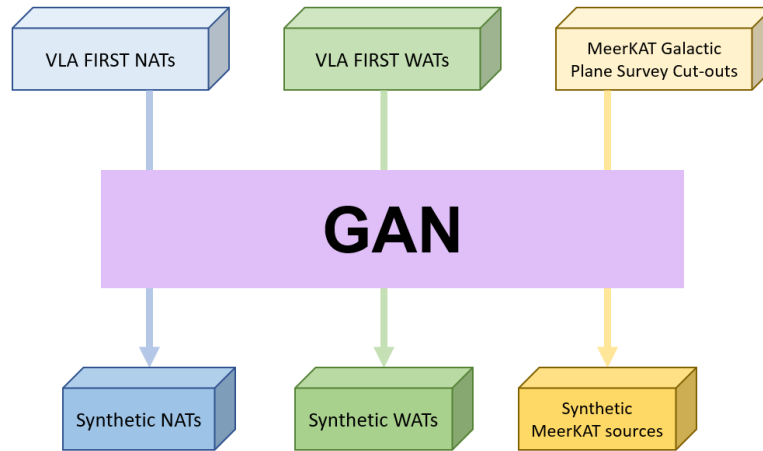


Figure 13: Input and output for three runs of the GAN.

The architecture and construction of the GAN for each run is as follows. The GAN was built using TensorFlow’s Keras package. The discriminator was built to have three 2D convolutional layers each with the activation function LeakyRELU. Unlike the RELU activation function, LeakyRELU has a small slope for negative values on the x axes instead of zero. It was observed that convergence was achieved faster thus increasing the training speed and consequently, higher quality images were produced. Following this, the three layers were connected in a process called flattening which converted the data into a 1D array or vector. Next, the data underwent dropout where noise was removed to improve output quality and reduce processing time. Finally, the dense layer was applied along with the sigmoid activation function. This layer ensured that every neuron was connected to every neuron of the preceding layer resulting in a fully-connected layer. The generator was constructed similarly with four convolutional layers instead of 3 and a dense layer with the same activation functions as the discriminator [29]. It was observed that the algorithm converged faster to distinguishable radio objects with four layers instead of three in the generator thus prompting this choice. The discriminator and generator functions were then compiled and set to run for 3000 epochs on a GPU cluster. Figures 14 and 15 show the structures of the two neural networks.

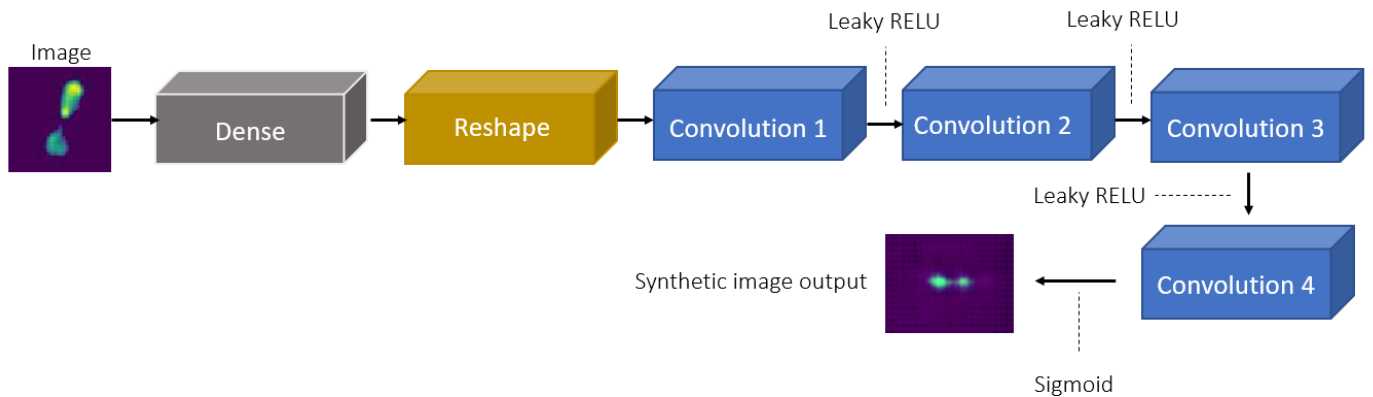


Figure 14: Architecture of the generator network.

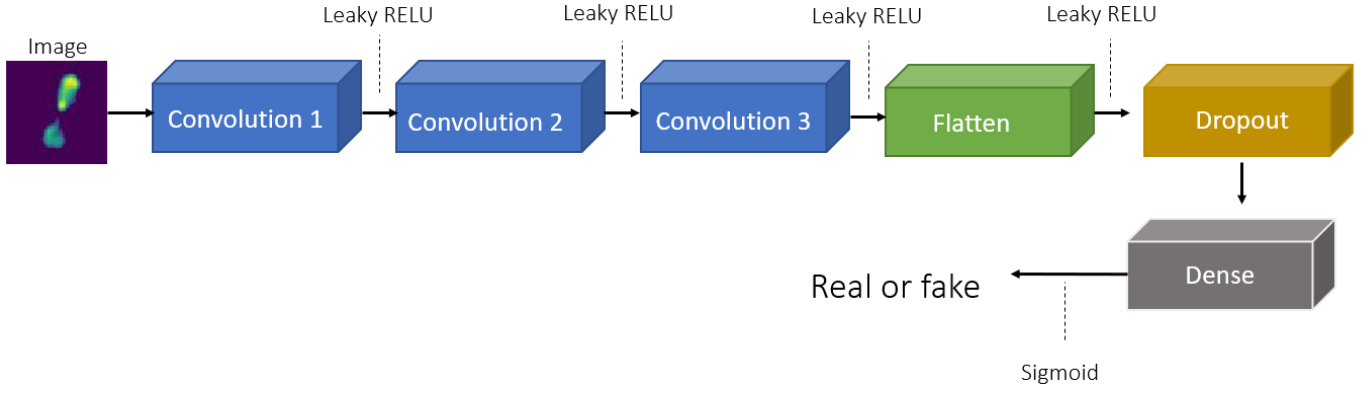


Figure 15: Architecture of the Discriminator

Each of the three sets of images underwent augmentation in the form of three rotations. Copies of each image were rotated by 90, 180 and 270 degrees were produced. This increased the number of input images. The number of training images for each set is shown in Table 1. Models perform best when they are supplied with training images of the order of 1000s however this is dependent on the specific task [30].

Table 1: Number of images for each training set for the GAN, after augmentation.

Category	Number of images
VLA FIRST NATs	1144
VLA FIRST WATs	1392
MeerKAT Galactic Plane Survey (GPS) Cut-outs	5492

4.2 Detecto

Detecto is a Python package for building object detection models concisely. It is built on the machine learning framework PyTorch [31]. Detecto uses region-based convolutional neural networks (Fast R-CNN) for object detection by merging superpixels with low-level features. It classifies regions into object categories or background using bounding boxes and runs best on GPUs [32]. The object of interest that is referred to as the label data, and is an individual XML file corresponding to one image. Using the open source tool Labellmg, the radio object of interest was manually located in an image using the bounding box feature. It was assigned a label and this was saved as an XML file. This is done for every training image where each image has its own XML file with coordinates and labels of the regions of interest. This was performed on all the WATs and NATs from VLA FIRST with the appropriate category assigned. Following this, Detecto was trained for 10 epochs and test images were input next.

When run on test images, Detecto output the coordinates of the object detected and the original image with a bounding box around the region of interest with a label assigned. The test images in this case were original MeerKAT Galactic Plane Survey images. To increase the efficiency of detecting small objects, the original images were cropped into 5 x 5 and 4 x 4 segments and fed into the model. Using the coordinates of the objects detected, the regions of interest were cropped out and saved. These cut-outs were then fed into the multiclass classification algorithm to get a class assigned to each of the objects of interest.

4.3 Multiclass Classification

Using the synthetic NATs, synthetic WATs, synthetic MeerKAT GPS images, original FIRST WATs and FIRST NATs as the training images, three classes were defined: NATs, WATs, Double-Lobed galaxies and miscellaneous radio objects. The miscellaneous radio objects class contained supernova remnants, radio galaxies which do not fall into either WATs, NATs or HT sources, and ORCs amongst other radio objects. This was due to insufficient images (less than 1000) for each such category, as at least a thousand images are necessary for the model to generate reliable results. Double-lobed objects were primarily identified from the synthetic images generated from the MeerKAT GPS data, as objects appearing to be two compact radio sources in close proximity to each other (approximately 1-3 arcseconds separation). This may be explained by having observations of bent-tail sources from an angle such that the ‘tails’ would be pointed towards the

telescope. This category would also include FR II objects with diffuse tails connecting the bright hot spots. The number of images used for each class is shown in Table 2 below. Classification models such as this perform best when all classes have a similar number of training images [30].

Table 2: Classes and images per class for training multiclass classification model.

Class	Number of Images
NATs	1480
WATs	1798
Double-Lobed	1466
Miscellaneous Radio Object	1504

The architecture and parameters of the model are as follows. First, an 80-20 split was applied to the images to create the training and validation set. Hence, 5000 images were used for training and 1247 for validation. The images were then rescaled to normalise them. Data augmentation was then applied in the form of random rotation and random zoom. The values of the parameters set in TensorFlow are shown in Table 3. Next, the model was built with three convolutional layers with the SoftPlus activation function, a dropout layer, a flatten layer and two dense layers. The activation function for the dense layer was RELU as it provided optimal results when compared against sigmoid and SoftPlus as the most used activation functions. SoftPlus was used for the convolution layers as it is a smoother version of RELU and this enhances the stability and results of the CNN. It is defined as shown in Equation 1 below [33].

$$f(x) = \log (1 + \exp ^x) \tag{1}$$

Table 3: Parameters for multiclass CNN with TensorFlow.

Parameter	Value
Dropout	0.2
Epochs	200
Random rotation	0.4
Random zoom	0.1

The model was trained over 200 epochs. Following this, the GAN was run once again to generate synthetic images of WATs, NATs and other radio objects from the MeerKAT GPS. These were then used as the test images. When fed into the trained model, the model output a percentage of the class the image most likely belonged to. Each image was assigned a probability of belonging to each of the four classes and the final class assigned would be the class with the highest probability percentage.

5. Results and Discussion

The methods outlined in Section 4 produced quantifiable results. The synthetic images from the GAN, objects located with Detecto and the classification results from the multiclass classification model along with the further science enabled by these results are presented in the following subsections.

5.1 Synthetic Images

Using the GAN generated in Section 4.1, synthetic images were successfully produced. On a single Broadwell GPU, training with 3000 epochs for each of the three sets of input images consumed roughly three hours. Credible images of WATs, NATs, miscellaneous radio objects and double-lobed radio galaxies were produced, with similar characteristics to the input images as shown in the preceding section.

After training, some example of the NATs, WATs and radio objects generated are shown in the collage in Figure 16. The GAN was tested with three and four layers for both the discriminator and the generator along with combinations of the two. Optimal image results were obtained for the combination of three convolutional layers for the discriminator and four for the generator. As discussed previously, the quality of the synthetic images produced is enhanced when the generator and discriminator losses are of similar values due to the competition between the two neural networks. Plots were obtained comparing the discriminator and generator losses for three layered and four layered generator networks for each of the three input sets. Majority of the

images obtained for multiclass classification were from the regions with the lowest differences in the generator and discriminator loss.

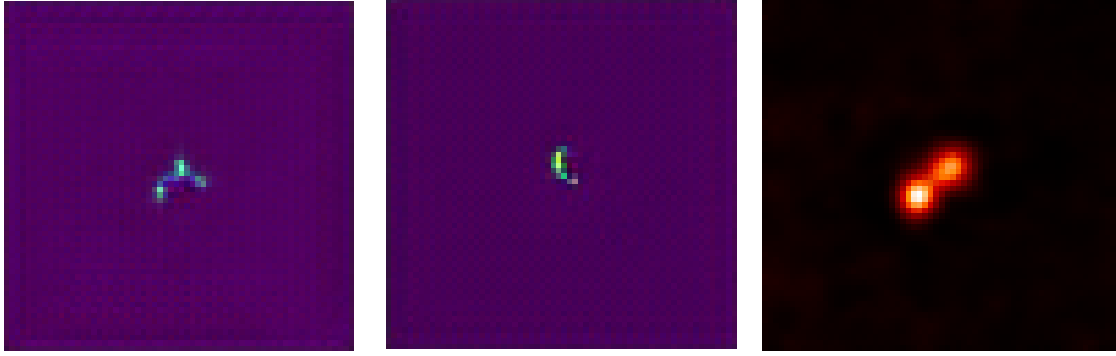


Figure 16: From left to right – a synthetic NAT, a synthetic WAT and a synthetic double-lobed radio galaxy.

For NATs generated with four convolutional layers in the generator network, the following plot was obtained for the losses over a span of 3000 epochs.

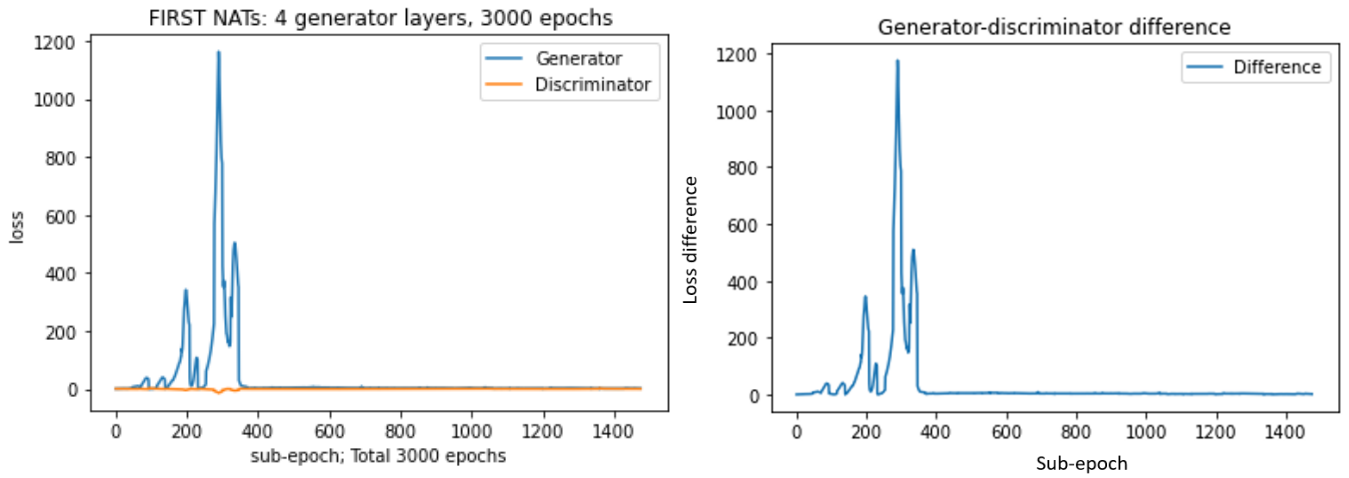


Figure 17a (*left*): Generator and discriminator loss for synthetic images generated from the VLA FIRST NATs images with four generator convolution layers.

Figure 17b (*right*): Difference between the generator and discriminator loss corresponding to Figure 17a.

Similarly, Figure 18 below shows the plots for three generator convolution layers.

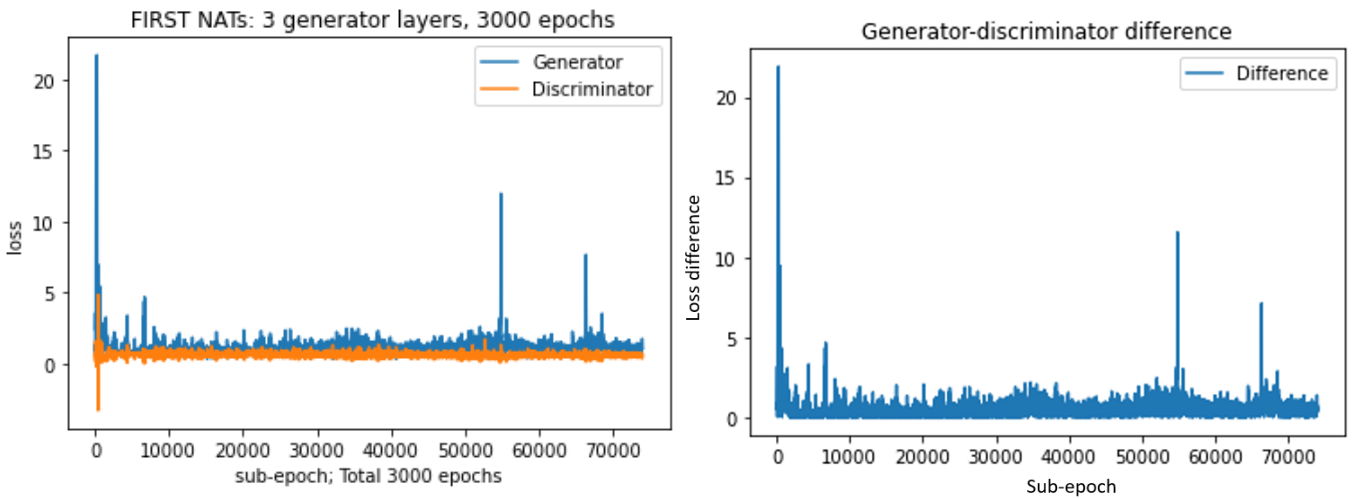


Figure 18a (*left*): Generator and discriminator loss for synthetic images generated from the VLA FIRST NATs images with three generator convolution layers.

Figure 18b (*right*): Difference between the generator and discriminator loss corresponding to Figure 18a.

It can be observed that overall, the values for the losses have fewer fluctuations in the case with four generator convolutional layers. Despite larger values in the losses as seen on the y-axis, it is the smoothness of the difference curve and relative change in loss values in Figure 17b that directly impacted the quality of images produced. Similar trends were observed for the WATs. The trend for synthetic images produced from the MeerKAT GPS images did not match this as seen in Figures 19 and 20 respectively.

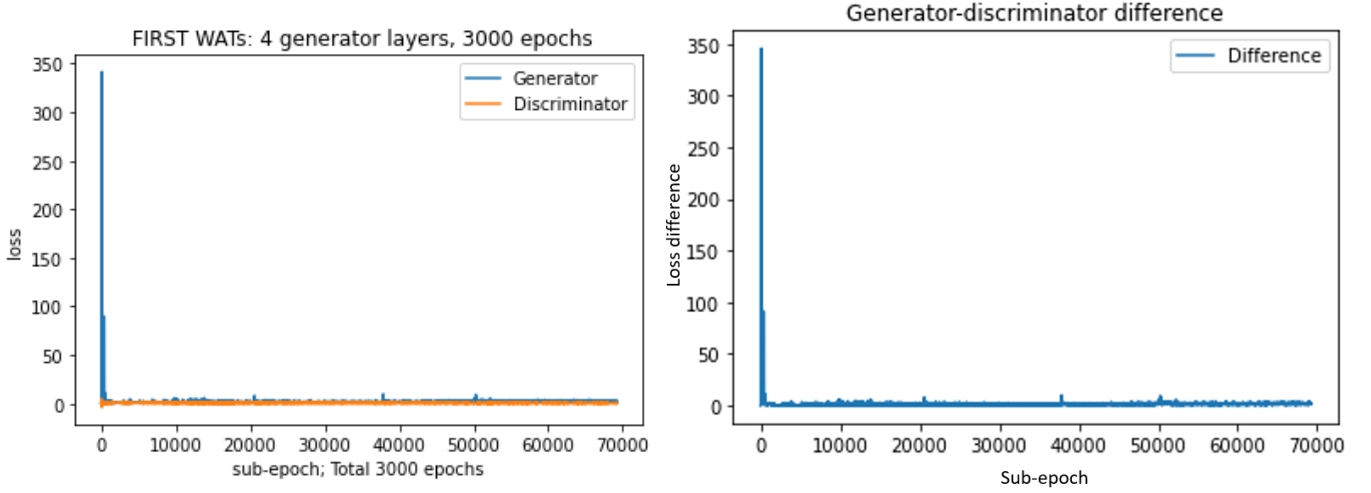


Figure 19a (*left*): Generator and discriminator loss for synthetic images generated from the VLA FIRST WATs images with four generator convolutional layers.
Figure 19b (*right*): Difference between the generator and discriminator loss corresponding to Figure 19a.

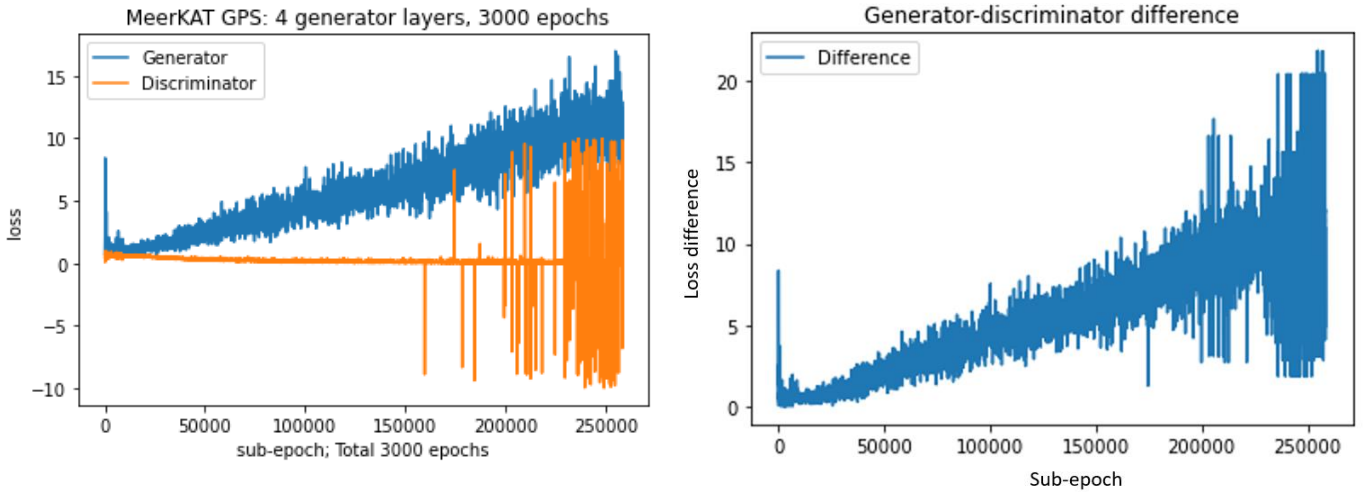


Figure 20a (*left*): Generator and discriminator loss for synthetic images generated from the MeerKAT GPS radio object images with four generator convolutional layers.
Figure 20b (*right*): Difference between the generator and discriminator loss corresponding to Figure 20a.

The GAN for synthetic NATs produced identifiable radio objects with a resolution of 64 x 64 pixels from epoch 500 onwards, tentatively. These included double-lobed NATs and objects similar to FR II radio galaxies. Similar to the FIRST catalogue, the images correspond to a size of approximately 5 arcseconds wide. The highest quality NATs were produced after approximately 850 epochs. This coincides with sub-epoch 397 from Figure 17. Due to the continuous learning and training of the model, some images appeared to be single lobed AGN which may be representative of viewing double-lobed radio galaxies head-on. From epoch 1500 to epoch 3000, majority (> 55%) of the images generated were bent-tailed with angles less than or approximately 90° however a significant number of images generated appeared to be objects similar in morphology to FR 0 objects. Additionally, some of the NATs depicting FR II characteristics were bent to such a great extent that they appeared to have diffusely connected lobes thus creating a resemblance to ORCs. In addition to highlighting the limitations of the GAN, this highlights one of the key issues in radio astronomy

with such bent-tail sources as there are objects which do not fit definitions of classes. Depending on the angle of observation, the object classes may differ. This contributed to creating a class of objects for miscellaneous radio objects in the multiclassification CNN model. Some examples of NATs like this are shown in the panel of images in Figure 21 below.

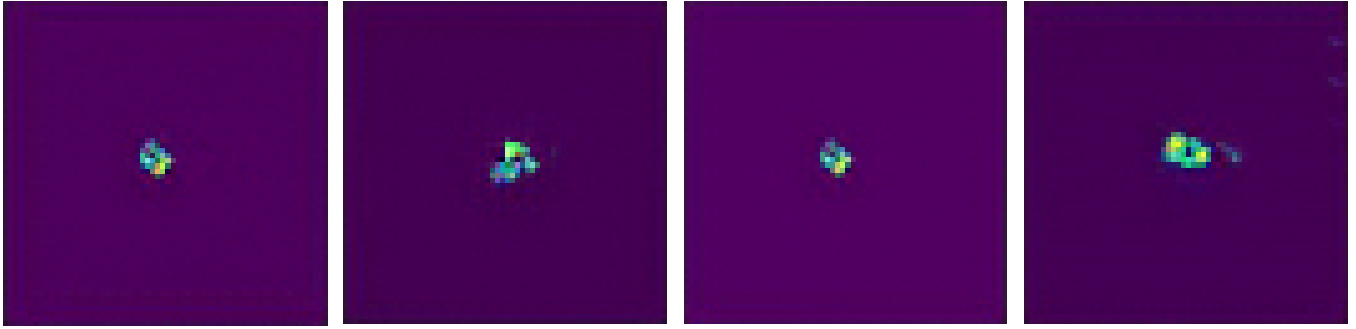


Figure 21 a, b, c, d (from left to right) : Synthetic NATs with extreme angles bearing resemblance to ORCs.

WATs with a resolution of 64×64 pixels with a width of approximately 5 arcseconds were generated at earlier epochs with distinguishable features. This corresponded to sub-epoch 3000 and epoch 100 as seen in Figure 19 previously. Over half the objects produced are double-lobed, most of which are bent and appear similar in morphology to FR II objects due to the lobes being brighter than the cores. Several objects appear to have more than a single lobe and these can be associated with having a bright core as well as bright lobes. Objects with angle distributions close to the cut-off between WATs and NATs were also produced hence the sample of WATs also included FR 0 objects. No ORC-like objects were generated and this indicates that the GAN produced reliable results as this would demand angles of opening significantly lower than 90° . The synthetic images were visually inspected and compared to WATs from the FIRST catalogue and a set of 1798 images were identified for use in the multiclass classification algorithm.

The GAN produced synthetic radio objects with identifiable features from the MeerKAT GPS data however some evidence of overfitting was obtained from the generator and discriminator loss trends. The gradually increasing difference in the losses as seen in Figure 20b suggests that the synthetic images produced after epoch 150 corresponding to sub-epoch 12,500 declined in quality however the absolute values of the losses are consistently below 30. From Figure 19, it is observed that loss values up to 350 are not unusual and the quality of images improves significantly when loss values are below 50. Upon visually inspecting the synthetic images produced, they were noted to be of very high quality with striking similarities to those of the original MeerKAT GPS images, suggesting that the increasing loss did not impair the image quality. Appendix B includes a select set of synthetic images and the complete set can be obtained on the GitHub repository for the project.

Kummer et al. performed a similar study in 2022 with a Wasserstein GAN (wGAN) where synthetic images were generated for different radio galaxy classes. It was observed that incorporating generated images into the multiclass classification algorithm significantly increased the results of the classes assigned, further supporting the results of this project. A key difference between the GAN used in this project and the wGAN is that the wGAN has an added gradient penalty term applied to the loss function to satisfy a key condition of the metric used, the Wasserstein-1 metric. Kummer et al. used images corresponding to FR I, FR II, compact and bent sources however this project expanded the set of images to include objects such as ORCs and miscellaneous radio objects similar to those in the MeerKAT GPS data, thus increasing the utility of GANs [34]. The reliability of GANs has been tested multiple times in astronomy including feature retrieval in galaxies and atmospheric retrieval for exoplanets. Using a large and heterogeneous training set is crucial to such models. The Lightweight GAN used to generate images of celestial objects including planets and galaxies in Coccomini et al. 2021 used 283 images for the training set for one of their instances and distinct high quality images with extractable features were obtained. Given that this project used images on the order of 10^3 for the GAN, the resultant radio objects are reliable reproductions of the input [35].

It has been noted in previous studies that a key limitation for GANs occurs if they are supplied with training samples with a lack of diversity, as noted in Saxena et al, 2021. This issue is referred to as the mode collapse problem and is one of the current areas of development for GANs. Additionally, the generator and

discriminator losses may be observed to oscillate significantly during training instead of converging to a point of minimal difference in the losses. This would result in instability and the model would fail to learn the image features. The GAN constructed in this project thwarts the issue of instability and oscillations due to a carefully chosen training set. However, the issue was briefly observed in the case with three convolutional layers in the generator as documented in Figure 18. Despite converging around a minimal difference in losses, significant oscillations were observed even in the final thousand epochs, thus making the model more unreliable than the model with four convolutional layers [36].

5.2 Detecto Object Detection

Upon training Detecto with WATs and NATs from the FIRST survey and testing upon MeerKAT GPS data, Detecto identified several candidates as radio objects of interest. Although it assigned a label of either WAT or NAT, the labels did not seem accurate for most instances further strengthening the need for the multiclass classification model to allocate object classes. Some of the objects identified and cut-outs obtained consequently are shown below.

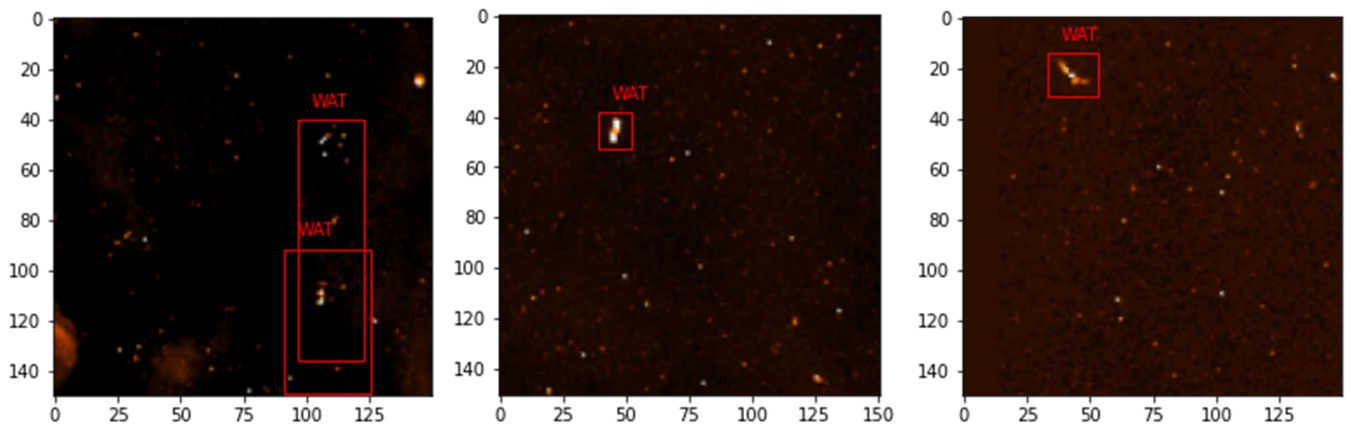
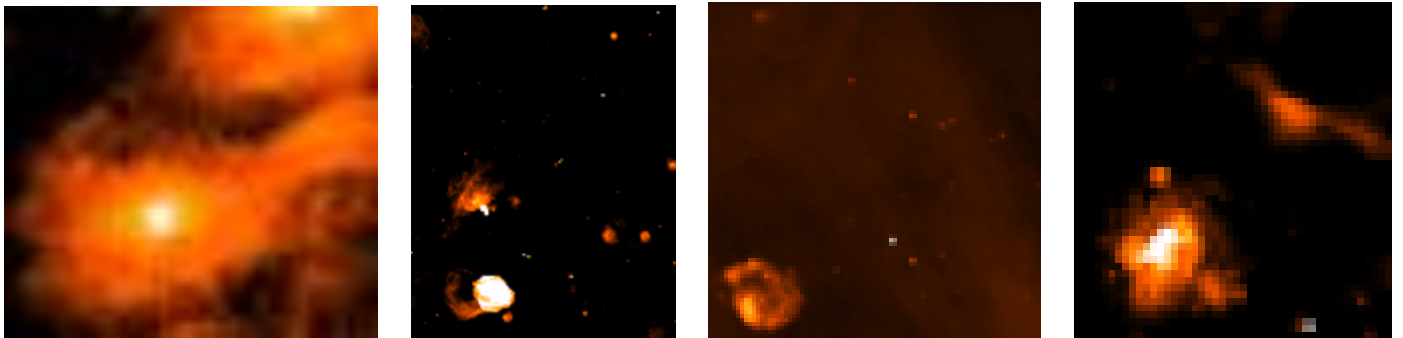


Figure 22 a, b, c (left to right): Examples of radio objects detected by Detecto in segments of MeerKAT GPS images. The right-most image resembles both a WAT and an FR II object.

From the objects within the bounding boxes as shown above, some of the objects within the cut-outs are shown below.



Left to right:

Figure 23a: Cut-out of object identified as NAT by Detecto.

Figure 23b: Cut-out of object identified as WAT.

Figure 23c: Cut-out of object identified as both a NAT and a WAT.

Figure 23d: Cut-out of object identified as WAT.

As observed, while the objects in the cut-outs were radio objects, the classes assigned are not optimal. Figure 23a may be a NAT viewed edge-on so the line of observation points directly at the lobes however this does not coincide with the definition of NATs or the training images for NATs. Figure 23b may be a successful detection of a WAT with a faint band of gas connecting the two lobes however it is also equally likely that this cut-out may simply be two separate radio objects. Figure 23c resembles an ORC or a supernova remnant.

Due to the angle of the ‘arms’ around the bright hotspot, it is reasonable that the network was unable to arrive at a single conclusion for the object class. Although Figure 23d is identified as a WAT, upon visual inspection it resembles a compact radio object within the class of miscellaneous radio objects as defined in Section 4. The examples above highlight the reason for restricting Detecto to locating objects rather than using it as a classifier. As observed, Detecto is useful for identifying larger objects of interest rather than smaller, complex objects with a size of a few arcseconds as identified with Aegean as explained in Section 3.1. The limitations of using Detecto may be due to an insufficient training set. Additionally, the resolution of training images and the segments of the MeerKAT GPS images used in testing were different resulting in objects of different sizes and resolutions being detected. Lastly, a source for errors could be due to different colour schemes being used in the training and test images. This may not have contributed significantly as objects of interest were correctly identified despite having inaccurate labels. Along with other images tested in the multiclass classification model, these cutouts were also tested and the results are presented in the subsequent section.

It is worth noting that radio objects have an inherent ambiguity associated with them depending on the angle of observation and the objects stage in their evolution. For instance, FR 0 radio galaxies have the potential to evolve into FR I radio galaxies should they have sufficient fuel. If such an object would be imaged during the transition period, Detecto may identify the object as being both a WAT and a NAT since the bright region of the galaxy may span a larger area resulting in a ‘blob’ of bright regions instead of the distinct double-lobed structure. Classification models need to account for the evolutionary link between classes of the radio galaxy population to accurately identify objects and deduce their mechanisms [37].

5.3 Multiclass Classification

After constructing the multiclass classification algorithm, a set of synthetic WATs, NATs and synthetic MeerKAT GPS images were produced using the GAN with the parameters as described in the preceding sections. The synthetic images produced were used as test images, in addition to the cut-outs obtained from Detecto. Note that the cut-outs obtained from Aegean were not used in training the multiclass classification model implying that using Detecto cut-outs did not result in redundancy or inaccurate results. Plots were obtained depicting the spread of the probabilities assigned to each class (WAT, NAT, double-lobed, miscellaneous radio object). The training and validation accuracy and loss of the model are shown in Figure 24 below.

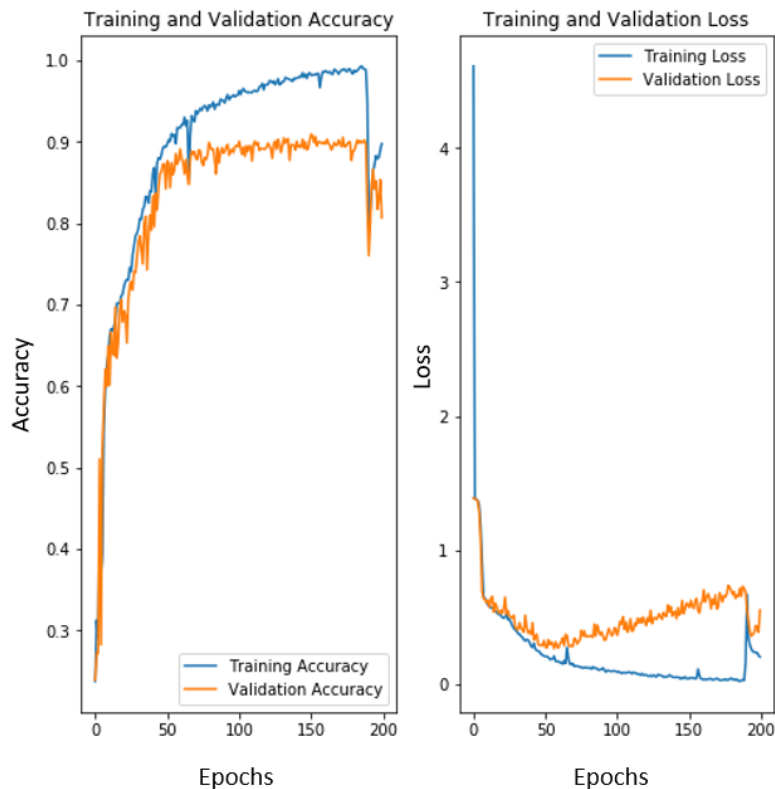


Figure 24: Training and validation accuracy and loss for multiclass classification over 200 epochs.

High values of accuracy and low values of loss correspond to the model providing better classification predictions. However, as the training accuracy values surpassed 0.95 and approached 1.0 in the trial runs, it was observed that overfitting was an issue. There were two potential solutions to this. Either the model could be trained for 50 – 70 epochs or it could be trained for over 100 epochs and the accuracy would then drop as a result of overfitting. Training the model for fewer than 100 epochs is insufficient in multiclass models such as these and is not recommended [17]. Hence, the model was trained for 200 epochs and as expected, the accuracy reduced and eliminated the issue of overfitting. Accuracy values above 70% for both training and validation are accepted as reliable [38]. The validation accuracy at the end of the final epoch was 80.7% and the validation loss was 0.5507. The training accuracy corresponding to this was 89.78% thus the accuracy of the model is within the accepted range. However, this can be improved to obtain accuracy values for training and validation in the range of 90 – 95%. This could be done by increasing the number of epochs and observing which epoch corresponds to this range and restricting the model to run till that epoch, or running the model for up to 90 epochs as the model surpasses 95% training accuracy in the region of the hundredth epoch. The former is a preferable solution however this has not been studied due to time constraints as each run of the algorithm consumed at least 24 hours.

5.3.1 Synthetic WATs and NATs

A total of 3992 synthetic WATs produced using the GAN had identifiable features deeming them suitable to be used as test images. Of these, 2735 were correctly identified as WATs and 1191 were identified as NATs. There were 9 objects identified as double-lobed radio galaxies and 7 as miscellaneous radio objects. Figure 25 below depicts the spread of the probability likelihoods of the being correctly allocated.

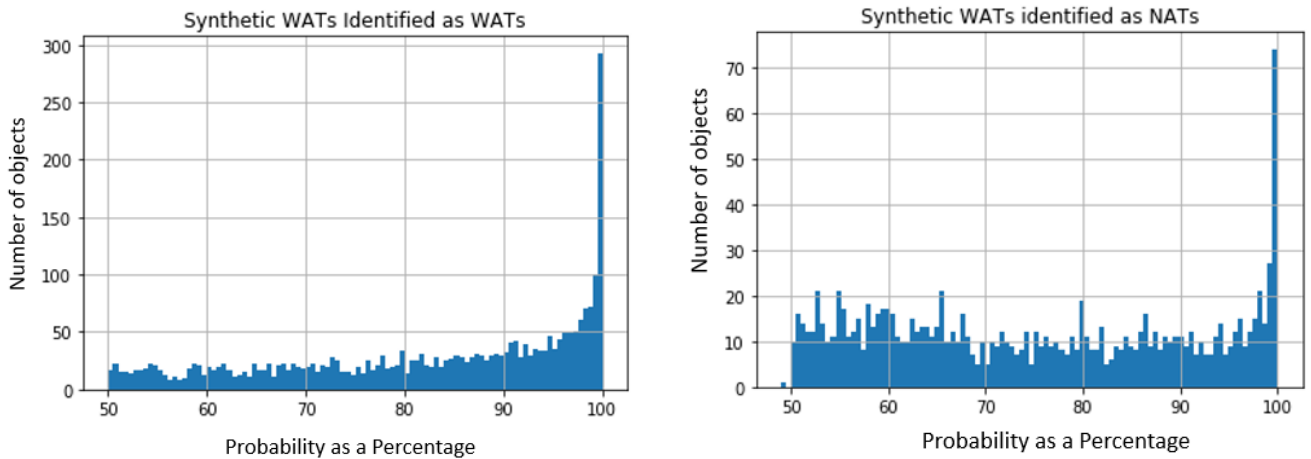


Figure 25a (*left*): Spread of synthetic WATs correctly identified as WATs.

Figure 25b (*right*): Spread of synthetic WATs identified as NATs.

Crudely, this implies that 70% of the test images were correctly identified as WATs. Figure 25a has an exponential increase in the number of WATs identified with the largest proportion lying in the range from 90 – 100% probability. This suggests that the model was trained to a satisfactory degree as the bulk of the probabilities assigned are not in the range from 50 – 80%. Additionally, although Figure 25b depicts an exponential increase in the range from 95 – 100% probability, the proportion of objects identified as NATs overall is approximately 50% of those identified as WATs. Moreover, 3926 of the test images were identified as bent-tail sources (NATs or WATs), implying that the model was sufficiently trained.

The identification of only 70% of objects as WATs may be due to the following and would be a suitable source of improvement for the model. While the test images produced by the GAN were trained with FIRST WATs, upon visual inspection, a number of the objects were of poor resolution with the arms not having distinct separation. This would imply in a significant number of synthetic WATs being produced with poor features thus increasing their resemblance to NATs. Additionally, it must be noted that the catalogue of WATs produced in Sasmal et al. 2022 had sources selected manually through visual inspection. Despite overlaying FIRST images with Digital Sky Survey images in grayscale to identify contours, due to limited pixel resolution from the FIRST data, there is a source of error in identifying object boundaries [28]. Consequently, objects may be mis-

classified to begin with. The accuracy of the multiclass classification model could also be improved by increasing the training set for WATs by adding synthetic radio objects from more runs of the GAN as larger training sets result in better results.

A total of 5744 synthetic NATs were used for testing the multiclass model. Of these, 3313 synthetic NATs were correctly identified as NATs and 2409 were identified as WATs. There were 11 miscellaneous radio objects identified and 11 double-lobed radio galaxies. Given that 5722 of 5744 objects were correctly identified as bent-tail sources, this suggests that the model is adequately trained. Figure 26 below depicts the spread of the number of NATs identified as NATs or WATs.

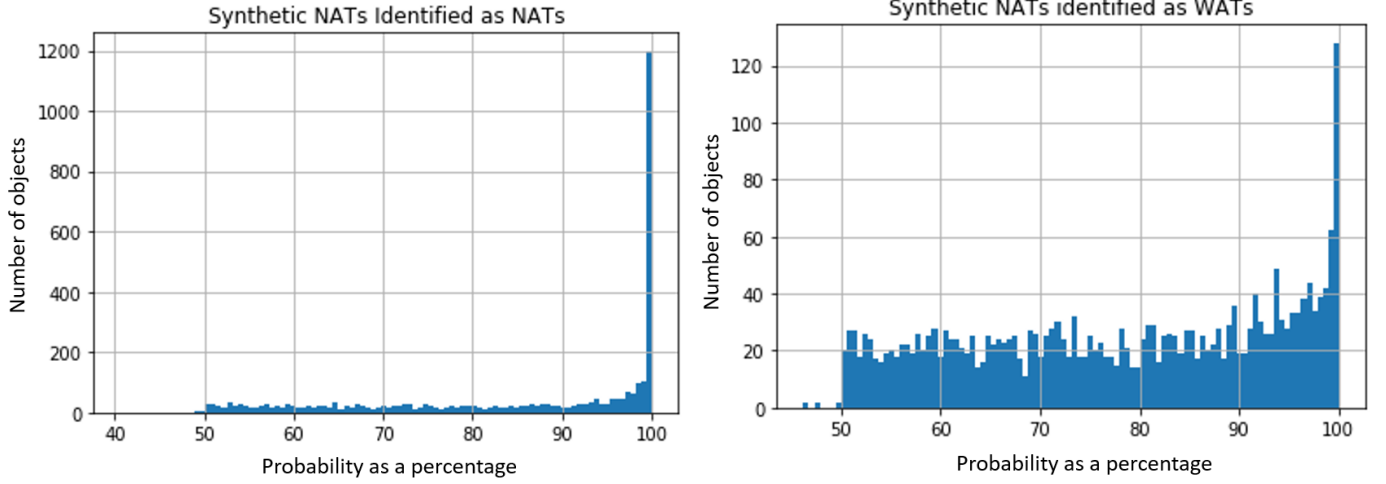


Figure 26a (*left*): Spread of synthetic NATs correctly identified as NATs.

Figure 26b (*right*): Spread of synthetic NATs identified as WATs.

A crude analysis of the number of synthetic NATs correctly identified suggests that only 58% of NATs input into the model were identified positively. Upon a visual inspection, it was noted that a large number the test images were not distinctly NATs suggesting that it was the quality of test images which prompted this result. Some examples the test images are shown in the panel in Figure 27 below.

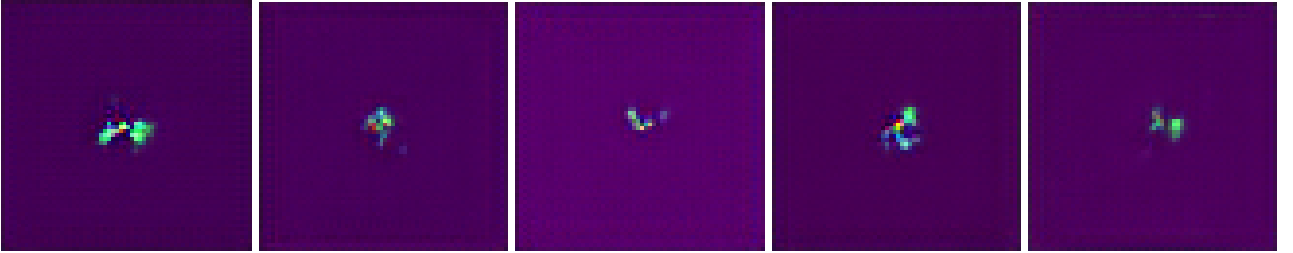


Figure 27: Panel of some synthetic NATs used as test images.

Given that 42% of the test NATs were not identified as NATs suggests that in addition to the training images being ambiguous, the model parameters for the GAN may be improved. Running the GAN for 4000+ epochs may result in better NATs being produced however this may risk overfitting. Omitting NATs of poor resolution with ambiguous 'tails' would be most effective in improving the training for the GAN. These may be replaced by augmenting the remaining NATs further by inserting their images with more random rotations and zooms to avoid mode collapse. Another source of error for the classification of NATs as WATs may be due to the value of training and testing accuracy for the multiclass model being below 90%. This solution to this issue is described previously in this section following Figure 24.

5.3.2 MeerKAT GPS Detecto Cut-outs

A total of 448 cut-outs were obtained from Detecto. Of these, 9 were identified as WATs, 2 as NATs, 62 as miscellaneous radio objects, and 375 as double-lobed objects. The spread of the

percentage probabilities assigned to the objects identified as miscellaneous and double-lobed is given in Figures 28a and 28b respectively.

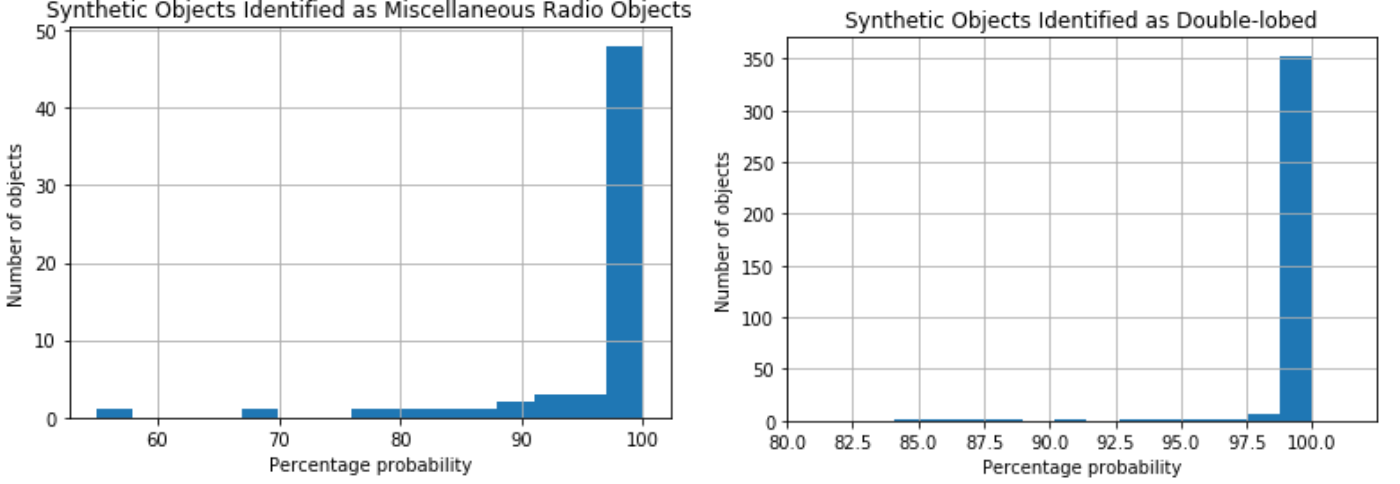


Figure 28a (left): Detecto cut-outs identified as miscellaneous.

Figure 28b (right): Detecto cut-outs identified as double-lobed radio galaxies.

The trend observed in the classes allocated corresponds with expectations as the training set for miscellaneous radio objects and double-lobed galaxies included synthetic MeerKAT GPS images as such objects were primarily observed in MeerKAT GPS images. This further supports the model providing reliable results. Given that a number of objects were identified as NATs and WATs further strengthens this as it verifies that the differing colour schemes of the training images did not adversely impact the results and that the model identified the morphological features of the radio objects when training.

5.3.3 Synthetic MeerKAT GPS Images

A total of 7509 synthetic MeerKAT GPS images were generated using the GAN to be used as test images. Of these, 352 were identified as miscellaneous radio objects, 7157 as double-lobed radio galaxies, and none were identified as WATs or NATs. The spread of the percentage probabilities for double-lobed and miscellaneous radio objects are shown in Figures 29a and 29b below.

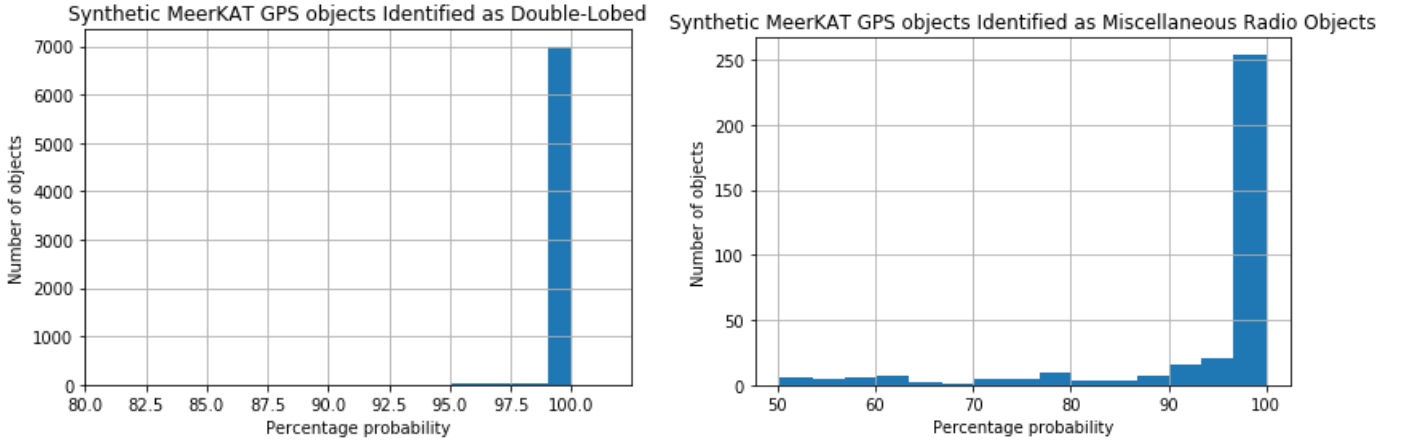


Figure 29a (left): Synthetic MeerKAT GPS images classified as double-lobed radio galaxies.

Figure 29b (right): Synthetic MeerKAT GPS images classified as miscellaneous radio objects.

Upon visual inspection of the test images, it was verified that majority of the objects were double-lobed compact radio sources with no connecting bands or tails. A significant number had diffuse gas and noise eminent in the background and these were identified as miscellaneous objects by the algorithm. Thus, the distribution of the probabilities coincided with the expectations implying that model was trained sufficiently well.

5.4 Prospects

Radio galaxies are complex structures and their distinct features can make classification a challenging and ambiguous task as has been observed with the multiclass classification model studied in this project. This project utilised classification using distinct features, or as suggested by Rudnick 2021, “boxes”. Rudnick identifies this issue and addresses it by proposing that radio galaxies be organised using a system of “tags” which acknowledges the evolving nature of objects. The method of “tags” suggests that instead of allocating a radio object into a category or a “box”, one can assign it a number of *#tags* given that the source satisfies the criteria for each such *#tag*. This method implies that there would be fewer disagreements concerning the characteristic of ambiguous radio objects [39]. Using *#tags* has the potential to improve the reliability of the multiclass classification model used in this project, especially with the case of synthetic NATs which were identified as WATs. As supported by the panel of images in Figure 27, some synthetic NATs do satisfy the criteria for double-lobed radio objects (first from left) and WATs (fourth from left). Additionally, the scale of the object of interest can further influence the category assigned if the method of ‘boxes’ is used, as explained with Figure 29 below, from Rudnick 2021 [39].

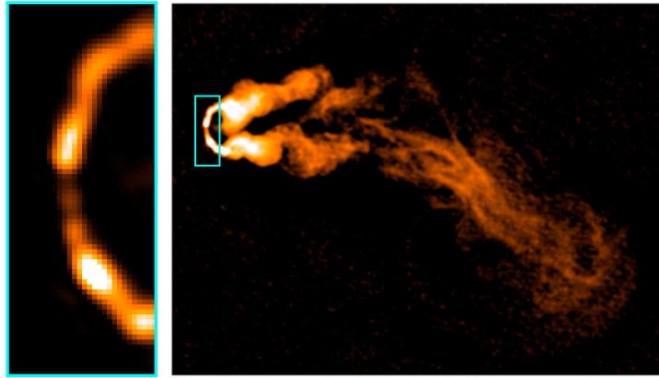


Figure 29: NGC 1265 The left panel appears to be a WAT whereas the zoomed-out image is a NAT [39].

It should be noted that approximately 10% of radio galaxies have components in other wavelengths. For instance, in cases with double-lobed sources with unresolved radio components, the components may be the lobes of a double radio source however they could equally be radio emissions from star-forming galaxies. This demands cross-identification with optical and infrared data [40]. Incorporating this into the multiclass classification model would improve the class allocation if the training set included data on infrared and optical data for the radio images.

6. Conclusion

The use of CNNs and computer vision are crucial in big data astronomy applications such as radio astronomy. In this project, it has been demonstrated that extracting science from gargantuan amounts of data can be made possible with machine learning models for object extraction and classification. With an automated system, it is increasingly likely that identification of major objects of interest will be made through programs such as those constructed and used in this project.

It was successfully demonstrated that increasing the training size of the multiclass classification model using synthetic images improved the classification results. Using 8028 synthetic images to train the GAN and 6248 images to train the multiclass classification model on four image classes: NATs, WATs, double-lobed and miscellaneous radio objects, a validation accuracy of 80.7% and training accuracy of 89.78% was obtained. Consequently, 70% of synthetic WATs were correctly identified as WATs and 58% of synthetic NATs were identified as NATs. The relatively low value of NATs being identified as such can be explained by the ambiguity of the training set of NATs obtained from the VLA FIRST Survey as catalogues in Sasmal et al. [28]. Of the 7509 synthetic MeerKAT GPS images used for testing the multiclass the vast majority of which were double-lobed compact radio objects as verified by visual inspection, 95% were correctly identified as being double-lobed implying that the model was trained to a satisfactory extent despite the issue of overfitting. It was determined that the factor which would impact the quality of the synthetic images produced greatest is

the quality of the training images as visual inspection of the WATs sources depicted much less ambiguity with tails more clearly observed. The project quantitatively and qualitatively proved that deep learning for generating synthetic images can successfully generate high quality images for use in big data astrophysics.

In future works, it is recommended to investigate the impact of training the multiclass classification model for further epochs to improve the accuracy, and to incorporate the method of *#tags* instead of the strict classes to account for the ambiguity in the morphology of radio objects. The methods used in this report may be employed in classification tasks for other fields of astronomy including characterising stellar and galactic populations. The limitations discussed in this report demand further research into the applications of deep learning to probe visual data. We are at the precipice of yet another era of high-quality data with the upcoming SKA along with the breakthroughs in machine learning over the past decade. This is undoubtedly a cause for maximising on the thrill of automation in astronomy to discover more unexpected objects and unveil the physics behind little-understood phenomena such as ORCs.

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Sources

- [1] Lo, K.Y., Carilli, C.L., Frail, D.A., Jewell, P.R., Myers, S.T. and Webber, J.C., 2009. The Impact of the National Radio Astronomy Observatory. *astro2010: The Astronomy and Astrophysics Decadal Survey*, 2010, p.P32.
- [2] https://assets.press.princeton.edu/chapters/s1077_1.pdf Condon, J.J. and Ransom, S.M., 2016. *Essential radio astronomy* (Vol. 2). Princeton University Press.
- [3] Norris, R.P., 2010, December. Data challenges for next-generation radio telescopes. In 2010 Sixth IEEE International Conference on e-Science Workshops (pp. 21-24). IEEE. <https://arxiv.org/ftp/arxiv/papers/1101/1101.1355.pdf>
- [4] Aniyar, A.K. and Thorat, K., 2017. Classifying radio galaxies with the convolutional neural network. *The Astrophysical Journal Supplement Series*, 230(2), p.20. <https://iopscience.iop.org/article/10.3847/1538-4365/aa7333>
- [5] Dieleman, S., Willett, K.W. and Dambre, J., 2015. Rotation-invariant convolutional neural networks for galaxy morphology prediction. *Monthly notices of the royal astronomical society*, 450(2), pp.1441-1459. <https://arxiv.org/pdf/1503.07077.pdf>
- [6] Abdel-Salam, R., 2021. Relating CNNs with brain: Challenges and findings. *arXiv preprint arXiv:2108.09768*. <https://arxiv.org/pdf/2108.09768.pdf>
- [7] Donoso, E., 2010. *Evolution of radio galaxies across cosmic time* (Doctoral dissertation, Imu). https://www.imprs-astro.mpg.de/sites/default/files/Donoso_Emilio_2010_0.pdf
- [8] Goodfellow, I., 2016. Deep Learning-Ian Goodfellow, Yoshua Bengio, Aaron Courville-Google Books.
- [9] Mitchell, T.M., 2007. *Machine learning* (Vol. 1). New York: McGraw-hill.
- [10] Lawaniya, Himanshu 2020. Computer Vision. IET Computer Vision. https://www.researchgate.net/publication/341313012_Computer_Vision
- [11] Mueller, J.P. and Massaron, L., 2021. *Machine learning for dummies*. John Wiley & Sons.
- [12] Shorten, C. and Khoshgoftaar, T.M., 2019. A survey on image data augmentation for deep learning. *Journal of big data*, 6(1), pp.1-48.
- [13] Dubey, S.R., Singh, S.K. and Chaudhuri, B.B., 2022. Activation functions in deep learning: A comprehensive survey and benchmark. *Neurocomputing*.
- [14] Genc, B. and Tunc, H.Ü.S.E.Y.İ.N., 2019. Optimal training and test sets design for machine learning. *Turkish Journal of Electrical Engineering and Computer Sciences*, 27(2), pp.1534-1545.
- [15] Yoon, H., 2021. Finding Unexpected Test Accuracy by Cross Validation in Machine Learning. *International Journal of Computer Science & Network Security*, 21(12spc), pp.549-555.
- [16] Salehi, P., Chalechale, A. and Taghizadeh, M., 2020. Generative adversarial networks (GANs): An overview of theoretical model, evaluation metrics, and recent developments. *arXiv preprint arXiv:2005.13178*.
- [17] TensorFlow. 2022. Image classification. [ONLINE] Available at: <https://www.tensorflow.org/tutorials/images/classification>. [Accessed 24 April 2023].
- [18] Hardcastle, M.J. and Croston, J.H., 2020. Radio galaxies and feedback from AGN jets. *New Astronomy Reviews*, 88, p.101539.
- [19] Aniyar, A.K. and Thorat, K., 2017. Classifying radio galaxies with the convolutional neural network. *The Astrophysical Journal Supplement Series*, 230(2), p.20.
- [20] Barkov, M.V. and Lyutikov, M., 2019. On the nature of radio filaments near the Galactic Centre. *Monthly Notices of the Royal Astronomical Society: Letters*, 489(1), pp.L28-L31.
- [21] Norris, R.P., Collier, J.D., Crocker, R.M., Heywood, I., Macgregor, P., Rudnick, L., Shabala, S., Andernach, H., Da Cunha, E., English, J. and Filipović, M., 2022. MeerKAT uncovers the physics of an odd radio circle. *Monthly Notices of the Royal Astronomical Society*, 513(1), pp.1300-1316.
- [22] Booth, R.S. and Jonas, J.L., 2012. An overview of the MeerKAT project. *African Skies*, 16, p.101.

- [23] Stevens, Ian. 2023. Private Communications. April 2023.
- [24] Padmanabh, P.V., Barr, E.D., Sridhar, S.S., Rugel, M.R., Damas-Segovia, A., Jacob, A.M., Balakrishnan, V., Berezina, M., Bernadich, M.C., Brunthaler, A. and Champion, D.J., 2023. The MPIfR-MeerKAT Galactic Plane survey I--System setup and early results. *arXiv preprint arXiv:2303.09231*.
- [25] Joye, W.A. and Mandel, E., 2003. New features of SAOImage DS9. In *Astronomical data analysis software and systems XII* (Vol. 295, p. 489).
- [26] Hancock, P.J., Murphy, T., Gaensler, B.M., Hopkins, A. and Curran, J.R., 2012. Aegean: Compact source finding in radio images. *Astrophysics Source Code Library*, pp.ascl-1212.
- [27] Becker, R.H., Helfand, D.J., White, R.L. and Laurent-Muehleisen, S.A. (2014). *Faint Images of the Radio Sky at Twenty-Centimeters*. [online] The VLA FIRST Survey. Available at: <http://sundog.stsci.edu/> [Accessed 10 November 2022].
- [28] Sasmal, T.K., Bera, S., Pal, S. and Mondal, S., 2022. A New Catalog of Head–Tail Radio Galaxies from the VLA FIRST Survey. *The Astrophysical Journal Supplement Series*, 259(2), p.31.
- [29] Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G.S., Davis, A., Dean, J., Devin, M. and Ghemawat, S., 2016. Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv preprint arXiv:1603.04467*.
- [30] Shin, H.C., Roth, H.R., Gao, M., Lu, L., Xu, Z., Nogues, I., Yao, J., Mollura, D. and Summers, R.M., 2016. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. *IEEE transactions on medical imaging*, 35(5), pp.1285-1298.
- [31] Bi, A. (2019) *Welcome to Detecto's documentation!*, *Detecto*. Available at: <https://detecto.readthedocs.io/en/latest/> [Accessed: February 26, 2023].
- [32] Ren, S., He, K., Girshick, R. and Sun, J., 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28.
- [33] Nwankpa, C., Ijomah, W., Gachagan, A. and Marshall, S., 2018. Activation functions: Comparison of trends in practice and research for deep learning. *arXiv preprint arXiv:1811.03378*.
- [34] Kummer, J., Rustige, L., Griesse, F., Borrás, K., Brüggen, M., Connor, P.L., Gaede, F., Kasieczka, G. and Schleper, P., 2022. Radio Galaxy Classification with wGAN-Supported Augmentation. *arXiv preprint arXiv:2206.15131*.
- [35] Coccomini, D., Messina, N., Gennaro, C. and Falchi, F., 2021. Generative adversarial networks for astronomical images generation. *arXiv preprint arXiv:2111.11578*.
- [36] Saxena, D. and Cao, J., 2021. Generative adversarial networks (GANs) challenges, solutions, and future directions. *ACM Computing Surveys (CSUR)*, 54(3), pp.1-42.
- [37] Garofalo, D. and Singh, C.B., 2019. FR0 radio galaxies and their place in the radio morphology classification. *The Astrophysical Journal*, 871(2), p.259.
- [38] Barkved, K. (2022) *How to Know If Your Machine Learning Model Has Good Performance, Obviously AI*. Available at: <https://www.obviously.ai/post/machine-learning-model-performance> (Accessed: April 29, 2023).
- [39] Rudnick, L., 2021. Radio Galaxy Classification: # Tags, Not Boxes. *Galaxies*, 9(4), p.85.
- [40] Norris, R.P., 2016. Astroinformatics Challenges from Next-generation Radio Continuum Surveys. *Proceedings of the International Astronomical Union*, 12(S325), pp.103-113.

Appendices

Appendix A

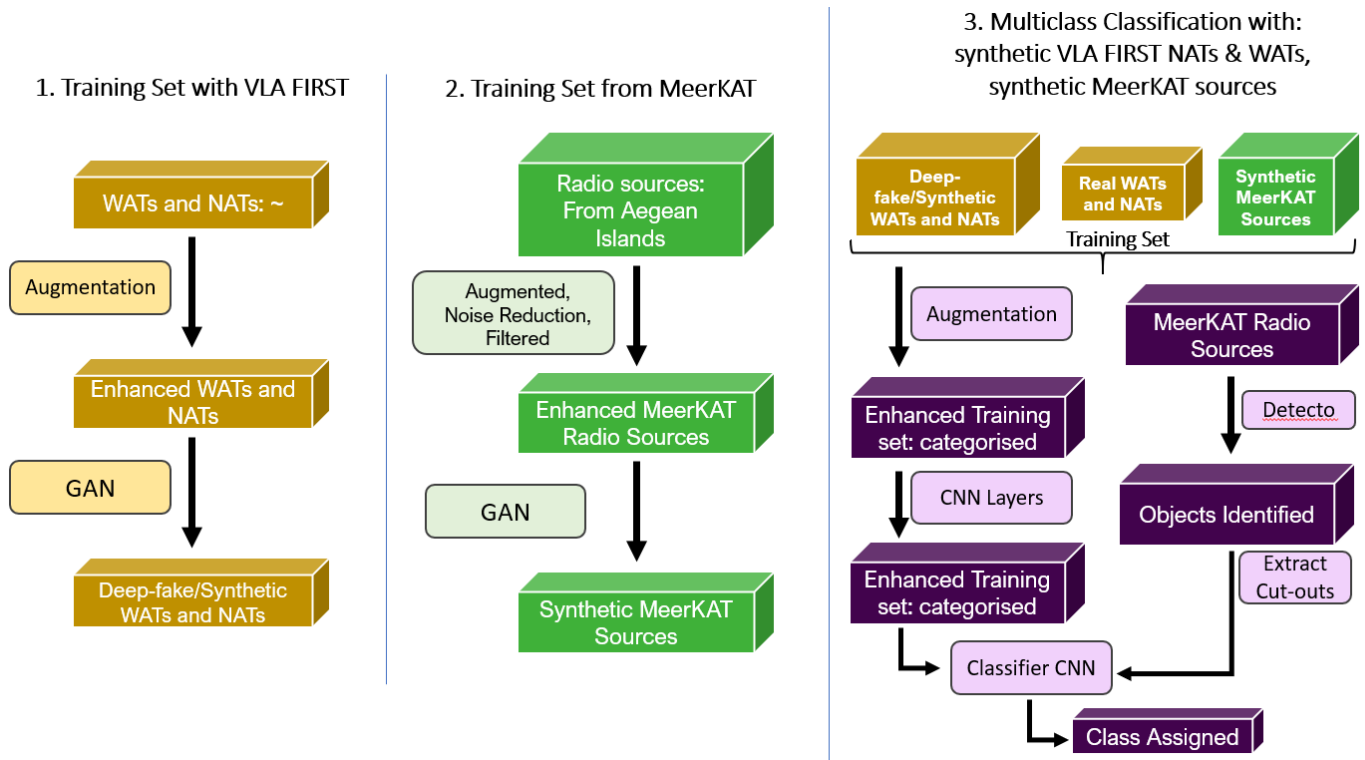


Figure 1: Overall project structure.

Appendix B

Links can be accessed by users within the University of Birmingham

1. Link for synthetic WATs for testing multiclass: [BEAR15_testWAT](#)
2. Link for synthetic NATs for testing multiclass: [BEAR14_testNAT](#)
3. Link for synthetic MeerKAT GPS Images for testing multiclass: [BEAR_17_testMEERKAT](#)
4. Link for Aegean cut-outs from MeerKAT GPS Survey: [Miscellaneous Radio Object](#), [DoubleLobed](#)
5. Link for Detecto cut-outs: [DetectoCutOuts](#)
6. Link to GAN Python file (WATs but applicable to all): [kerasDCGAN_WATs_v2_4LAYERS.py](#)
7. Link to Multiclass Classification Python file: [Classifier.ipynb](#)
8. Link to Detecto file: [Detecto_ColabCodeFile.ipynb](#)
9. Link to full project repository: [MSciProjectWorkSem_2_Submission](#)