AI Applications in Radio Astronomy

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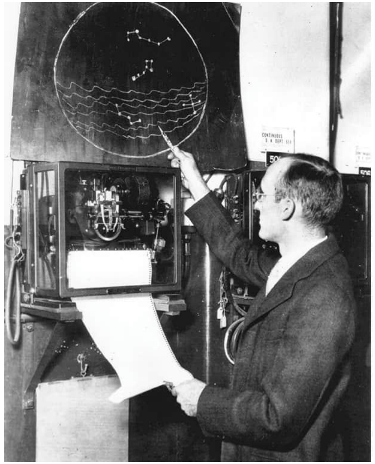
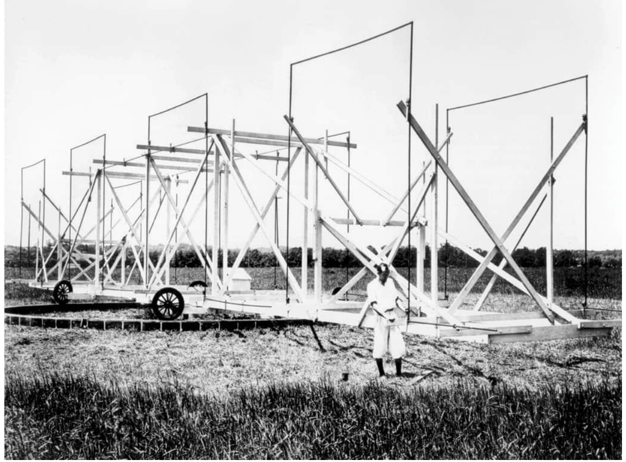
Outline

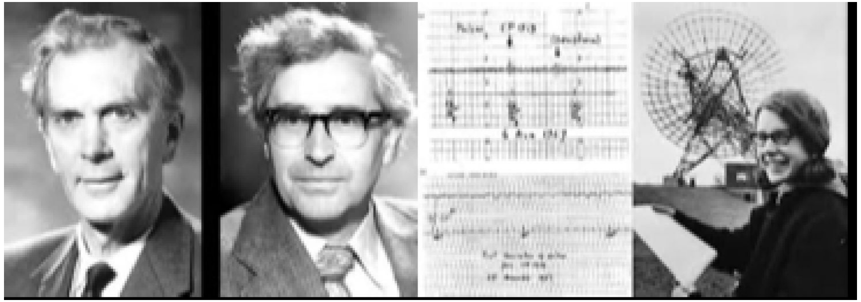
1. Introduction to Radio Astronomy
2. Challenges in Modern Radio Astronomy and need for AI
3. AI Applications in Radio Astronomy
4. Future of AI in Radio Astronomy

1. Introduction to Radio Astronomy

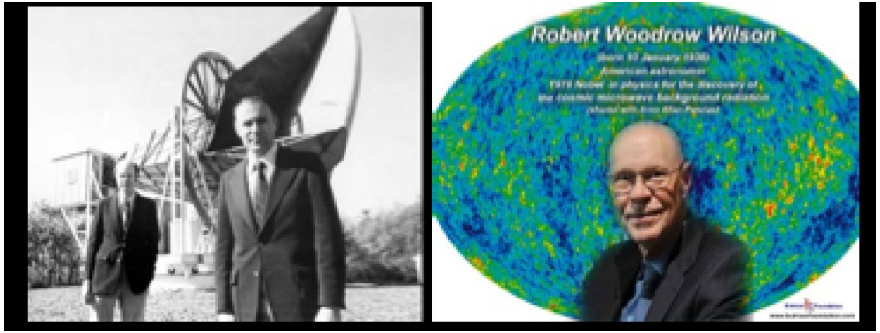
Brief History of Radio Astronomy







aperture synthesis technique, discovery of pulsars (Sir Martin Ryle and Antony Hewish 1974)



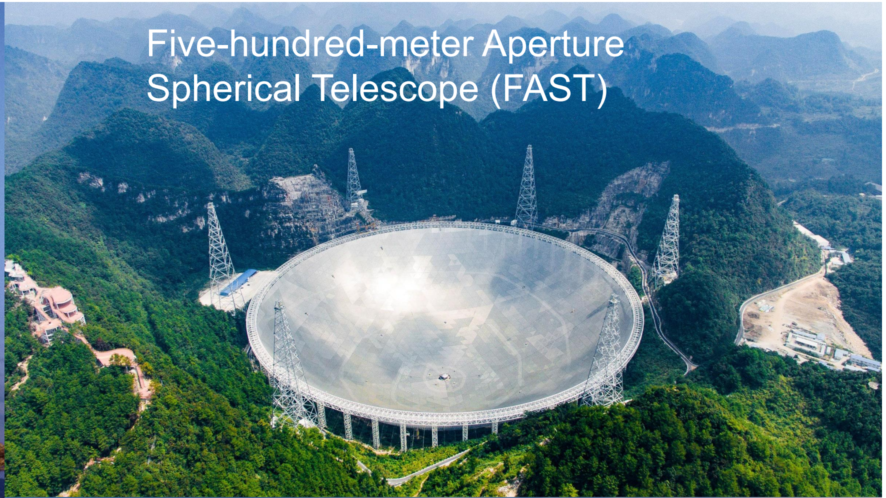
discovery of cosmic microwave background radiation, evidence for the Big Bang theory (Arno Penzias, Robert Wilson 1978)

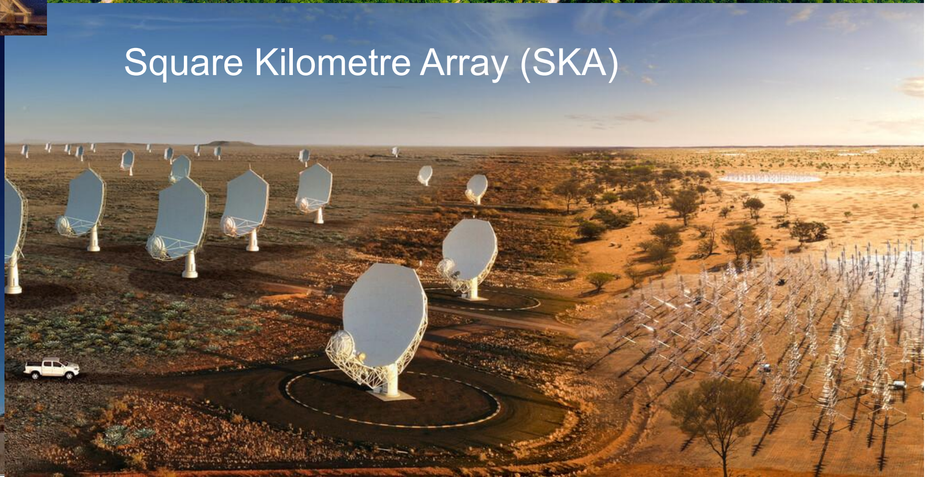
- Early discoveries (Karl Jansky's work)
- Landmark discoveries (e.g., pulsars, cosmic microwave background)

"Star Noise: Discovering the Radio Universe" by Kenneth I. Kellermann and Paul A. Bouton

Radio astronomy: phenomena not visible in other wavelengths

World-class radio astronomy telescopes



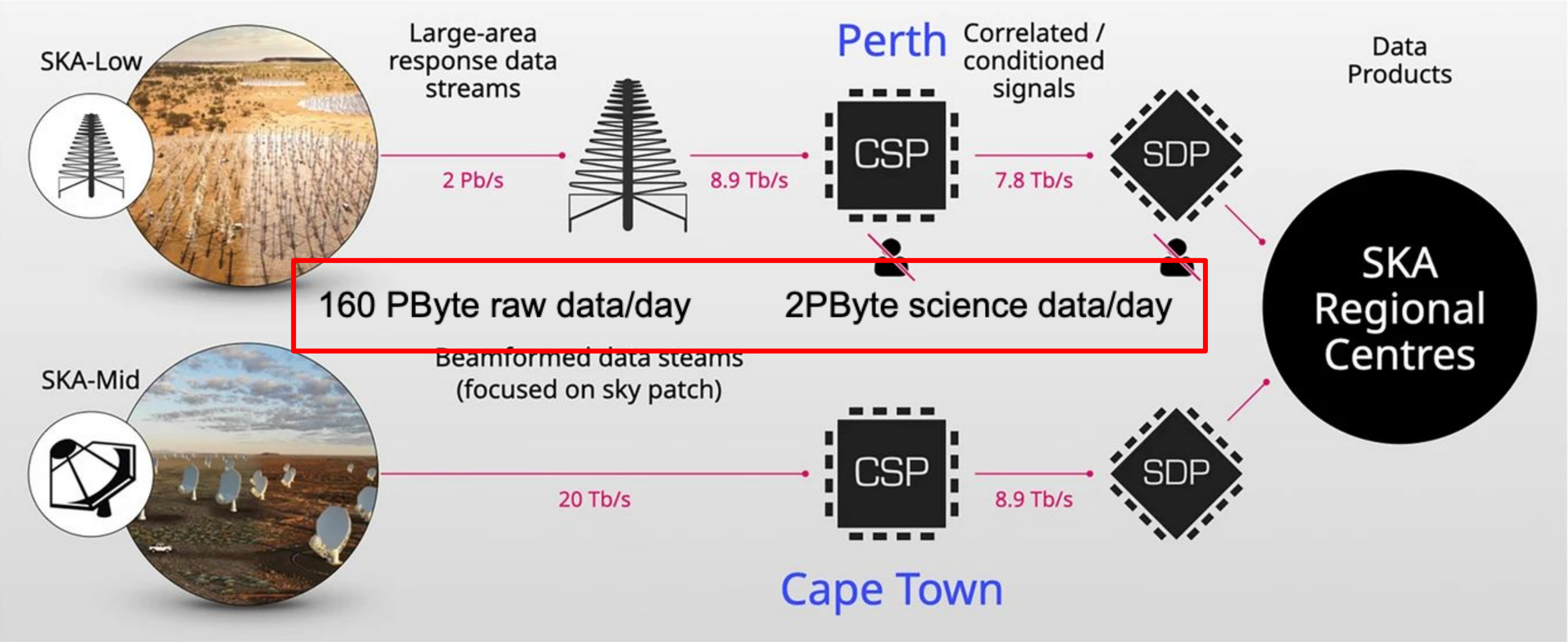


2. Challenges in modern radio astronomy

Data challenges - massive data volumes

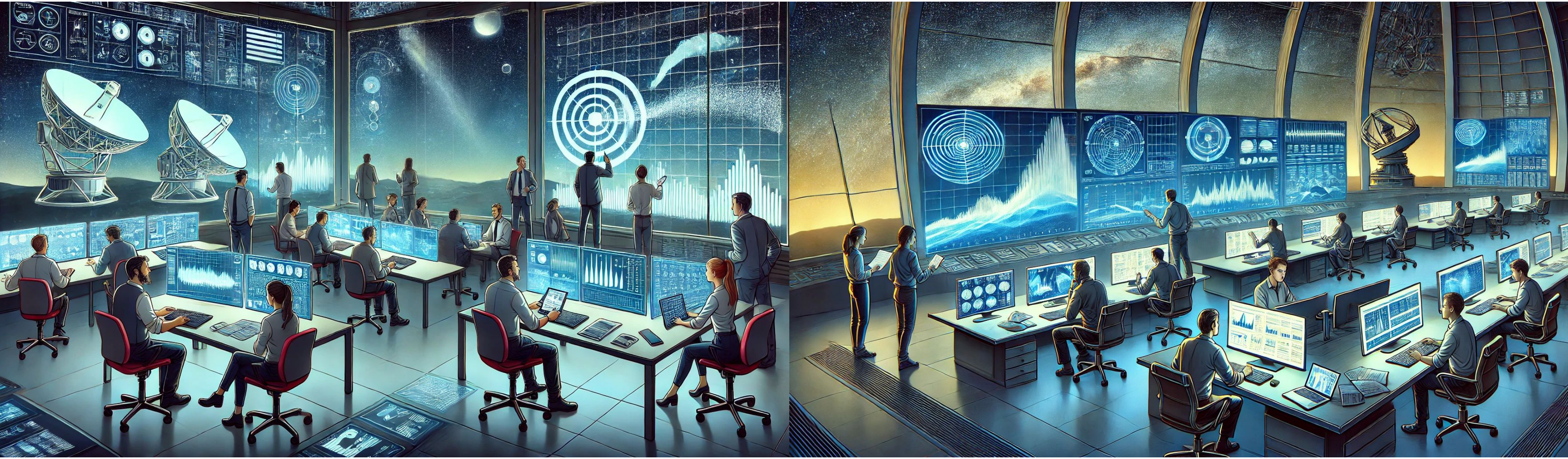
Need for automated processing and analysis

One of the biggest challenges is managing SKA Big Data → cutting-edge technologies incl Machine Learning



AI revolutionises radio astronomy - automation

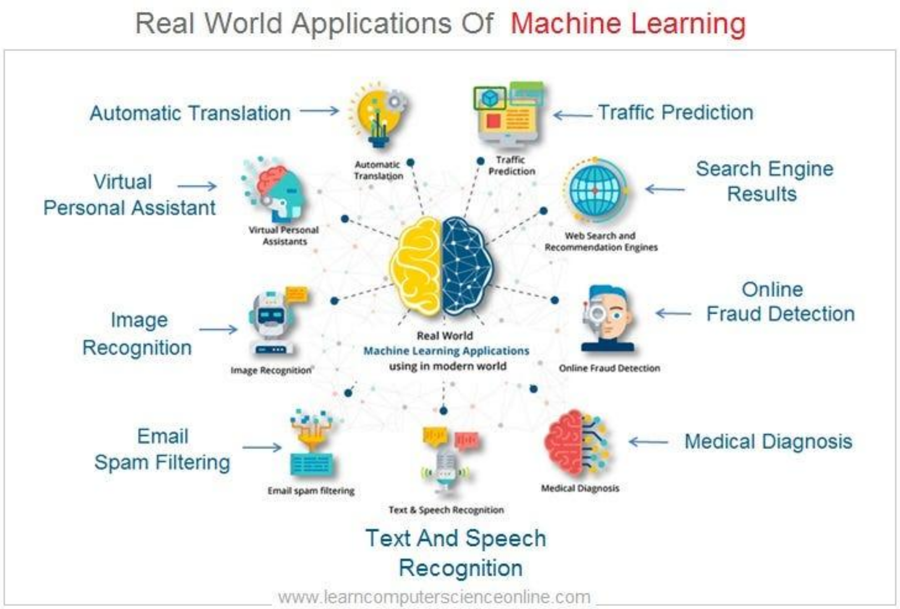
- **Manual processing limitations:**
  - Volume of data, PB daily; Human error; Time-consuming, delay discovery; Scalability issues
- **Benefit of automation:**
  - efficiency , consistency, scalability, resource allocation, enhanced discovery
  - allow astronomers to focus on deeper thinking and interpretation.



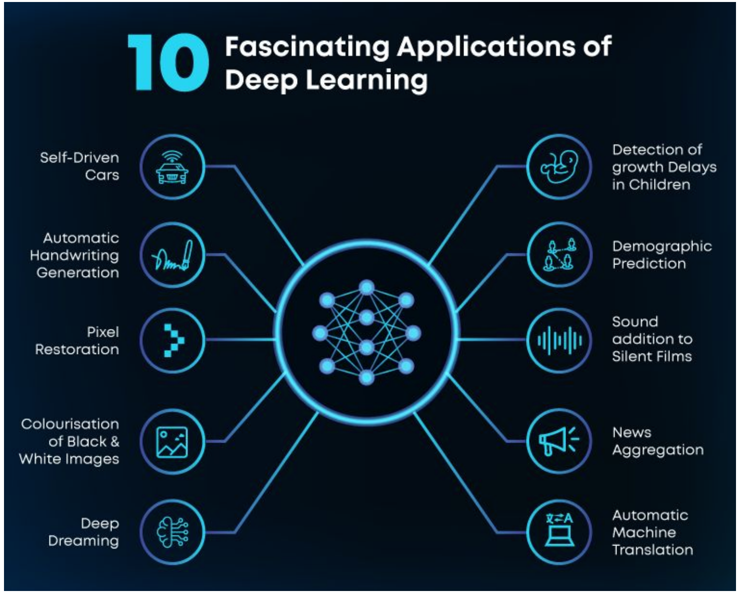
Generated by AI

Applications of Machine Learning and Deep Learning

ML: learn from data, identify patterns, make decisions with minimal human intervention, DT, SVM
DL: use neural networks with many (deep) layers to analyze complex patterns in large datasets, CNN, RNN



structured data tasks like regression, classification, clustering, and recommendation systems



unstructured data, such as **computer vision, natural language processing**, **Autonomous vehicles, and generative models**

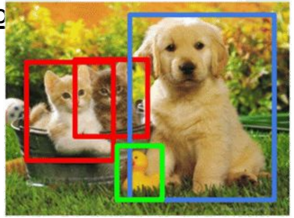
Deep Learning for Computer Vision

Deep learning models achieved impressive results in image/videos understanding and generation

Classification

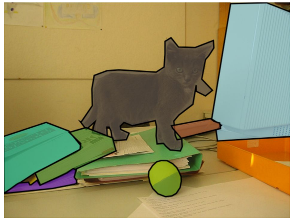
CAT

Object Detection



CAT, DOG, DUCK

Instance segmentation



Keypoint detection

Image

io

Video Action Recognition

Generation

Object Tracking

Image Generation

Midjourney

Conversation

Example of GPT-4 visual input:

User: What is funny about this image? Describe it panel by panel.

Source: https://www.reddit.com/r/hmmm/comments/ubab5v/hmmm/

GPT-4: The image shows a package for a "Lightning Cable" adapter with three panels.

Panel 1: A smartphone with a VGA connector (a large, blue, 15-pin connector typically used for computer monitors) plugged into its charging port.

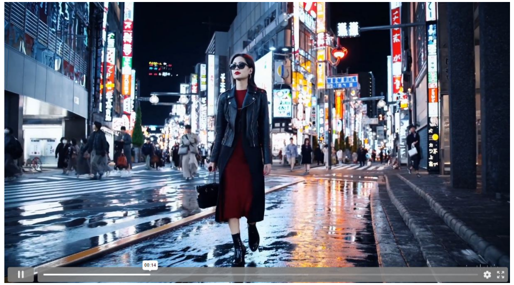
Panel 2: The package for the "Lightning Cable" adapter with a picture of a VGA connector on it.

Panel 3: A close-up of the VGA connector with a small Lightning connector (used for charging iPhones and other Apple devices) at the end.

The humor in this image comes from the absurdity of plugging a large, outdated VGA connector into a small, modern smartphone charging port.

GPT-4

Video



SORA

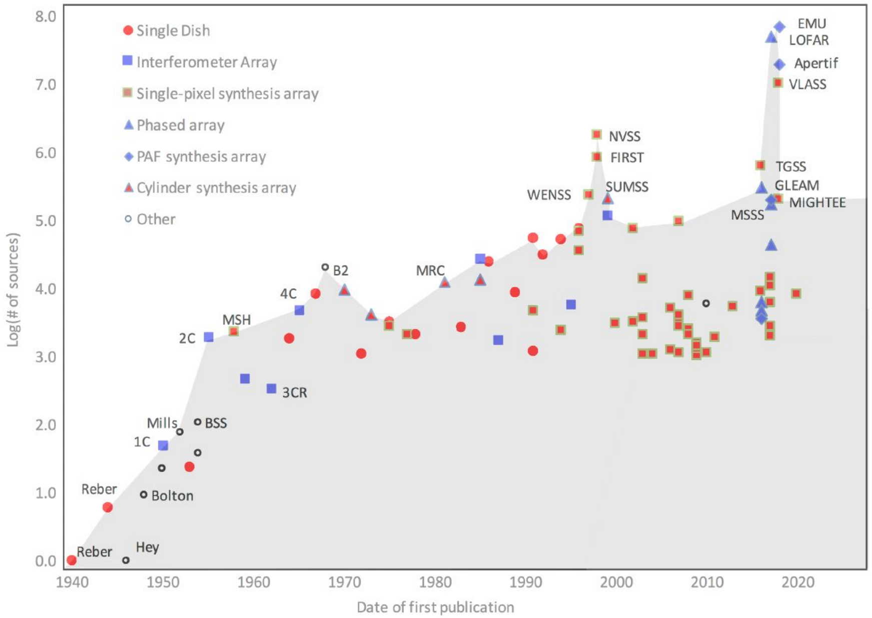
3. AI Applications in Radio Astronomy

AI Applications in Radio Astronomy

- Telescope optimization:
  - telescope settings and scheduling to maximize scientific output.
- Data Processing:
  - Handling massive data volumes: distributed computing, cloud storage, parallel processing.
  - real-time processing: Stream processing frameworks, real-time analytics platforms.
  - interference mitigation: Supervised learning for RFI classification, unsupervised learning for anomaly detection and noise reduction.
- Image Reconstruction:
  - CNNs for feature extraction and enhancement; GANs for super-resolution and de-noising.
- **Source Finding: Identifying and classifying radio sources.**
  - Catalogue -> sky models -> further calibrations
- Transient Detection:
  - Real-time detection of fast radio bursts (FRBs) and pulsar glitches, efficient follow-up
  - AI-assisted discoveries of new FRBs, unknown, SETI
- Radio interferometry:
  - AI-driven algorithms enhance radio interferometry techniques, leading to more accurate synthesized images from multiple telescopes.

Radio source finding and classification

- In SKA era, even the simplest and fundamental source finding task becomes challenging!
- Exponential growth in radio sources over past decade → Catalog creation **difficult**
- Big data analysis: major challenge for astronomers
- The integrity, reliability and accuracy of the created catalogue is the primary concern of any standard source search software.
- **AI: promising solution for data processing challenges**



1990-2000 NVSS: 1.8M
2020 EMU: 70 M

Norris+2021

Source Finding Tools: from basic algorithms to AI-driven solutions

- Early source search algorithms were integrated in data processing packages. E.g. SAD in AIPS -> FIRST, NVSS
- Independent source finding software
  - SExtractor, DUCHAMP,, Aegean, and PyBDSF
  - greater reliability and accuracy than older ones and are widely used in modern radio observations.

Traditional source finding tools

Software	compact source	extended source	completeness	reliability	flux density estimate	parallel mode
SExtractor	Y	N	high	high	poor	multithreading
DUCHAMP	Y	N	poor	poor	poor	multithreading
Selavy	Y	N	high	poor	high	multiprocessing
BLOBCAT	Y	N	high	high	high	multiprocessing
Aegean	Y	N	high	high	high	multithreading
PyBDSF	Y	Y	high	high	high	multithreading
ProFound	Y	Y	-	-	high (extended)	multithreading
CAESAR	Y	Y	-	-	high (extended)	multiprocessing

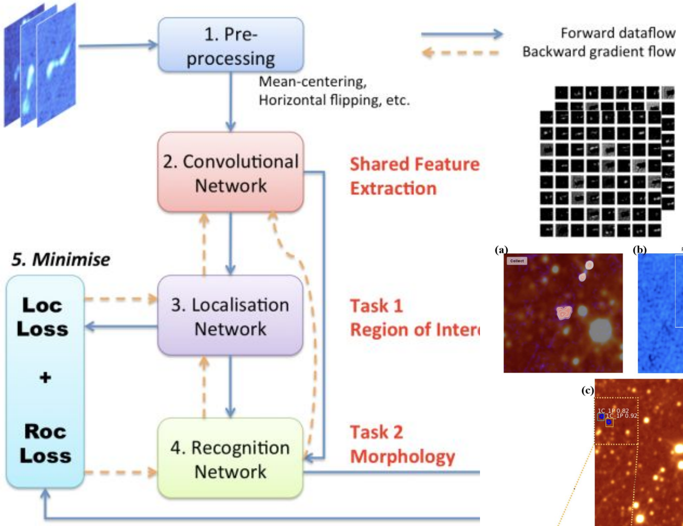
- Limitations of Traditional Component (Gaussian) Fitting Methods:
  - Time-Consuming, especially for large datasets; Systematic Errors: Prone to biases from initial model assumption;
  - only Gaussian fitting, effective for point sources only, but not good for extended sources;
  - only identify, lack ability to classify
  - Challenges in detecting extended sources, faint features, contamination signals / interference
- New-generation source finding tools are

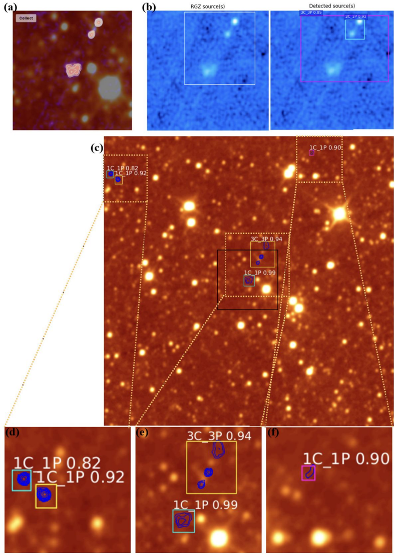
AI-based :

CLARAN → HeTu v1 → HeTu v3

CLARAN
Classifying Radio Sources Automatically with Neural Networks

- Objective: Automate the classification of radio source morphologies
- Developer: Chen Wu, Ivy Wong et al. at ICRAR
- Architecture:
  - Pre-trained ResNet, Region Proposal Network (RPN), Faster Region-based (Faster R-CNN)
  - Components: Uses a pair of WCS-aligned images for cross-matching.
- Training Data: VLA FIRST (radio) and WISE (IR)
  - Annotations: Data from the Radio Galaxy Zoo project https://radio.galaxyzoo.org/ DR1
- Locates and associates discrete and extended components of radio sources based on comp and peaks.
- Speed: <200 ms per image; Accuracy: >=90%
- Usage: Applied to the GMRT 610 MHz survey in the ELAIS-N1 region. Potential for large datasets



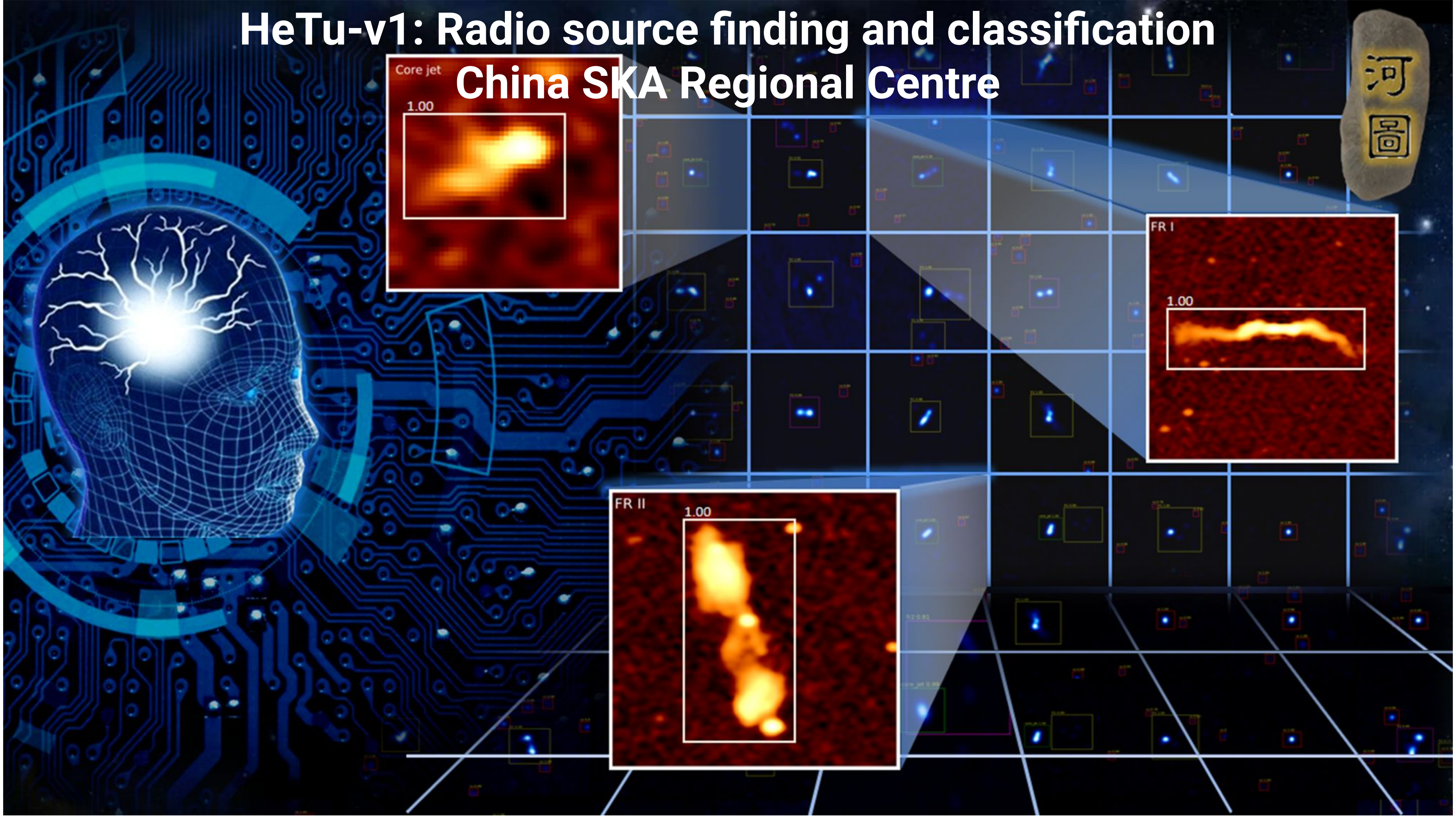


CLARAN is the first DL tool for automated radio source classification. Open source.

Wu et al. 2019 MNRAS, 482, 1211

Limitations of CLARAN

- **Multi-source fields**: relatively lower success rates in fields containing multiple radio sources.
- **Limited field size**: currently designed for smaller image fields, challenges in larger fields
- **Classification:** N components M peaks, not capture the full complexity of radio morphologies.
- **Computational requirements**: While faster than manual classification, CLARAN still requires significant computational resources, especially for processing large surveys.
- **Performance** sensitive to image quality: noise levels and resolution.
- **Lack of explainability**: As with many deep learning models, CLARAN's decision-making process is not always transparent, which can be a limitation for scientific applications requiring interpretability.
- **Dependency on training data**: It may struggle with rare or unusual morphologies not well represented in the training data. And limited to specific surveys: CLARAN was primarily trained on FIRST and WISE survey data, which may limit its generalizability to other radio surveys with different characteristics.
- **Ongoing development**: As a proof-of-concept, CLARAN is still evolving, and some limitations are expected to be addressed in future versions.

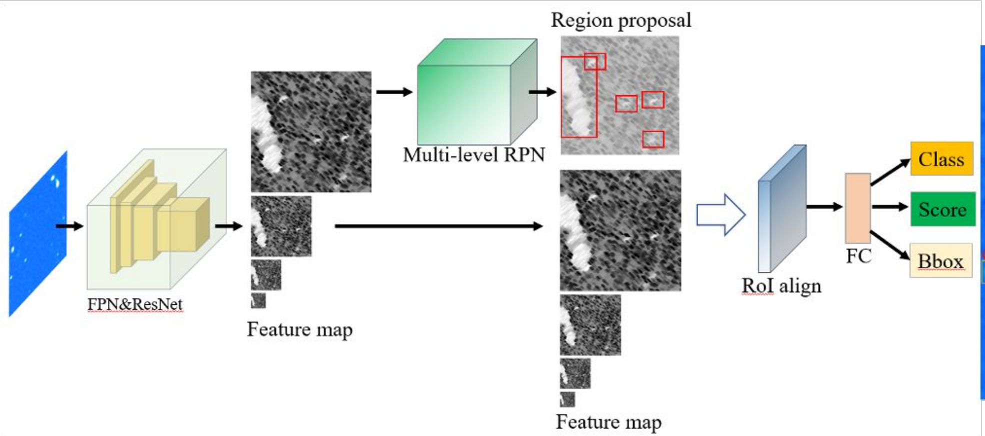

HeTu-v1: Radio source finding and classification
China SKA Regional Centre
Core jet
1.00
FR I
1.00
FR II
1.00
河
圖

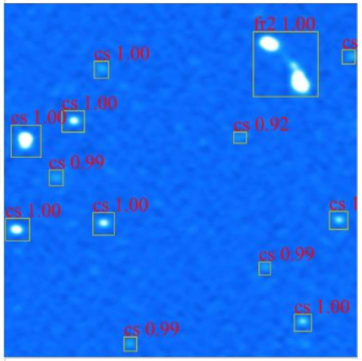
HeTu-v1

- Characteristics compared with CLARAN:
  - More efficient backbone network : faster; high accuracy; ability to detect and classify multiple objects in same image;
  - good scalability: with GPU acceleration to meet processing needs of different scales
- Classification type:
  - four astrophysical meaningful classes: Compact Source, FRI, FRII and Core-Jet

1. **Image pre-processing**: image resizing and data normalization.
2. **Feature extraction:** use ResNet-FPN network to generate multi-scale feature maps from the processed images.
3. **Proposal generation**: use a multi-level RPN proposal network to generate proposal scores and proposal bounding boxes
4. **Classification and box regression:** use Faster R-CNN network to create multi-scale features maps, proposal results, processed images and ground truth boxes
5. **Output**: Label names, scores and boxes of detected sources

- Network: a combined ResNet+FPN network
- ResNet-101: balancing high recognition precision and computational cost
- Feature Pyramid Networks (FPN) - advantage in multi-feature object detection





HeTu-v1: training

- Training data: VLA FIRST radio images
- Each PNG image → log-min-max color scale
- All images were labeled by visual recognition according to our four classification sc
- HeTu vs. ResNet:
  - HeTu combined ResNet + FPN enhances multi-feature object detection
  - HeTu: Faster and higher accuracy
- HeTu vs CLARAN
  - More efficient backbone network (ResNet vs Fast R-CNN), higher precision and faster processing

Class Name	Training (# sources)	augmented (# sources)
CS	1,720	**3,949**
FRI	157	**2,512**
FRII	825	**2,475**
CJ	132	**2,628**
Total	2,834	**11,564**

FRI: 15x; CJ: 20x FRII: 3x; CS: 2.3x

Training: higher precision ~87%

Table D.3: *AP* and *mAP* results of evaluation on D1 datasets

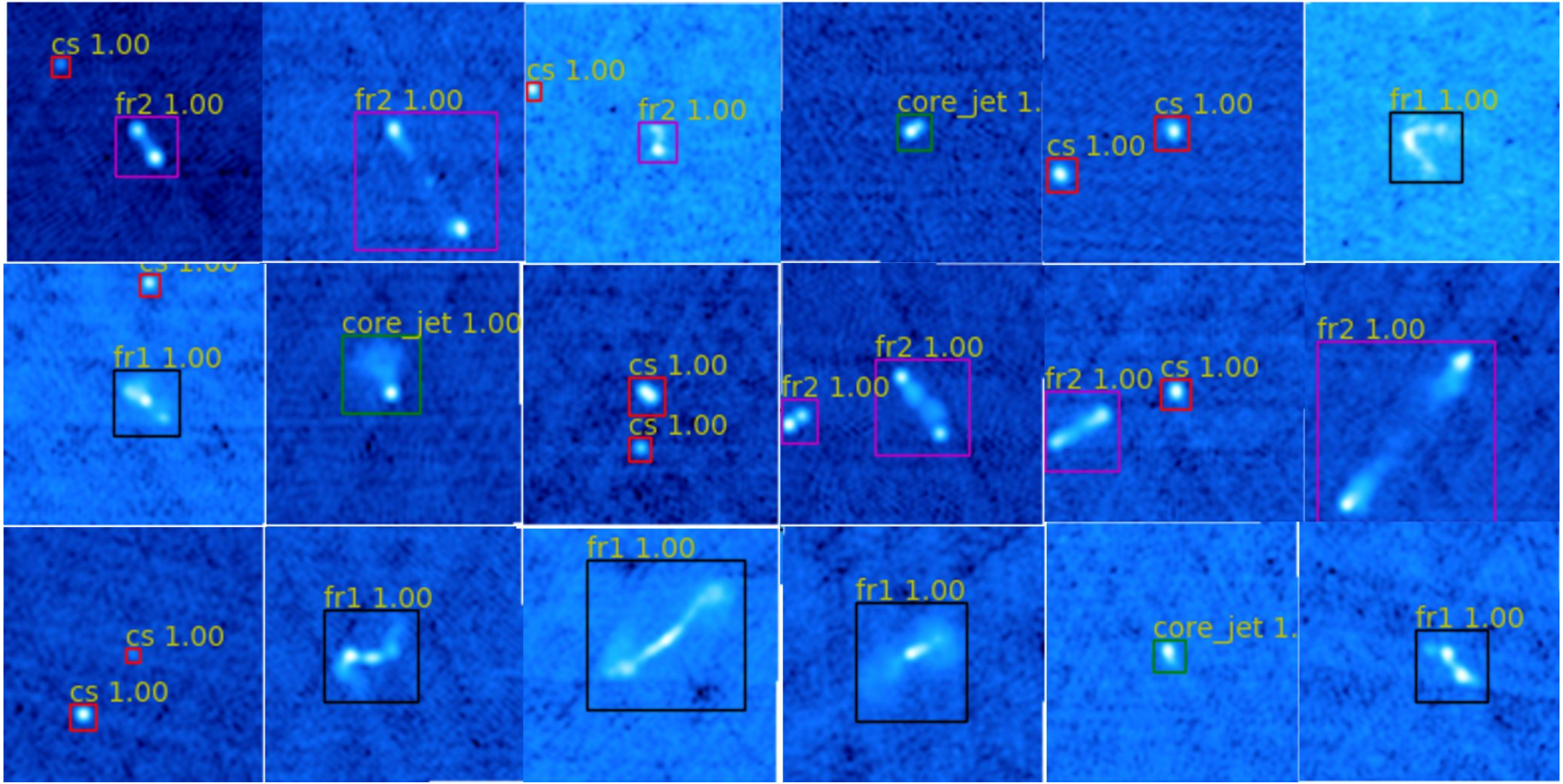
Class name	ResNet-50	ResNet-101	HeTu-50	HeTu-101	CLaRAN v0.1 [5]
1C_1P	0.8904	0.9180	0.9519	0.9621	0.8580
1C_2P	0.6583	0.6782	0.7597	0.7636	0.6882
1C_3P	0.8920	0.9004	0.9126	0.9186	0.8816
2C_2P	0.7836	0.8358	0.8398	0.8674	0.7014
2C_3P	0.8013	0.7809	0.8037	0.8057	0.7099
3C_3P	0.9269	0.9230	0.9322	0.9413	0.8636
mAP	82.5%	83.9%	86.7%	87.6%	78.4%

Address class imbalance

Table D.7: *AP* and *mAP* results of the re-labelled dataset

Class name	HeTu-50	HeTu-101	HeTu-50 (augmented)	HeTu-101 (augmented)
CS	0.9849	0.9860	0.9950	0.9940
FRI	0.8167	0.8507	0.8824	0.8962
FRII	0.9810	0.9643	0.9889	0.9806
Core-jet	0.7625	0.7951	0.8934	0.8961
mAP	88.6%	89.9%	94.0%	94.2%

Examples of outputs



HeTu-v1: Prediction on MWA GLEAM images

Threshold	Methods	CS	FRI	FRII	CJ	Runtime
$\sigma_s = 6\sigma$	HeTu	69,263 (94.5%)	751 (94.9%)	685 (100%)	801 (98.9%)	23.87 mins
	Aegean	69,405 (94.3%)	1,298 components*	1,415 components	1,207 components	499.35 mins
	Cross match	65,476	713	685	799	–
$\sigma_s = 5\sigma$	HeTu	76,328 (96.9%)	767 (97.4%)	685 (100%)	872 (97.6%)	...
	Aegean	82,894 (89.2%)	1,347 components	1,415 components	1,293 components	501.50 mins
	Cross match	73,967	747	685	851	–
$\sigma_s = 4\sigma$	HeTu	81,834 (96.2%)	770 (97.9%)	685 (100%)	961 (95.5%)	...
	Aegean	96,340 (81.7%)	1,367 components	1,415 components	1,395 components	504.52 mins
	Cross match	78,694	754	685	918	–

- HeTu runs 100ms per image, **21** times faster than Aegean (traditional source finder);
  - **Cross-match rate 100% for FRII, 97.4% for FRI and 97.6% for CJ**
- HeTu automates classification, new findings:
  - ~2300 extended sources from a part of GLEAM survey image
  - HeTu found more weaker sources (5>SNR>4), less artefacts (sidelobes, edge sources)

what we learn from HeTu-v1 and future work directions

- **HeTu - what we learn**
  - 99% of time on building datasets, 1% of the time is spent optimizing AI algorithms for training
  - Detection speed in milliseconds, scalable for larger datasets

- **Future work :**
  - **Dataset argumentation**: Add more CJ and FRI sources to train model; Label larger size of images for higher precision on larger images to accelerate; Include more morphological types; data augmentation methods
  - **Network:** advanced backbone network, advanced object detection algorithmic framework
  - **Training techniques:** Transfer learning, pre-trained model, self-supervised learning, small amount of label data

- **Goal of Application**
  - Apply to large-volume image sets, e.g., FIRST (>900000), RACS (4M), EMU (>20M)

HeTu-v1 →HeTu-v3
a revolutionary change in the working mode

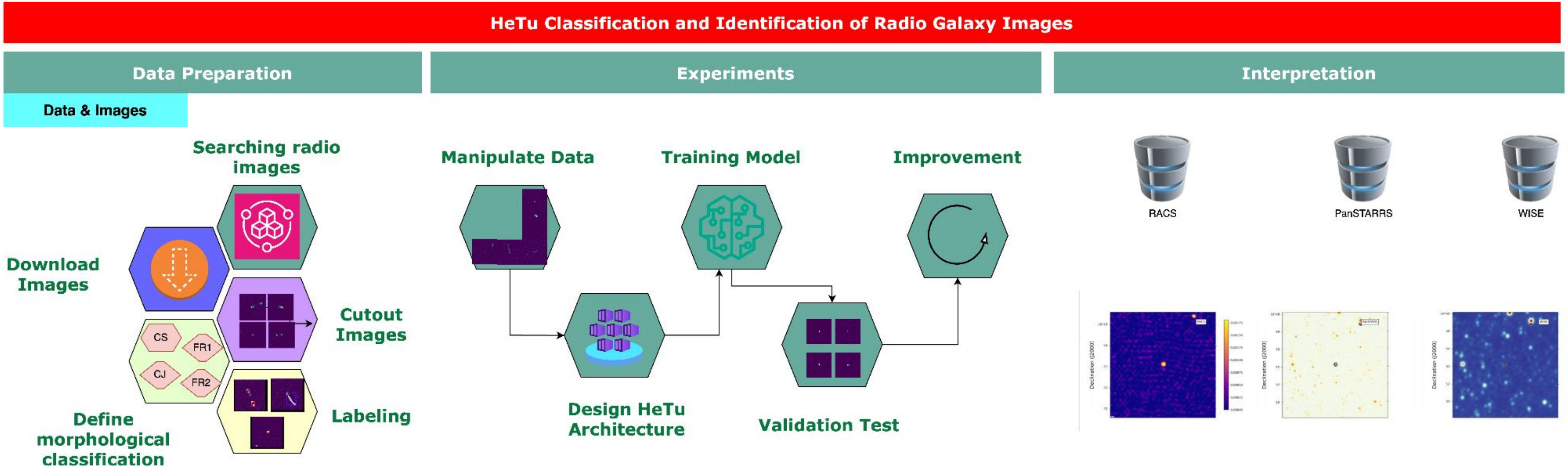
- HeTu-v1 and other traditional approaches:
  - **Manual label -> Training (small data) -> Validation -> Prediction (larger data)**
  - Limitations: labor-intensive labeling (99% of time on labeling datasets, 1% on optimizing AI algorithms), limited dataset for training, sensitive to training data, fixed model and only for specific application
  -
- HeTU-v3 revolutionary changes:
  - **Pretrain foundation model on Large Data → small labeled data for fine-tune and transfer to downstream applications**
  - **Building foundational models is a new cutting-edge way of working that has emerged only in recent years with the development of big models and big data.**
  - Self-supervised pretraining, advanced architectures (VitDet, InternImage), efficient unlabeled data use, improved transfer learning, automated workflow, enhanced scalability and adaptability for large-scale radio astronomy image analysis.
  - Cutting-edge scalable solution for large-scale surveys

HeTu-v3: overview and compare with HeTu-v1

- **More advanced architecture**:
  - VitDet and InternImage models, advantages over ResNet in HeTu v1
- **Larger datasets**:
  - ASKAP RACS-Mid survey, 50 times more objects, Potentially better performance on extended and complex sources
- **Classification**:
  - four classes (CS/CJ/FRI/FRII) with guessed label
- **New Training methods**: two-step approach:
  - Pretraining a foundation model (unsupervised learning with big data)
  - Transfer learning to downstream applications with little training data
- **Performance** Metrics:
  - mAP, processing speed per image, accurate rates for different types
- **Applications**: ASKAP RACS, EMU,
- **Outcome** and future directions
  - Multi-source data, larger-scale datasets

Workflow of HeTu v3

1. Three stages: data preparation, experimentation, interpretation.
2. Large multi-band datasets, advanced AI architectures
3. HeTu-v3 is **not just a technical improvement, but a reimagining** of how we approach the complex downstream astronomical tasks.

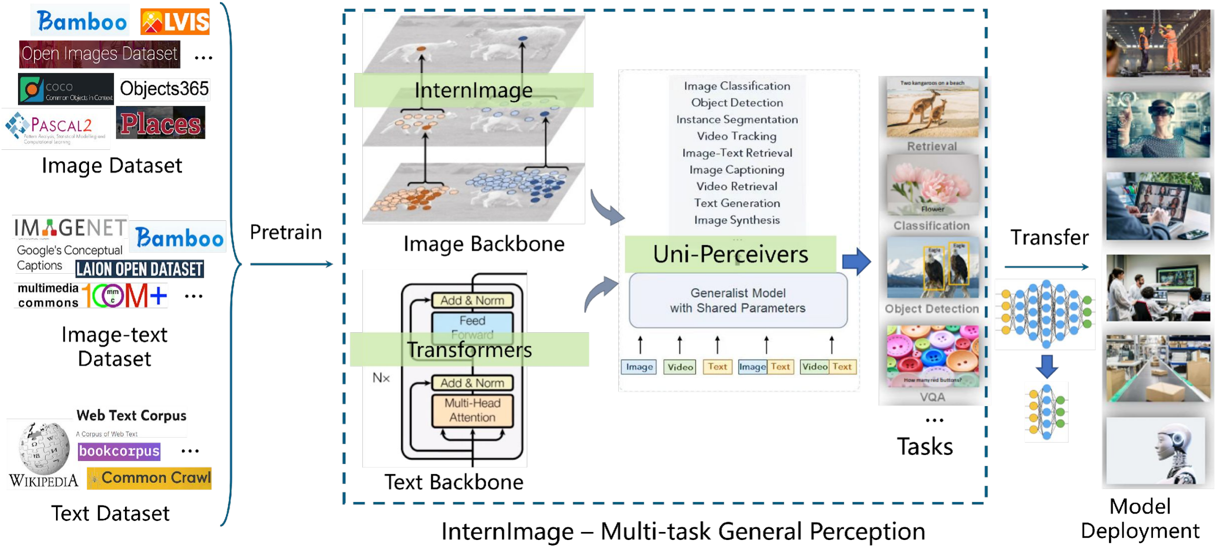


Foundation models: paradigm change in computer vision

The Foundation Model has been widely adopted and used since around 2020 with the release of OpenAI's GPT-3

Step 1 Pretrain foundation model. Unsupervised or supervised learning with big training data

Step 2 Transfer to downstream applications. Incorporate downstream module and use little training data, flexibly applied to a wide range of tasks such as classification, target detection, and image synthesis.



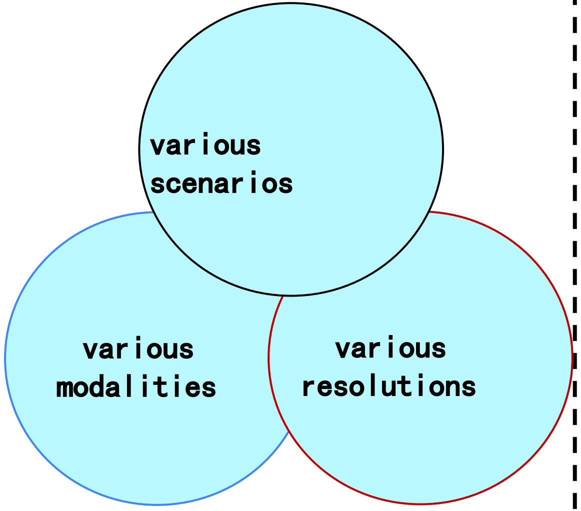
An overview of of InternImage's training and applications

Popular foundation vision models

CLIP	OpenAI	2021
Florence	Microsoft	2021
DINO	Meta	2021
InternImage	Shanghai AI Lab	2022
EVA	BAAI	2022
Flamingo	Deepmind	2022
ImageBind	Meta	2023
LVM	UCB	2023

HeTu v3: Pretraining Step

- Radio data: diverse freq
- Optical data: diverse band
- Infrared data
- X-ray data
- etc...



Pretraining data

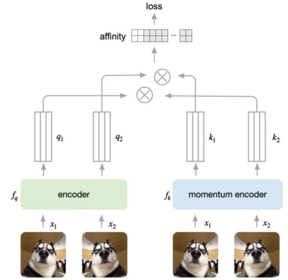
(Unlabeled radio images)

Pretraining method

(self-supervised learning)

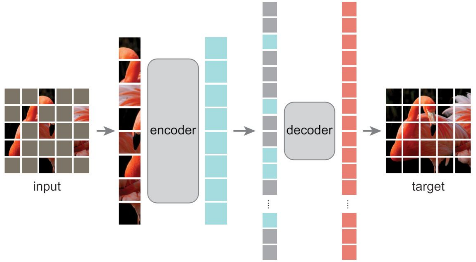
Constrastive learning: MoCo v3

(for CNN models)

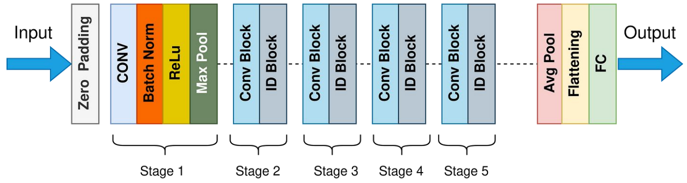


Masked AutoEncoder

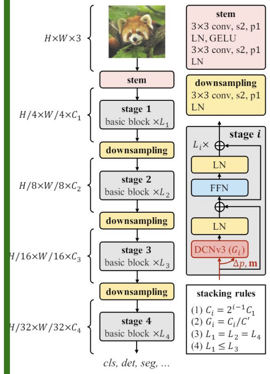
(for transformer models)



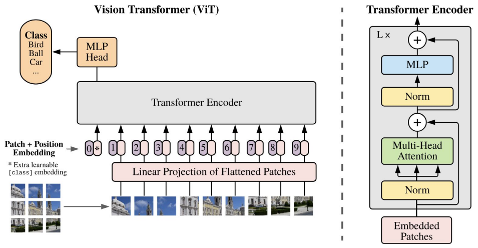
ResNet



InternImage



Vision Transformer



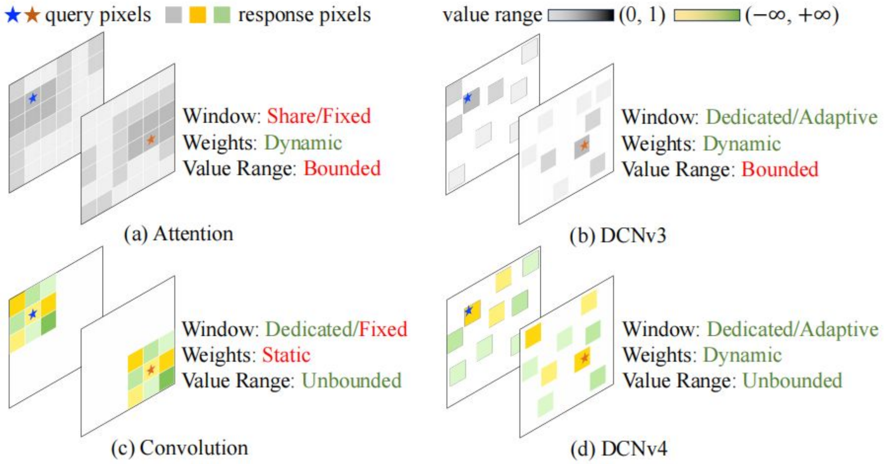
Foundation models

Foundation Model: ResNet, VitDet, InternImage

Advantages of InternImage and Vision Transformer

- **Larger receptive field** (Vision Transformer) and **learnable convolution kernels' shapes** (InternImage)

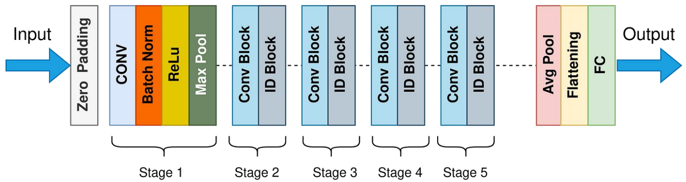
Capture more information (e.g., especially for sources with strange shapes)



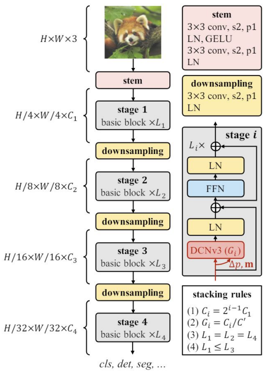
- **Scaling law**

Much better performance on big data or big model.

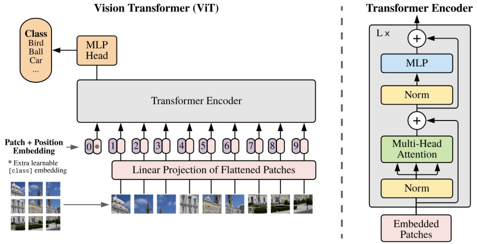
ResNet



InternImage



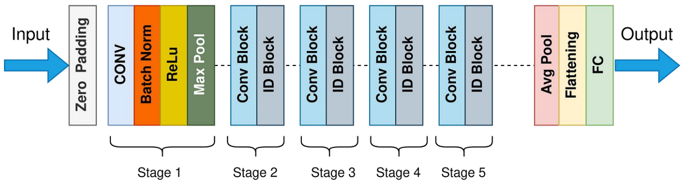
Vision Transformer



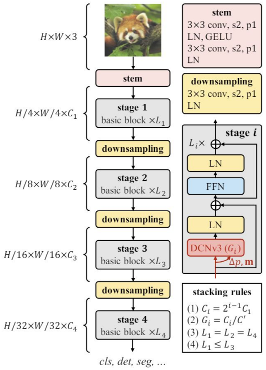
Foundation model

Experimental Results on Model Architecture

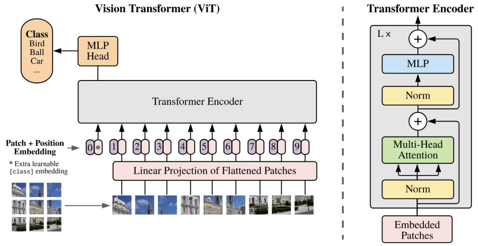
ResNet



InternImage



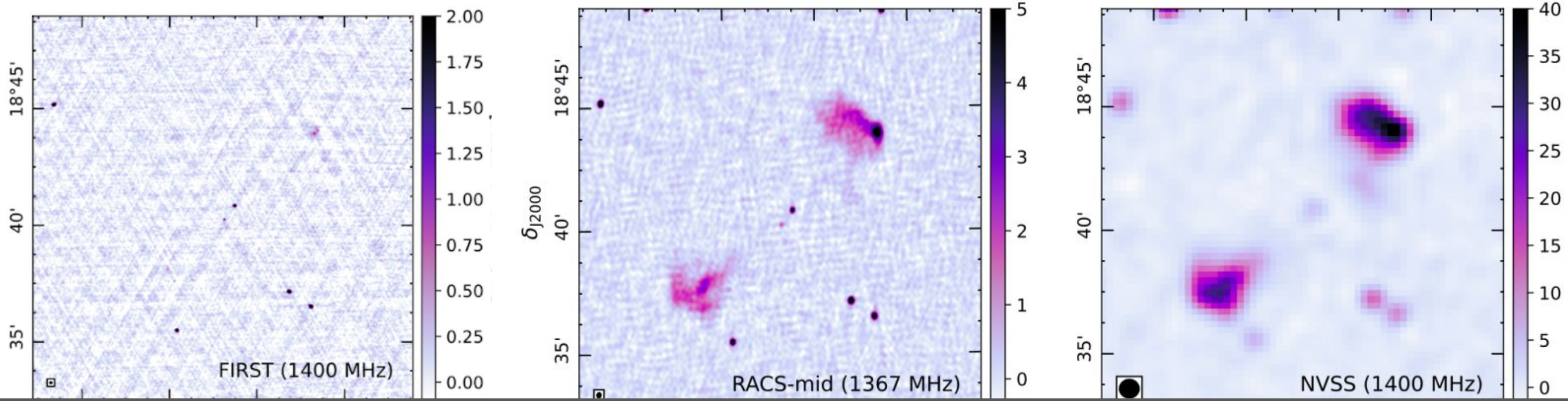
Vision Transformer



Model (pretrained by ImageNet)	Flops	Detection mAP	Detection AP@50	Instance Segmentation mAP	Instance Segmentation AP@50
ResNet-50	0.113T	0.452	**0.747**	0.380	0.717
Vision Transformer-B	0.286T	0.490	**0.800**	0.404	0.773
InternImage-T	**0.105T**	**0.503**	**0.840**	**0.429**	**0.833**

Data used in HeTu v3: ASKAP RACS-mid survey

- Survey : the entire southern sky up to a declination of +49 degrees at a frequency of 1367.5 MHz, with a declination-dependent resolution of 8.1-47.5 arcsec, and a median sensitivity of **0.2 mJy/PSF**.
- Intermediate resolution between FIRST and NVSS: getting more detail without losing the full structure
- The release consists of **1493** unique tiles (and 88 duplicate observations), more than **800GB** (raw data)
- ~ 3000 images per observation data
- **4 million objects (50 x more than HeTu v1) → to train foundation model**

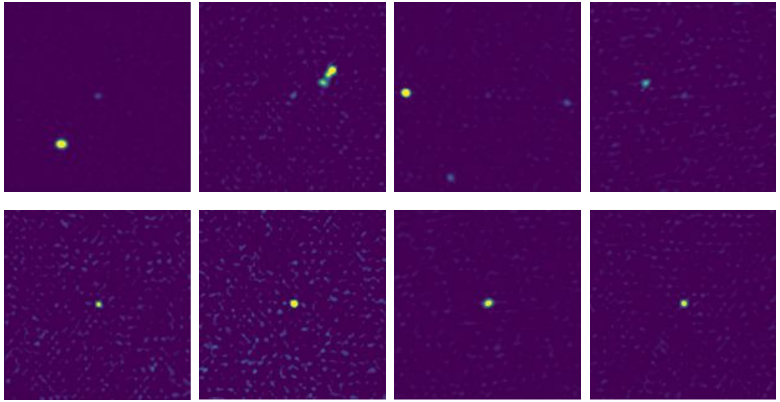


Improvement in sensitivity and resolution available with RACS-mid compared with NVSS and FIRST.
https://research.csiro.au/racs/ & S. W. Duchesne et al. 2023

Experiments on Pretraining

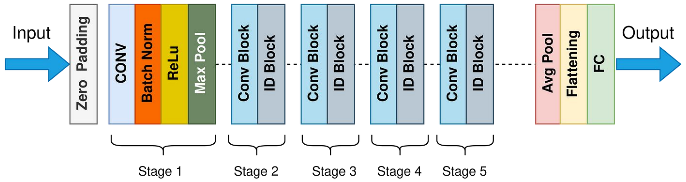
Pretraining using 4.5M unlabeled radio images on VitDet and InternImage are ongoing, should be even better

Model	Pretraining Data	Pretraining Method	Detection		Instance Segmentation	
			mAP	AP@50	mAP	AP@50
ResNet-50	ImageNet	Supervised learning	0.452	**0.747**	0.380	0.717
ResNet-50	**4.5M radio images**	**Self-supervised learning**	**0.502**	**0.843**	**0.434**	**0.836**

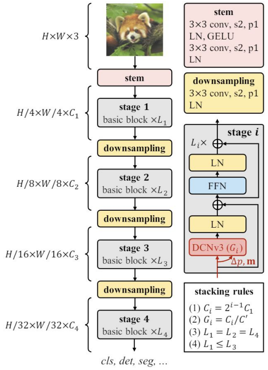


HeTu-v3: Transferring downstream tasks

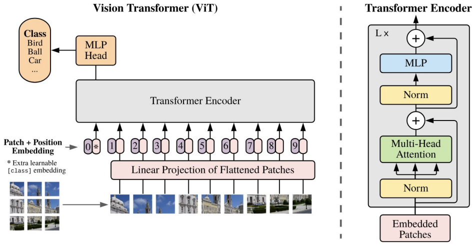
ResNet



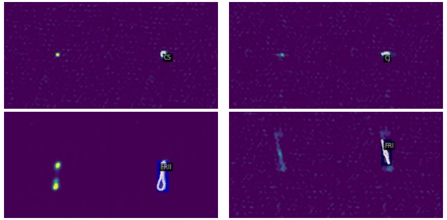
InternImage



Vision Transformer



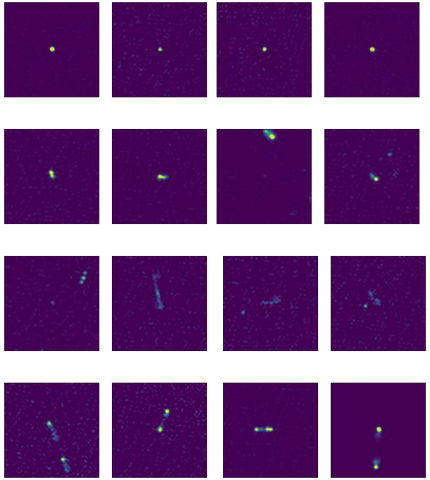
Foundation models



Transfer

- Manual labeling
- Imbalance: augmentation on CJ, FRI, FRII classes; Seesaw Loss function to tackle class imbalance
- Uncertain classifications: reduce their weights during training to reduce contamination and misrepresentation

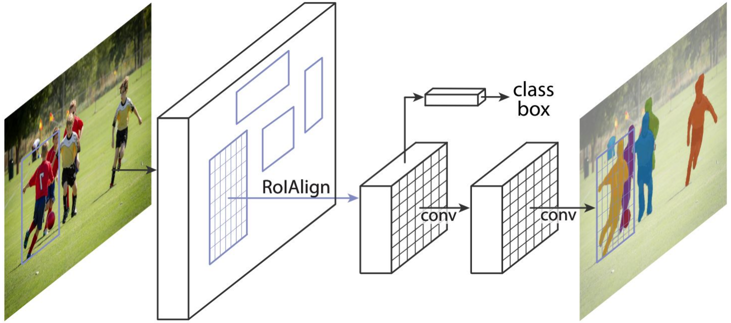
Downstream Tasks
E.g. galaxy morphological classification
Select 2000 images for training



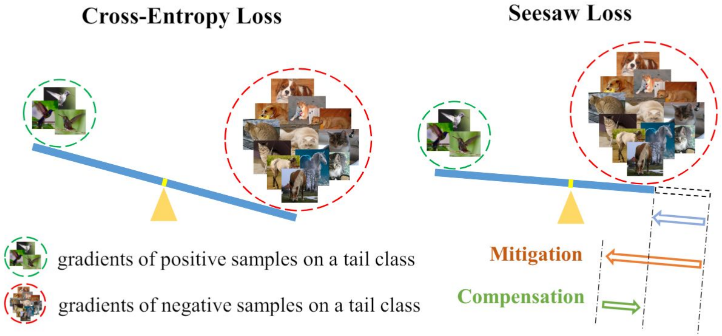
	CJ	CS	FRI	FRII	Total Object	# Image
Training	278	1349	49	335	2011	1601
Validation	68	347	14	91	520	401

HeTu-v3: Transfering Details

Incorporate **MaskRCNN** module to enable foundation model to do instance segmentation

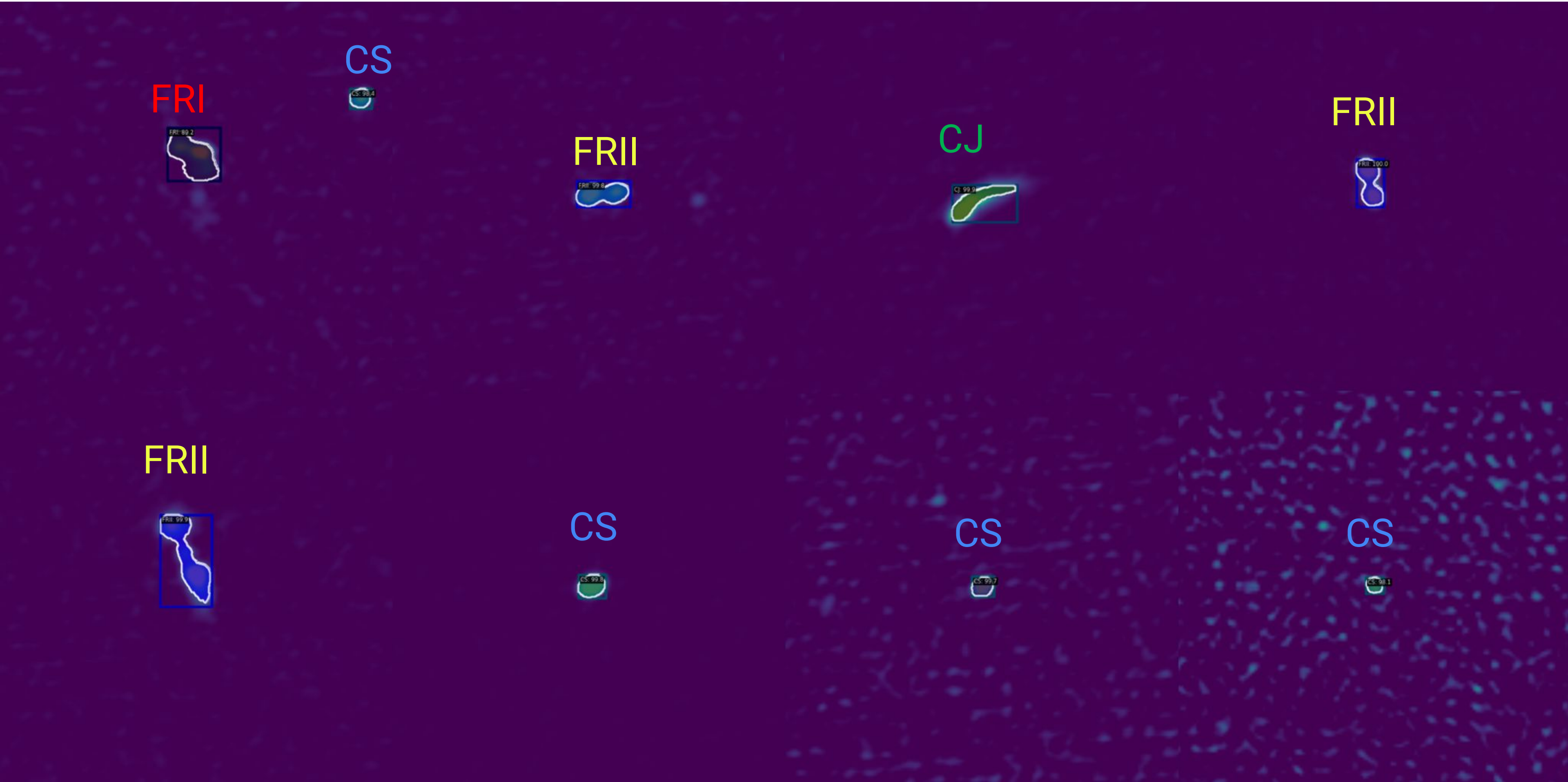


Seesaw Loss: A loss function to tackle class imbalance problem



Model	Loss function	Detection		Instance Segmentation	
		mAP	AP@50	mAP	AP@50
ResNet-50	Cross-entropy	0.502	0.843	0.434	0.836
ResNet-50	**Seesaw Loss**	**0.525**	**0.870**	**0.451**	**0.865**

Output example using HeTu - v3



Summary of HeTu-v3

CLARAN
ResNet
Faster R-CNN
(ICRAR)

→

HeTu v1
ResNet + FPN
Faster R-CNN
(China SRC)

→

HeTu v2
ResNet + FPN
Mask R-CNN

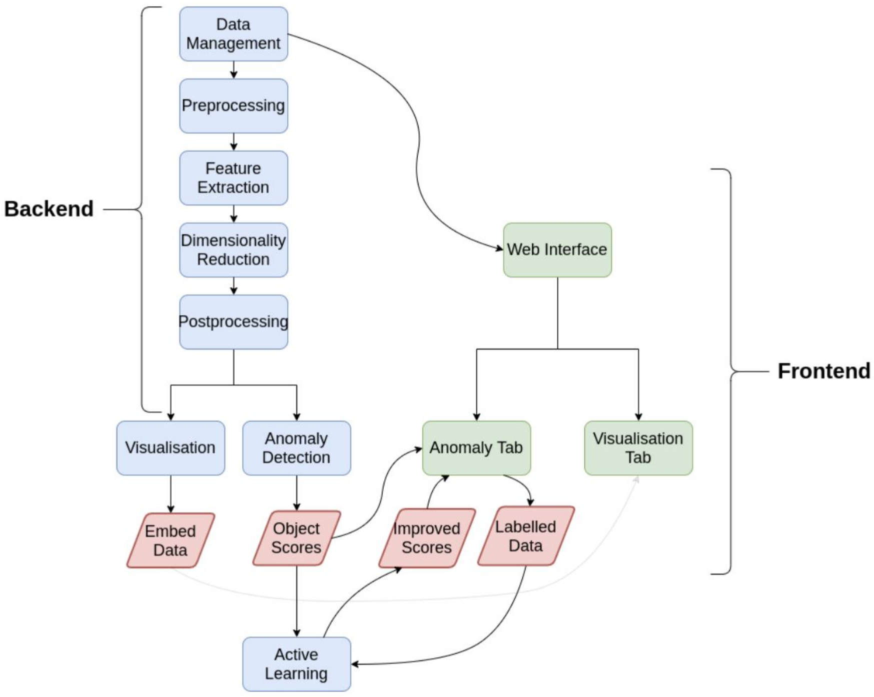
→

HeTu v3
ResNet, VitDet & InternImage + FPN
Mask R-CNN
(China SRC + Shanghai AI Lab)

HeTu-v3 represents a paradigm change in astronomical image analysis, revolutionizing the traditional workflow with an innovative approach to building large-scale foundation models. It uses massive unlabeled data to train a generic foundation model, and then employs efficient transfer learning to tackle specific tasks. This approach not only achieves superior generality and generalization capabilities, but also greatly reduces the dependence on limited labeled data. Using advanced visual models such as VitDet and InternImage, HeTu-v3 is able to handle complex radio source morphology and shows even better scalability and performance improvement potential as data volumes increase.

HeTu-v3: not only a source finder

- Astronomaly: Active Learning for Anomaly Detection
- Discovery of New Anomalous Objects: Successfully used to discover new Odd Radio Circles (ORCs) (Lochner et al. 2023)
- HeTu v3's pretrained foundation model could be fine-tuned for anomaly detection and other downstream tasks
- Feature Extraction: advanced vision models (VitDet, InternImage) could provide rich feature representations for anomaly detection
- Efficiency: HeTu-v3's ability to handle large datasets efficiently could complement active learning approach
- Complementary Strengths: HeTu v3's strong performance in source detection and classification could be combined with active learning approach for more effective anomaly detection
- Potential Workflow:
  - Use HeTu-v3 for initial source detection and feature extraction
  - Apply active learning framework to identify potential anomalies
  - Leverage human expertise for final verification and discovery

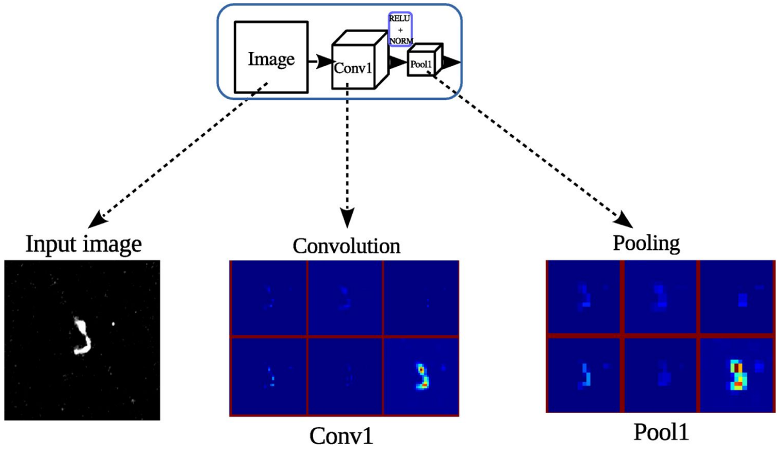


(Lochner & Bassett 2020)

Other source finding and classification tools

Classifying Radio Galaxies with CNN

- Objective: Apply deep machine learning to classify radio images of extended sources based on morphology using CNN
- Focus: Fanaroff-Riley (FR) class radio galaxies and bent-tailed morphology radio galaxies.
- Data Source: VLA-FIRST
- Training Data: ~200 sources per class, augmented with rotated.
- Methodology: Used a "fusion classifier" combining results of binary classifications.
- Performance:
  - Bent-tailed galaxies: 95% precision, 79% recall
  - FRI class: 91% precision, 91% recall
  - FRII class: 75% precision, 91% recall
- Processing Speed: <0.17 s per image classification.
- Advantages:
  - Comparable accuracy to manual classification
  - Significantly faster processing
  - Eliminates need for handcrafted feature extraction
- Implications: **Demonstrates the potential of deep learning for handling large datasets**



Aniyan, A. K.; Thorat, K. 2017 ApJS

- Objective: SKA Big Data makes automatic object detection and instance segmentation crucial for source finding and analysis. Evaluate and compare the performance of multiple DL models for object detection and semantic segmentation in radio images.
- Methodology:
  - Applied various DL methods to radio astronomical images
  - Two types of tasks: object detection and semantic segmentation.
- Data: Used images obtained from ATCA, ASKAP, VLA, RGZ
- Metrics: Evaluated models based on prediction performance (precision, recall, F1 score) and computational efficiency.
- Significance: aims to guide astronomers in selecting appropriate deep learning methods for analyzing large-scale radio astronomy datasets, particularly in preparation for the SKA era
- **Conclusion:**
  - YOLO-Based Methods: Best for object detection, particularly effective for images with low signal-to-noise ratios.
  - Tiramisu Model: Best for semantic segmentation, balancing performance and computational efficiency.
  - Transformer-Based Models: Limited by high computational needs and data requirements.

Radio astronomical images object detection and segmentation: a benchmark on deep learning methods

Original Article | Published: 05 May 2023
Volume 56, pages 293–331, (2023) Cite this article

Renato Sortino et al. 2023, ExpAs

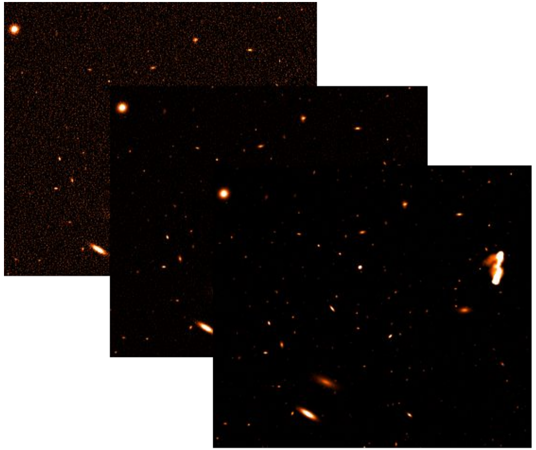
Renato Sortino, Daniel Magro, Giuseppe Fiameni, Eva Sciacca, Simone Riggi, Andrea DeMarco, Concetto Spampinato, Andrew M. Hopkins, Filomena Bufano, Francesco Schillirò, Cristobal Bordiu & Carmelo Pino

Abstract

In recent years, deep learning has been successfully applied in various scientific domains. Following these promising results and performances, it has recently also started being evaluated in the domain of radio astronomy. In particular, since radio astronomy is entering the Big Data era, with the advent of the largest telescope in the world - the Square Kilometre Array (SKA), the task of automatic object detection and instance segmentation is crucial for source finding and analysis. In this work, we explore the performance of the most affirmed deep learning approaches, applied to astronomical images obtained by radio interferometric instrumentation, to solve the task of automatic source detection. This is carried out by applying models designed to accomplish two different kinds of tasks: object detection and semantic segmentation. The goal is to provide an overview of existing techniques, in terms of prediction performance and computational efficiency, to scientists in the astrophysics community who would like to employ machine learning in their research.

YOLO-CIANNA: Galaxy detection with deep learning in radio data applied to the SKAO SDC1

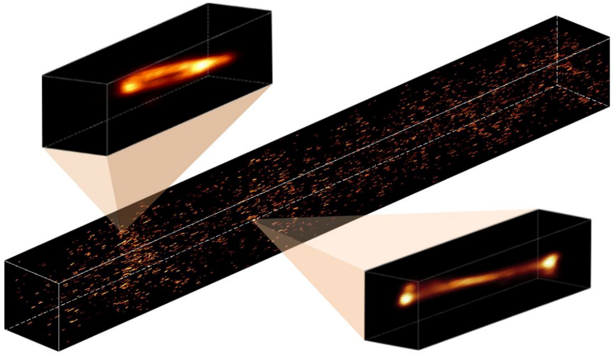
- Objective: Develop a new source detection and characterization method for massive radio astronomical datasets using deep learning techniques.
- Method: YOLO-CIANNA, a customized deep-learning object detector specifically for astronomical datasets.
- Key Features:Adapted from YOLO (You Only Look Once) object detection framework
- Dataset: Tested on simulated 2D continuum images from the SKAO SDC1 (SKA Science Data Challenge 1) dataset.
- Performance: Outperforms previous published results on the SDC1 dataset
- Efficiency: Capable of real-time detection
- Innovations: Addresses specific challenges of radio-astronomical images (high dynamic range, crowded fields, small objects)
- Availability: Open-source and included in the CIANNA framework
- Implications:Promising for handling the massive data volumes expected from the upcoming SKA



- source finding (RA, Dec) to locate the centroids and/or core positions,
- source property characterization (integrated flux density, possible core fraction, major and minor axis size, major axis position angle)
- source population identification (one of SFG, AGN-steep, AGN-flat)

YOLO-CHADHOC in SDC2 by MINERVA team

- Dual Pipelines:
  - YOLO-CIANNA and CHADHOC, Final catalog merges results from both pipelines for improved completeness and purity
- YOLO-CIANNA:
  - Customized version of YOLO network developed in SDC1
  - Implemented in CIANNA framework (GPU-accelerated)
  - Works on 64x64x256 (RA, Dec, Freq) pixel sub-volumes
  - 21 3D-convolutional layers
  - Predicts source parameters: Flux, HIsize, w20, PA, and I
  - Processes 70 input cubes per second on a V100 GPU
- CHADHOC (Convolutional Hybrid Ad-Hoc pipeline):
  - Three-step: detection, selection, parameter estimation
  - Detection: Traditional algorithm with smoothing and S/N thresholding
  - Selection: CNN to identify true sources among detections
  - Parameter estimation: Separate CNNs for each source parameter
- Merging Catalogs: Combines strengths of both pipelines
  - CHADHOC better at typical sources, YOLO better at low-brightness sources
  - Careful merging improves overall catalog quality

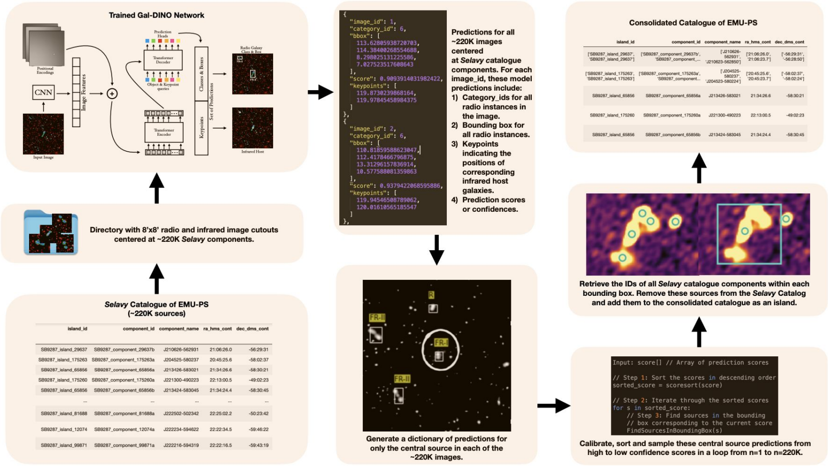


2683 Hi sources. 1286 × 1286 × 6668 pixels to represent a 1degree^2 field of view across the full Challenge frequency range 0.95–1.15 GHz (redshift 0.235–0.495) Credits: SKAO

- Achieved highest score in SDC2
- Effective in handling large data volumes expected from SKA
- Demonstrated robustness in dealing with varying noise levels and source morphologies

EMU's ML-Enabled Pipeline

- Uses Gal-DINO computer vision networks
- Predicts:
  - Radio morphology categories
  - Bounding boxes for radio sources
  - Potential infrared host positions
- Training:
  - ~5,000 visually inspected radio galaxies
  - Includes compact and extended morphologies
- Performance:
  - 99% of predicted bounding boxes have Intersection over Union (IoU) > 0.5
  - 98% of predicted host positions within 3" of ground truth
- Application:
  - Applied to EMU Pilot Survey (EMU-PS)
  - Processed 220,102 Selavy components
  - Identified 211,625 radio sources
- Advantages:
  - Efficient processing of large datasets
  - Handles complex morphologies
  - Enables automated catalogue construction



RG-CAT: Detection Pipeline and Catalogue of Radio Galaxies in the EMU Pilot Survey (Gupta et al. 2024)

- Trained on approximately 5,000 visually inspected radio galaxies and their infrared hosts.
- Designed specifically for radio galaxy detection and classification.
- Focuses on radio and infrared image pairs.

SimCLR - self-supervised learning for radio data analysis

- Objective: Explore contrastive learning methods to learn suitable radio data representations from unlabeled images for various downstream tasks.
- Data Source: Unlabeled images from ASKAP EMU and SARAO MeerKAT GPS surveys; Smaller labeled datasets from different radio surveys for evaluation
- Methodology: Used self-supervised learning to build foundational models; Explored two image extraction modes
- Evaluation Tasks:
  - Radio source morphology classification
  - Radio source instance segmentation
  - Search for objects with peculiar morphology
- Key Findings:
  - **Demonstrated benefits of self-supervised foundation models for radio data analysis**
  - Assessed performance on larger test datasets compared to previous studies
  - Explored advantages of models trained on "random" survey datasets vs. "source-centric" datasets

S. Riggi et al. (2024)

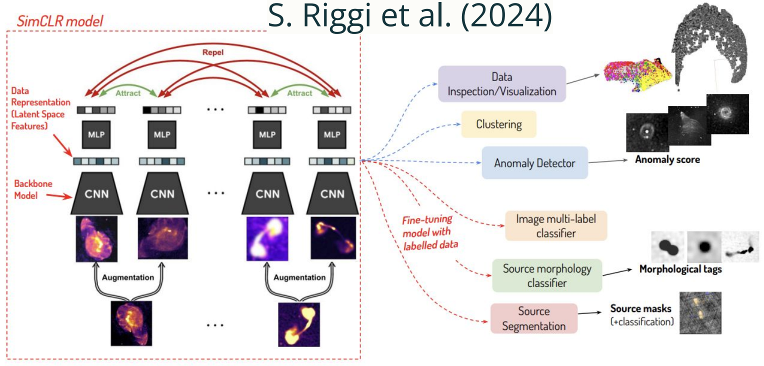


Figure 1. Schema of self-supervised learning for radio data analysis.

- Implications:
  - Provides ready-to-use foundational models for SKA precursor and other radio surveys
  - Models can be used as feature extractors for similar analyses or new tasks
- Future Directions:
  - Further exploration of advantages from different training dataset construction methods
  - Potential applications in upcoming large-scale radio surveys

Potential challenges and limitations

- Data Quality: Performance dependent on training data quality and completeness
- Extended Sources: Difficulty in accurately detecting and characterizing complex, extended structures
- Rare Morphologies: Limited ability to identify unusual or rare source types
- Scalability: Computational demands for processing extremely large datasets
- Interpretability: "Black box" nature of deep learning models can limit understanding of decisions
- Generalization: Models may not perform well on data from different instruments or surveys
- Class Imbalance: Underrepresentation of rare source types in training data
- Noise Handling: Varying performance in presence of different noise characteristics
- False Positives: Risk of misclassifying artifacts as real sources
- Adaptability: Need for retraining or fine-tuning for new data types or scientific goals

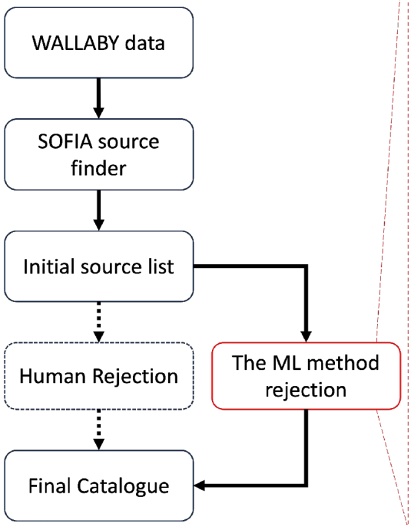
Other AI applications in Radio Astronomy

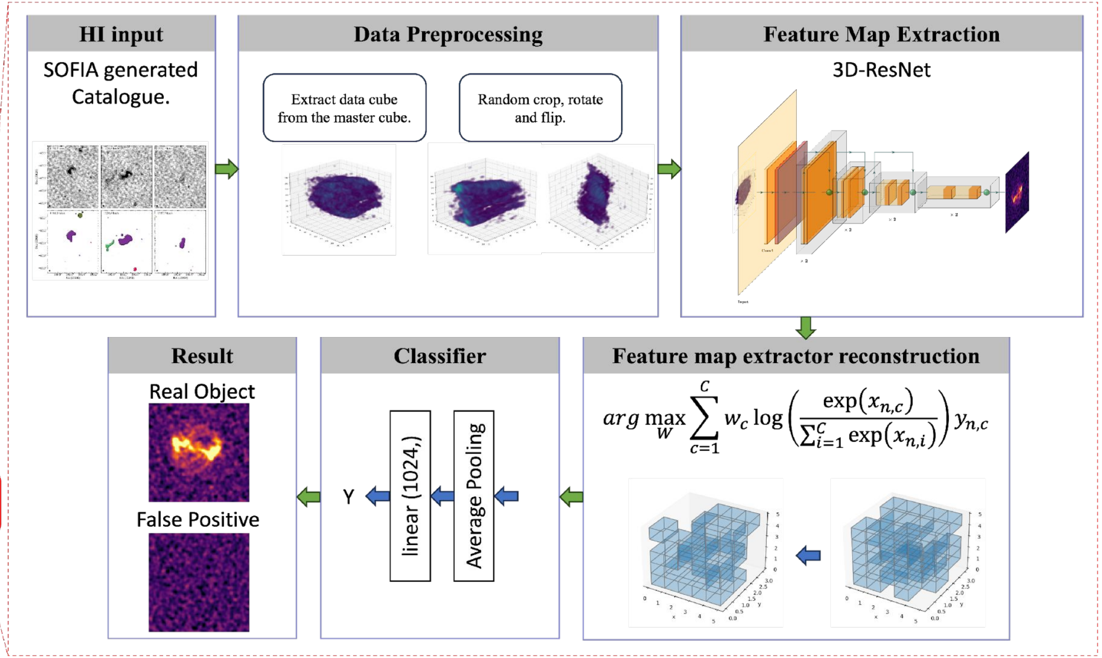
AI applications in SKAO Data Challenge 2: 3D souce finding

- Machine Learning Frameworks **TensorFlow and PyTorch** were commonly used for **building and training models**
- **CNNs** were used for image-based tasks, such as **source detection and classification**
- **Random Forests**: Employed for **classification** tasks and **parameter estimation**
- **Ensemble Methods**: Combining **predictions** from multiple independent techniques
- **Transfer Learning**: Some teams used pre-trained models and fine-tuned them for specific HI source detection tasks
- **Data Augmentation** techniques used to address class imbalance and improve model generalization
- **Automated Pipelines**: Development of efficient, automated source-finding pipelines to handle large data volumes
- **Custom AI Models**: Some teams developed specialized models tailored for HI source detection and characterization
- **Either algorithmic (e.g. SoFiA) or ML/DL-based methods are not perfect,** combining classical source finding methods with machine learning techniques **for improved performance**
- **Unsupervised Learning**: Some approaches used unsupervised methods for initial source detection or data preprocessing

HI source finding workflow: SOFIA + DL

Wang et al 2024
submitted to PASA
SOFIA workflow

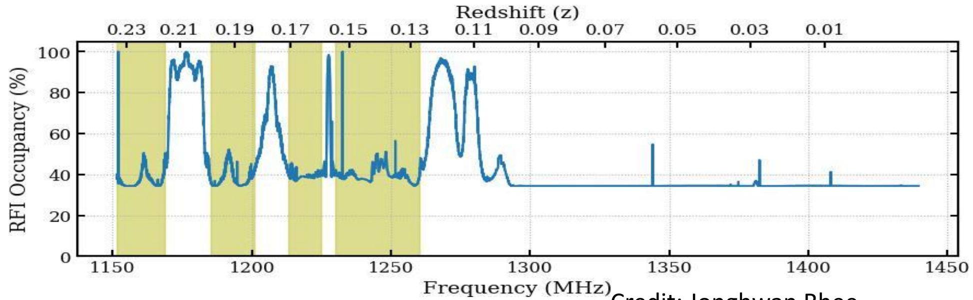




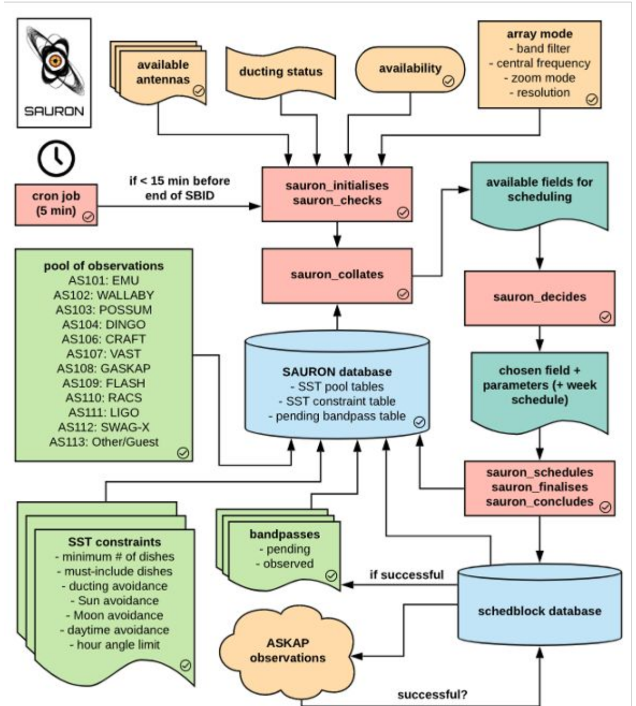
HI source finding workflow: FLASHfinder → *Working on a more efficient way to filter out good from bad candidates*
Overwhelming imbalance between false positives (due to systematic/processing artefacts) → visual inspection required !

AI in radio astronomy: application areas

- **Telescope operation**: Automated survey scheduler for ASKAP, Maximises efficiency (both $$ & time)
- **Diagnose system health** of large telescope arrays such as LOFAR (NL; Mesarcik + 2020)
- **Data validation**: RFI removal from observations using (e.g Yang+2020; Sadr+2020; Mesarcik+2022; Pritchard+2024)
- **Reduce noise artefacts** in reconstructed images by filling the gaps in the Fourier plane → bypass typically bespoked imaging decisions (Schmidt + 2022)
- **Synthesis imaging**: closure invariants + ML (Thyagarajan, Hoefs & OIW 2024 *submitted to RASTI*)



Credit: Jonghwan Rhee



SAURON Scheduling Autonomously Under Reactive Observational Needs

Moss & ASKAP Operations /Computing team 2021

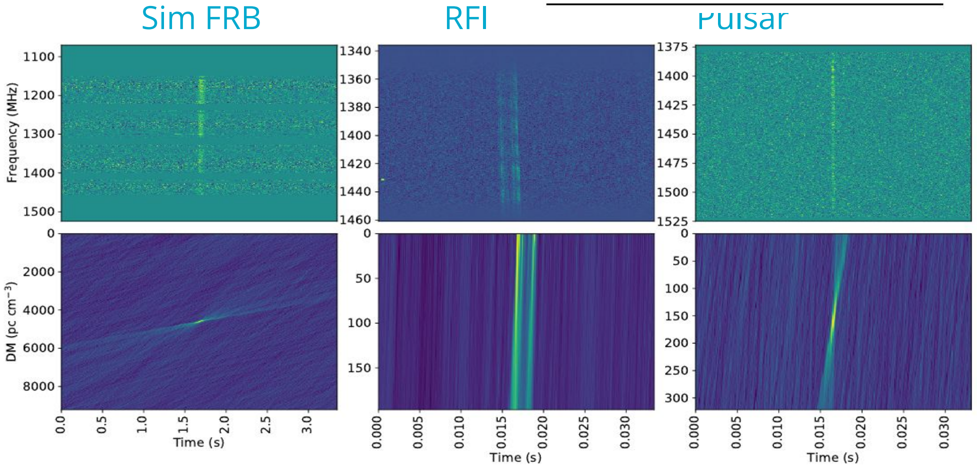
AI in radio astronomy: application areas

- Fast Extragalactic Transient Candidate Hunter (FETCH) is a deep learning-based software designed to classify fast radio burst (FRB) candidates and distinguish them from radio frequency interference (RFI).
- transfer learning techniques to train state-of-the-art deep neural networks for classifying FRB and RFI candidates.
- Data: simulated FRBs and real RFI candidates from Green Bank telescope
- 11 deep learning models, each achieving an accuracy and recall above 99.5% on the test datasets

FT Model	Val Acc (%)
VGG19 (4)	99.78
VGG16 (4)	99.40
DenseNet169 (11)	95.40
DenseNet201 (7)	94.05
DenseNet121 (4)	88.23

DMT Model	Val Acc (%)
VGG16 (2)	99.92
Xception (21)	99.87
VGG19 (0)	99.73
InceptionV3 (31)	99.46
InceptionResNetV2 (34)	99.35

- Able to detect all FRBs with SNR>10 in data from other telescopes, e.g. ASKAP and Parkes
- While other approaches like those developed by Connor & van Leeuwen (2018) and Zhang et al. (2018) have shown success with specific telescopes, FETCH aims to provide a more generic solution that can be widely applied across different instruments



Agarwal, D+2020;
https://github.com/devanshkv/fetch

Key challenges for future AI in radio astronomy

- **Developing explainable AI**: As AI becomes more integral to discoveries, ensuring the interpretability and explainability of AI models will be crucial.
- **Handling increasing data volumes**: Next-generation telescopes will produce even more data, requiring continued advances in AI processing capabilities.
- **Integrating AI across the full astronomy workflow**: Expanding AI from specific tasks to more holistic integration across observation, analysis, and theory.
- **Balancing automation and human expertise**: Finding the right balance between AI-driven automation and human scientific insight and creativity.
- **Ethical considerations**: Addressing potential biases in AI systems and ensuring responsible use of AI in scientific research.
- **Cross-disciplinary collaboration**: Fostering collaboration between astronomers, computer scientists, and AI researchers to drive further innovations.

Development Platform: OpenMMLab

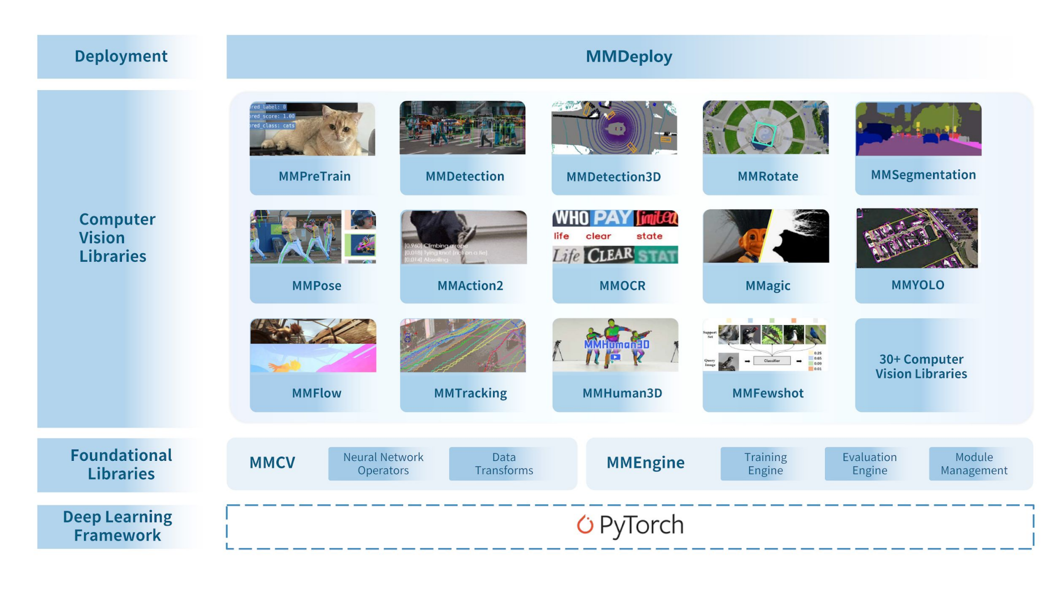
上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

OpenMMLab (from Shanghai AI Lab)

One of the most popular **open-source algorithm platforms** for computer vision.

We use OpenMMLab to train foundation models, transfer to downstream tasks, and deploy models.

https://github.com/open-mmlab



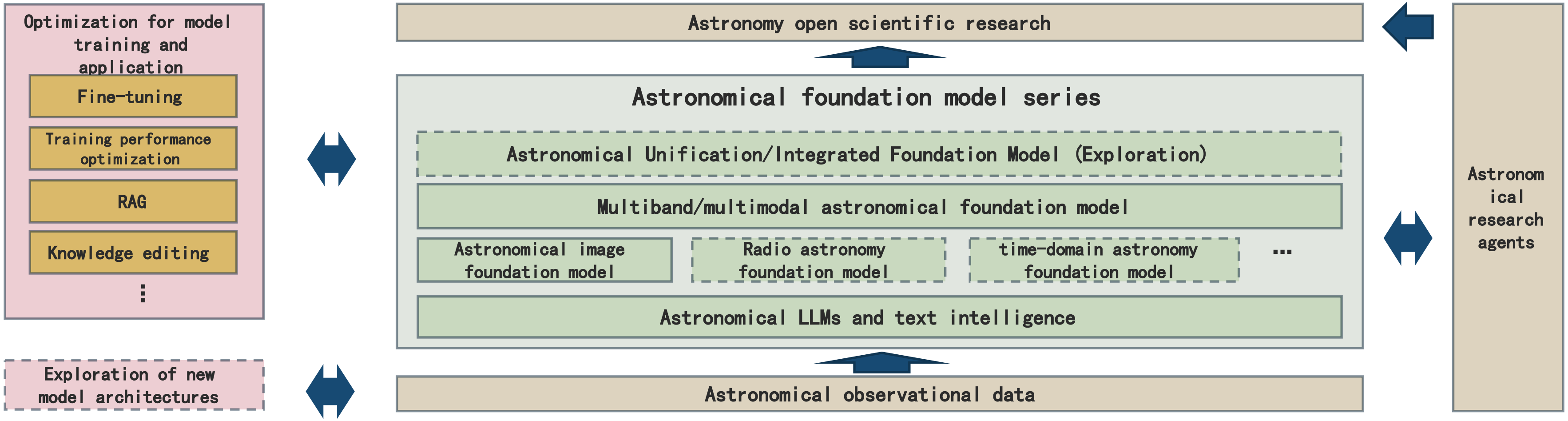
Astronomical Foundation Models

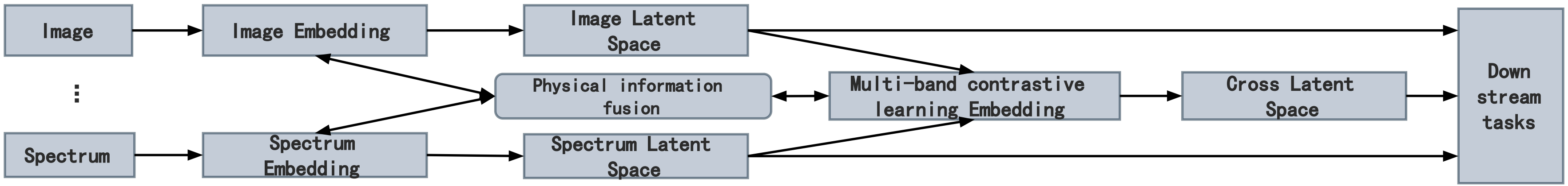
Key challenges

The design of models tailored for astronomical observational data represents a cutting-edge exploration. However, the results can sometimes lack interpretability and may not always adhere to physical laws.

Solutions and innovations

Delve into the sophisticated capabilities of LLMs to intelligently interlink astronomical knowledge and data, all grounded in textual analysis.
Leveraging the state-of-the-art advancements in foundation models. Embedding is designed for astronomical data analysis
The design of single-band and multi-band embeddings integrates physical information.





Thank you for your attention

- HeTu-v3 combines advanced AI networks, self-supervised learning, and foundation models, representing a major leap forward in the way of astronomical image analysis
- The foundation models will continue to fuse data from multiple sources, empowering astronomers to accelerate research, discover rare phenomena.
- By enabling efficient processing of massive datasets, HeTu-v3 enables automated analysis in future SKA-scale surveys, pushing the frontiers of cosmic exploration

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Teams from China SKA Regional Centre, Shanghai AI Lab, Zhejiang (AI) Lab