RGC-BENT: A Novel Dataset for Bent Radio Galaxy Classification

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Introduction to Bent Radio AGN

Active Galactic Nuclei (AGN): Luminous objects powered by accretion onto supermassive black holes, crucial for understanding galaxy evolution.

Bent Radio AGN: A subset of radio-loud AGN characterized by distinctly curved jet structures due to interactions with the intergalactic medium (ICM).

- Commonly observed in galaxy clusters.
- Bending often linked to ram pressure from relative motion between host galaxy and ICM.

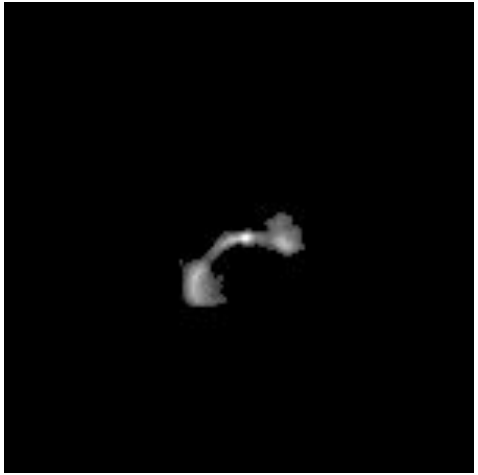


Fig. 1 Sample Bent Radio AGN

Introduction to Bent Radio AGN

Two Subtypes:

- **Wide-Angle Tailed (WAT) Galaxies:** Two-sided jets forming a wide 'C' shape with an opening angle exceeding 90°.
- **Narrow-Angle Tailed (NAT) Galaxies:** Closely aligned jets forming a narrow 'V' shape with an opening angle under 90°.

Significance: Studying bent radio AGN provides insights into galaxy cluster dynamics, ICM behavior, galaxy-environment interactions, and AGN jet dynamics.

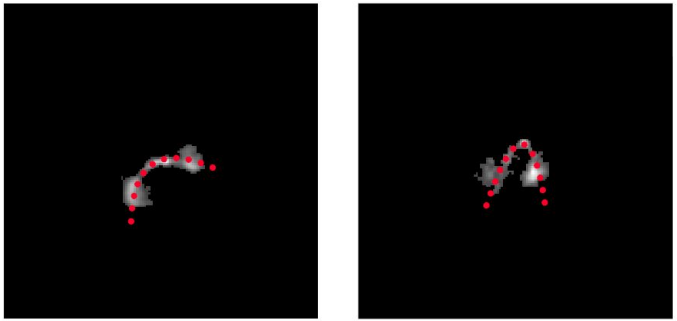


Fig. 2: Examples of WAT and NAT radio galaxies

Limitations of Prior Works

- **Scarcity of Data**: Lack of specialized datasets and benchmarks for bent radio AGN.
- **Existing Datasets**:
  - ***Galaxy Zoo [1]****:* Focuses on general galaxy classification.
  - ***Radio Galaxy Zoo [2]****:* Lacks specific WAT and NAT labeling.
  - ***MiraBest [3]****:* Provides labeled Fanaroff-Riley Type I and II sources, but not WATs and NATs.
- **Previous Catalogs**: *Proctor et al. [4]* contains unreliable automated annotations.
- **Our Data Source**: The *Sasmal et al. [5]* catalog requires extensive preprocessing and validation to be machine learning-ready.

Key Contributions

- Introduction of a novel machine learning dataset of bent radio AGN images (from Very Large Array - VLA).
- Detailed data acquisition and processing steps, including expert validation.
- Evaluation of state-of-the-art deep learning models (CNNs and transformers) on this dataset, establishing a baseline.
- Release of all source code for key data preprocessing tasks (background estimation, source identification, mask generation, background removal).

Dataset Creation: Data Acquisition

- **Raw Data**: Sourced from the Faint Images of the Radio Sky at Twenty-cm (FIRST) survey using the VLA telescope.
- **Source Coordinates**: Obtained from the *Sasmal et al.* catalog.
- **Data Format**: Images are downloaded from the NASA SkyView virtual observatory in Flexible Image Transport System (FITS) format.
- **Key Specs**:
  - **Frequency**: 1.4 GHz
  - **Resolution**: 5-arcsecond
  - **Sensitivity**: 0.15 mJy

Fig. 3: VLA Telescope

Dataset Creation: Data Processing

1. **Background Estimation**

   Goal: To figure out the average "noise level" in each image.
   We calculate the **local background level** using this formula:

$$B(x, y) = \mu_{\text{local}} + k \cdot \sigma_{\text{local}}$$

   - $B(x, y)$: background intensity at pixel (x, y)
   - μ_{local}: average brightness in a small region
   - σ_{local}: variation in brightness (standard deviation)
   - k: a scaling factor to account for noise (e.g., 3 or 5)

   This helps us distinguish between background noise and actual galaxy signals.

Dataset Creation: Data Processing

2. Source Identification

Goal: To detect the bright regions (potential galaxies) in the image.

We use thresholds to find regions that stand out:

- **Island Threshold:**
  $$I(x, y) > B(x, y) + T_{\text{isl}} \cdot \sigma_{\text{local}}$$
- **Peak Threshold:**
  $$I(x, y) > B(x, y) + T_{\text{pix}} \cdot \sigma_{\text{local}}$$
- $I(x, y)$: pixel intensity
- T_{isl}: minimum level for a region (set to 3)
- T_{pix}: minimum level for a peak (set to 5)

This allows us to identify and isolate potential bent AGN sources.

Dataset Creation: Data Processing

3. Modeling the Galaxy Shape

Goal: To mathematically describe each galaxy's appearance.

We fit a 2D Gaussian model to each detected source:

$$I(x, y) = I_0 \cdot \exp\left(-\left(\frac{(x' - x_0)^2}{2\sigma_{\text{maj}}^2} + \frac{(y' - y_0)^2}{2\sigma_{\text{min}}^2}\right)\right)$$

With the corresponding variable definitions:

- I_0: peak brightness
- (x_0, y_0): center coordinates
- $\sigma_{\text{maj}}, \sigma_{\text{min}}$: major and minor axis widths
- θ: angle of rotation (used to calculate x', y')

This helps us extract meaningful features like size, orientation, and intensity.

Dataset Creation: Data Processing

4. Mask Generation

Goal: To create a binary mask that delineates the precise spatial extent of each source. A binary mask, M(x,y), is generated by thresholding the fitted Gaussian model using the equation:

$$M(x,y) = \begin{cases} 1, & \text{if } I(x,y) > B(x,y) + T_{\text{pix}} \cdot \sigma_{\text{local}}, \\ 0, & \text{otherwise.} \end{cases}$$

Dilation: For extended or diffuse sources, a dilation operation is applied to expand the mask boundary and ensure complete coverage.

Dataset Creation: Data Processing

5. Image Conversion (FITS to PNG)

Goal: To prepare the images for visualization and deep learning models, we scale them from radio signal values to pixel brightness (0–255):

$$\text{img}_{\text{PNG}} = \left(\frac{\text{img} - \min(\text{img})}{\max(\text{img}) - \min(\text{img})} \right) \cdot 255$$

Dataset Creation: Data Processing

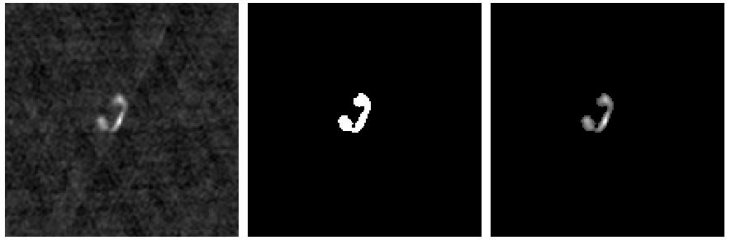
6. Background Removal

We clean the images by applying a binary mask:

$$\text{img}_{\text{masked}} = \text{img} \times M$$

With the corresponding definitions:

- M: the mask (1 = keep pixel, 0 = remove pixel)
- $\text{img}_{\text{masked}}$: cleaned image with only the galaxy



(a) Original Image (b) Generated Mask (c) Masked Image

Fig. 4: Background Removal Process

Dataset Creation: Final Dataset Curation

Expert Validation:

- Two expert astronomers manually reviewed each processed image.
- Verified presence of bent AGN, mask validity, background removal quality, and overall image quality.
- From a total of 703 sources, 64 sources got rejected.
- Resulting in a final dataset of 639 bent radio AGNs.

Dataset Creation: Final Dataset Curation

Dataset Splitting:

- Split into 10 batches (9 for training, 1 for testing).
- Each batch contains 64 images, except the last (63 images).
- Stratified based on source type (NAT or WAT) to ensure even distribution.
- Stored as separate pickle files.
- **Training Set:** First 9 batches (576 images)
- **Test Set:** Last batch (63 images)
- **Total:** 639 images (254 NAT, 385 WAT)

Batch No.	Source Count		Total Sources	Cumulative Total (Train/Test)
	WAT	NAT		
Training Set				
0	39	25	64	
1	39	25	64	
2	39	25	64	
3	39	25	64	
4	39	25	64	576
5	38	26	64	
6	38	26	64	
7	38	26	64	
8	38	26	64	
Test Set				
9	38	25	63	63
Total	385	254	639	639

Tab. 1 Distribution of NAT and WAT sources in RGC-Bent

Benchmarking Experiments:

Experimental Setup:

- **Baseline Models:** VGG-16, ResNet-50 (CNNs), Vision Transformer (ViT-B-16), SWIN Transformer (SWIN-B) (Transformer-based), ConvNeXT (CNN-based).
- All models pre-trained on ImageNet and fine-tuned on our dataset.
- Input images: grayscale 150×150 pixels, resized to 224×224 and converted to RGB (duplicated grayscale channel).
- Optimizers: Adam (CNNs), AdamW (Transformers).
- Batch size: 32; Epochs: 20; Early stopping.

Evaluation Metrics: Accuracy, Precision, Recall, F1-score (class-wise for NAT and WAT).

Quantitative Results

Model	Accuracy [%]	WAT			NAT		
		Precision	Recall	F1-score	Precision	Recall	F1-score
VGG-16	74.60	0.73	0.92	0.81	0.80	0.48	0.60
ResNet-50	77.77	0.79	0.87	0.82	0.76	0.64	0.70
ViT-B-16	76.19	0.76	0.89	0.82	0.77	0.73	0.74
SWIN-B	80.95	0.80	0.92	0.85	0.84	0.64	0.73
ConvNeXT	84.12	0.85	0.89	0.87	0.83	0.76	0.79

Tab. 2 Performance comparison of different deep learning models on RGC-Bent

Key Finding: ConvNeXT achieved the highest F1-scores for both WAT (0.87) and NAT (0.79) sources, demonstrating its robustness.

Qualitative Analysis

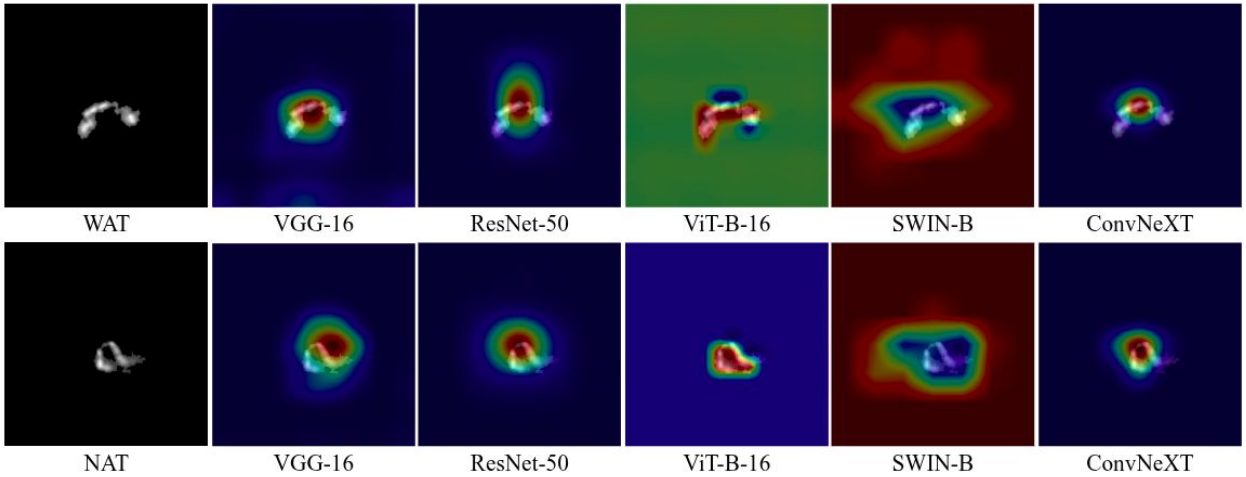


Fig. 5 CAMs generated by different models for a sample NAT and WAT source.

Key Finding: CNNs focus on the core regions of the source. Transformer-based models capture the elongated structure more effectively. This explains why transformers show higher recall for WAT sources.

Conclusion

- Introduced RGC-BENT, a novel, expertly curated dataset of 639 bent radio AGN images (WAT and NAT).
- Provided detailed data acquisition, processing, and validation methodologies.
- Benchmarked various deep learning models, showing the effectiveness of advanced machine learning for bent radio AGN classification.
- ConvNeXT emerged as the top performer, achieving the highest F1-scores for both WAT and NAT sources.
- Dataset and code are open-source, facilitating further research.

Thank You

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