Detecting Dual Nuclei in closely merging Galaxies using Machine Learning Techniques over SDSS Images

Bhavesh Mukheja - 21PH10008

Bachelor Thesis Project-I Presentation

Professor Somnath Bharadwaj (Internal Supervisor)
Professor Mousumi Das (External Supervisor)

Indian Institute of Technology Kharagpur
Department of Physics

November 29th 2024

Contents

1. Introduction
2. Motivation
3. Previous Research in Brief
4. Contribution to the project during internship
5. Contribution to the project during BTP-I
6. Image Processing Techniques
7. Understanding and Training the YOLO Model
8. Scopes of Error
9. The Way Ahead
10. Notable Achievements
11. Acknowledgment

Introduction

Introduction

- I have my Bachelor Thesis Project under **Professor Somnath Bharadwaj** as my **internal supervisor** and **Professor Mousumi Das** (Indian Institute of Astrophysics, Bangalore) as **my external supervisor.**

- My work during BTP-Involved conducting a thorough literature review of the new technology available and work on collaborations, preparing the training data set, and training the YOLO Model capable of detecting Dual Active Galactic Nuclei (DGNs) within a sample of SDSS (Sloan Digital Sky Survey) images.

Motivation

Motivation

- Although galaxy mergers are common, the detection of dual Active Galactic Nuclei (DAGN) is rare.
- Their detection is very important as they help us understand the formation of supermassive black hole (SMBH) binaries, SMBH growth and AGN feedback effects in multiple nuclei systems.
- There is thus a need for an algorithm to do a systematic survey of existing imaging data for the discovery of DANGs.

Previous Research in Brief

GOTHIC Algorithm Explanation

The **GOTHIC** algorithm detects DAGNs in galaxy images based on their visual and structural features. Here's an outline of the algorithm's steps.

1. Image Normalization and Smoothing
   - The algorithm starts by normalizing the input images to standardize their brightness.
   - Gaussian Blur is used for smoothing the images to suppress noise and enhance features like bulges.

GOTHIC Algorithm Explanation

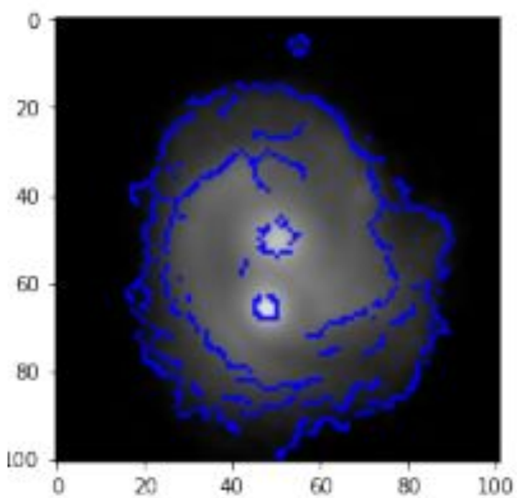
- Log normalization of all pixel values is applied in the cutout followed by appropriate scaling of the image within the range of [0, 255]

$$\boxed{I_{\mathrm{log}}(x,y)=\log(I(x,y)+1)}$$

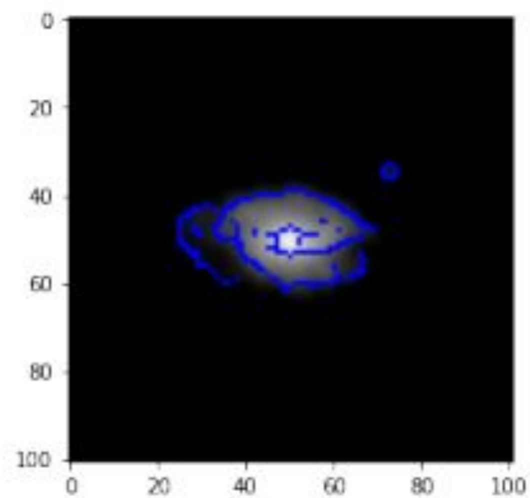
$$\boxed{I_{scaled}(x,y) = \frac{I_{log}(x,y)-min(I_{log})}{max(I_{log})-min(I_{log})}\times 255}$$

GOTHIC Algorithm Explanation

2. Edge Detection
   - The **Canny edge detection algorithm** is used to identify the boundaries of the galaxy in the 40" × 40" SDSS image cutout.



1237667734504407133

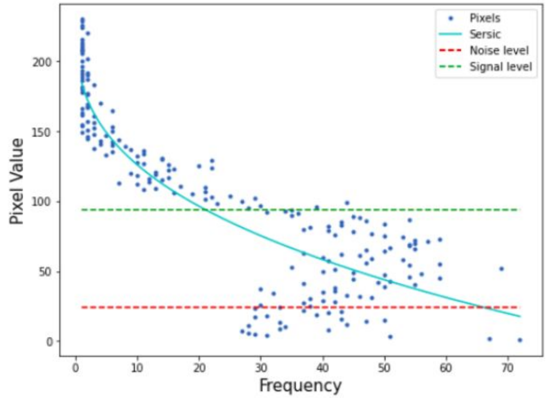


1237650794609246465

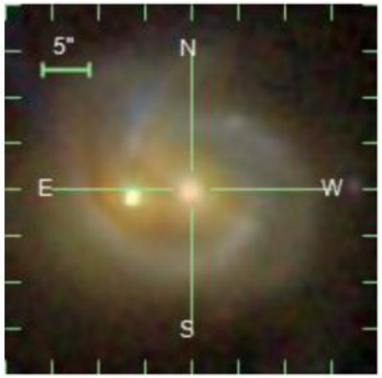
Examples of Edges detected by Canny

GOTHIC Algorithm Explanation

3. Light Profile Fitting
   - The pixel intensity histogram of the galaxy is fitted to a **Sérsic light profile**, which describes how light intensity varies with radius.
   - The **Sérsic index** helps distinguish between single and double nuclei systems.



Sersic Fit



1237667734504407133

Example of a Seric fit of a DGN

GOTHIC Algorithm Explanation

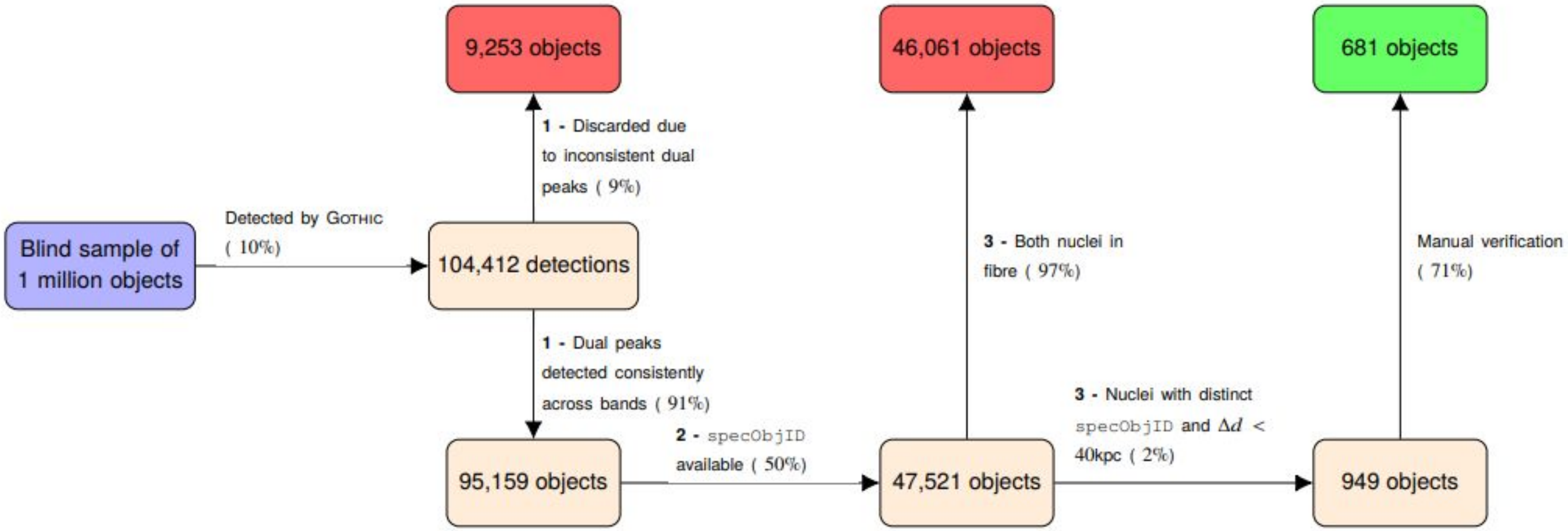
4. Determination of the Search Region
   - Based on the light profile, a pixel intensity cutoff value is defined.
   - Only pixels above this cutoff are considered part of the galaxy's high-intensity regions, narrowing the search for nuclei.
5. Iterated Hill Climbing
   - A peak-finding algorithm is applied to locate regions of maximum brightness within the search region.
   - This step ensures that the detected peaks correspond to potential nuclei.

GOTHIC Algorithm Explanation

6. Final Classification
   - **DNG**: If two distinct, well-separated peaks are identified.
   - **Single Nucleus Galaxy**: If only one peak is found.
   - **Three Peaks**: Very few images contain three peaks

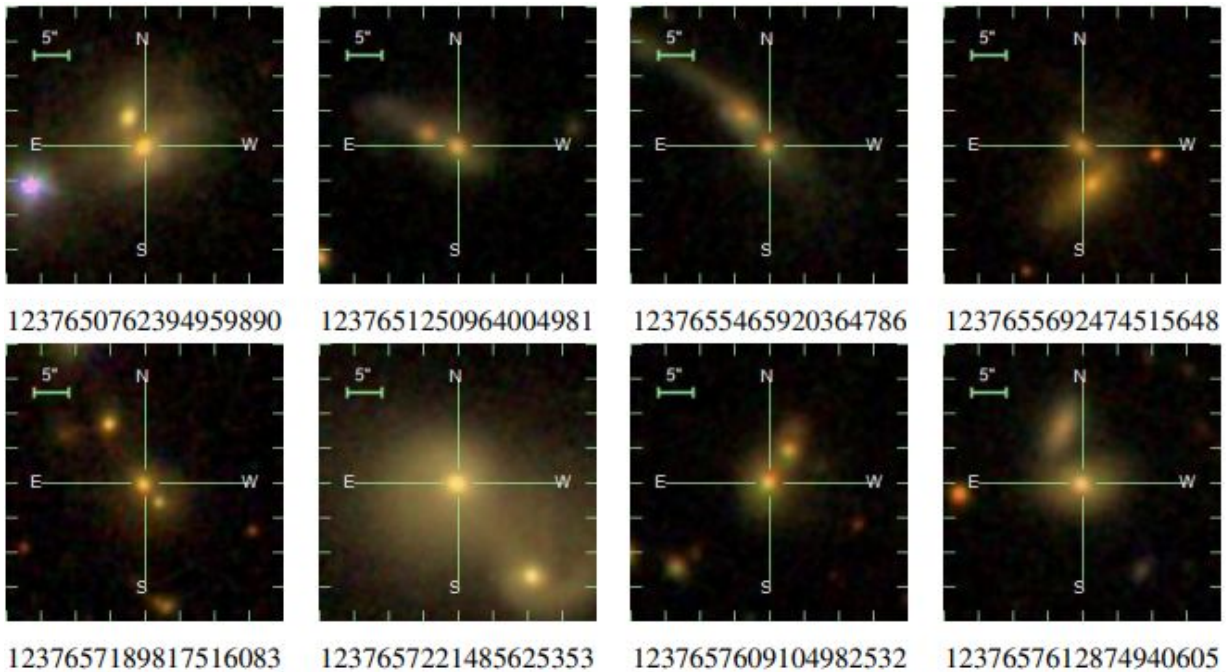
Results and Conclusion

Results and Conclusion



Flowchart demonstrating the filtration of the blind sample down to the visually confirmed sample. The bold numbers refer to the filtration steps in Section 4 and the numbers in parenthesis indicate the percentage reduction in the sample size caused by each filtration step

Results and Conclusion



Panel of a subset of 6 out of the 681 discovered DGNs (with SDSS objIDs listed)

Contribution to the Project during Internship

Contribution to the project during internship

- Data Analysis
  - Rerunning the GOTHIC Algorithm and obtaining the data of interest i.e. 46,081 probable DGNs candidates
  - Developing the python code to get images with dual peaks across u,g,r & i bands.
  - Filtered out the objects which are present in all the 4 bands (u,g,r,&i) **~2.5k** and in 2 bands (r&i)

Contribution to the project during internship

```
# Define the directory containing the CSV files
csv_dir = '/content/Double in 4 bands'

# List all CSV files in the directory
csv_files = [f for f in os.listdir(csv_dir) if f.endswith('.csv')]

# Initialize an empty list to hold DataFrames
dataframes = []

# Iterate over the CSV files and read them into DataFrames
for file in csv_files:
    file_path = os.path.join(csv_dir, file)
    df = pd.read_csv(file_path)
    dataframes.append(df)

# Concatenate all DataFrames into a single DataFrame
merged_df = pd.concat(dataframes, ignore_index=True)

# Save the merged DataFrame to a new CSV file
output_file = os.path.join(csv_dir, '47kSDSSSample.csv')
merged_df.to_csv(output_file, index=False)

print(f"All CSV files have been merged and saved to {output_file}")
```

```
All CSV files have been merged and saved to /content/Double in 4 bands/doubleIn4bandsMain.csv
```

Code snippet for finding "DOUBLE" Peaks in u,g,r,i bands in the raw_doubles data

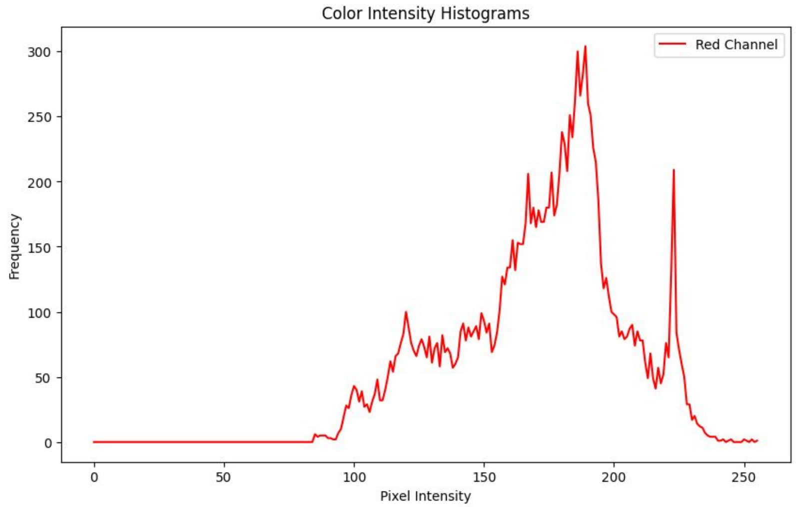
Contribution to the project during internship

	A	B	C	D	E	F	G	H	I	J	K
1	objid	ra	dec	u-type	u-peaks	g-type	g-peaks	r-type	r-peaks	i-type	i-peaks
2	1.24E+18	244.3774	46.0917	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(3	DOUBLE	[(50, 50)(36, 40)]
3	1.24E+18	116.6311	42.89139	DOUBLE	[(51, 36)(5	DOUBLE	[(51, 37)(5	DOUBLE	[(51, 37)(5	DOUBLE	[(51, 37)(50, 50)]
4	1.24E+18	117.5319	43.6445	DOUBLE	[(64, 69)(6	DOUBLE	[(65, 67)(6	DOUBLE	[(62, 67)(6	DOUBLE	[(65, 68)(66, 78)]
5	1.24E+18	197.5538	65.47992	DOUBLE	[(51, 62)(5	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 51)(5	DOUBLE	[(51, 51)(51, 62)]
6	1.24E+18	217.7719	-0.91944	DOUBLE	[(9, 52)(16,	DOUBLE	[(8, 52)(50,	DOUBLE	[(8, 53)(50,	DOUBLE	[(9, 53)(50, 50)]
7	1.24E+18	217.4418	-0.1524	DOUBLE	[(35, 55)(4	DOUBLE	[(35, 55)(4	DOUBLE	[(50, 50)(3	DOUBLE	[(52, 50)(36, 55)]
8	1.24E+18	14.07227	-0.36902	DOUBLE	[(55, 44)(5	DOUBLE	[(56, 44)(5	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 50)(55, 44)]
9	1.24E+18	156.3485	64.9987	DOUBLE	[(50, 50)(3	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 50)(41, 42)]
10	1.24E+18	179.0024	-2.72006	DOUBLE	[(68, 42)(5	DOUBLE	[(68, 43)(5	DOUBLE	[(69, 43)(5	DOUBLE	[(69, 42)(51, 50)]
11	1.24E+18	179.3016	-2.68647	DOUBLE	[(50, 50)(2	DOUBLE	[(50, 50)(2	DOUBLE	[(50, 50)(2	DOUBLE	[(29, 45)(49, 50)]
12	1.24E+18	144.2059	57.9921	DOUBLE	[(49, 50)(4	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 50)(51, 36)]
13	1.24E+18	144.1331	59.40518	DOUBLE	[(17, 15)(1	DOUBLE	[(13, 1)(17,	DOUBLE	[(13, 1)(17,	DOUBLE	[(12, 1)(17, 15)]
14	1.24E+18	146.5368	58.53046	DOUBLE	[(51, 50)(5	DOUBLE	[(50, 49)(5	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 49)(57, 55)]
15	1.24E+18	194.5769	51.13008	DOUBLE	[(50, 49)(5	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(6	DOUBLE	[(60, 60)(50, 50)]
16	1.24E+18	133.4081	40.73002	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(6	DOUBLE	[(50, 50)(67, 34)]
17	1.24E+18	122.4675	35.19424	DOUBLE	[(51, 57)(5	DOUBLE	[(51, 57)(5	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 50)(51, 58)]
18	1.24E+18	122.1046	34.9047	DOUBLE	[(47, 44)(4	DOUBLE	[(47, 44)(5	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 50)(47, 44)]
19	1.24E+18	252.8739	40.29336	DOUBLE	[(51, 41)(5	DOUBLE	[(51, 41)(5	DOUBLE	[(52, 40)(5	DOUBLE	[(52, 41)(51, 50)]
20	1.24E+18	154.4533	4.615416	DOUBLE	[(48, 73)(4	DOUBLE	[(48, 70)(4	DOUBLE	[(48, 70)(4	DOUBLE	[(48, 70)(48, 83)]
21	1.24E+18	155.0912	4.888983	DOUBLE	[(58, 61)(5	DOUBLE	[(58, 61)(5	DOUBLE	[(50, 50)(5	DOUBLE	[(50, 50)(58, 60)]
22	1.24E+18	221.9567	1.051977	DOUBLE	[(36, 42)(4	DOUBLE	[(33, 46)(4	DOUBLE	[(33, 46)(5	DOUBLE	[(33, 46)(49, 50)]
23	1.24E+18	156.6218	20.23355	DOUBLE	[(26, 23)(4	DOUBLE	[(5, 7)(26,	DOUBLE	[(6, 8)(13,	DOUBLE	[(7, 7)(13, 3)]
24	1.24E+18	130.7751	26.80619	DOUBLE	[(67, 36)(5	DOUBLE	[(66, 36)(5	DOUBLE	[(67, 36)(5	DOUBLE	[(66, 37)(50, 50)]
25	1.24E+18	211.3107	9.275822	DOUBLE	[(45, 29)(4	DOUBLE	[(44, 29)(4	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 49)(45, 29)]
26	1.24E+18	241.3946	7.457648	DOUBLE	[(41, 55)(5	DOUBLE	[(51, 49)(4	DOUBLE	[(50, 51)(4	DOUBLE	[(50, 50)(41, 55)]
27	1.24E+18	198.8336	33.00119	DOUBLE	[(45, 44)(5	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 50)(4	DOUBLE	[(50, 49)(45, 43)]

Snippet of the filtered objects that have “DOUBLE” peaks in all four bands

Contribution to the project during internship

- Removing the false positives from the sample
  - Developed the python code to detect the false positive images by using threshold filtering technique



1237651252046921791

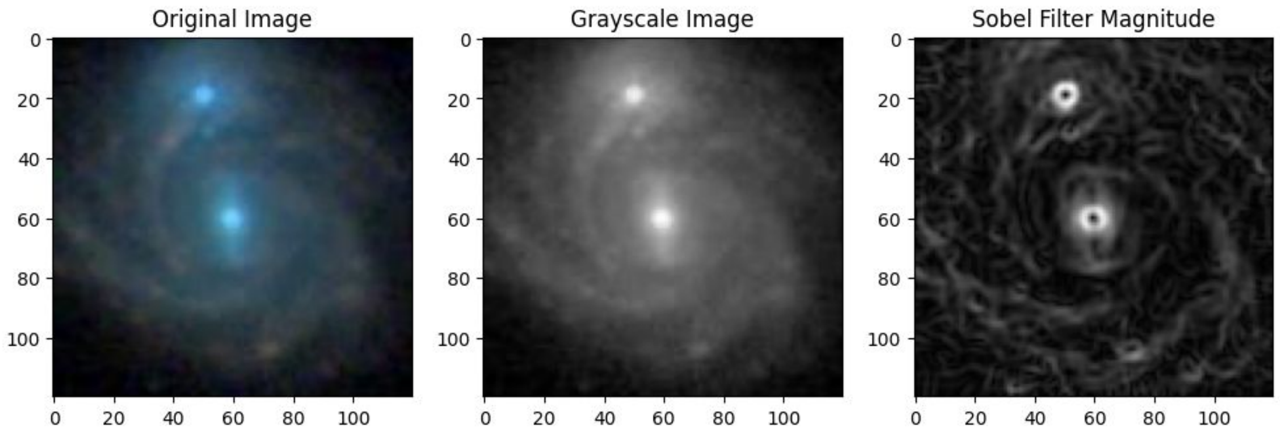
Example of a false positive in the sample. On left, is the Color intensity profile of the red channel which is used for threshold filtering. On right, is the image from the SDSS server of object with objID(1237651252046921791)

Contribution to the project during internship

- Proposed the Machine Learning Model
  - After extensive study proposed YOLOv8 [**Y**ou **O**nly **L**ook **O**nce] object detection Machine Learning Model.
  - YOLOv8 was tentatively selected as the model because of its computational efficiency, high accuracy, and good performance on small objects
- Categorized the Training, Testing, and Validating Dataset
  - Training Dataset:- 681 confirmed DGNs
  - Testing and Validation Dataset:- 45,380 probable DGNs candidates

Contribution to the project during internship

- Applying various Image Processing Techniques over training dataset for better accuracy
  - Programed the python code to try various Image Processing Techniques over images for better results
  - Sobel filter over grayscale image proved to be better for edge detection purpose



Contribution to the project during BTP-I

Image Processing Techniques

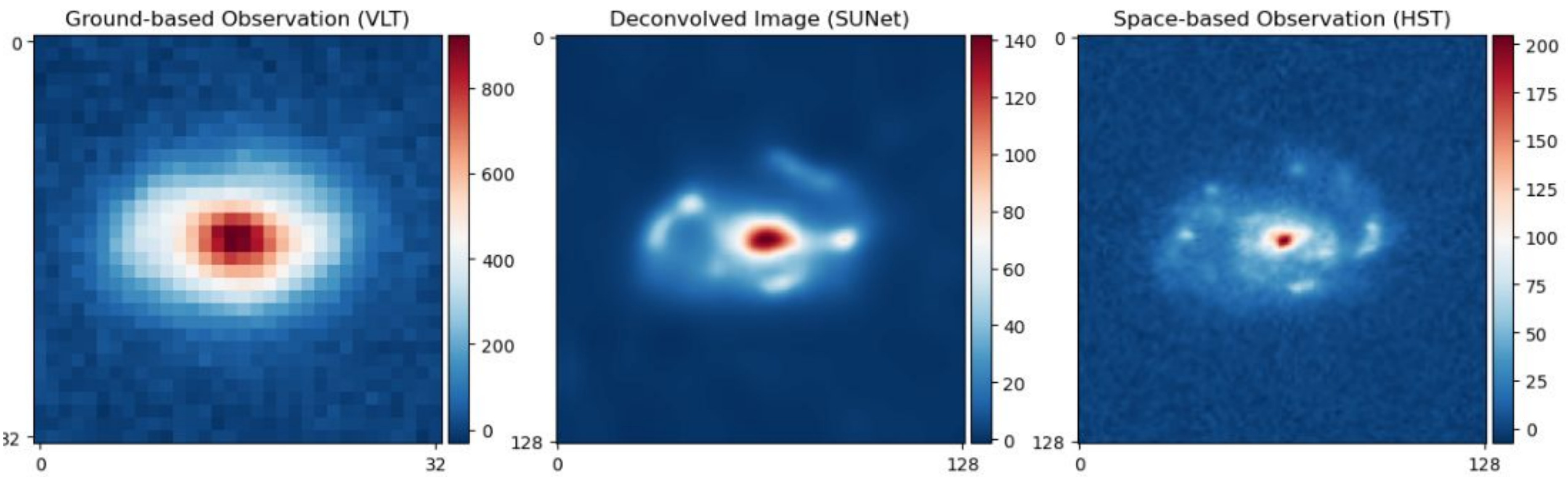
Image Processing Techniques

1. Swin Transformer-based UNet (SUNet), by EPFL Researcher, Mr. Utsav Akhaury
   - SUNet is a deep learning-based deconvolution algorithm designed to enhance spatial resolution in astronomical images.
   - Algorithm Principle:

$$\boxed{y = h * x_t + \eta}$$

Where:
$\boldsymbol{y \in R^{nxn}}$: Observed image
$\boldsymbol{h \in R^{nxn}}$: Point Spread Function (PSF)
$\boldsymbol{x_t \in R^{nxn}}$: True image (ground truth)
$\boldsymbol{\eta \in R^{nxn}}$: Additive Gaussian noise
$\boldsymbol{*}$: Convolution operation

Image Processing Techniques



Results of using SUNeT over an image of a galaxy captured by Very Large Telescope.
(ESO Distant Cluster Survey (EDisCS)

https://arxiv.org/pdf/2405.07842

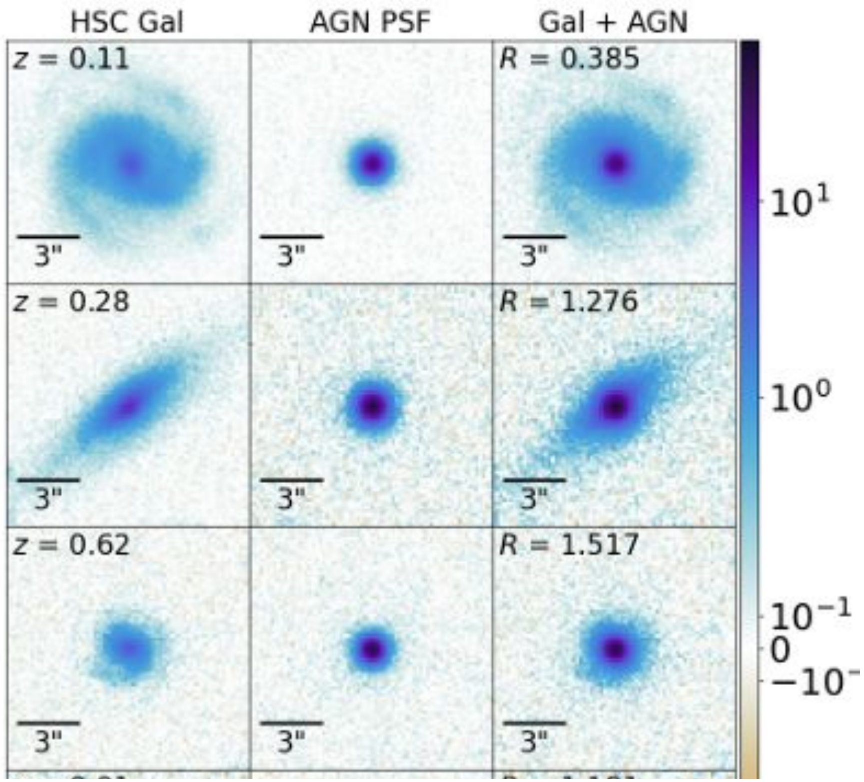
Image Processing Techniques

- This approach was discarded because of the two main reason
  - SUNet works the best with high resolution images. SDSS (Sloan **Sloan Digital Sky Survey)** does not provided clear and high resolution images.
  - SUNet also requires to have a defined PSF (Point Spread Function) for each image it deconvolutes.

Image Processing Techniques

2. PSFGAN by Yale University Researchers, Professor Meg Urry Research Group
   - PSFGAN stands for Point Spread Function Generative Adversarial Network. A Generative Adversarial Network (GAN) that removes AGN light contamination from galaxy images.
   - It uses a generator-discriminator architecture to recover the host galaxy image.The generator estimates what the galaxy looks like without the AGN light, while the discriminator compares this to known galaxy images to improve accuracy
   - **NOTE:** The Researchers are working with Hyper Supreme-Cam Wide Survey (HSC)

Image Processing Techniques



Examples of adding artificial AGN point sources to real HSC galaxies.

https://arxiv.org/pdf/2210.12264

Image Processing Techniques

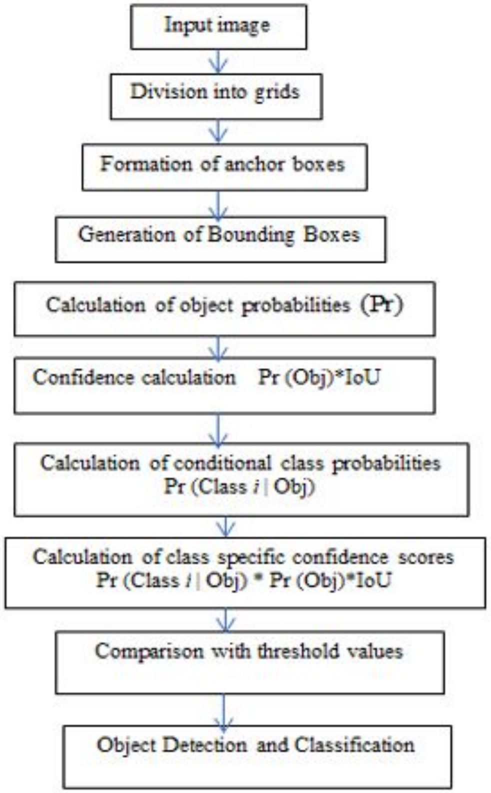
- This approach was discarded because of the three main reasons
  - PSFGAN uses artificial PSF to enhance the image. It works well with ANG but when there are two nuclei is involved it may fail.
  - Just like SUNet it also needs a high definition image with defined PSF. And makes it unsuitable for SDSS images we have.
  - Since we are dealing with the image where it is not sure there are 2 nuclei present or not. If used PSFGAN, it may add two artificial sources on its known making a false positive.

Hence, in the end it would be the best to have the model trained over raw SDSS images for the initial part of the project

Understanding and Training the YOLO Model

Selecting the YOLO Model

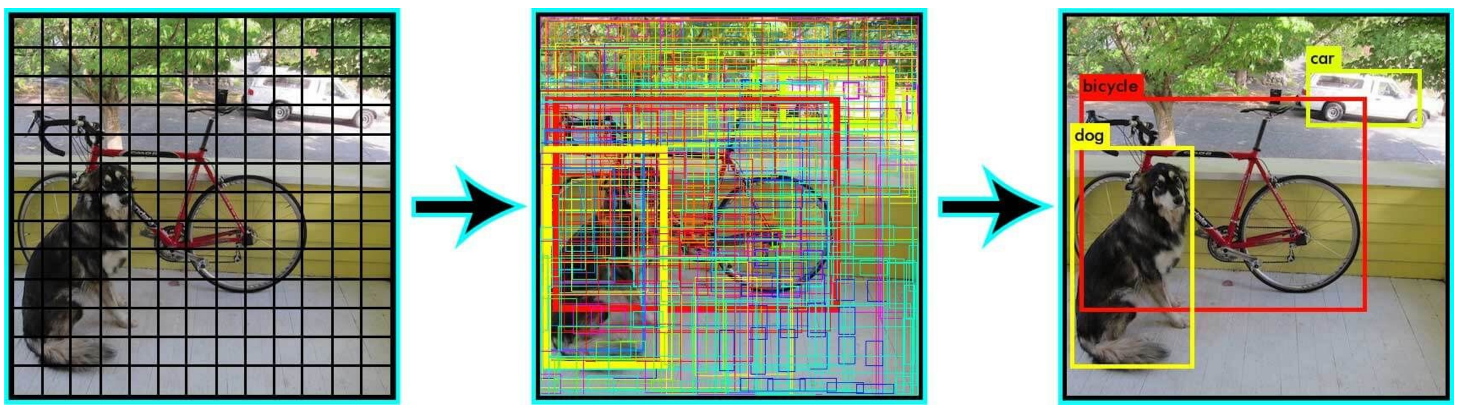
- What is YOLO?
  - YOLO Stands for:- **Y**ou **O**nly **L**ook **O**nce
  - It is an Computer Vision and AI based algorithm that can detect objects in real-time and can also be used to detect objects in a static frame.
  - YOLO leavarges CNN for feature extractions, object localization, and object detection, making it the fastest object detection technique so far.



Flow diagram of YOLO Model

Selecting the YOLO Model

- How does YOLO Work



YOLO divides an image in a grid (could be any number depending on the dimensions of the input image, in the image above it is 13x13)

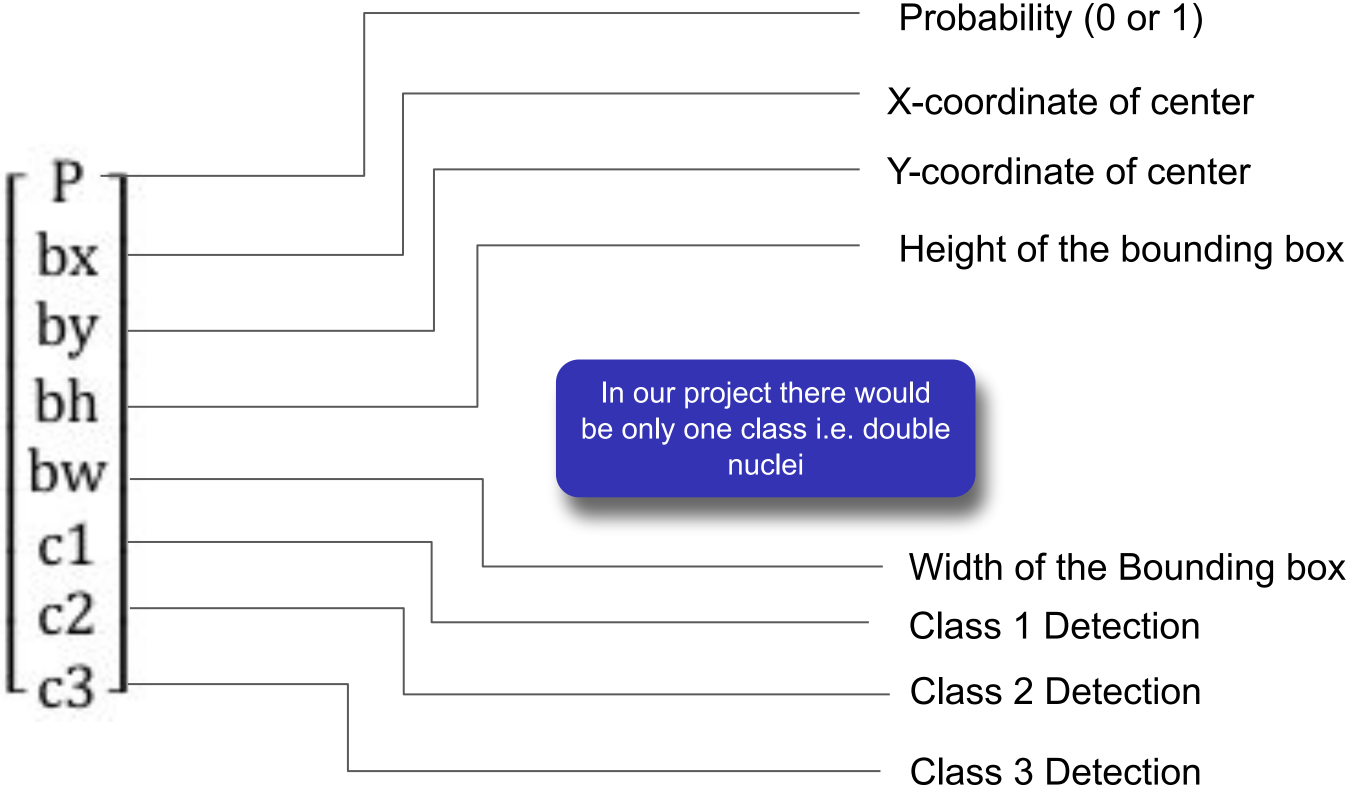
YOLO iterates over each grid box to see if there is any object to detect (pre-trained). It centers the box and makes a bounding box around it.

YOLO outputs the most probable bounding boxes using IOU (Intersection of Unions) method.

Working of YOLO

YOLO Model

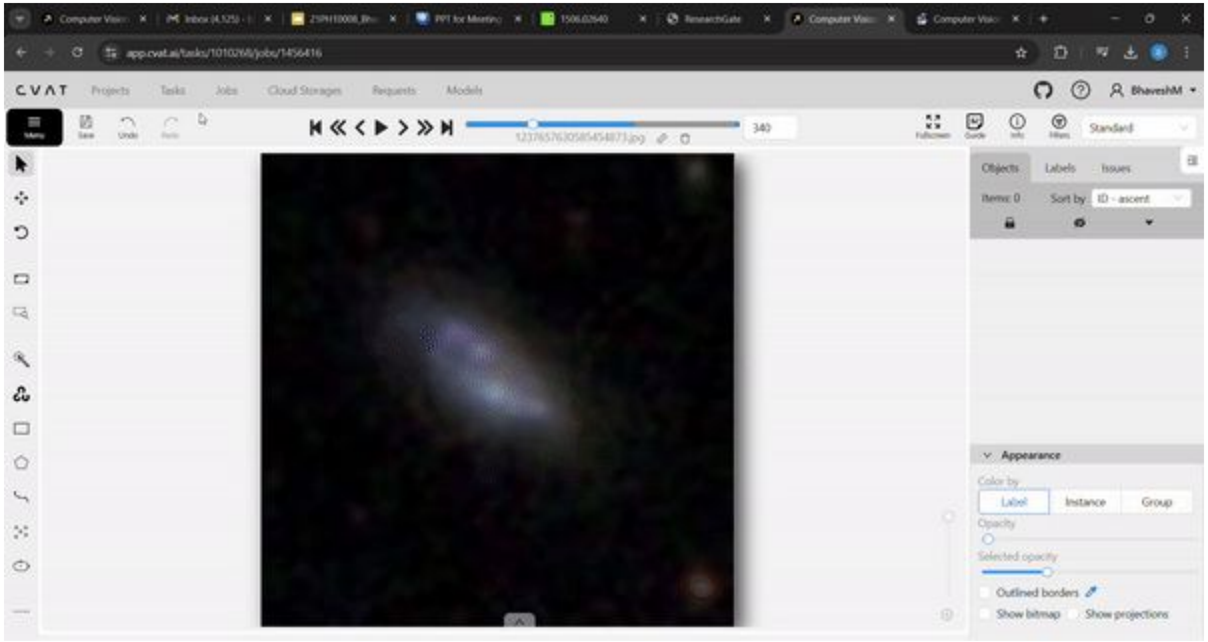
- How does YOLO Work



In our project there would be only one class i.e. double nuclei

YOLO Model

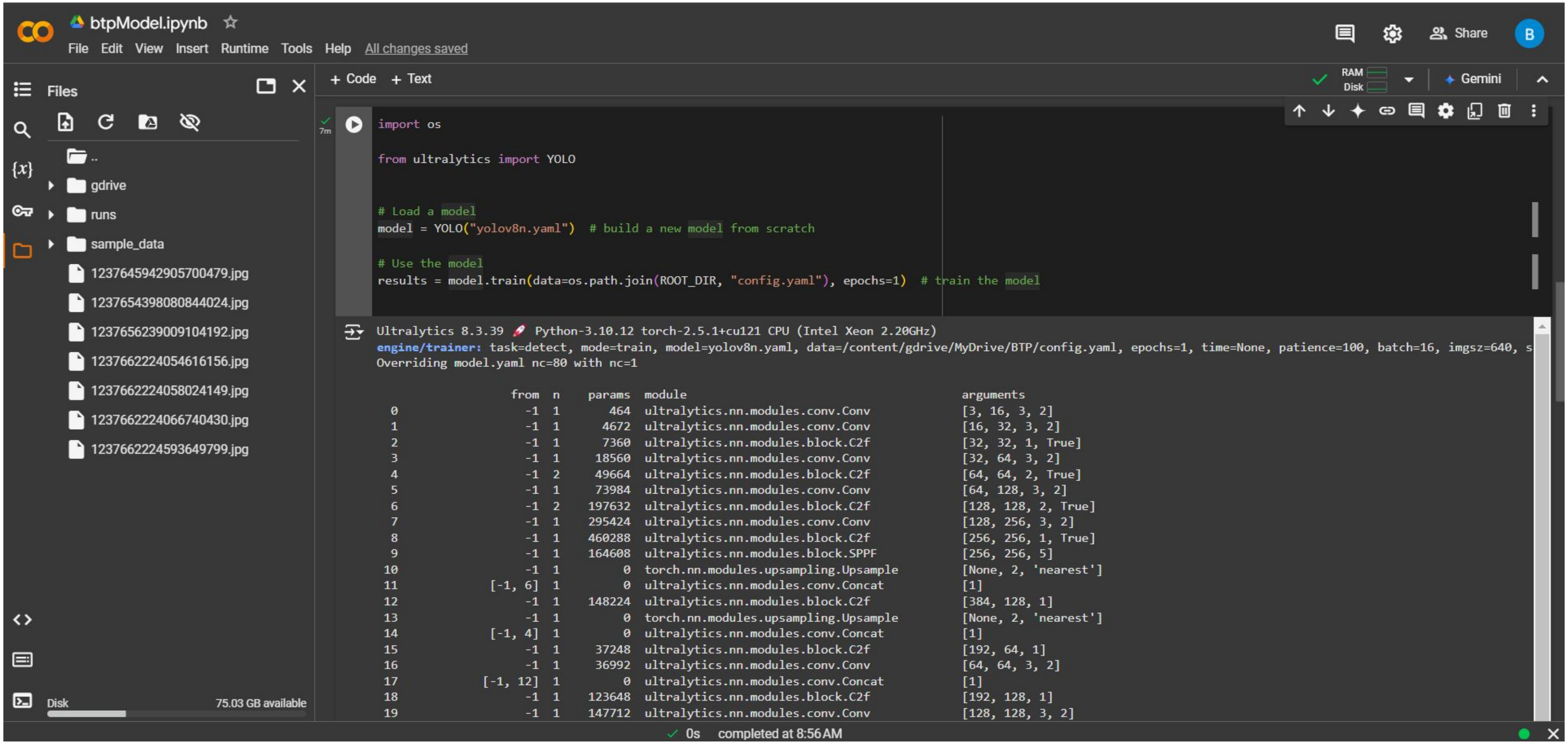
- Annotating the training dataset
  - ~400 out of 681 confirmed DGNs are manually annotated using an online Computer Vision Annotating Tool called CVAT.



A gif showing the annotation process of objId(1237657630585454873)

https://app.cvat.ai/tasks

YOLO Model



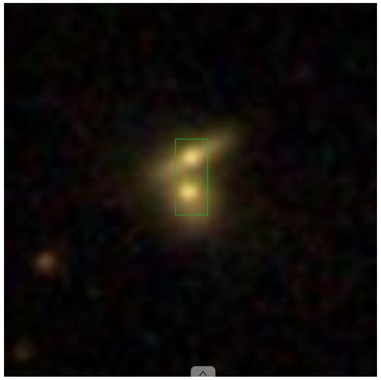
Snippet of Google Colab showing the training of YOLO Model

https://drive.google.com/drive/u/0/folders/149gCHTnr2AZCLv2-tdzKV5-x9-HCrD5G

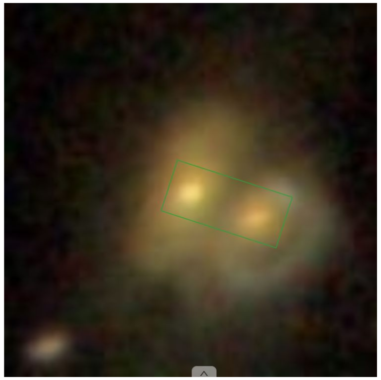
Contribution to the project during BTP-I

- Advantages of using YOLO
  - Can work with different merger shapes
  - YOLO is highly accurate, faster than other models (like RNN based), and works good with small objects

1237657628439085288



1237657628437774574



1237657628437053654

Versatility of YOLO to work with different shapes of mergers

Results

Results

- Because of small training data set and low resolution images, the current model (which is trained for ~400 annotated images) is not able to detect DNGs in the testing dataset.

Scope of error

Scope of error

- Quality of Training Dataset may be compromised because of less number of confirmed DGNs to train the model upon
- One major error is that the model either detects some unnecessary objects in the background hence resulting in poor accuracy
- It does not detect anything at all because of too much noise in the image or low intensity of the sources

The Way Ahead

The Way Ahead

- Augmenting the images to increase the size of the training data set and hence increasing the model accuracy
- Exploring better and more advanced image processing techniques for improving the data set
- Thorough review of the YOLOv8 model shall be done to know if it is right model for this task.

Notable Achievements

Notable Achievements

- Exploring new technologies for the project and getting in consult with the researchers who made those technologies, paved the way for collaboration.


Draft version September 20, 2024
Typeset using LaTeX **twocolumn** style in AASTeX631

DRAGON: A Deep Learning Approach to Discover and Study Dual AGN and Galaxy Merger Candidates in Large Sky Survey Fields.

Isaac Moskowitz[a,1] Jeremy Ng[a,1,2] C. Megan Urry[1,3,4] Aritra Ghosh[5,6,7] Mousumi Das[8] Anwesh Bhattacharya[9] Bhavesh Mukheja,[10] Chiara Mingarelli[11] and Andrew Casey-Clyde[11,12]

[1]Department of Astronomy, Yale University, New Haven, CT, 06511, USA.
[2]Department of Computer Science, Yale University, New Haven, CT, 06511, USA.
[3]Department of Physics, Yale University, New Haven, CT, 06511, USA.
[4]Yale Center for Astronomy and Astrophysics, New Haven, CT, 06511, USA.
[5]Department of Astronomy, Yale University, New Haven, CT, 06511, USA.
[6]DiRAC Institute, Seattle, WA, 98195, USA.
[7]Department of Astronomy, University of Washington, Seattle, WA, 98195, USA.
[8]Indian Institute of Astrophysics, Bangalore, India.
[9]Siebel School of Computing and Data Science, University of Illinois Urbana-Champaign, Champaign, IL, 61801, USA.
[10]Department of Physics, Indian Institute of Technology, Kharagpur, India.
[11]Department of Astronomy, Yale University, New Haven, CT, 06511, USA.
[12]Department of Physics, University of Connecticut, Storrs, CT 06269.

ABSTRACT

The recent detection of a nanoHertz gravitational wave (GW) background has intensified the search for mergers of supermassive black holes (SMBHs). Such events can drive rapid black hole growth, influencing the co-evolution of the SMBH and its host galaxy. Dual active galactic nuclei (AGN) signal a precursor stage whose numbers constrain models of the GW background. We developed the Data Reduced AGN and Galaxy Optical Network (DRAGON) convolutional neural network to efficiently identify dual AGN and galaxy mergers in current and upcoming large optical surveys. DRAGON was trained on 250,000 real and simulated images from the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP), achieving a classification accuracy of $\sim$ 94%. Our training set assumed a known quasar at the center of each (AGN) image, so this method works when a confirmed AGN is at the center of an image cutout. By testing multiple iterations of our model on an evaluation dataset comprising five known dual AGN and 2,621 single quasars, we identified 15 high-accuracy models, each successfully detecting the five dual AGN while returning varying numbers of additional candidates. Combining these 15 independently trained models with ensemble learning, we produced a list of 189 dual AGN candidates with a model confidence greater than 80%. We present the angular and physical separations of these candidates, along with their relative brightnesses. We plan to refine DRAGON to identify mergers and dual AGN across complete survey fields—not just around known quasars—and DRAGON

Draft of the abstract for the 245th meeting of the American Astronomical Society, by Yale Researchers

Acknowledgement

Acknowledgement

I would like to express my sincere gratitude to my supervisor, Professor Somnath Bharadwaj and my co-supervisor, Professor Mousumi Das for accepting my application and placing their trust in me. I am deeply thankful for the opportunity to work under her exceptional guidance Their mentorship not only paved the way for me to explore the vast field of astrophysics but also provided me with the invaluable chance to apply my knowledge of machine learning to the research project.

Bibliography

Bibliography

https://arxiv.org/pdf/2011.12177

https://arxiv.org/pdf/2405.07842

https://arxiv.org/pdf/2210.12264

https://www.geeksforgeeks.org/data-analysis-with-python/

https://www.geeksforgeeks.org/image-processing-in-python/

https://docs.ultralytics.com/

https://www.youtube.com/watch?v=vT1JzLTH4G4&list=PL3FW7Lu3i5JvHM8ljYj-zLfQRF3EO8sYv

https://github.com/ultralytics/ultralytics

https://github.com/utsav-akhaury/SUNet

https://www.researchgate.net/publication/339563145_YOLO_based_Detection_and_Classification_of_Objects_in_video_records?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uRG93bmxvYWQiLCJwYWdlIjoiX2RpcmVjdCJ9fQ