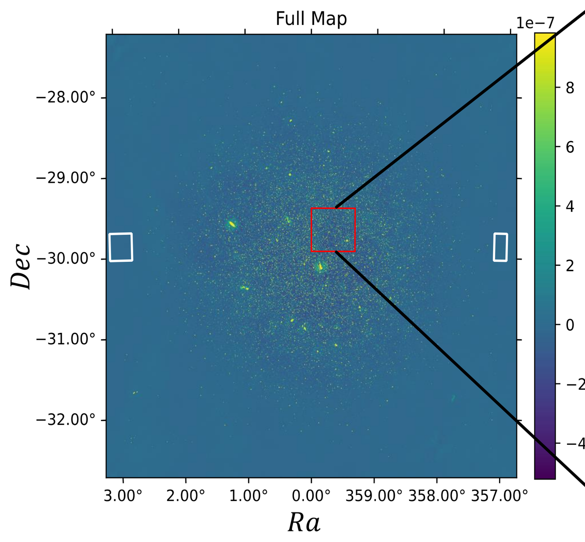
A Deep Learning Framework for Detection and Characterization of Radio Galaxies

Sanjay Khatik[1], Rohit Sharma[2] and Pankaj Jain[2]
[1]Department of Physics, Indian Institute of Technology Kanpur, U.P., India
[2]Department of Space, Planetary & Astronomical Sciences and Engineering, Indian Institute of Technology Kanpur, U.P., India
Email: sanjaykh@iitk.ac.in

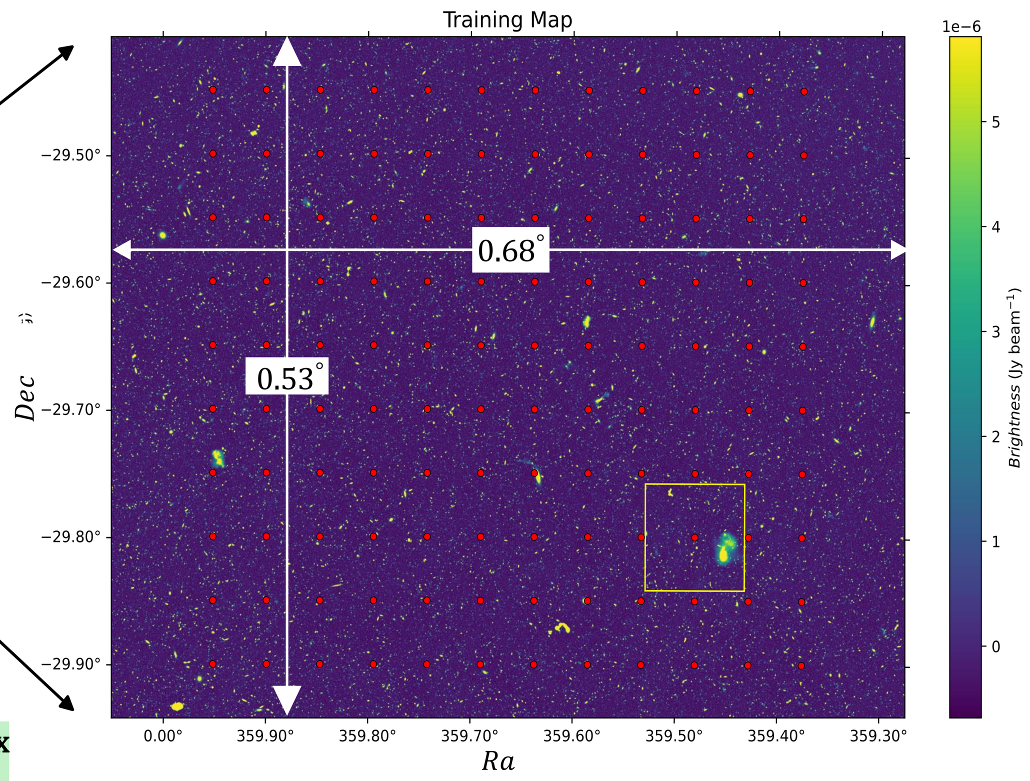
Introduction

Radio galaxies span a broad range of angular sizes and flux densities, from compact, bright sources to highly extended, faint systems. We develop a deep learning based method to detect radio galaxies and measure their key physical parameters — major axis, minor axis, integrated flux density, and position angle — across the full dynamic range of source sizes.

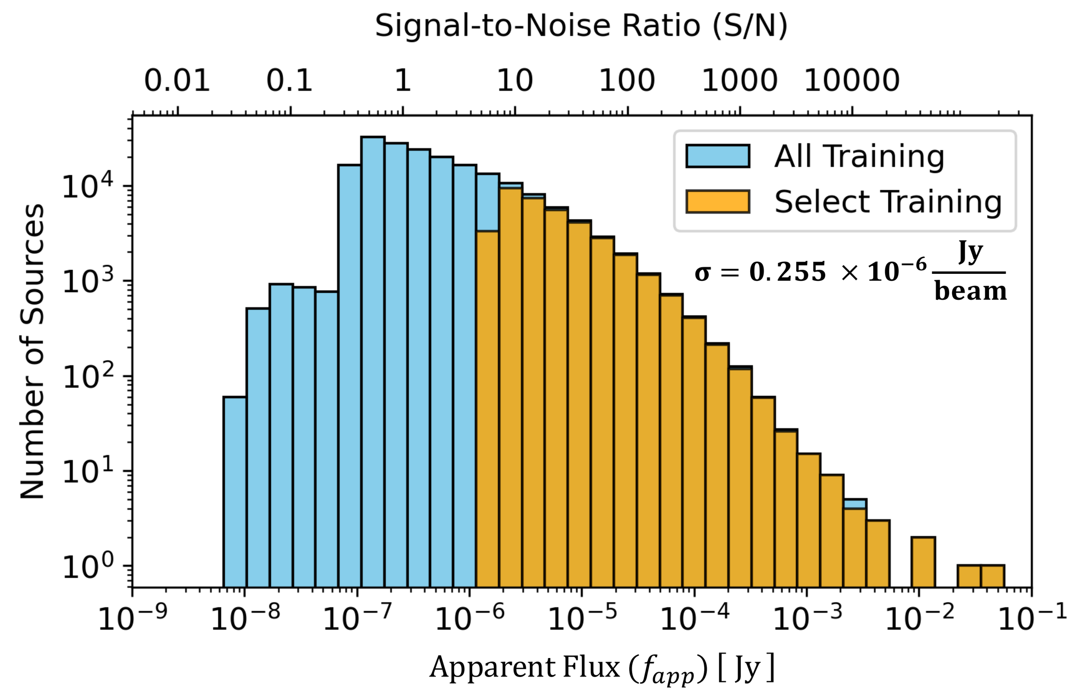
The model is designed to remain computationally efficient and scalable. Performance of the proposed method was evaluated using the Square Kilometre Array (SKA) Science Data Challenge 1 (SDC1) simulated sky map at 560 MHz, corresponding to a 1000-hour integration time.



Full map size ≈ 5.5° × 5.5°. The **red rectangular box** indicates the training region, and the **two white regions** are used for background learning.

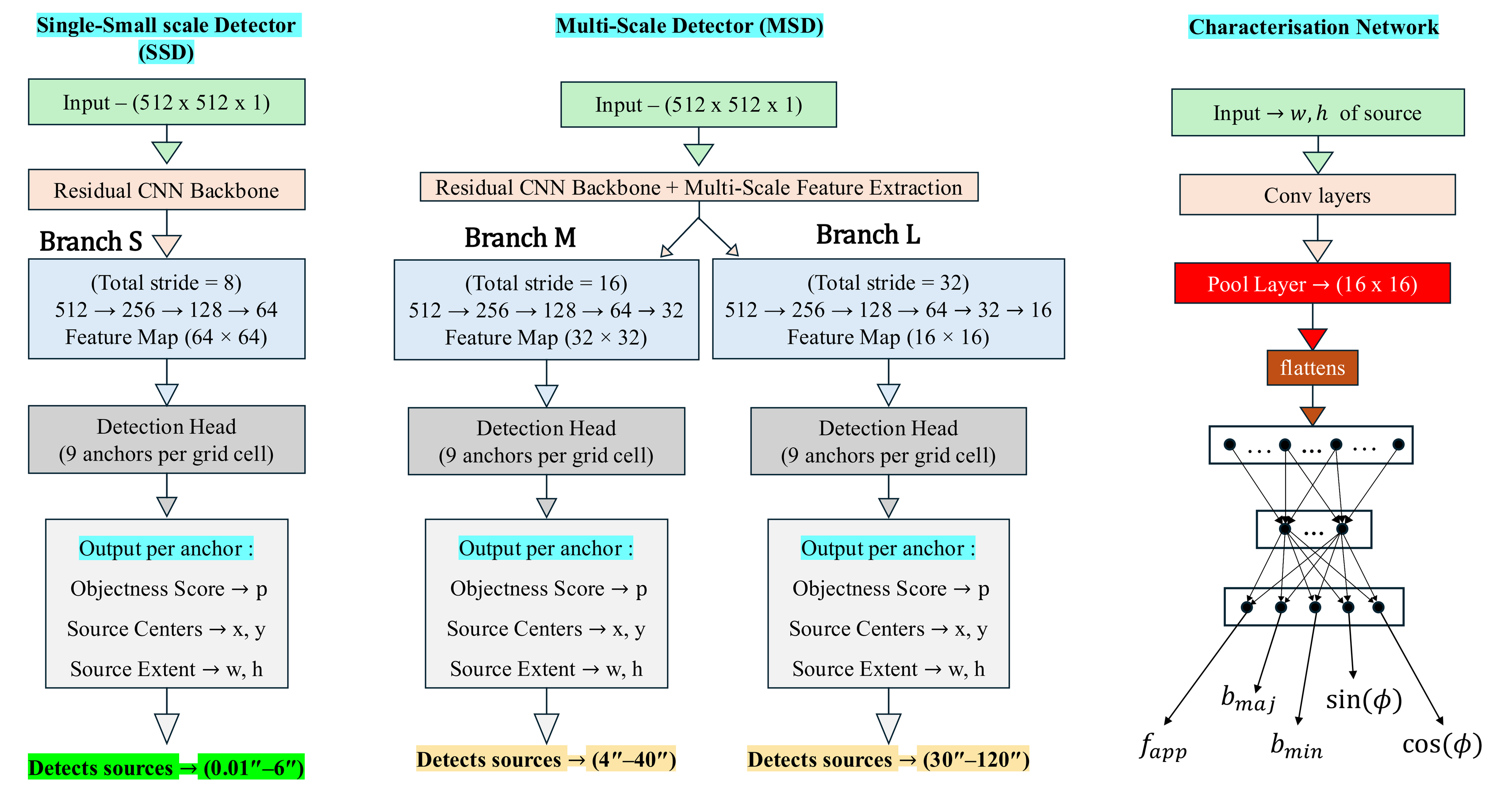


Zoomed view of the training region used for sample generation. Red dots mark sampling locations, and the yellow rectangle shows an example image patch used as input to the detection network.



Histogram of total sources (cyan) and selected training sources (yellow) in the training region. Apparent flux is computed as the integrated flux density multiplied by the primary beam sensitivity.

Detection and Characterisation Network → Two-Stage Pipeline → Detection + Characterization



Stage 1: Detection – Scale-Aware Design

SSD (Standalone High-Res Branch)
- 64×64 feature map (stride 8) → precise localization of **compact sources** (0.1″–6″) — Branch S
- Trained independently → maximizes tiny/point-like object accuracy (~7.2M params)

MSD (Multi-Scale Branch)
- Shared residual CNN (custom residual blocks) (~7.2M params)
- 32×32 grid (stride 16) → medium sources (4″–40″) — Branch M
- 16×16 grid (stride 32) → large extended sources (30″–120″) — Branch L

Each head: 9 anchors/cell → regresses (x, y, w, h) + objectness p → detection across 0.1″–120″.

Stage 2: Characterization Model

- Input: log-normalized, padded crops
- Outputs: f_{app}, b_{min}, b_{min}, $\sin(\boldsymbol{\phi})$, $\cos(\boldsymbol{\phi})$
- Lightweight CNN (~0.58M params): initial kernels → 5 × 5 + alt. 1×1/3×3 + pooling → FC
- Training: MSE loss + cyclical LR
- Benefit: end-to-end DL → fast, leverages multi-scale detections

Overall Performance Competitive on SKA SDC1: purity ~93.5%, avg. accuracy ~81.8% Integrated detection + DL characterization for scalable radio surveys

loss Function

$$focal\ loss = -\sum_{i=1}^{G}\sum_{j=1}^{A}\left[\begin{array}{c}\alpha\cdot y_{i,j}\cdot(1-\hat{p}_{i,j})^{\gamma}\cdot\log(\hat{p}_{i,j})\\ +\\ (1-\alpha)\cdot(1-y_{i,j})\cdot\ \hat{p}_{i,j}^{\gamma}\cdot\log(1-\hat{p}_{i,j})\end{array}\right]$$

$$ciou\ loss = \sum_{i=1}^{G}\sum_{j=1}^{A} y_{i,j}\left[1-IoU(B_{i,j}\ ,\hat{B}_{i,j})+\frac{\rho^2}{\delta^2}+\frac{v^2}{(1-IoU)+v}\right]$$

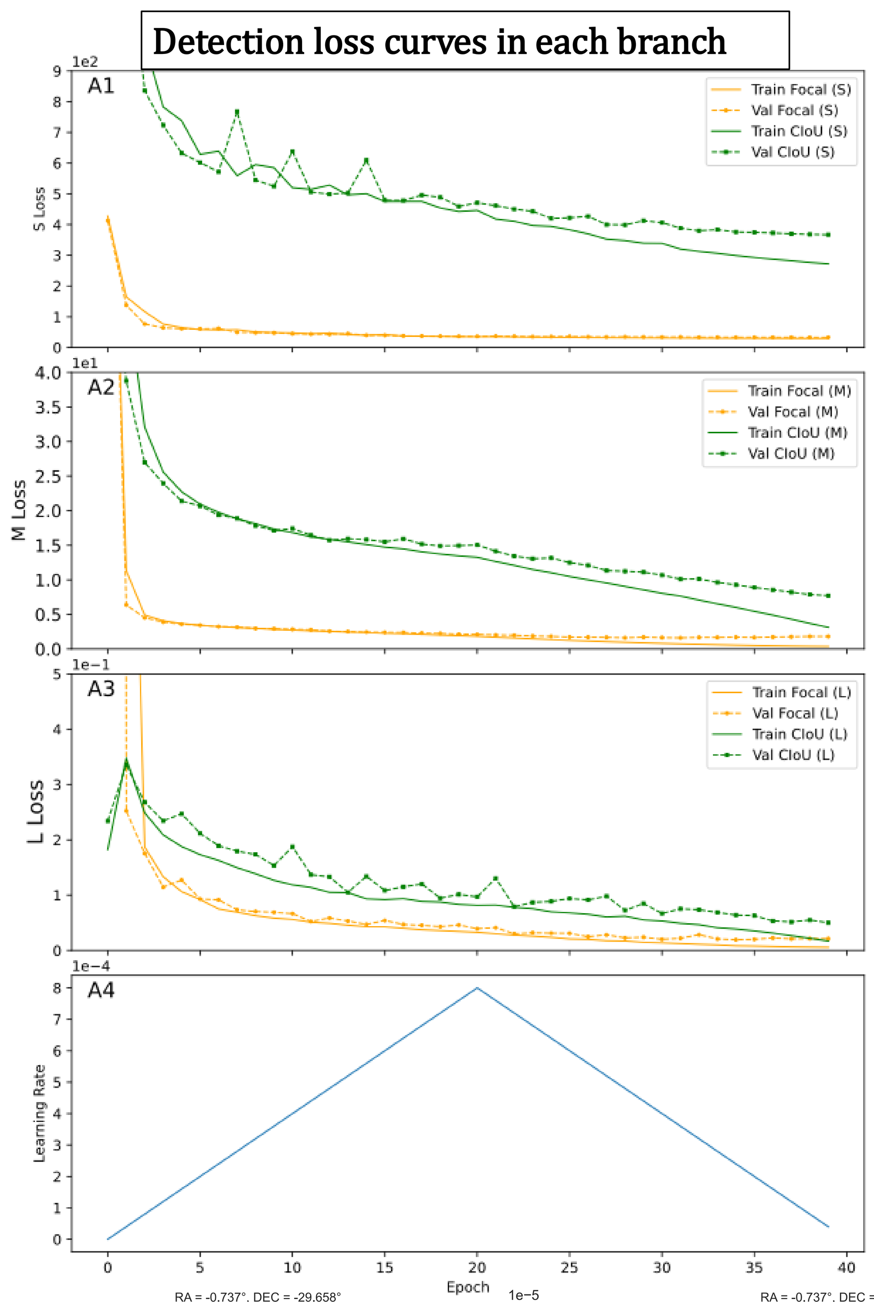
$$mse\ loss = \frac{1}{5}\sum_{l=1}^{5}(k_l-\hat{k}_l)^2$$

$$\mathcal{L}_{Detection} = focal\ loss + ciou\ loss$$

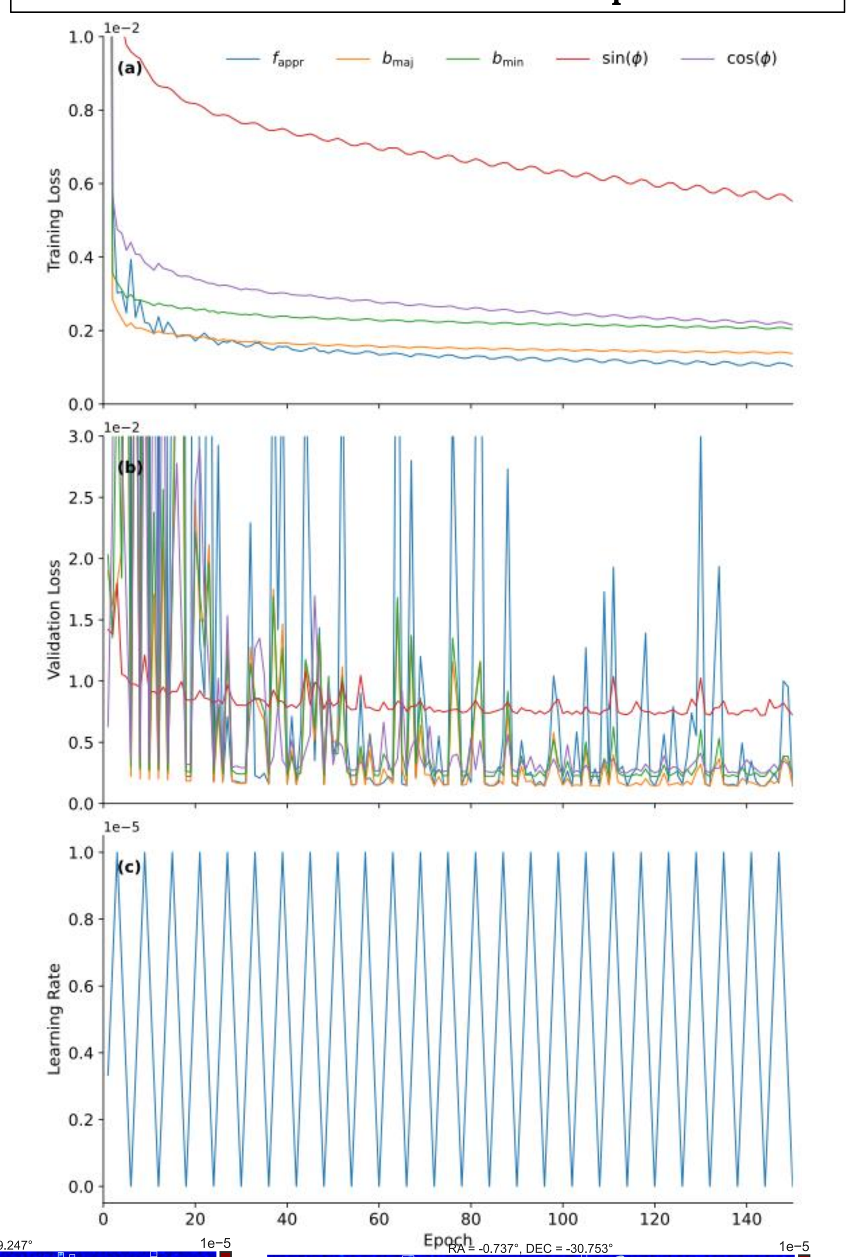
$$\mathcal{L}_{charactorisation} = mse\ loss$$

- $y_{i,j} = 1$ → *source present*
- $y_{i,j} = 0$ → *background*
- $\hat{p}_{i,j}$ → *predicted objectness probebility*
- α → *balanced source vs background*
- γ → *down – weights easy examples*
- G → number of grid cells.
- A → anchors per grid cell.
- IoU → *overlap between predicted and true box*
- ρ → *centre distance between boxes*
- δ → *diagonal of smallest enclosing box*
- $v = \frac{4}{\pi^2}\left[\tan^{-1}\frac{w}{h} - \tan^{-1}\frac{\hat{w}}{\hat{h}}\right]^2$ → *aspect ratio consistency term*

Detection loss curves in each branch

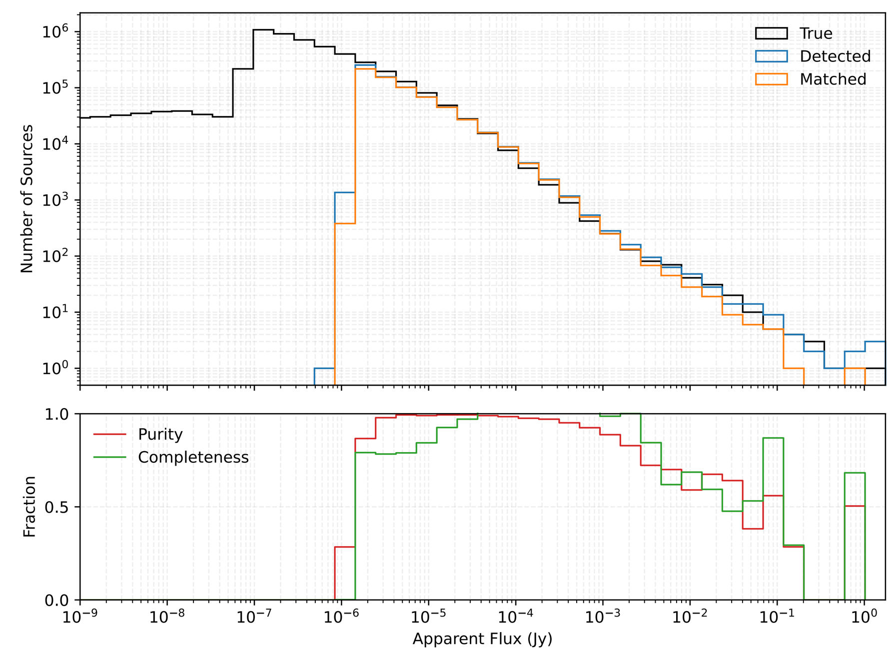


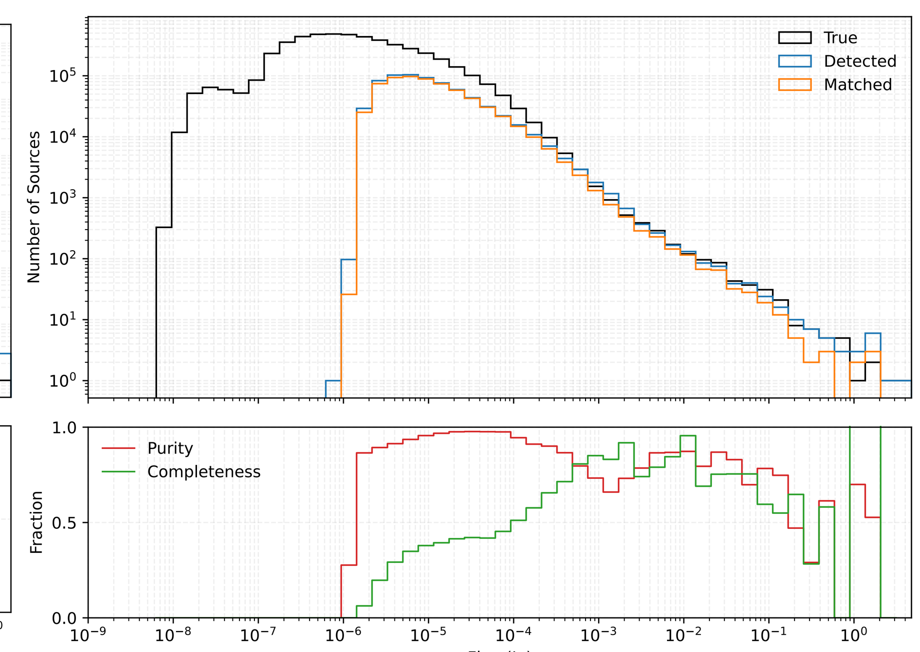
Characterization loss curves for each parameter



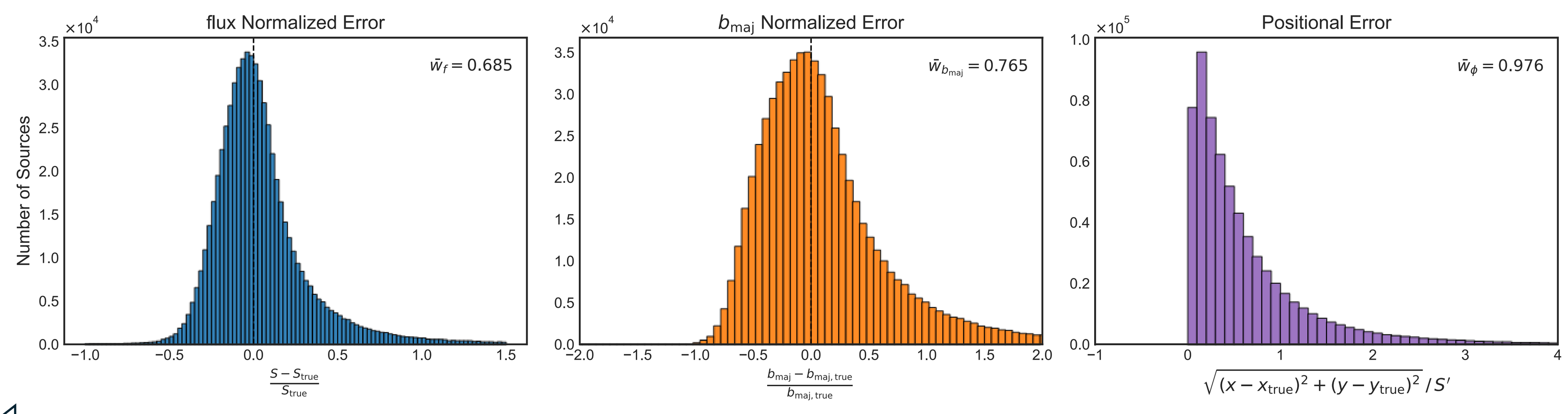
Results

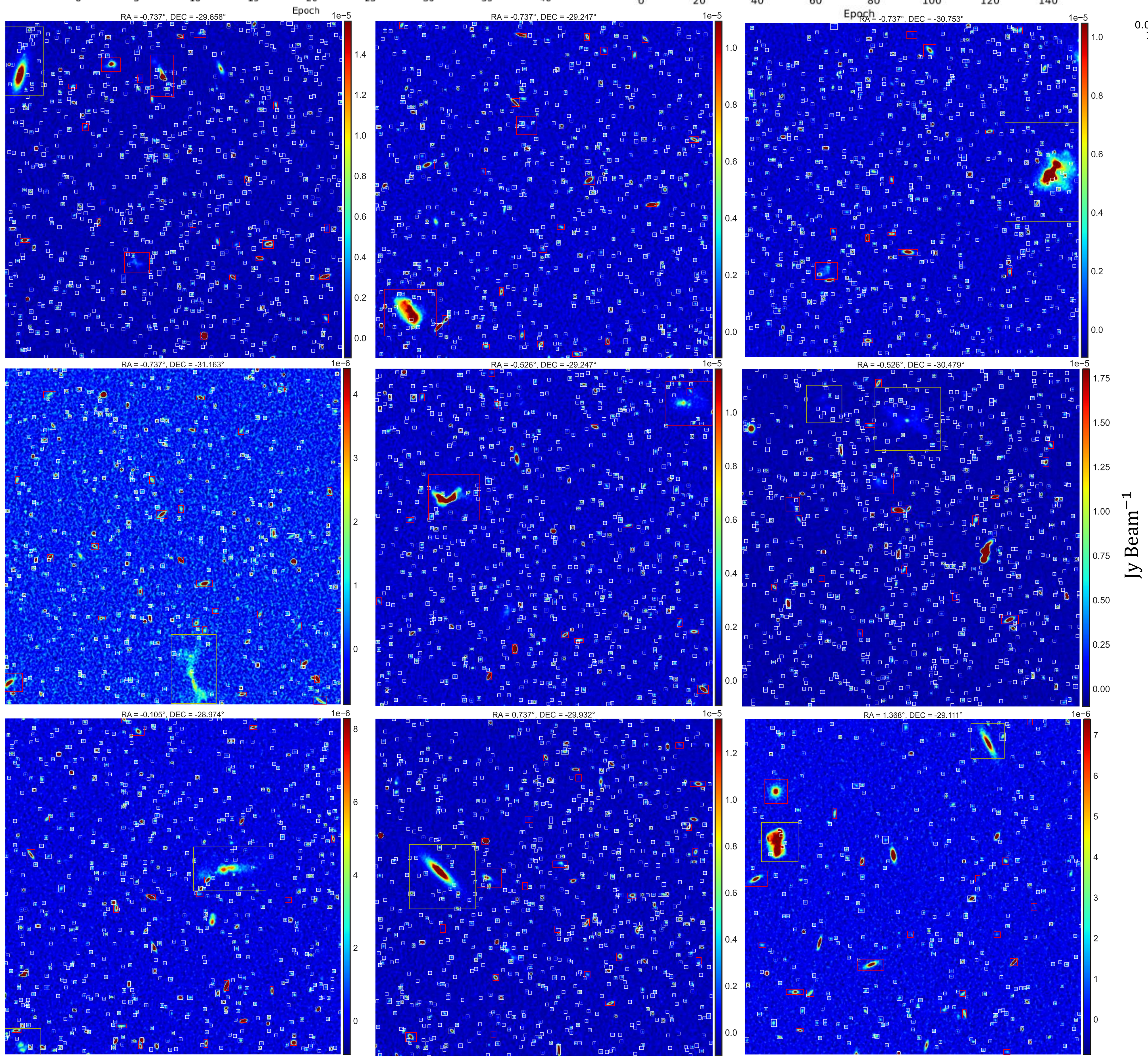
Model	Objectness score (p)	Final Score	Total Detections	Match Detections	False Detections	Bad Detections	Average accuracy ($\overline{w}$)	Purity
SSD	0.5	478634	669858	631021	38837	6890	0.820	94.20
Combined	--	483885	691233	646309	44924	8166	0.818	93.50
Individual Contribution in combined results								
SSD (S-branch)	0.5	456182	641838	603549	38289	6792	0.819	94.03
MSD (M-branch)	0.4	28544	49192	43162	6030	1437	0.801	87.74
MSD (L-branch)	0.3	106	203	182	11	21	0.697	89.65
Combined *results* with p>0.6, showing high purity								
Combined(high purity)	**0.6**	**412429**	**508774**	**502983**	**5791**	**1265**	**0.832**	**98.86**



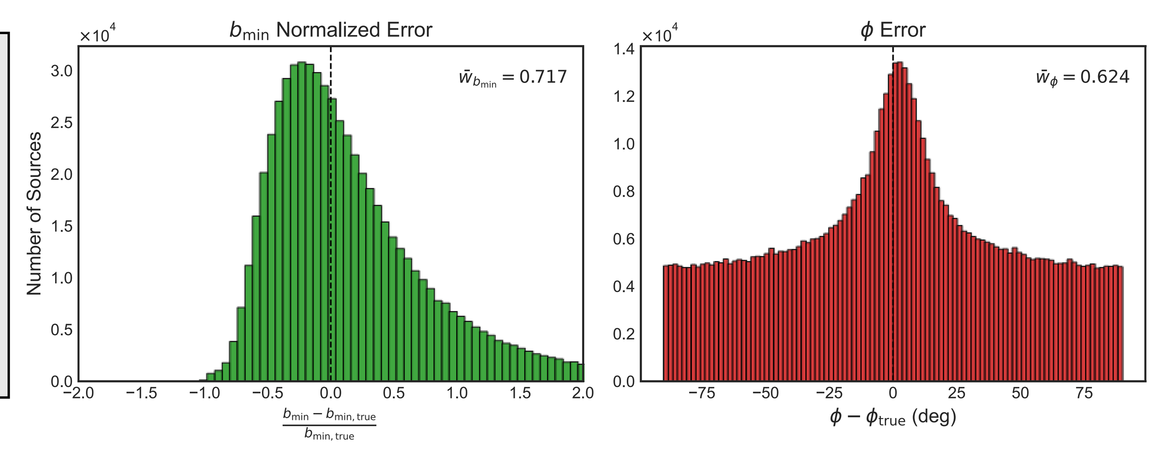


$$completeness = \frac{N_{match}(\log f)}{N_{true}(\log f)} \qquad \text{Reliability (purity)} = \frac{N_{match}(\log f)}{N_{detect}(\log f)}$$





- Predictions on sources from the matched catalogue outside the training region.
- Small white boxes: SSD detections (compact or small sources).
- Red boxes: MSD Medium branch (M-branch).
- Yellow boxes: MSD Large branch (L-branch).
- Each image is a 512 × 512 pixel cutout.



Work Status:
This work is part of our study **"Radio Galaxies Detection and Characterization Using Deep Learning Techniques,"** currently **submitted to** *MNRAS* and under review.

Future Directions:
- **Real-data adaptation:** Apply the framework to SKA precursor surveys such as **ASKAP/EMU** and **MeerKAT**.
- **3D / multi-frequency extension:** Extend the model to HI data cubes using 3D CNNs or hybrid architectures.
- **Source classification:** Incorporate SFG/AGN classification along with estimation of additional parameters such as core fraction.

References:

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- Tsung-Yi Lin et al. 2017, *Focal Loss for Dense Object Detection*, Proc. CVPR.
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