# Introduction

With the development of the technologies, astrophysics is exploring the night sky with a unprecedented speed, generating enormous amount of data.

Astrophysics is

Galaxies exhibit a remarkable diversity of forms that provide valuable insights into their formation histories and evolutionary processes. Among these, spiral and elliptical galaxies represent two dominant morphological categories. Spiral galaxies, characterized by their distinctive rotating disks, spiral arms, and often prominent central bulges, are typically associated with active star formation and dynamic interstellar medium processes. In contrast, elliptical galaxies are dominated by older stellar populations and feature smooth, spheroidal shapes, indicative of a more quiescent evolutionary stage. Understanding and classifying these galaxy types is essential for elucidating the mechanisms driving cosmic structure formation and evolution.

Accurate classification of galaxy morphology is pivotal in astrophysics, yet the sheer volume of data generated by contemporary and upcoming astronomical surveys presents a formidable challenge to traditional manual and algorithmic approaches. The Sloan Digital Sky Survey (SDSS) and the Vera Rubin Observatory’s Legacy Survey of Space and Time (LSST), for example, produce datasets containing millions of galaxy images, necessitating innovative solutions for efficient and reliable analysis.

This study proposes the development of a machine learning (ML) framework tailored to automate and enhance the classification of galaxies into spiral and elliptical categories. By leveraging advanced ML techniques, particularly convolutional neural networks (CNNs), the project aims to address these challenges, ensuring both scalability and accuracy. Through this approach, we aspire to minimize human intervention, mitigate biases inherent in manual classification, and unlock deeper insights into the morphological diversity of galaxies.

### Motivation for Machine Learning in Galaxy Classification

The adoption of machine learning for galaxy classification is driven by several compelling factors. First, the unprecedented data volumes from modern surveys demand automation. Manual classification, while historically foundational, becomes untenable when faced with millions of galaxies. ML algorithms, especially CNNs, are well-suited for processing large-scale imaging data with exceptional efficiency and precision.

Second, the morphological features distinguishing spiral and elliptical galaxies are often intricate and multidimensional. Traditional algorithmic approaches struggle to capture these subtleties. CNNs, with their ability to learn complex patterns and relationships within high-dimensional data, offer a transformative solution, enabling robust differentiation between galaxy types.

Third, the scalability of ML models ensures their applicability across diverse datasets and contexts. Once trained, these models can seamlessly classify new data, maintaining efficiency as the volume and complexity of astronomical surveys continue to expand.

Additionally, the superior performance of modern ML techniques is well-documented. These algorithms not only match but often exceed the accuracy of traditional methods and human classifiers in image recognition tasks. Beyond classification, ML models hold the potential to uncover previously unrecognized patterns and correlations, providing novel insights into galaxy dynamics, star formation processes, and other astrophysical phenomena.

### Objectives and Contributions

This project seeks to make meaningful contributions to the field of galaxy morphology by addressing the outlined challenges through a sophisticated ML-based classification framework. The primary objectives are to:

1. Automate the galaxy classification process, significantly reducing the dependence on manual efforts.

2. Achieve high accuracy and reliability in distinguishing between spiral and elliptical galaxies.

3. Develop a scalable and reproducible system that integrates seamlessly into broader astrophysical research workflows.

Ultimately, this work not only aims to support ongoing scientific investigations but also establishes a foundation for future interdisciplinary collaborations, driving innovations in data-driven astrophysical research.