University of Dhaka
Department of Robotics and Mechatronics Engineering

Morphological and Spectral Classification and Stratification of Celestial Objects using Physics Informed Deep Learning

Submitted By:
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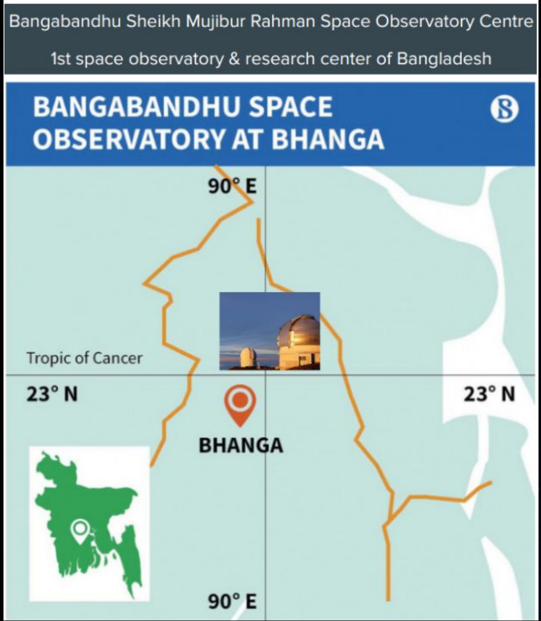

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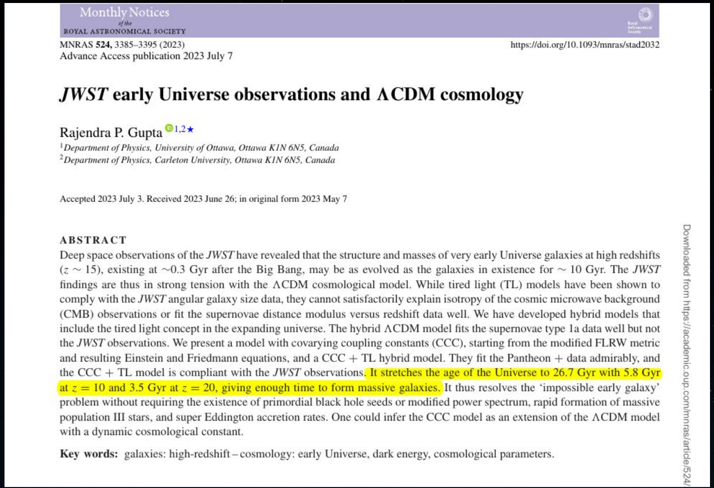

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JWST early Universe observations and ΛCDM cosmology

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ABSTRACT

Deep space observations of the *JWST* have revealed that the structure and masses of very early Universe galaxies at high redshifts ($z \sim 15$), existing at ~0.3 Gyr after the Big Bang, may be as evolved as the galaxies in existence for ~ 10 Gyr. The *JWST* findings are thus in strong tension with the ΛCDM cosmological model. While tired light (TL) models have been shown to comply with the *JWST* angular galaxy size data, they cannot satisfactorily explain isotropy of the cosmic microwave background (CMB) observations or fit the supernovae distance modulus versus redshift data well. We have developed hybrid models that include the tired light concept in the expanding universe. The hybrid ΛCDM model fits the supernovae type 1a data well but not the *JWST* observations. We present a model with covarying coupling constants (CCC), starting from the modified FLRW metric and resulting Einstein and Friedmann equations, and a CCC + TL hybrid model. They fit the Pantheon + data admirably, and the CCC + TL model is compliant with the *JWST* observations. It stretches the age of the Universe to 26.7 Gyr with 5.8 Gyr at $z = 10$ and 3.5 Gyr at $z = 20$, giving enough time to form massive galaxies. It thus resolves the 'impossible early galaxy' problem without requiring the existence of primordial black hole seeds or modified power spectrum, rapid formation of massive population III stars, and super Eddington accretion rates. One could infer the CCC model as an extension of the ΛCDM model with a dynamic cosmological constant.

Key words: galaxies: high-redshift – cosmology: early Universe, dark energy, cosmological parameters.

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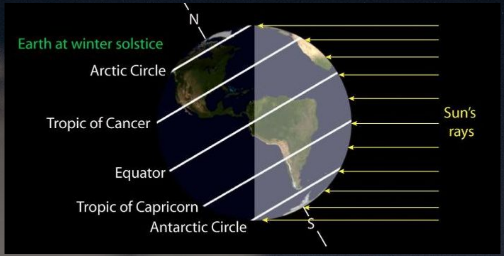
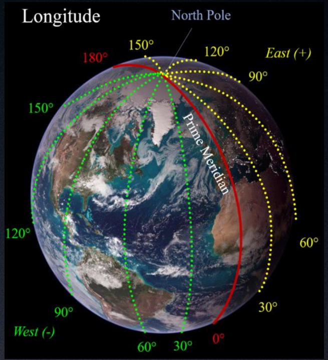
- Exploration and understanding of the Cosmos
- Accurate Prediction of the age of the universe and the early evolution of the universe
- Morphological of cataloguing of astronomical objects especially galaxies

<u>Geographical[152176] significance of Bhanga:</u> There are only 12 intersecting points of The **Equator**, the **Tropic of Cancer**, the **Tropic of Capricorn** (Encircle the earth from East to West) and 4 **longitude** lines (**0 Degree**, **90 Degree** East, **180 Degree** East-West and **90 Degree** West): 10 points are on the oceans, only 2 points are on land:

- Bhanga, Faridpur
- Sahara Desert



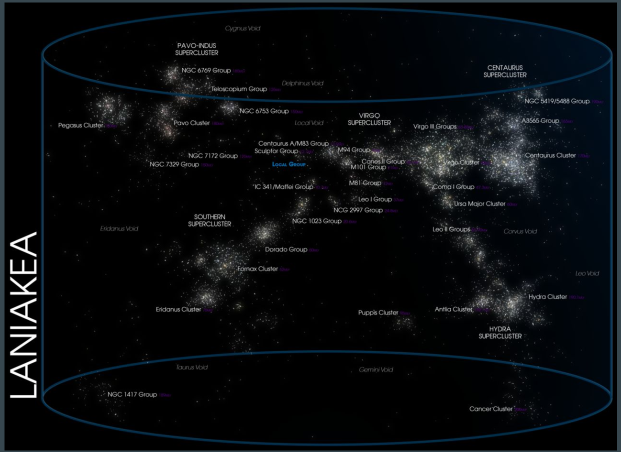


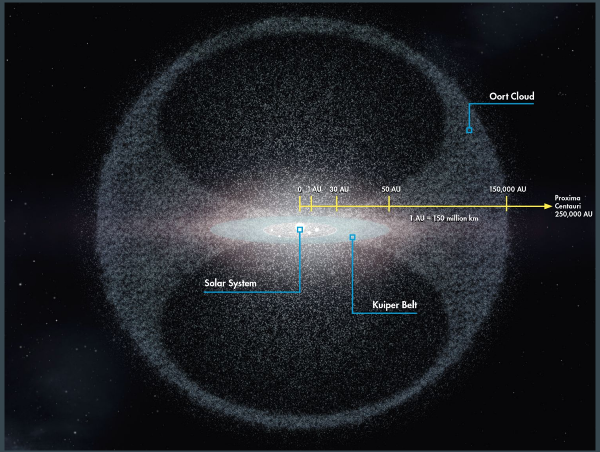
***https://en.wikipedia.org/wiki/Longitude**
***https://en.wikipedia.org/wiki/Tropic_of_Capricorn**
***https://en.wikipedia.org/wiki/Tropic_of_Cancer**

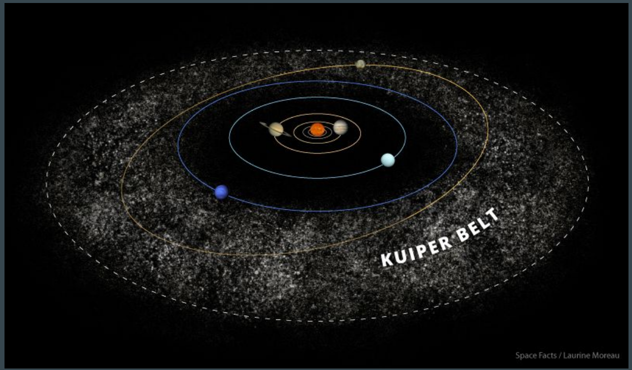
Introduction

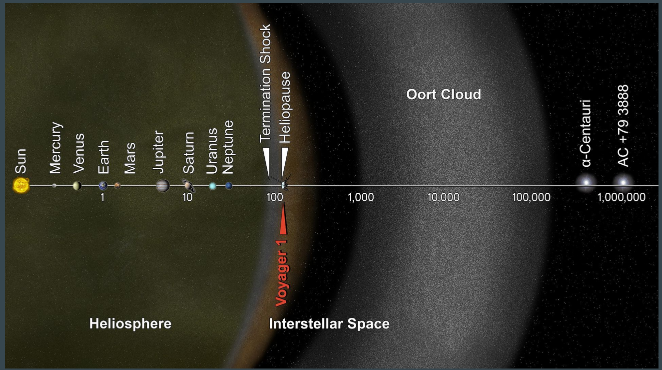
Our Cosmic Address:

1. The Observable Universe
2. The Laniakea Supercluster
3. The Virgo Supercluster
4. The Local Galactic Group
5. The Milky Way Galaxy
6. The Orion Arm
7. Local Bubble
8. Local Interstellar Cloud
9. Oort Cloud
10. Solar System
11. The Heliosphere
12. The Kuiper Belt
13. The Earth









*Tully, R., Courtois, H., Hoffman, Y. et al. The Laniakea supercluster of galaxies. Nature 513, 71–73 (2014). https://doi.org/10.1038/nature13674, *https://solarsystem.nasa.gov/solar-system/oort-cloud/overview/, https://solarsystem.nasa.gov/solar-system/kuiper-belt/overview/, https://earthsky.org/astronomy-essentials/which-spiral-arm-of-the-milky-way-contains-our-sun/,

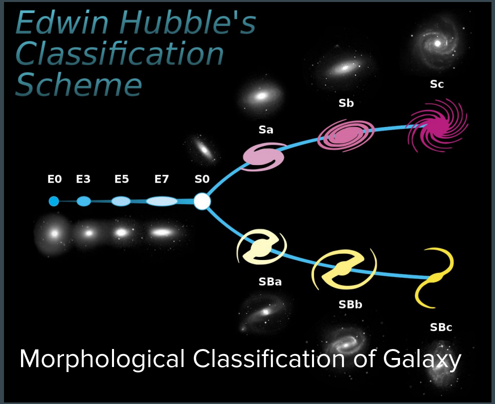
Research Questions

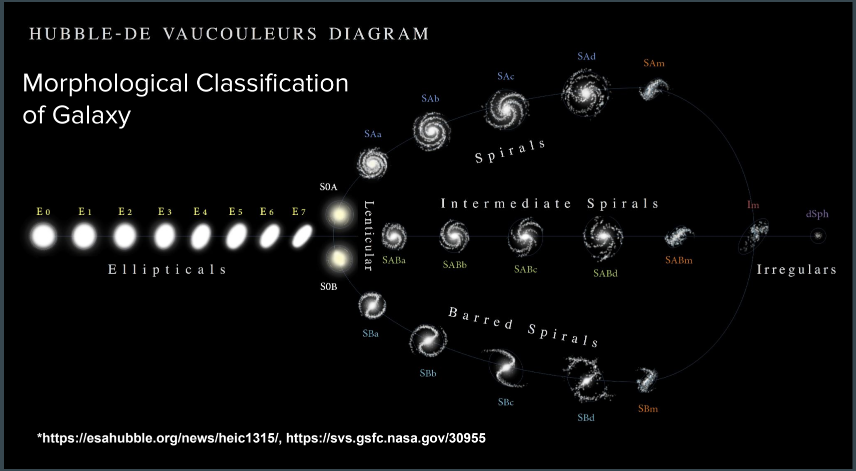
•Finding the way to analyse and classify the structures of celestial objects by understanding the morphology and spectra of the celestial objects.

•Evaluation of the existing physics informed neural networks on the basis of the contribution to improve the accuracy of celestial object classification. Comparison of the deep learning algorithms to investigate efficient approaches.

•Incorporation of the Redshift (Z-Values) of the galaxies to perform stratification according to their respective relative distance.

•Exploring the fields where the results of this research be used to advance the cataloguing of astronomical objects, accelerate exploration of searching for exoplanets, and contribute to a more accurate prediction of the age of the universe and the early evolution of the universe.





Research Objectives

• Development of a deep learning model capable of accurately classifying celestial objects based on their morphological features.

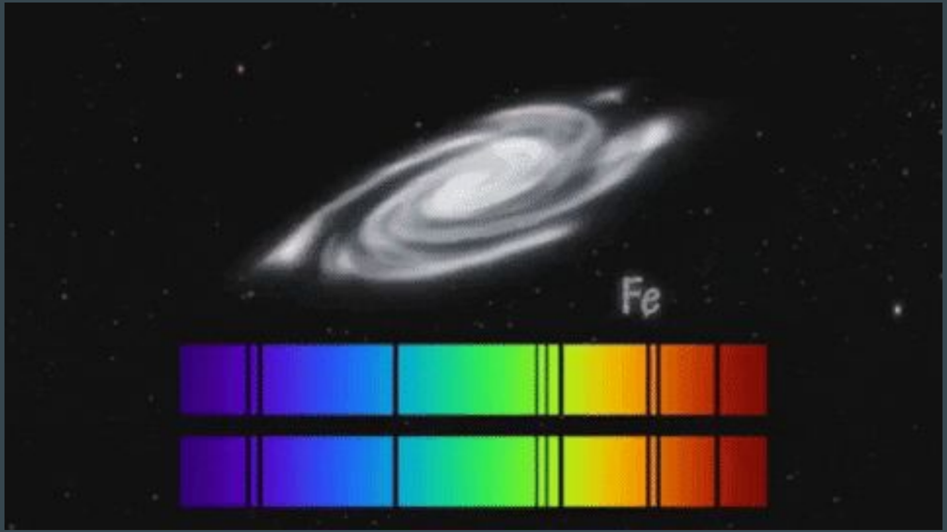
• Incorporation of spectral data into the classification process using physics-informed neural networks to improve classification accuracy.

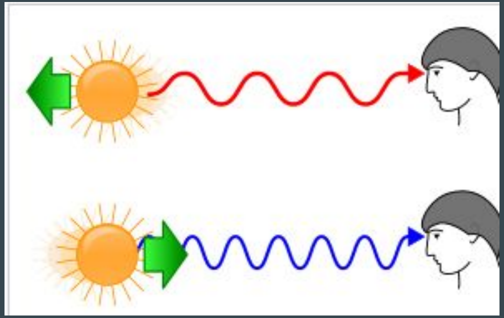
• Implementation of a Redshift-based stratification technique to enhance the precision of the classification process.

• Categorisation of the subdivision of the classification according to the orientation of the galaxies and the Redshift (z) value to extract information regarding the distance and age of the galaxies (Depth Perspective). Sorting of the 'Don't Know Category' into Stars, Quasars, Asteroids or Merging Galaxies. Processing of the CMB (Cosmic Microwave Background) Radiation, Anomalies, Artefacts or Noise.

• Validation of the proposed methodology using the Sloan Digital Sky Survey (SDSS) and Galaxy Zoo datasets and evaluation of the performance of the proposed models.

• Assessment of the impact of the proposed research on the advancement of the cataloguing of astronomical objects.





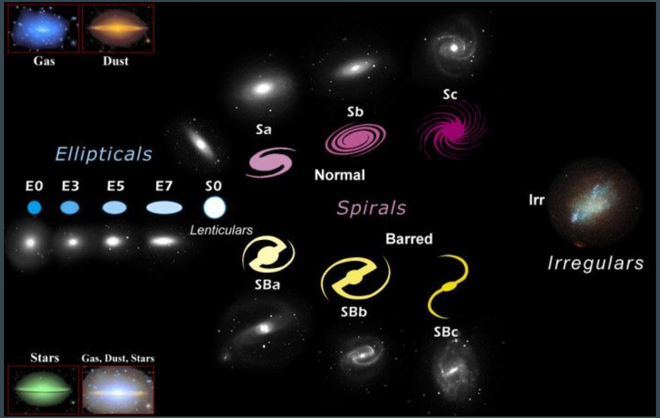
Calculation of redshift, z

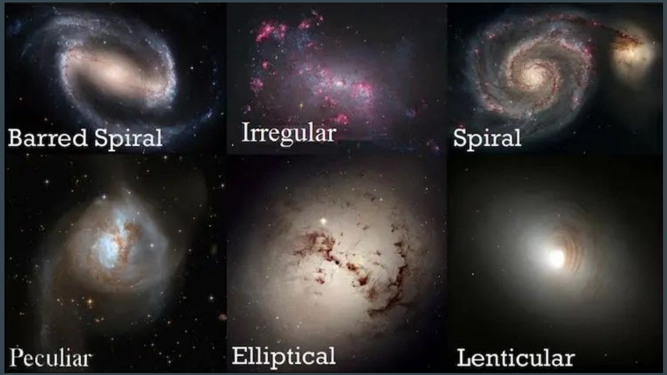
Based on wavelength	Based on frequency
$z = \frac{\lambda_{\mathrm{obsv}} - \lambda_{\mathrm{emit}}}{\lambda_{\mathrm{emit}}}$	$z = \frac{f_{\mathrm{emit}} - f_{\mathrm{obsv}}}{f_{\mathrm{obsv}}}$
$1 + z = \frac{\lambda_{\mathrm{obsv}}}{\lambda_{\mathrm{emit}}}$	$1 + z = \frac{f_{\mathrm{emit}}}{f_{\mathrm{obsv}}}$

*https://en.wikipedia.org/wiki/Redshift, *https://www.space.com/25732-redshift-blueshift.html

Literature Review

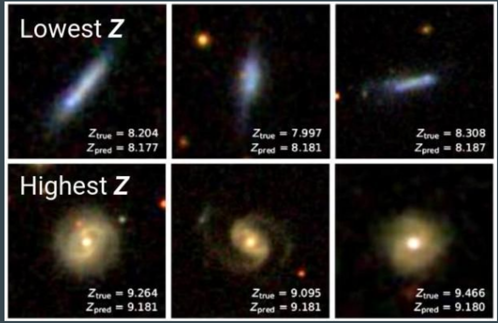
Hubble – de Vaucouleurs Diagram for Morphological Classification of Galaxy





*https://hubblesite.org/science/galaxies, https://astrobackyard.com/types-of-galaxies/

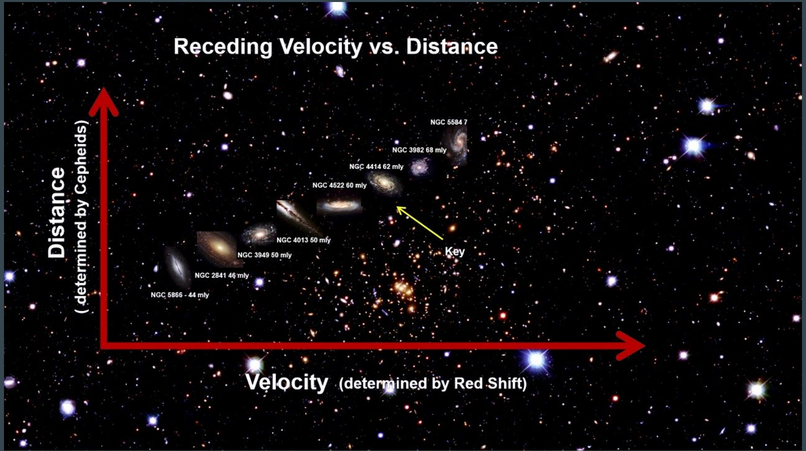
Galaxy Type	Description
Sa	spiral galaxy, type a
Sb	spiral galaxy, type b
Sc	spiral galaxy, type c
SBa	barred spiral galaxy, type a
SBb	barred spiral galaxy, type b
SBc	barred spiral galaxy, type c



Galaxies can be classified into various types based on their redshift value (z), which is a measure of how much their light has been shifted towards the red end of the electromagnetic spectrum due to the expansion of the universe. Redshift is often used as an indicator of distance and cosmic time.

- Low Redshift Galaxies ($z < 0.1$):
  - Elliptical Galaxies: These galaxies are often round or elongated in shape and contain mostly older stars. They have very little ongoing star formation.
  - Lenticular Galaxies: Also known as S0 galaxies, these are intermediate between elliptical and spiral galaxies. They have a central bulge like elliptical galaxies but also a flat, disk-like structure.
- Intermediate Redshift Galaxies ($0.1 < z < 1$):
  - Spiral Galaxies: These galaxies have a distinct spiral arm structure and often contain ongoing star formation. They can have a central bulge and a rotating disk.
  - Irregular Galaxies: Irregular galaxies have chaotic and irregular shapes. They often exhibit active star formation and may lack any specific structure.
- High Redshift Galaxies ($z > 1$):
  - Luminous Infrared Galaxies (LIRGs): These galaxies emit a significant portion of their energy in the infrared range due to intense star formation and/or an active galactic nucleus.
  - Lyman-Break Galaxies (LBGs): These are typically high-redshift star-forming galaxies that have been identified using a technique involving the Lyman-alpha break in their spectra.
  - Distant Galaxies: Galaxies with very high redshifts are often referred to as "distant galaxies." They are observed as they were when the universe was much younger.
- Very High Redshift Galaxies ($z > 5$):
  - Primeval Galaxies: These are extremely distant galaxies that formed during the early stages of the universe. They provide important insights into the early universe's conditions and evolution.

Hubble's Law



$$v = H_0 r$$

v = recessional velocity

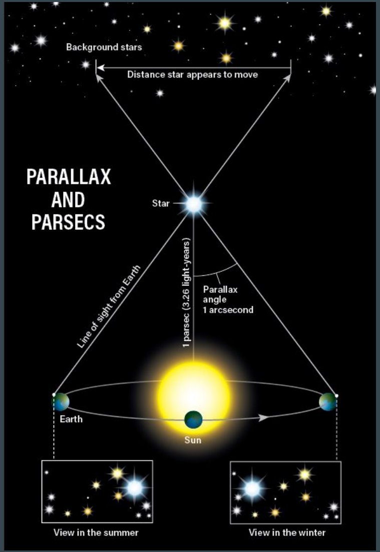
H_0 = Hubble constant

r = distance

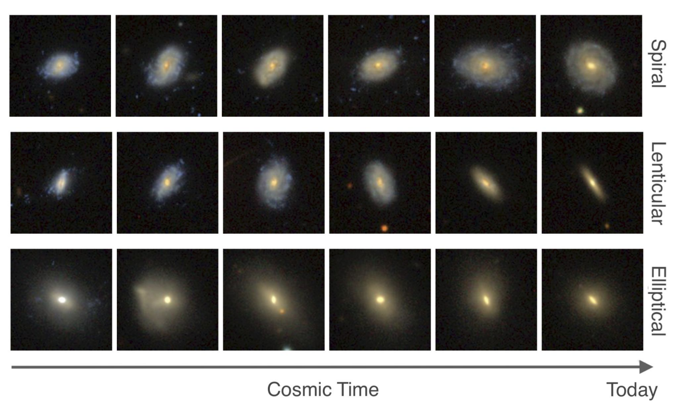
$$H_0 \approx \frac{70 km/s}{Mpc} \approx \frac{20 km/s}{Mly}$$

Mpc = million parsecs

Mly = million light years



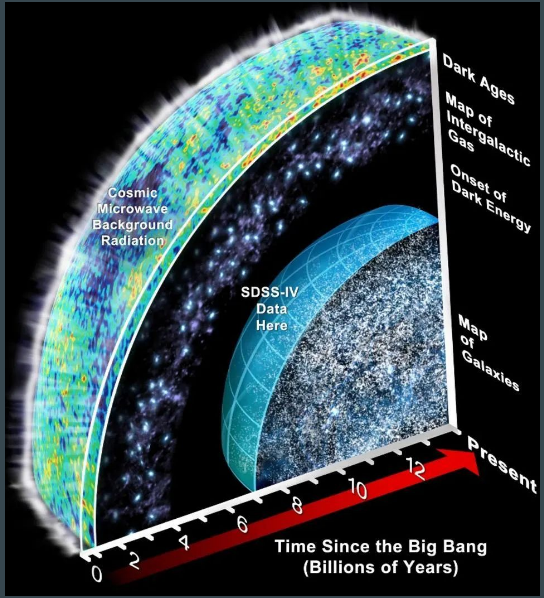
Evolution of Galaxies



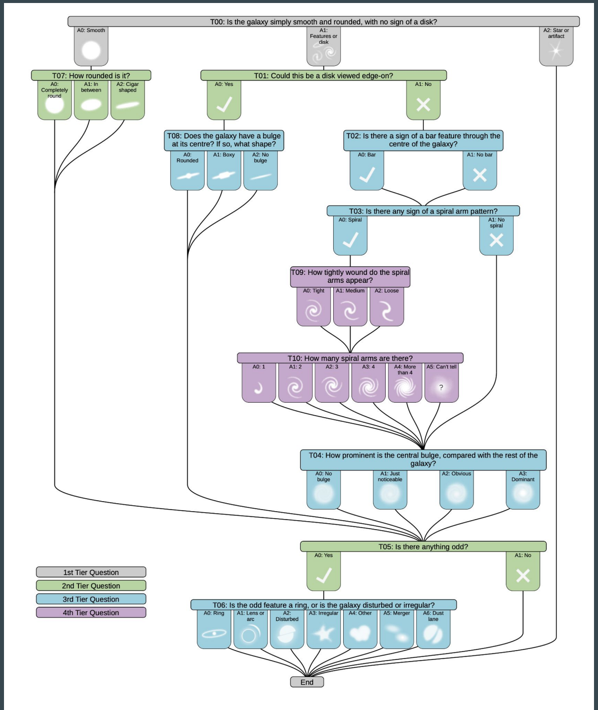
*https://en.wikipedia.org/wiki/Hubble%27s_law, http://hyperphysics.phy-astr.gsu.edu/hbase/Astro/hubble.html, https://www.astronomy.com/astronomy-for-beginners/why-is-a-parsec-3-26-light-years/

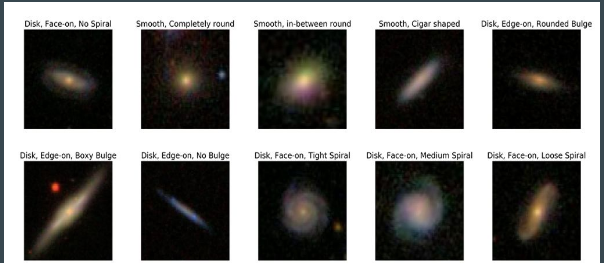
Datasets

- Sloan Digital Sky Survey (SDSS)
- Galaxy Zoo
- The James Webb Space Telescope (JWST)
- Cosmic Dawn
- DECaLS
- Dark Energy Spectroscopic Instrument (DESI)

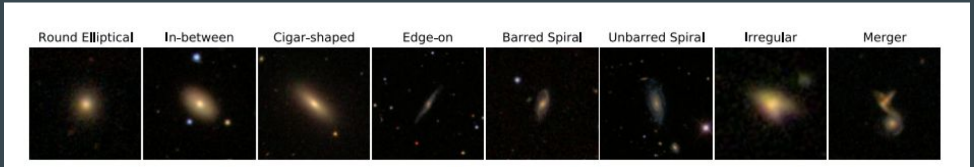


Galaxy Zoo Decision Tree



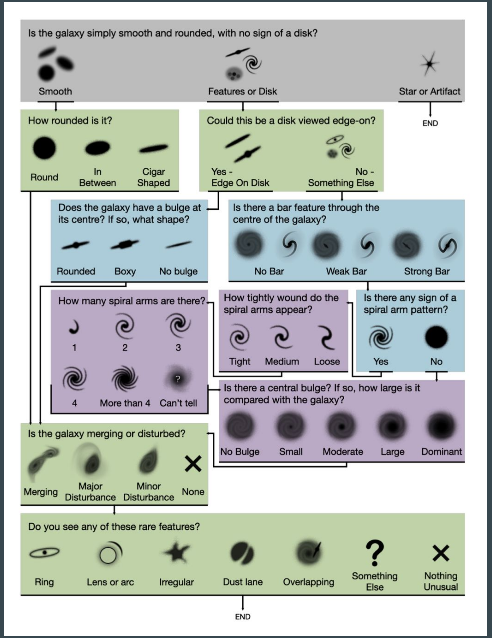


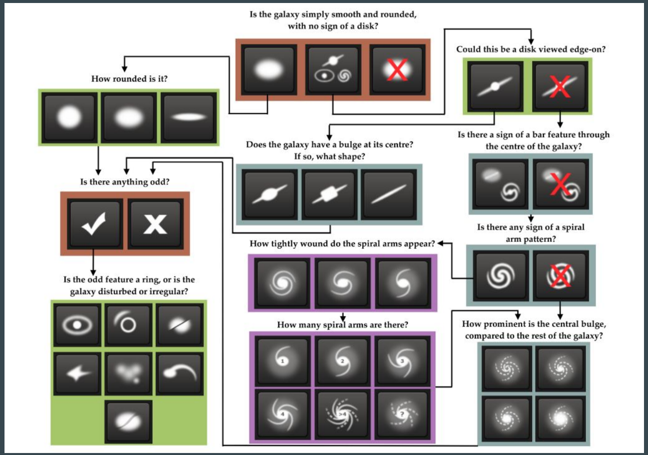
Galaxy10 Dataset: Henry Leung/Jo Bovy 2018, Data Source: SDSS/Galaxy Zoo

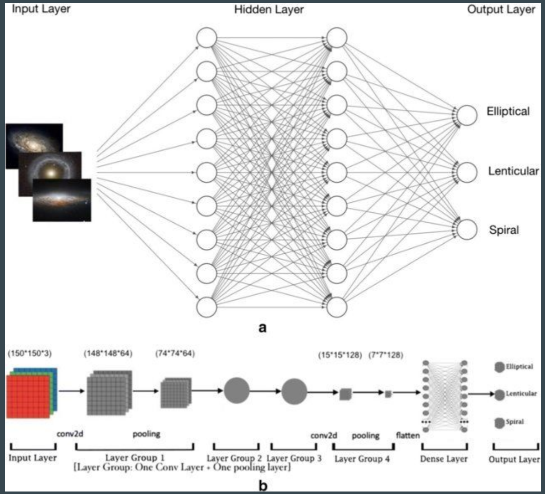


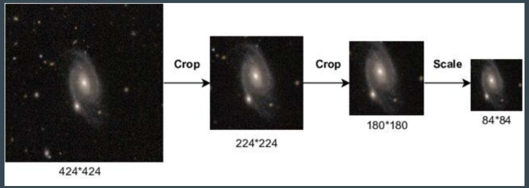
*https://hubblesite.org/science/galaxies, https://data.galaxyzoo.org/gz_trees/gz_trees.html, https://www.sdss.org/, https://blog.galaxyzoo.org/2015/04/06/visualizing-the-decision-trees-for-galaxy-zoo/, Gharat, S., & Dandawate, Y. (2022). Galaxy classification: a deep learning approach for classifying Sloan Digital Sky Survey images. Monthly Notices of the Royal Astronomical Society, 511(4), 5120–5124. https://doi.org/10.1093/mnras/stac457

Flowchart of Galaxy Classification



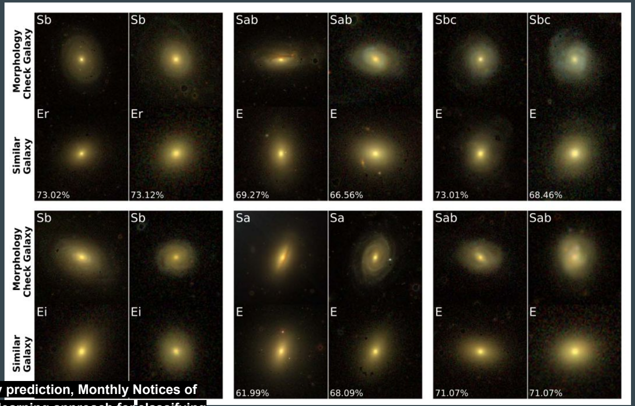






Class	Name	Number of Images
Class 0	Disk, Face-on, No Spiral	3461
Class 1	Smooth, Completely round	6997
Class 2	Smooth, in-between round	6992
Class 3	Smooth, Cigar shaped	394
Class 4	Disk, Edge-on, Rounded Bulge	1534
Class 5	Disk, Edge-on, Boxy Bulge	17
Class 6	Disk, Edge-on, No Bulge	589
Class 7	Disk, Face-on, Tight Spiral	1121
Class 8	Disk, Face-on, Medium Spiral	906
Class 9	Disk, Face-on, Loose Spiral	519
	Total	21785

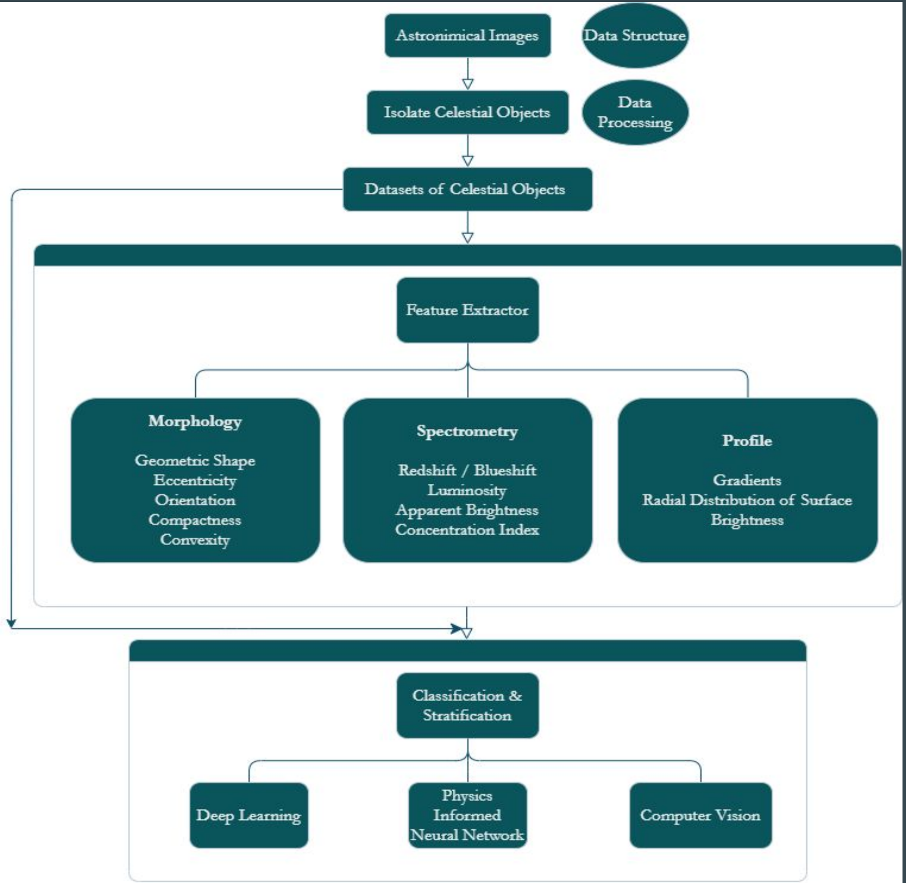
n=19246	Elliptical	Spiral	Edge-on	DK	Merge	Recall
Elliptical	9525	476	257	0	3	0.93
Spiral	940	2991	305	0	6	0.71
Edge-on	688	499	3063	0	4	0.72
DK	39	36	24	6	4	0.06
Merge	170	129	44	0	37	0.10
Precision	0.84	0.72	0.83	1.0	0.69	Accuracy=0.81



*https://hubblesite.org/science/galaxies, https://astrobackyard.com/types-of-galaxies/ , Sander Dieleman and others, Rotation-invariant convolutional neural networks for galaxy morphology prediction, Monthly Notices of the Royal Astronomical Society, Volume 450, Issue 2, 21 June 2015, Pages 1441–1459, https://doi.org/10.1093/mnras/stv632, Gharat, S., & Dandawate, Y. (2022). Galaxy classification: a deep learning approach for classifying Sloan Digital Sky Survey images. Monthly Notices of the Royal Astronomical Society, 511(4), 5120–5124. https://doi.org/10.1093/mnras/stac457

Research Methodology

- Data Collection and Preprocessing (Sloan Digital Sky Survey (SDSS), Galaxy Zoo)
- Deep Learning Architecture
- Physics-Informed Integration
  - The physics-informed neural networks will be utilised to model the celestial dynamics.
  - The network structure should incorporate relevant physical equations and constraints, like the redshift-distance relation, to guide the learning process and to enhance the estimation accuracy.
- Training and Validation
- Data Stratification and Interpretation
- Evaluation and Validation

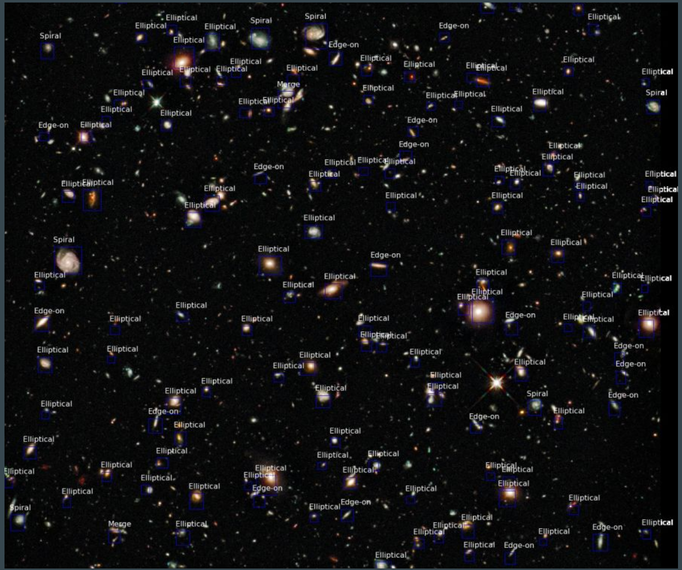


Conclusion

- This thesis proposes an approach that combines deep learning and physics-informed neural networks to address the challenge of morphological and spectral celestial stratification.

- We aim to enhance our understanding of celestial bodies, their characteristics, and their underlying physical processes through comprehensive and accurate stratification of celestial objects

- Future Advancements:
  - Accelerate the exploration of searching for exoplanets
  - Contribute to Asteroid / Comet detection and tracking



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Thank You