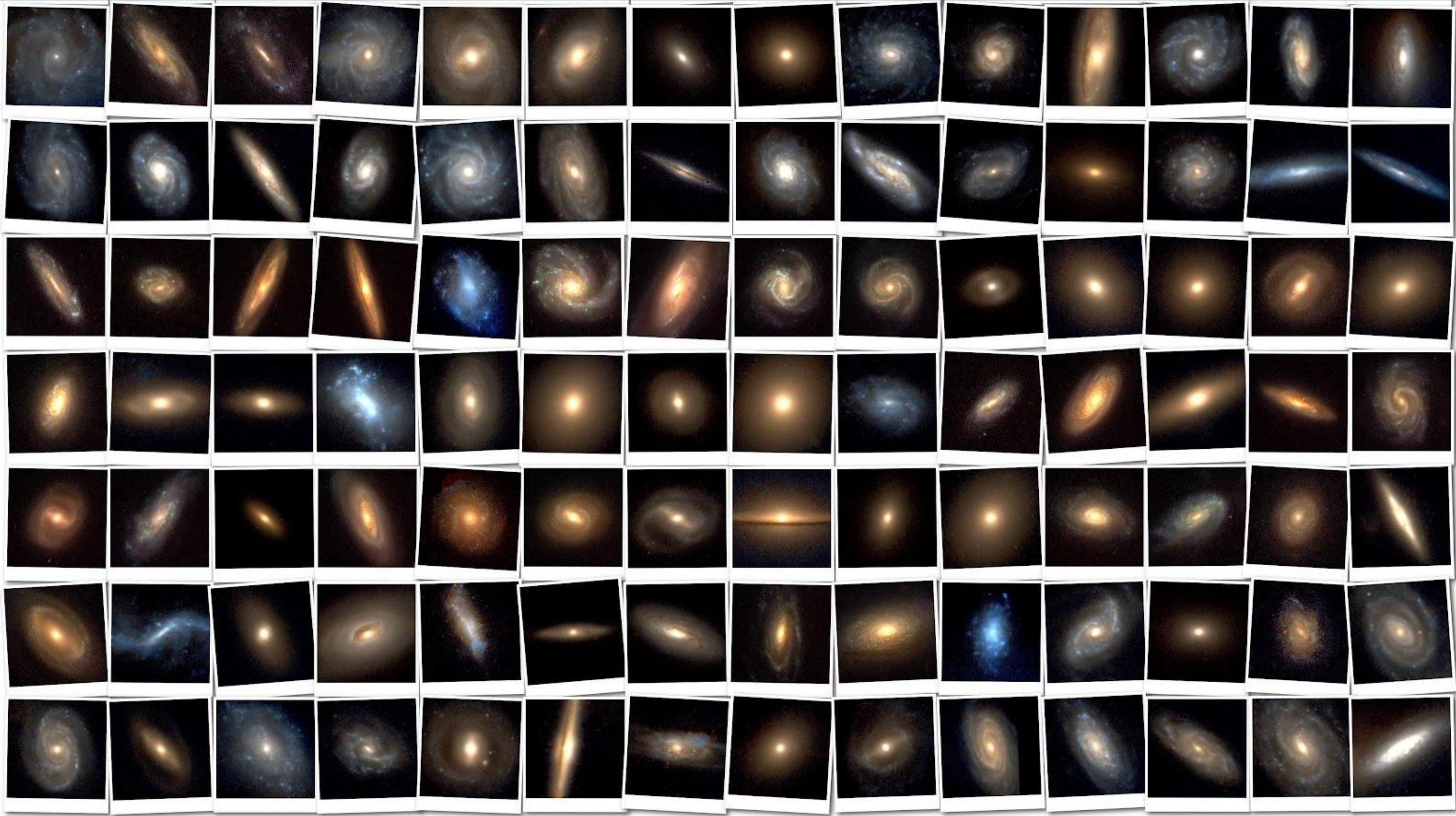
# One Model to Handle Them All:

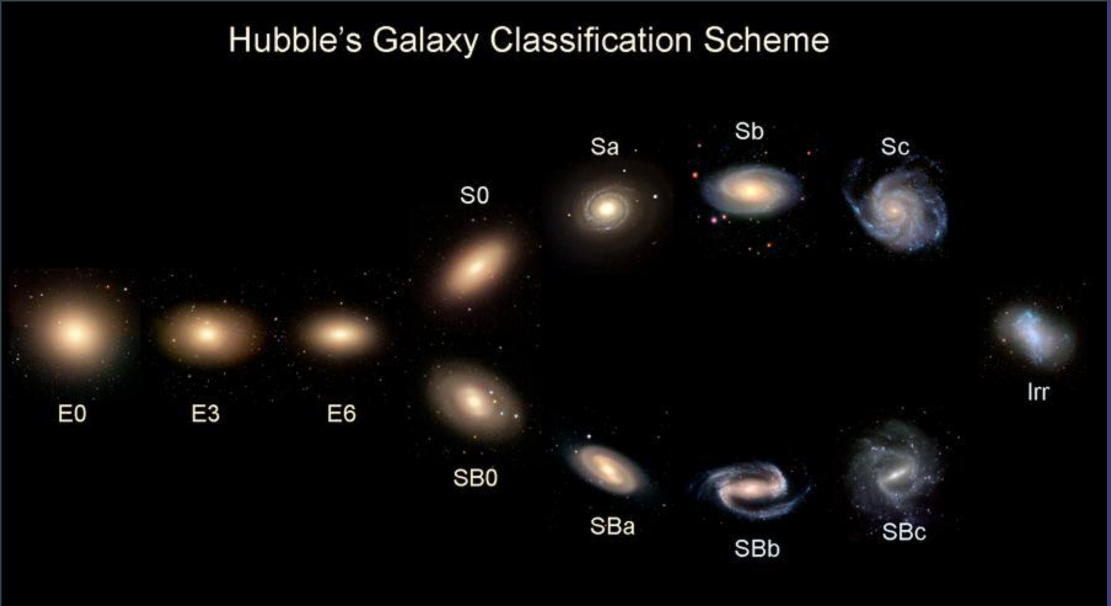
## A Versatile Framework for Analyzing Galaxy Images by Implanting Human-in-the-loop on a Foundation Vision Model

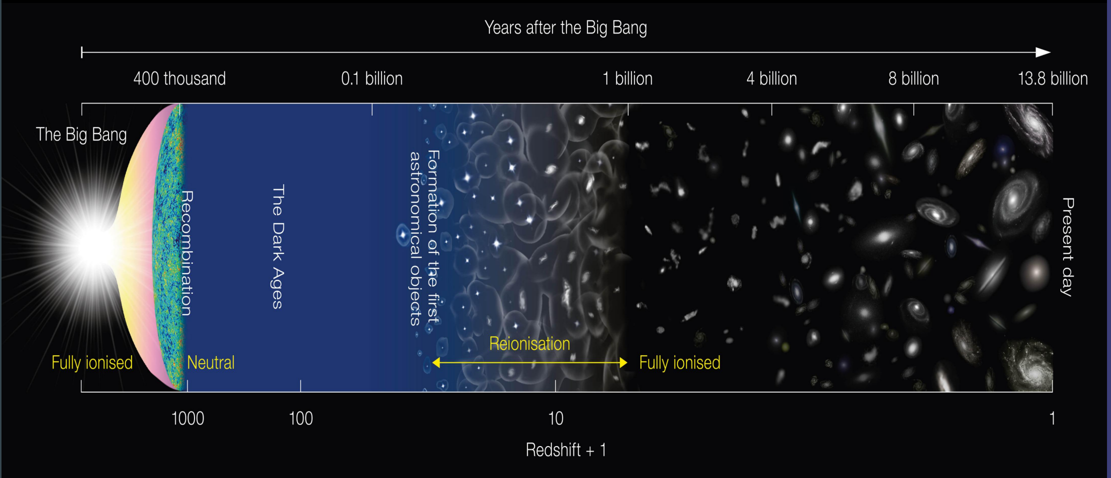
*Nan Li*
*(National Astronomical Observatories of China)*

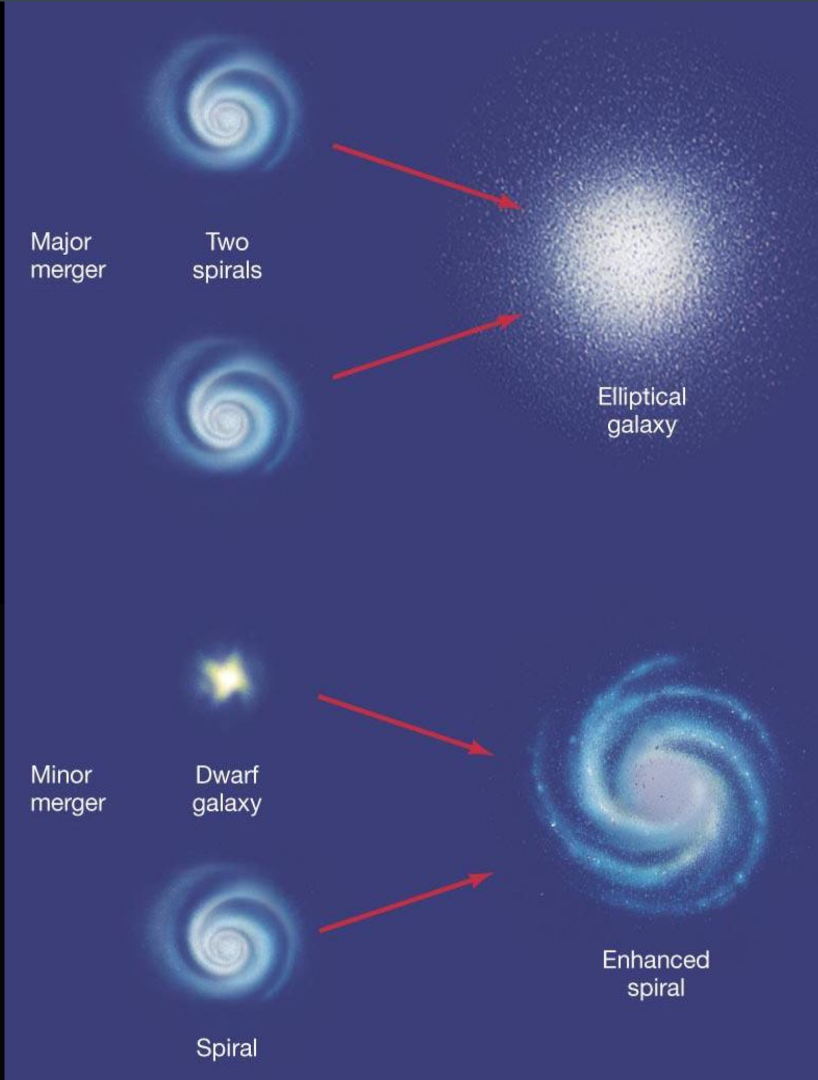
**In Collaboration with:**

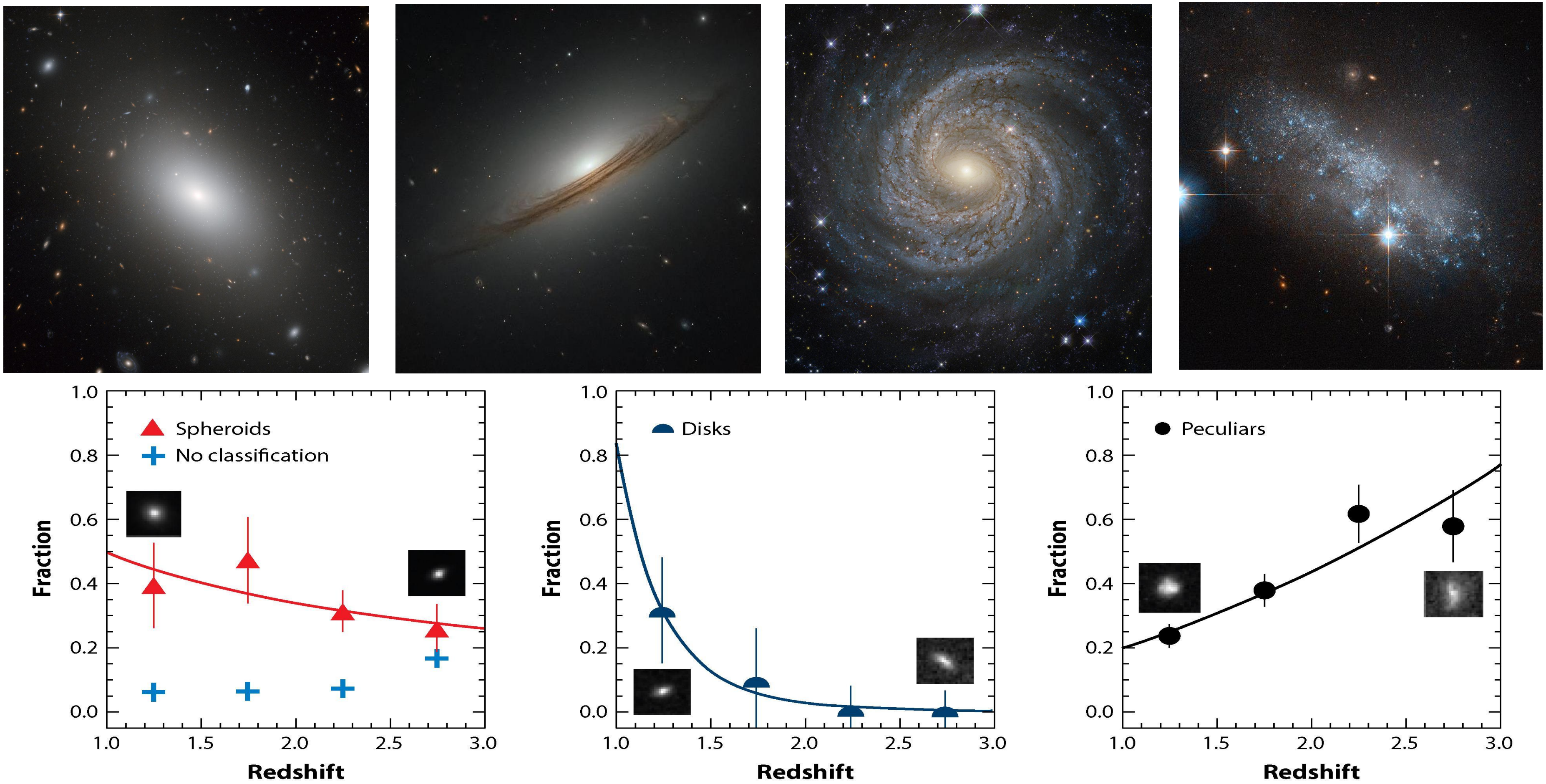
Mike Gladders, Salman Habib, Katrin Heitmann, Simon Dye, François Lanusse, Christopher Conselice, Ting-yun Cheng, Ben Matcalf, James Nightingale, Jacob Maresca, Zizhao He, Xu Li, Jiameng Lv, Yu Song, Pen Jia, Yushan Xie, Huanyuan Shan, ChenLiang Wei, GuoLiang Li, Mingxiang Fu, Shiyin Shen, Chenzhou Cui, Ali Luo, ChatGPT, etc.




Hubble's Galaxy Classification Scheme
E0
E3
E6
S0
Sa
Sb
Sc
SB0
SBa
SBb
SBc
Irr

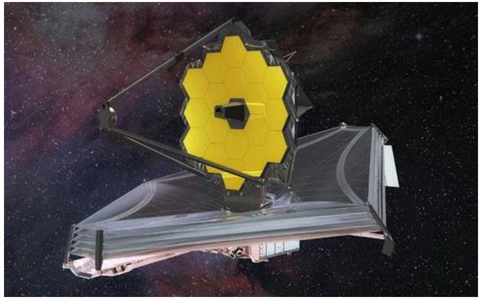
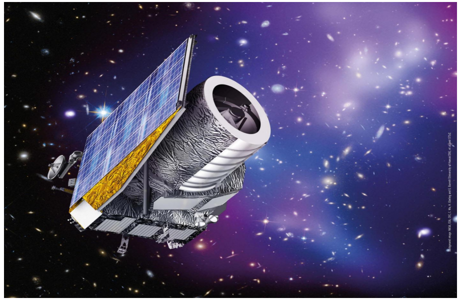
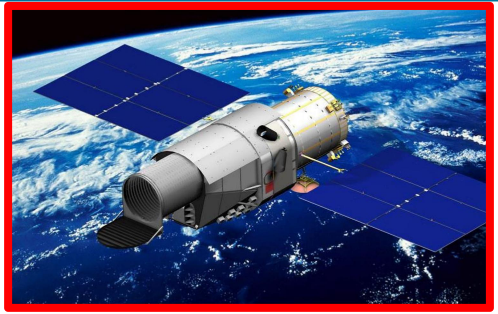

Years after the Big Bang
400 thousand
0.1 billion
1 billion
4 billion
8 billion
13.8 billion
The Big Bang
Recombination
The Dark Ages
Formation of the first astronomical objects
Present day
Fully ionised
Neutral
Reionisation
Fully ionised
1000
100
10
1
Redshift + 1

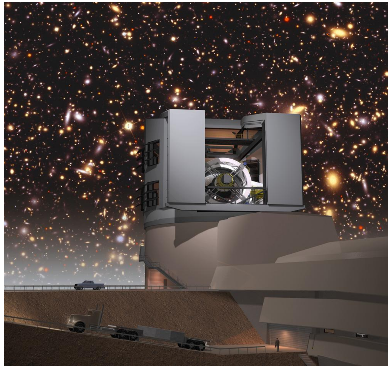
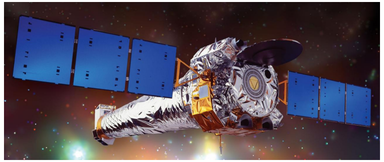
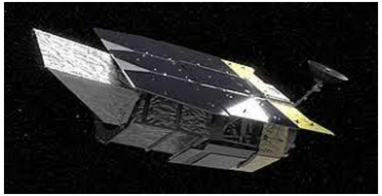
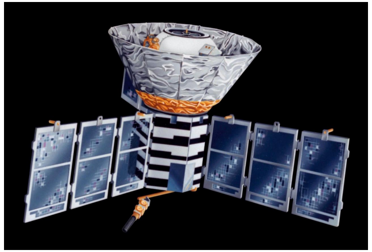

Major merger
Two spirals
Elliptical galaxy
Minor merger
Dwarf galaxy
Spiral
Enhanced spiral



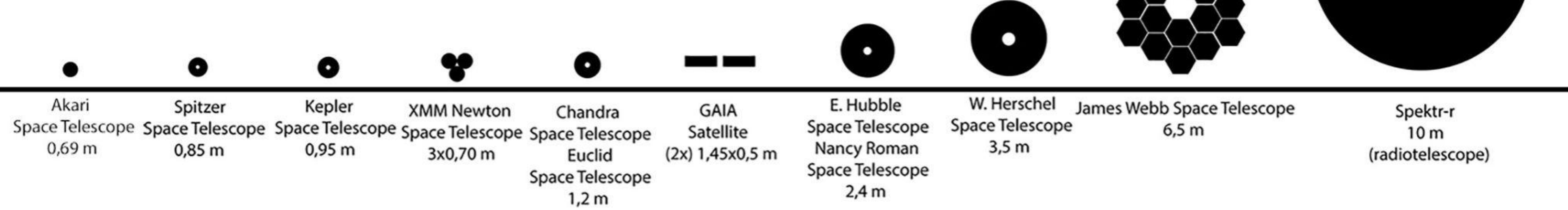

Conselice CJ. 2014.
Annu. Rev. Astron. Astrophys. 52:291–337

# Astronomy in the Era of Big Data

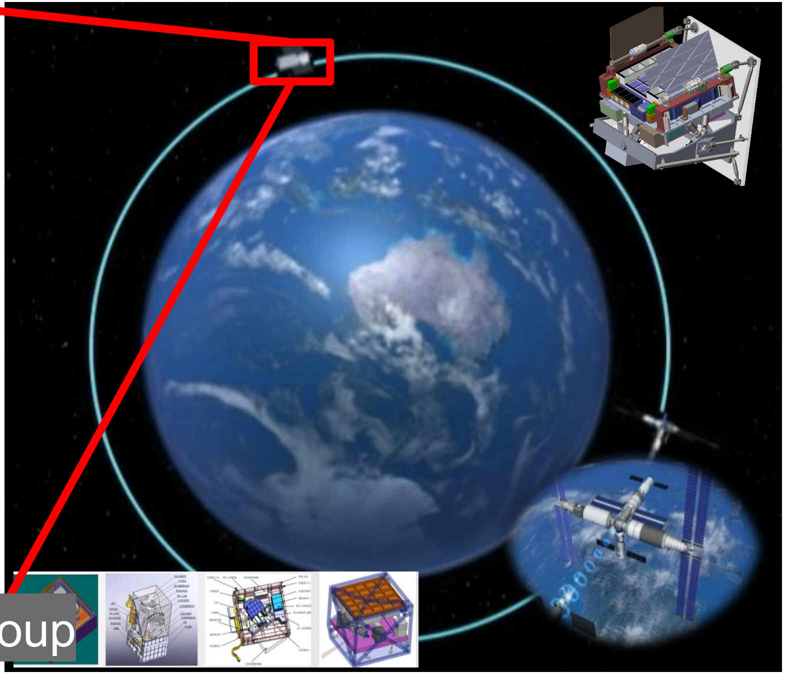





**Challenges & Opportunities**



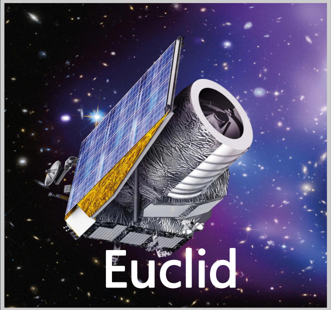
# The China Survey Space Telescope (CSST)

CSST is a **2-meter Space Telescope**, will orbit at **LEO** with the China Space Station and operate an **NUV-optical (ugrizy) Survey**, **a larger version of Euclid with ugriz bands**. To be Launched in **202***.

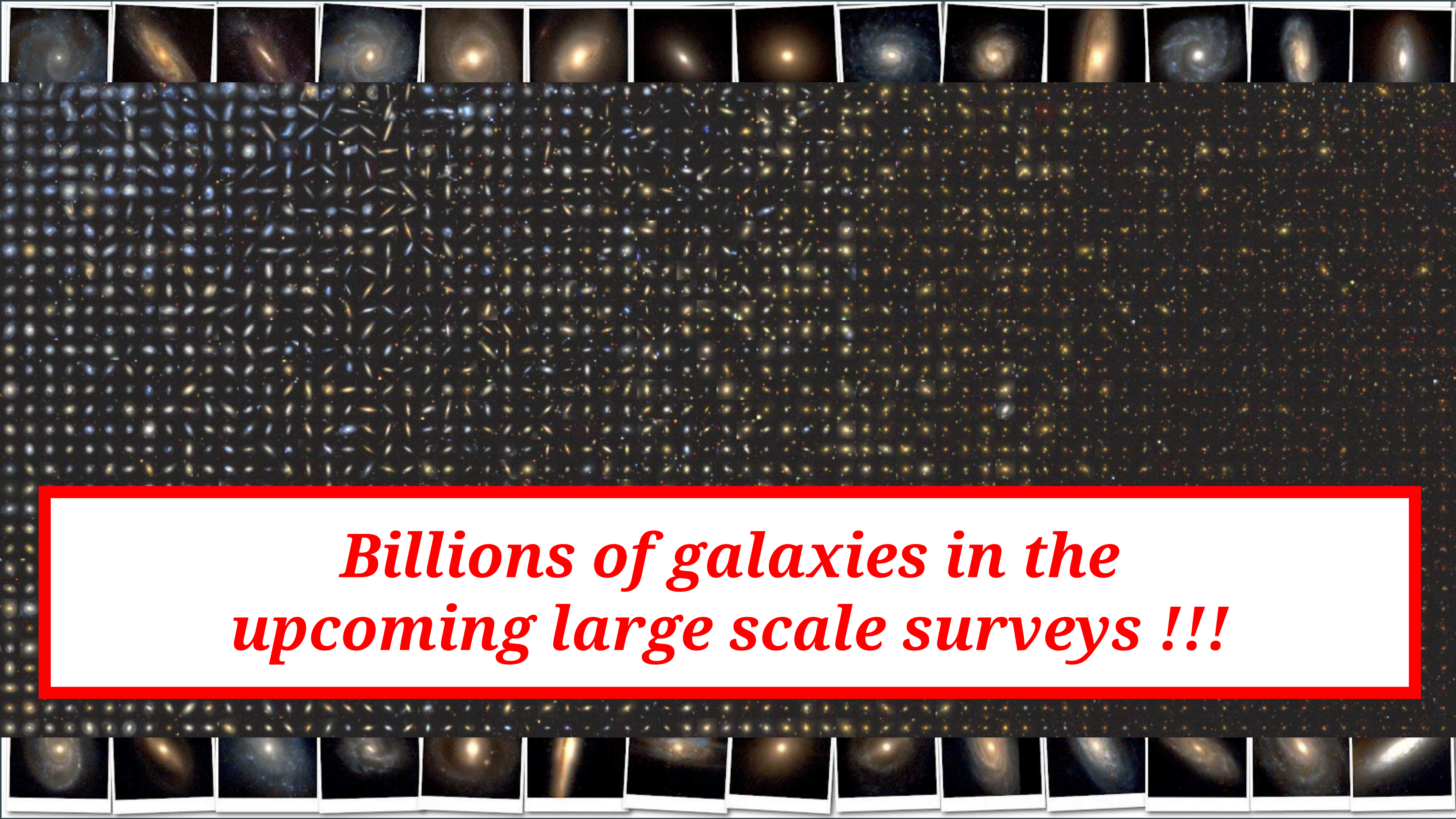



# Astronomy in the Era of Big Data

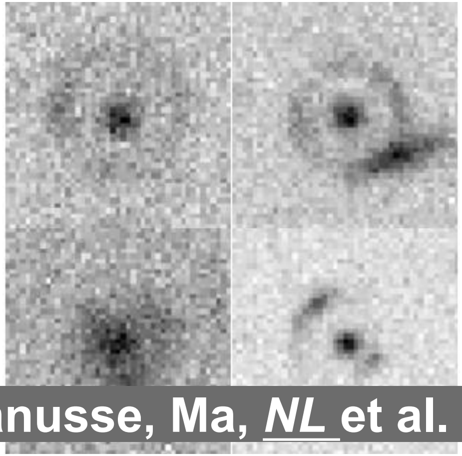
Zhang & Zhao 2015

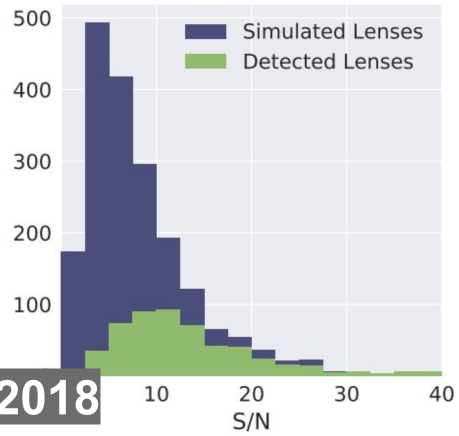



| Sky Survey Projects | Data Volume |
| --- | --- |
| SDSS (The Sloan Digital Sky Survey) | ~ 40 TB, > 3 m objs |
| Euclid (The Euclid dark Universe mission) | ~ 50 PB expected |
| **CSST (The China Survey Space Telescope)** | **~ 60 PB expected** |
| LSST (The Legacy Survey of Space and Time) | ~ 200 PB expected |
| SKA (The Square Kilometer Array) | ~ 4.6 EB expected |


Billions of galaxies in the
upcoming large scale surveys !!!

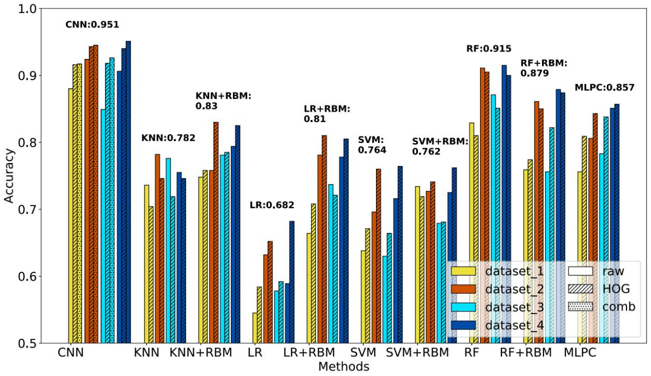
# 1. Classifying Galaxies with Supervised Learning






Lanusse, Ma, _NL_ et al. 2018

| Name | Author | AUC | $TPR_0$ | $TPR_{10}$ | short description |
|---|---|---|---|---|---|
| LASTRO EPFL | Geiger, Schäfer & Kneib | 0.93 | 0.00 | 0.08 | CNN |
| CMU-DeepLens-Resnet | Francois Lanusse, Ma, C. Li & Ravanbakhsh | 0.92 | 0.22 | 0.29 | CNN |
| GAMOCLASS | Huertas-Company, Tuccillo, Velasco-Forero & Decencière | 0.92 | 0.07 | 0.36 | CNN |
| CMU-DeepLens-Resnet-Voting | Ma, Lanusse & C. Li | 0.91 | 0.00 | 0.01 | CNN |
| AstrOmatic | Bertin | 0.91 | 0.00 | 0.01 | CNN |
| CMU-DeepLens-Resnet-aug | Ma, Lanusse, Ravanbakhsh & C. Li | 0.91 | 0.00 | 0.00 | CNN |
| ***Unsupervised technique** | **This Work (Training, Fig. 8)** | **0.87** | **0.08** | **0.08** | **Deep Clustering** |
| ****Unsupervised technique** | **This Work (Section 4.2.3)** | **0.83** | **0.00** | **0.00** | **Deep Clustering** |
| Kapteyn Resnet | Petrillo, Tortora, Kleijn, Koopmans & Vernardos | 0.82 | 0.00 | 0.00 | CNN |
| CAST | Bom, Valentín & Makler | 0.81 | 0.07 | 0.12 | CNN |
| Manchester1 | Jackson & Tagore | 0.81 | 0.01 | 0.17 | Human Inspection |
| Manchester SVM | Hartley & Flamary | 0.81 | 0.03 | 0.08 | SVM / Gabor |
| NeuralNet2 | Davies & Serjeant | 0.76 | 0.00 | 0.00 | CNN / wavelets |
| YattaLensLite | Sonnenfeld | 0.76 | 0.00 | 0.00 | Arcs / SExtractor |
| All-now | Avestruz, N. Li & Lightman | 0.73 | 0.05 | 0.07 | edges/gradiants and Logistic Reg. |
| **Unsupervised technique** | **This Work (Section 4.2.3)** | **0.72** | **0.00** | **0.00** | **Deep Clustering** |
| GAHEC IRAP | Cabanac | 0.66 | 0.00 | 0.01 | arc finder |



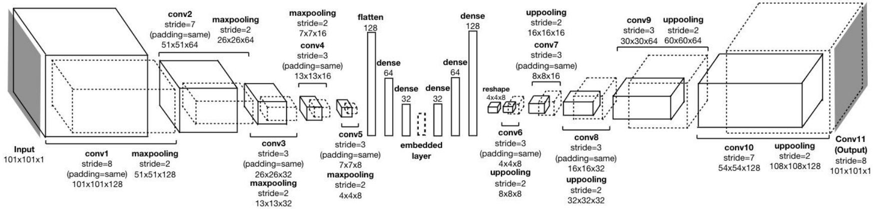

Cheng, ..., _NL_ et al. 2020

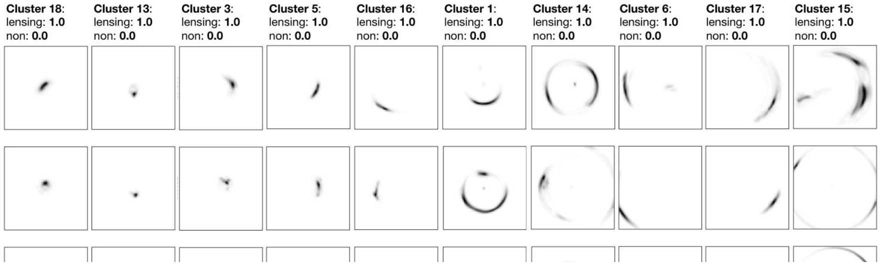
ifferent data sets and the different types of input shown. The
lue represents data set 1, 2, 3, 4 (Table 2), respectively. The
nal-line-filled, the dotted-filled represents the raw images (i),
highest value of the accuracy for each method.

**Table 3.** The comparison of the computing time (per ∼1000 galaxies) for each method. The 'accuracy' is the best accuracy shown in Fig. 9. The first 10 methods were run on the 2.3GHz Intel Core i5 Processor with 16GB 2133 MHz LPDDR3 memory, while the sixth method 'CNN (GPU) was run on the NVIDIA GeForce GTX 1080 Ti GPU.

| Methods | Training time (s) | Testing time (s) | Accuracy |
|---|---|---|---|
| KNN | ∼0.2 | ∼45 | 0.782 ± 0.027 (raw) |
| KNN+RBM | ∼3000 | ∼45 | 0.830 ± 0.007 (HOG) |
| LR | ∼7–8 | ≤1 | 0.682 ± 0.040 (HOG) |
| LR+RBM | ∼3000 | ≤1 | 0.810 ± 0.012 (HOG) |
| SVM | ∼800 | ≤8 | 0.764 ± 0.029 (HOG) |
| SVM+RBM | ∼3000 | ≤8 | 0.762 ± 0.001 (HOG) |
| RF | ≤1 | ≤5 | 0.913 ± 0.009 (raw) |
| RF+RBM | ∼3000 | ≤5 | 0.870 ± 0.031 (raw) |
| MLPC | ∼18 | ≤3 | 0.857 ± 0.010 (HOG) |
| CNN | ∼3000 | ≤5 | 0.951 ± 0.005 (comb) |
| CNN (GPU) | ∼360 | ≤5 | 0.951 ± 0.005 (comb) |

# 2. Classifying Galaxies with Unsupervised Learning




| Name | Author | AUC | $TPR_0$ | $TPR_{10}$ | short description |
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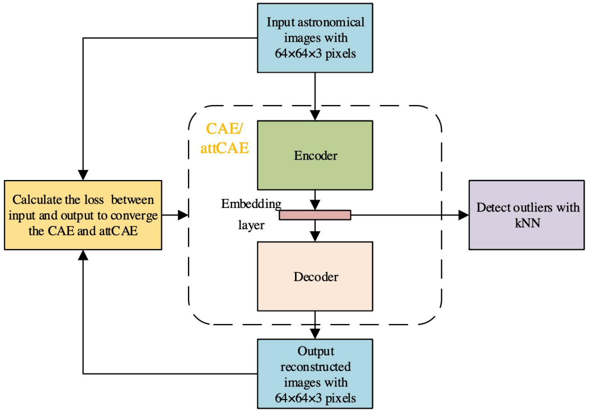
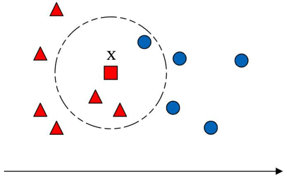
| YattaLensLite | Sonnenfeld | 0.76 | 0.00 | 0.00 | Arcs / SExtractor |
| All-now | Avestruz, N. Li & Ligh | | | | |
| **Unsupervised technique** | **This Work (Section** | | | | |
| GAHEC IRAP | Cabanac | | | | |

**Cheng, *NL* et al. 2020**




(b) K=3

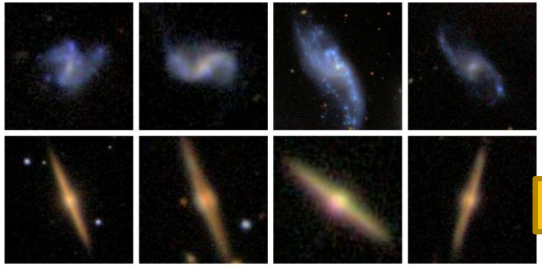
Fig. 7: The flow chart of the attCAE_KNN for detecting outliers in astronomical images.

Table 7: The results of Experiment 5, the bold entries highlight our results.

| | AUC | recall | precision | f1 | acc | Time |
|---|---|---|---|---|---|---|
| KNN | 0.77 | 0.22 | 0.22 | 0.22 | 0.84 | >4hour |
| CAE_KNN | 0.85 | 0.43 | 0.43 | 0.43 | 0.87 | 10min |
| **attCAE_KNN 5%** | **0.87** | **0.37** | **0.74** | **0.50** | **0.92** | **10min** |
| **attCAE_KNN 10%** | **0.87** | **0.53** | **0.53** | **0.53** | **0.92** | **10min** |
| **attCAE_KNN 15%** | **0.87** | **0.67** | **0.44** | **0.53** | **0.88** | **10min** |

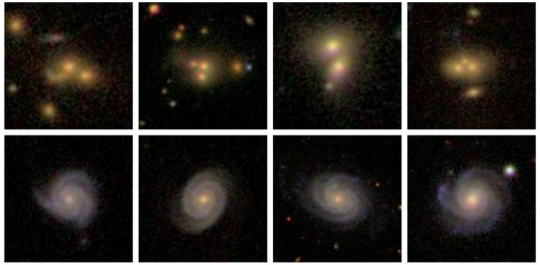
**Han, Zou, *NL** et al. 2022**

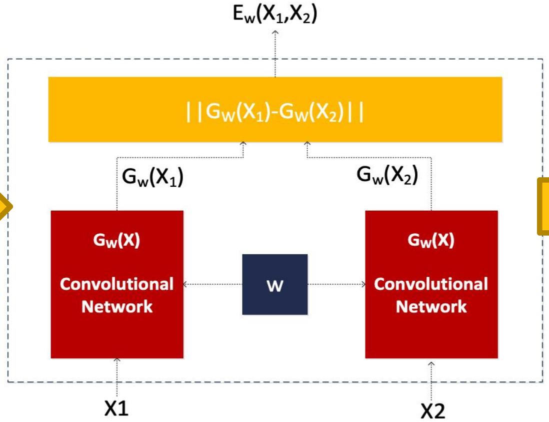
# 3. Classifying Galaxies with Few-shot Learning



(a)

(b)





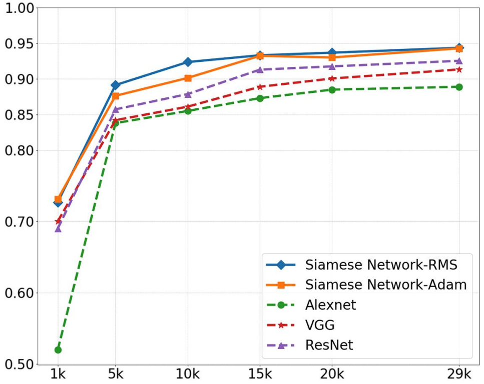
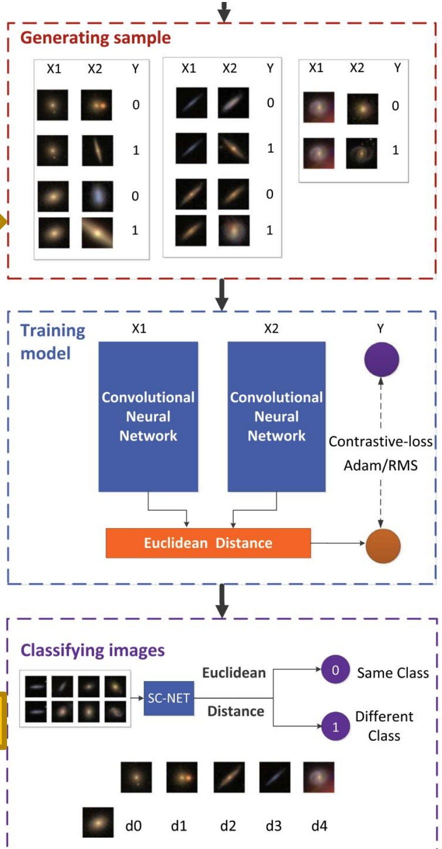




Fig. 7: Comparison of experimental results of 5 methods of ACC. The vertical axis represents the classification performance, the horizontal axis represents the size of the data set, and the broken lines with different colors represent different methods.




Zhou, Zou, *NL** et al. 2022

# 4. Classifying Galaxies with Contrastive Learning

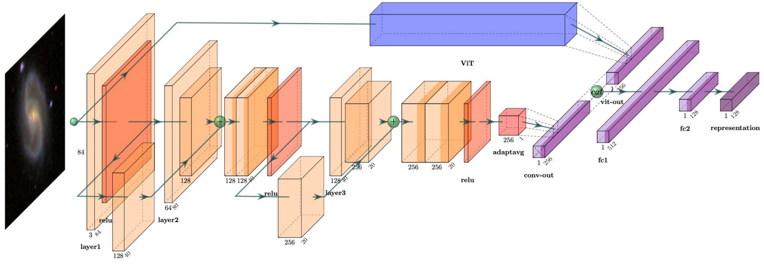
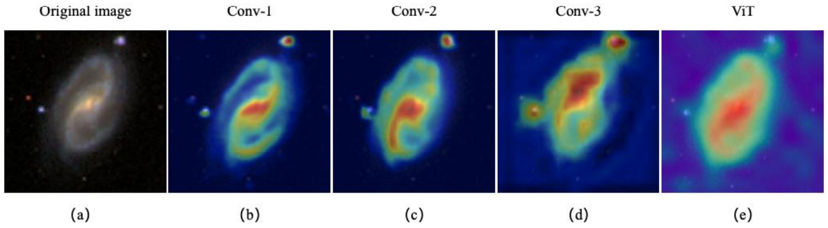
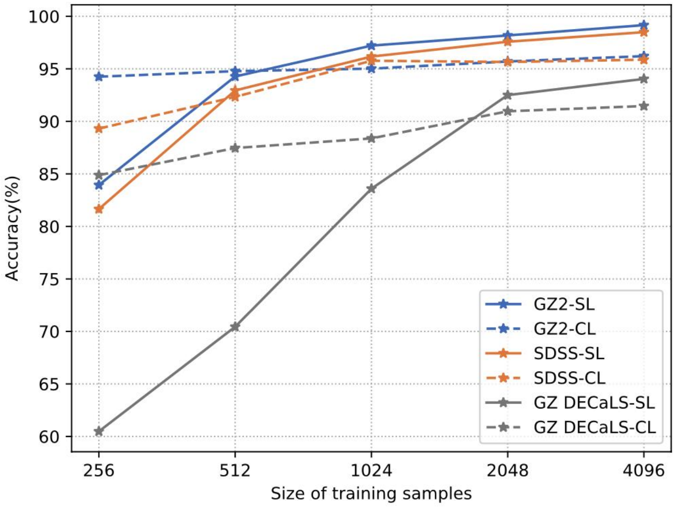



**Figure 5.** The illustration of components in *Encoder*, which use ResNet-18 as the backbone network fusing with ViT to learn multi-hierarchy features.

Hot pixels in the feature map



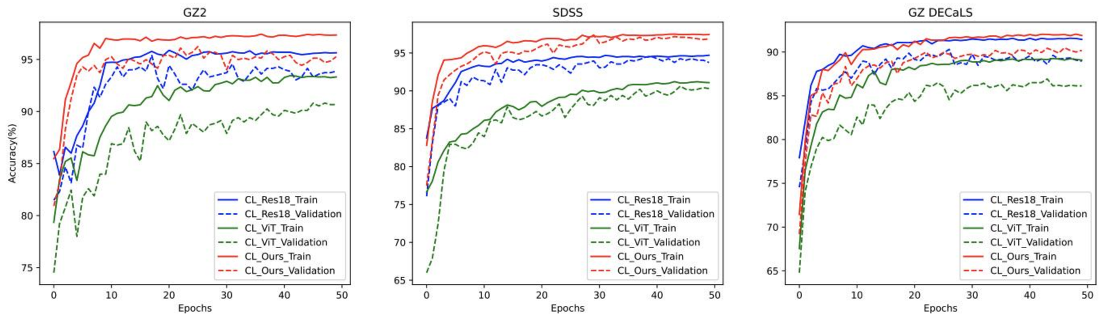
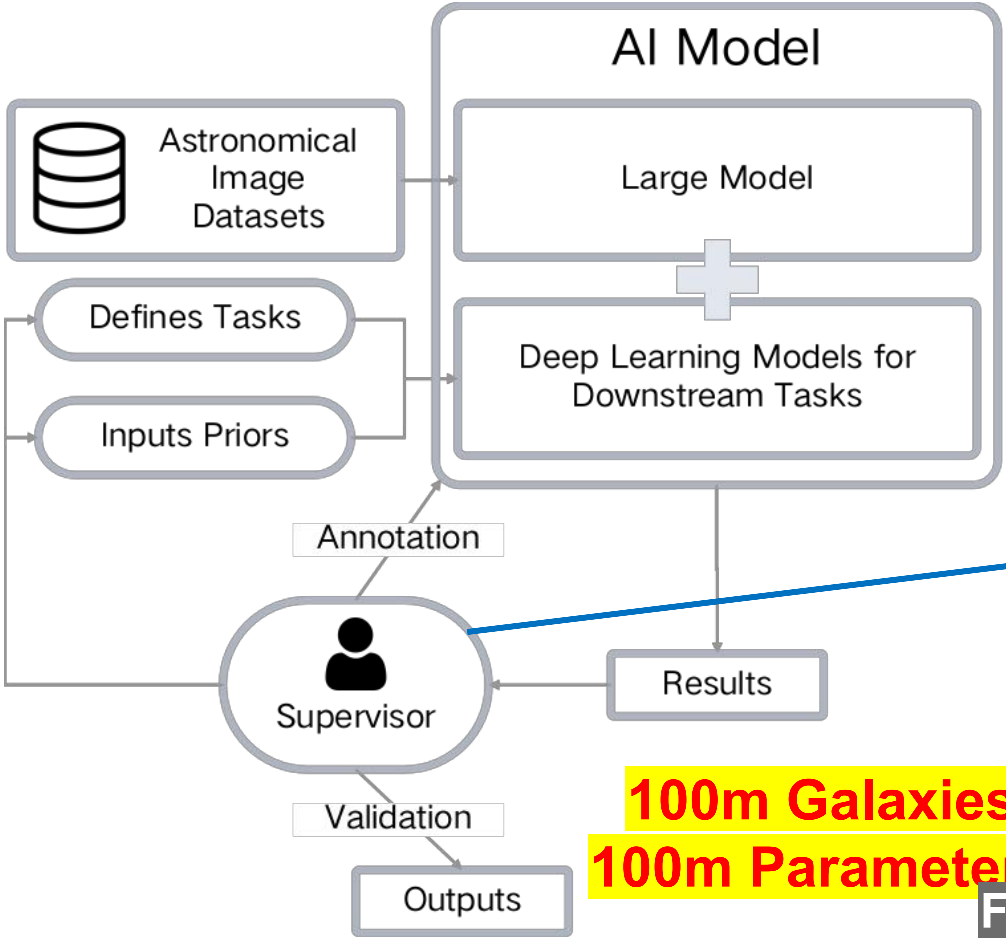




**Figure 6.** Performance comparison of the accuracy of training and validation along with the epochs. CL_Res18, CL_ViT and CL_Ours represents the CL methods using ResNet-18, ViT and our proposed model as encoder.

Wei, ..., *NL* et al. 2022

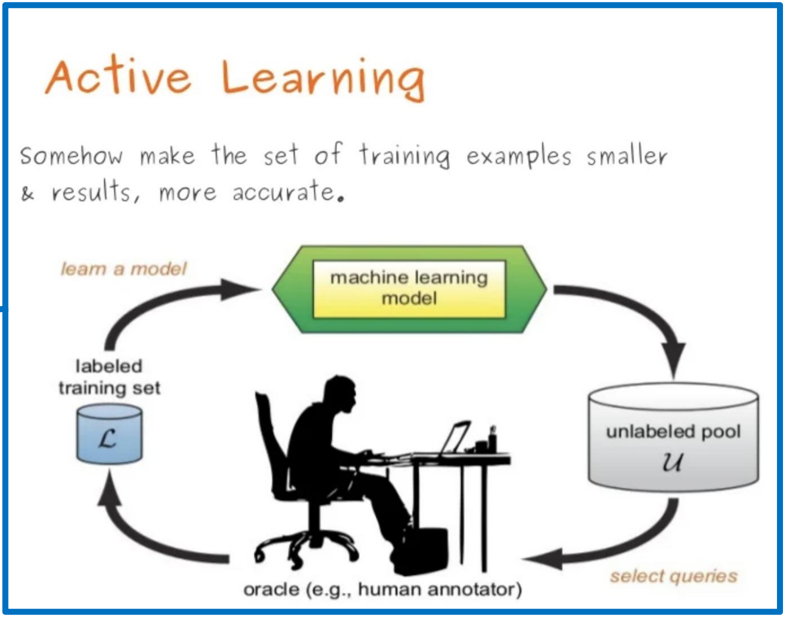
# Classifying Galaxies without Training Sets?




**Foundation Vision Model**

**+ Galaxy Classification**

**+ Human-in-the-loop**

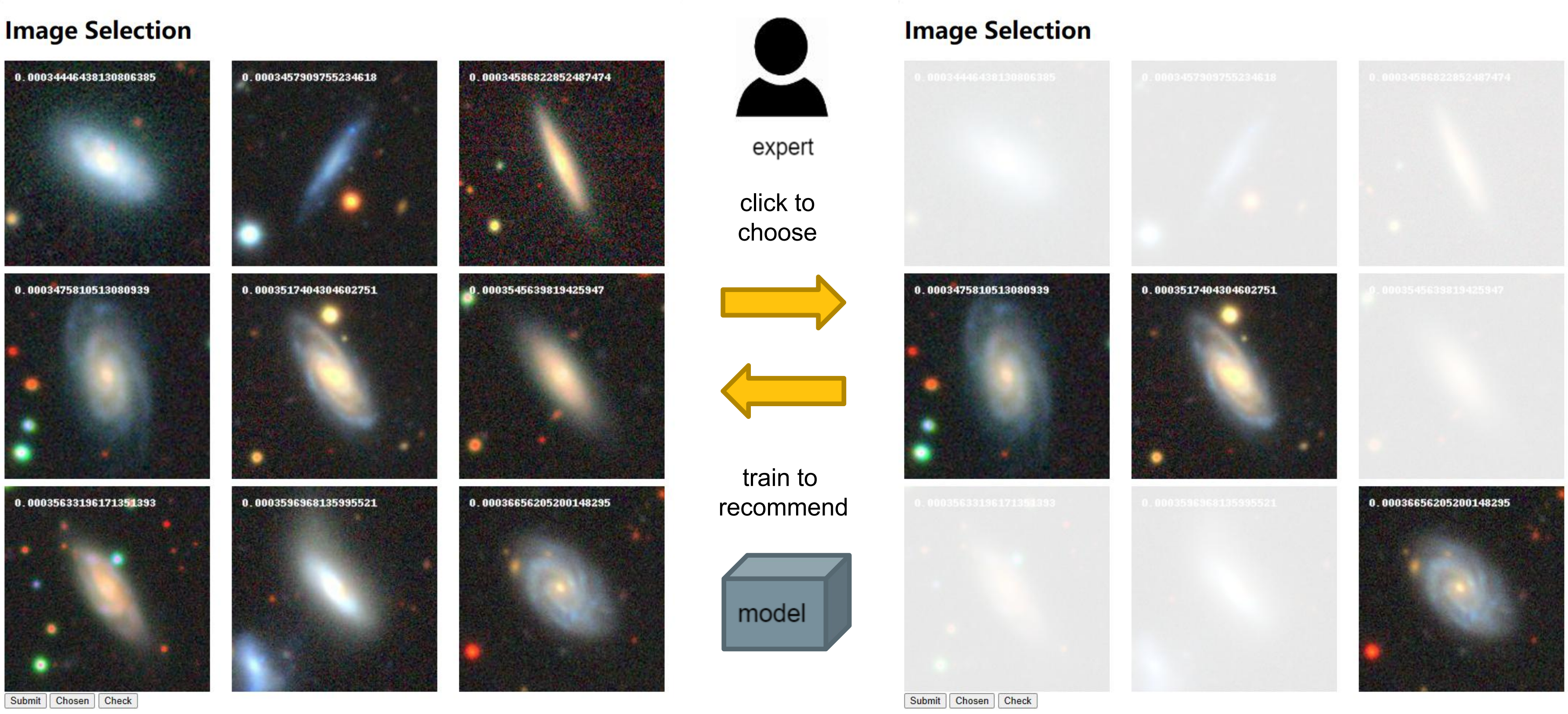



**100m Galaxies**

**100m Parameters**

Fu, ..., *NL** et al. 2024, arXiv:2405.10890

# Classifying Galaxies with HITL: User Interface



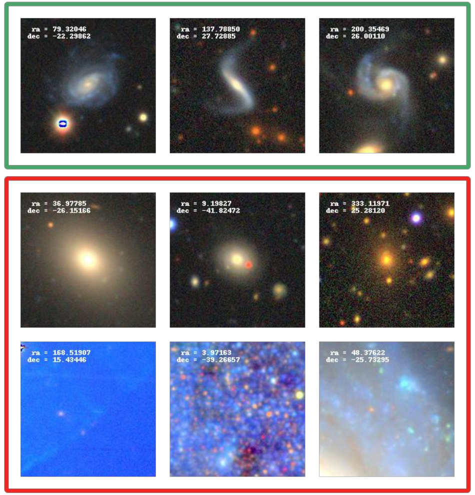

Fu, ..., *NL** et al. 2024, arXiv:2405.10890

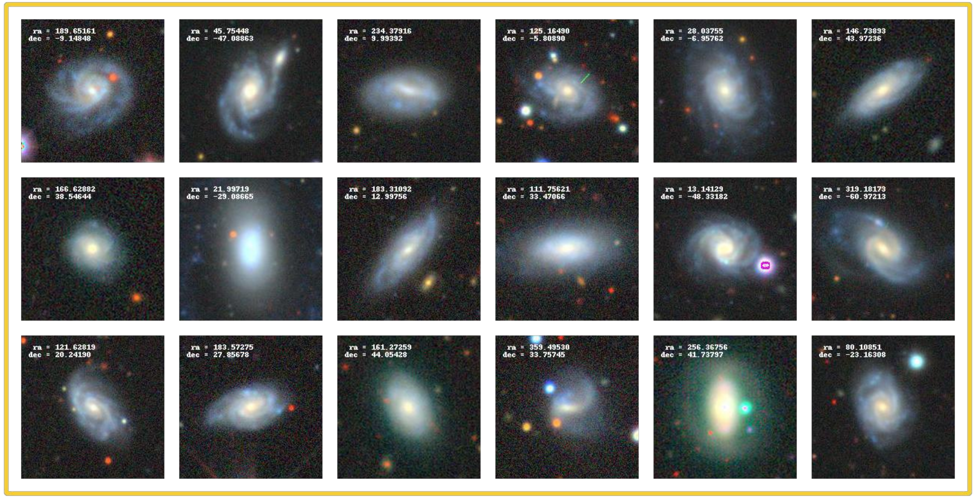
# Classifying Galaxies with HITL: Examples

**Basic Task**

Spirals
VS
Ellipticals

< 10 loops

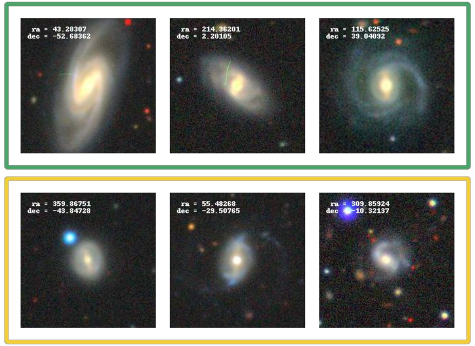




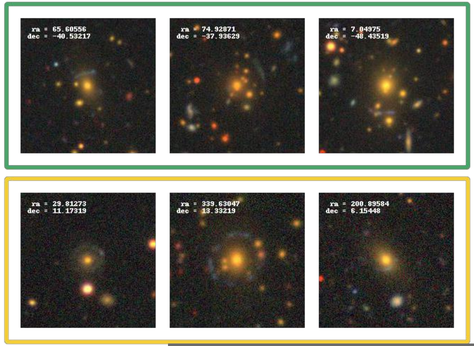
**Advanced Tasks**

~ 30 loops

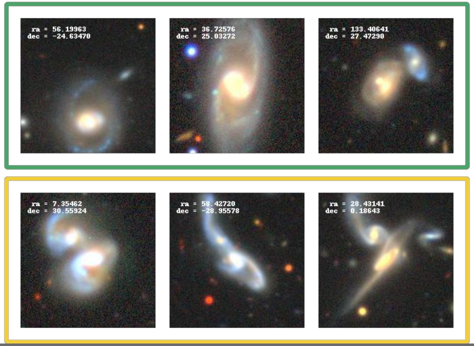
Barred Galaxies



Strong Lenses



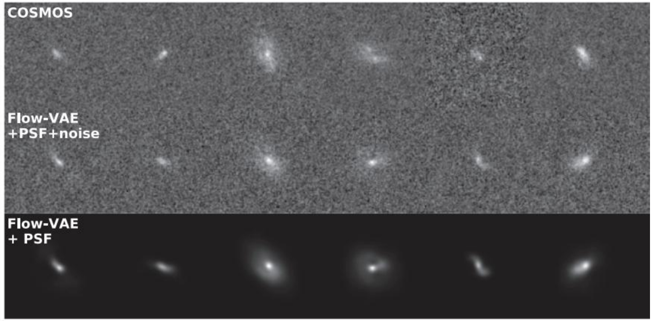
Mergers



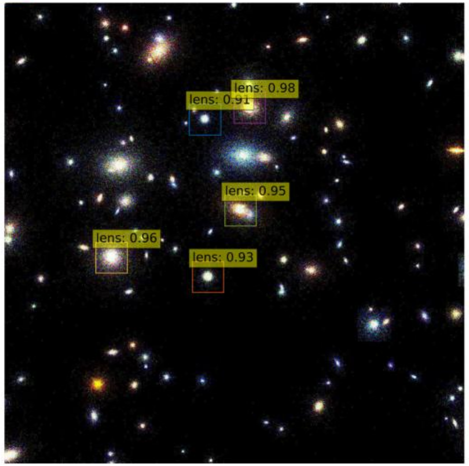
Fu, ..., *NL** et al. 2024, arXiv:2405.10890

# Beyond Galaxy Morphology Classification

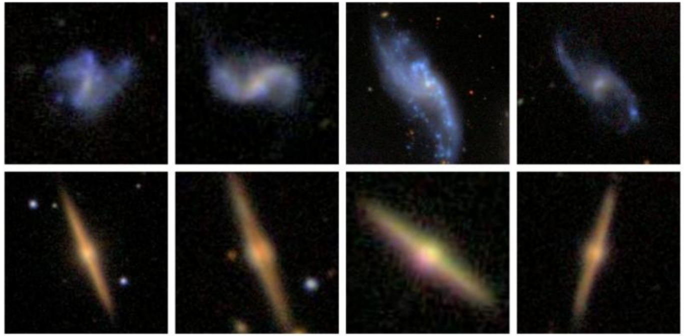
## 1. Simulation



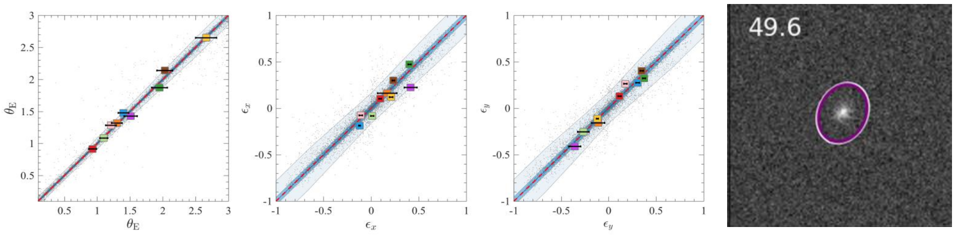

## 2. Detection



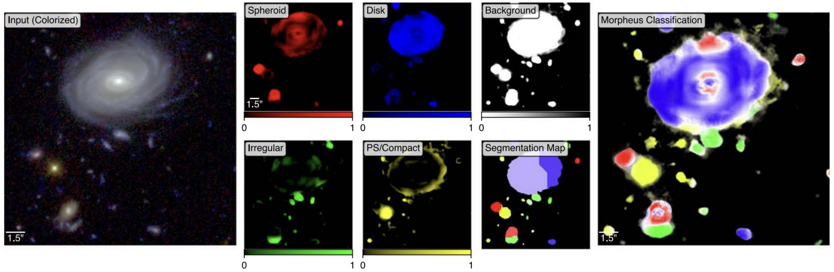

## 3. Classification



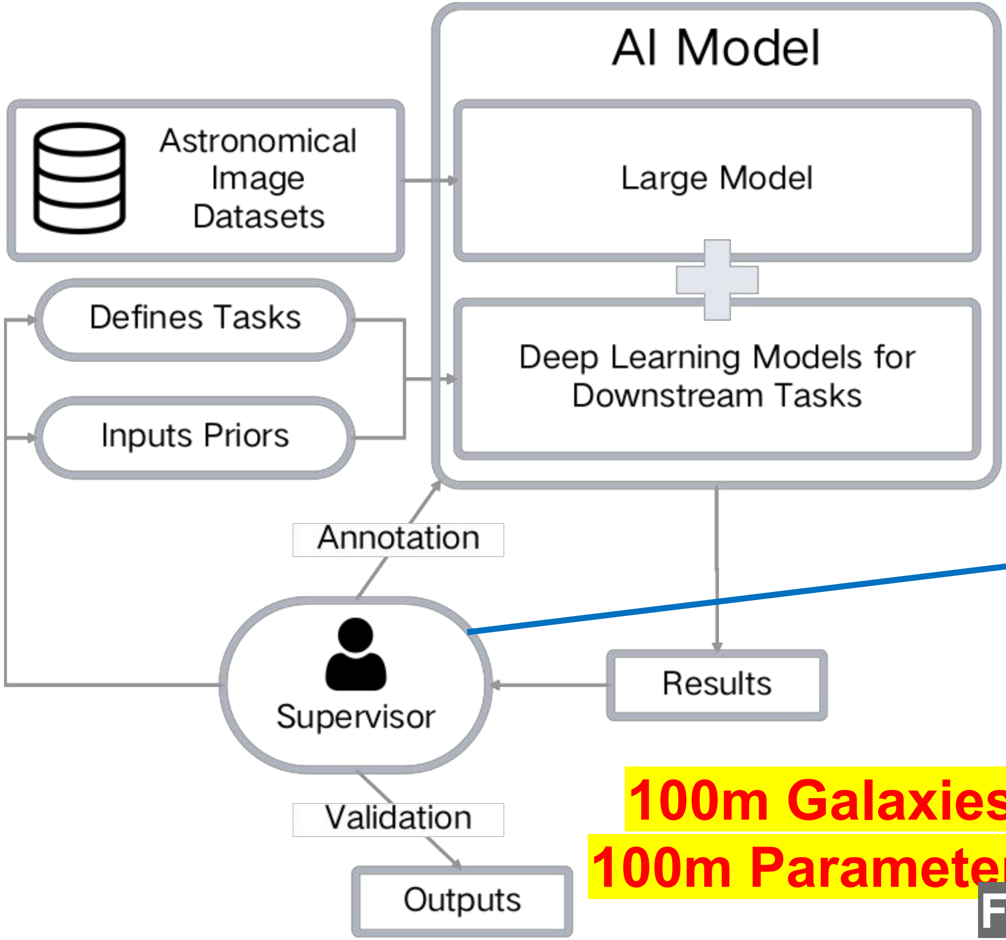
## 4. Modeling




## 5. Decomposition



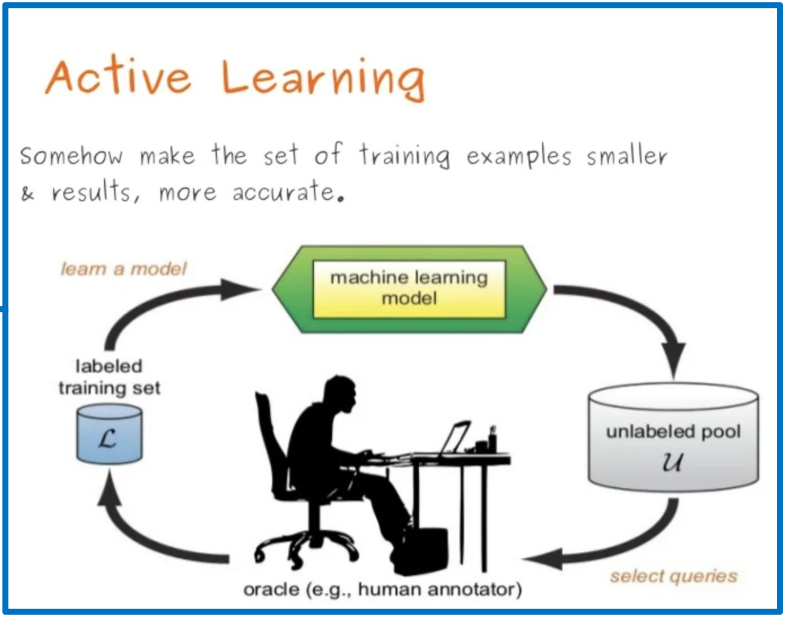
# A Versatile Framework for Galaxy Vision Tasks




**Foundation Vision Model**

**+ Galaxy Classification**

**+ Human-in-the-loop**




**100m Galaxies**

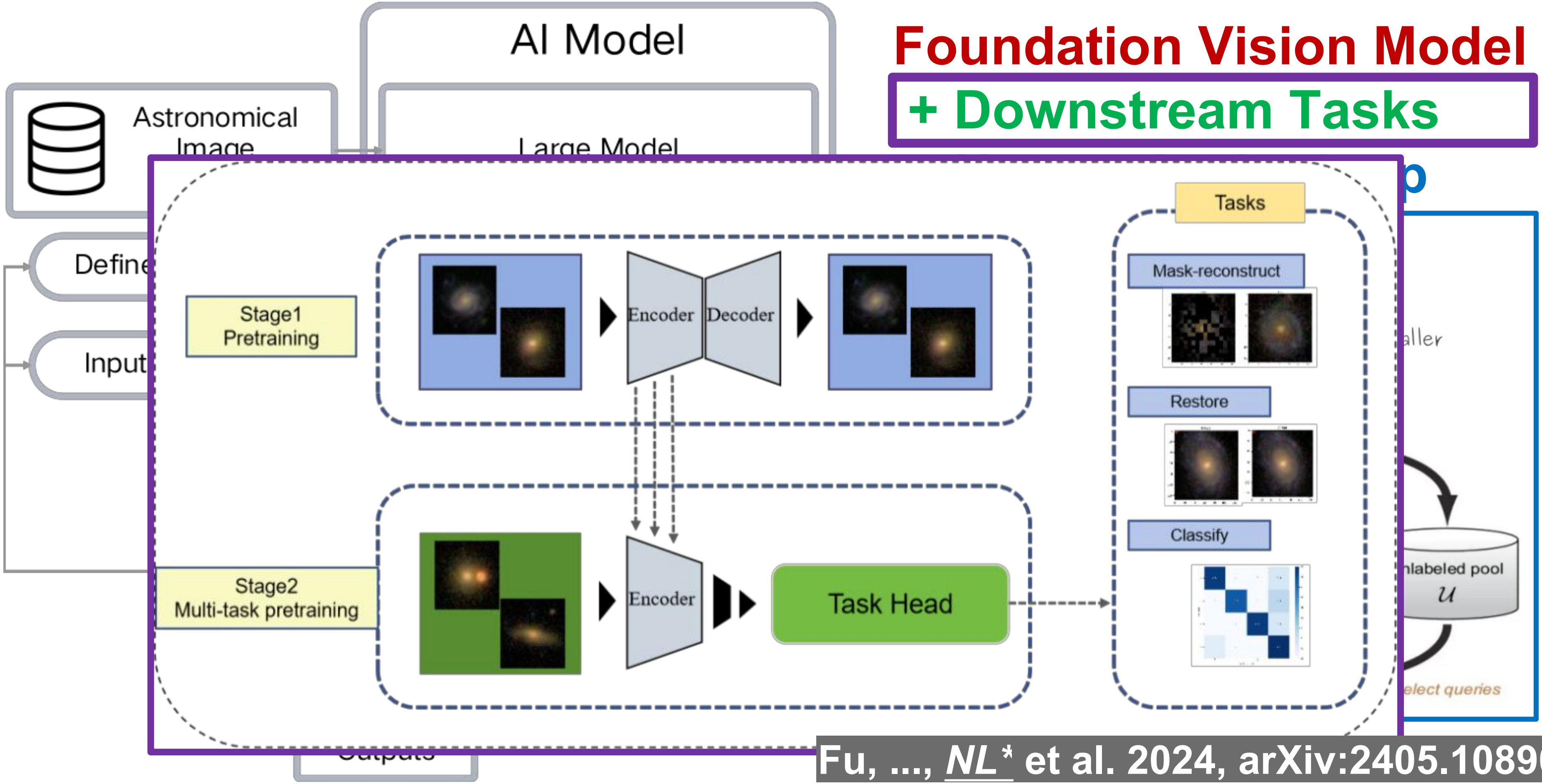
**100m Parameters**

Fu, ..., *NL** et al. 2024, arXiv:2405.10890

# A Versatile Framework for Galaxy Vision Tasks

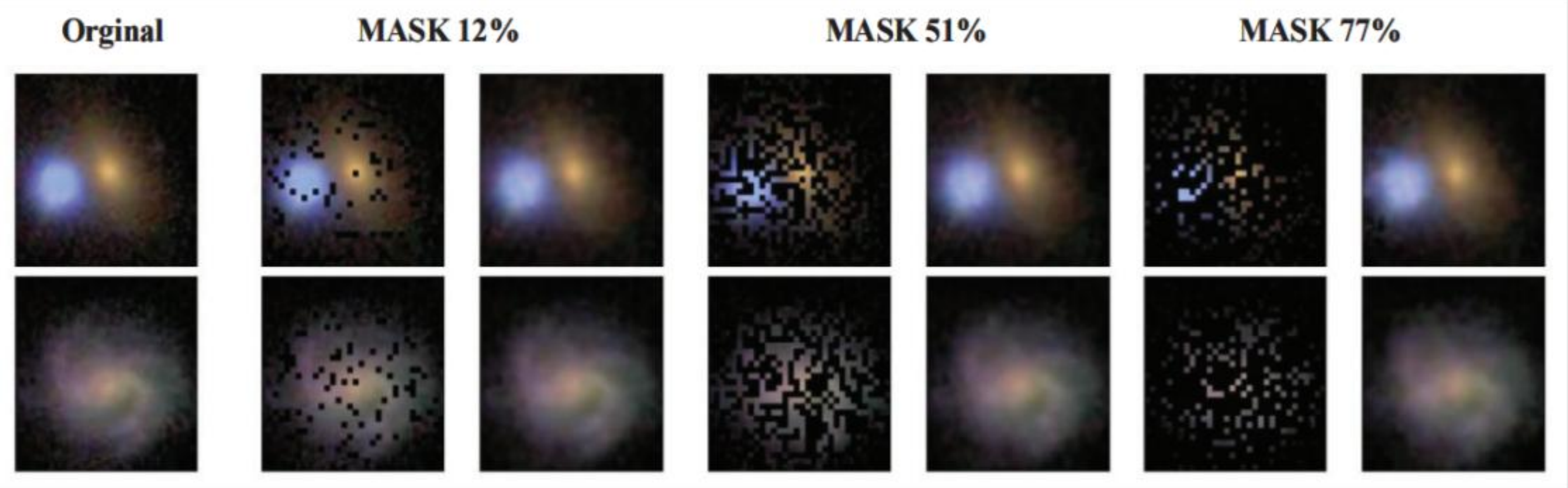
## Foundation Vision Model

## + Downstream Tasks




Fu, ..., *NL** et al. 2024, arXiv:2405.10890

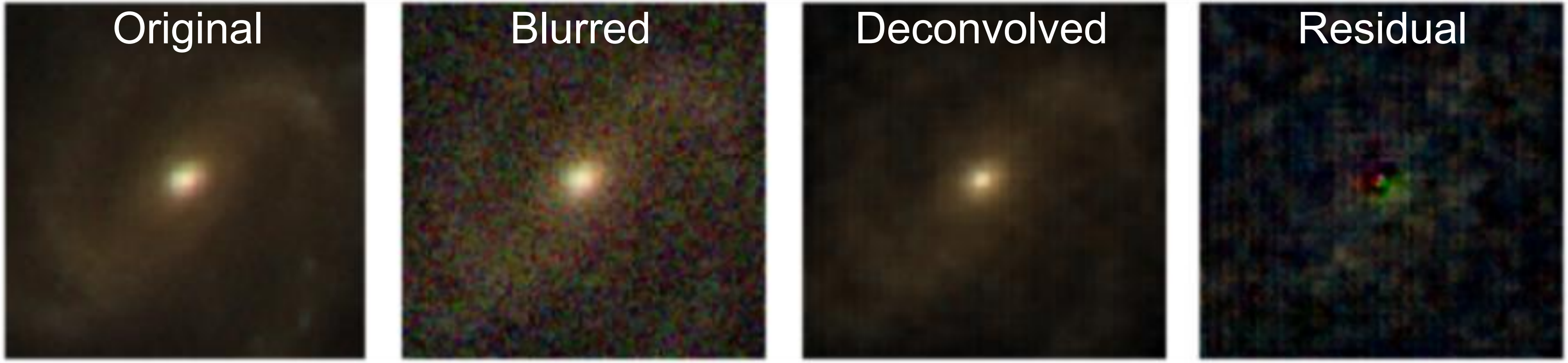
# FVM+DST+HITL: Image Reconstruction




| | MSE↓ | PSNR↑ | SSIM↑ |
|---|---|---|---|
| Masked image | 0.0248 | 15.64 | 0.36 |
| Pre_train | 0.0089 | 22.36 | 0.49 |
| Multi_umiform | 0.0040 | 26.07 | 0.61 |
| Multi_acivate | 0.0038 | 26.84 | 0.64 |

Fu, ..., *NL** et al. 2024, arXiv:2405.10890

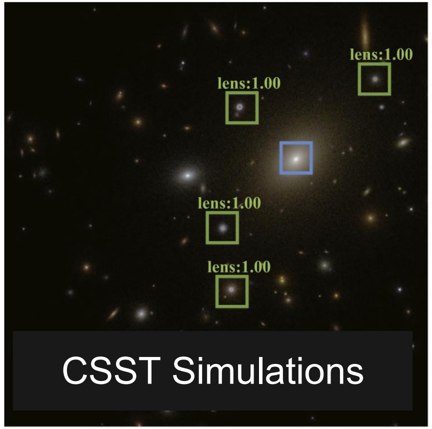
# FVM+DST+HITL: PSF Deconvolution

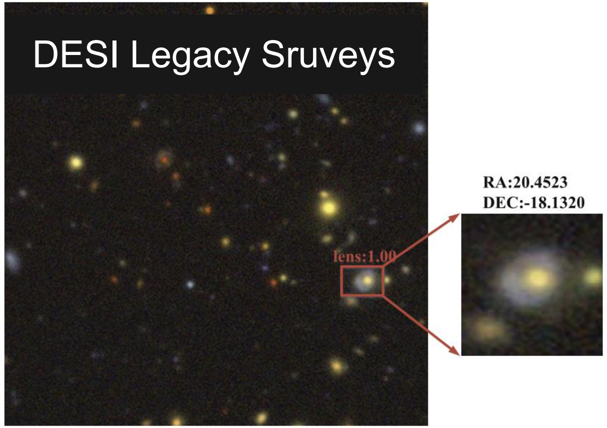


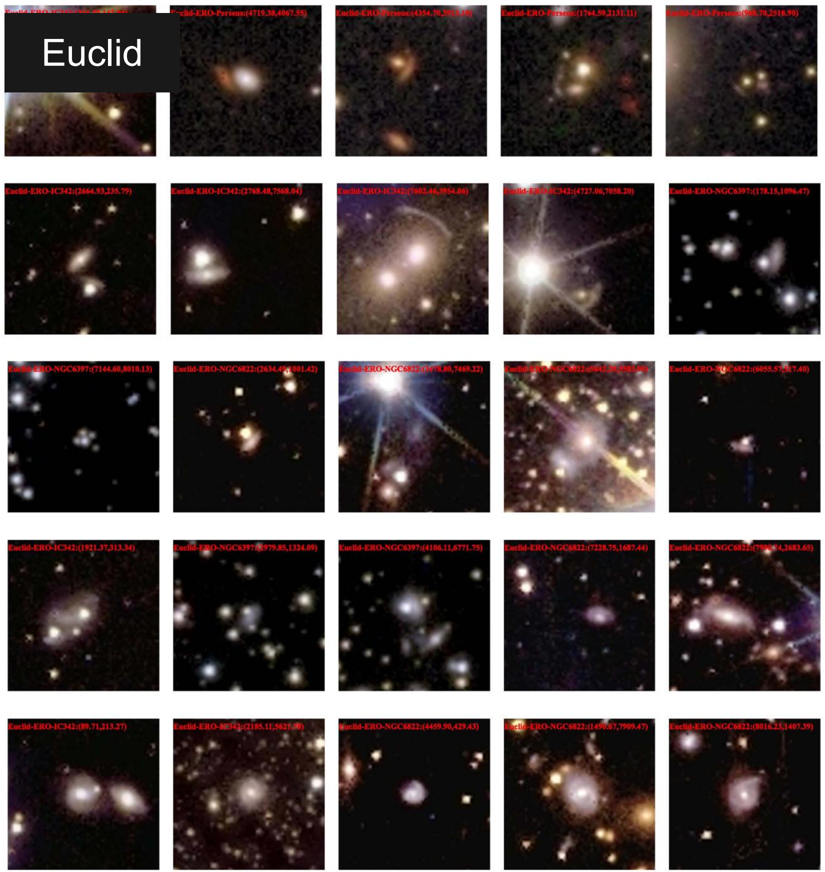

| | MSE↓ | PSNR↑ | SSIM↑ |
|---|---|---|---|
| Blurred image | 0.00094 | 31.11 | 0.48 |
| Pre_train | 0.00084 | 31.31 | 0.51 |
| Multi_uniform | 0.00083 | 31.48 | 0.54 |
| Multi_activate | 0.00049 | 33.34 | 0.56 |

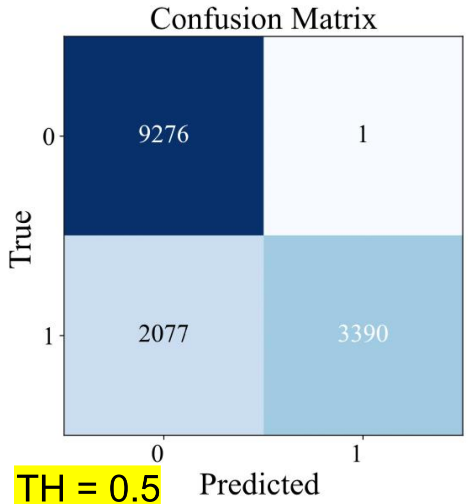
Fu, ..., *NL** et al. 2024, arXiv:2405.10890

# FVM+DST+HITL: Object Detection (Strong Lenses)

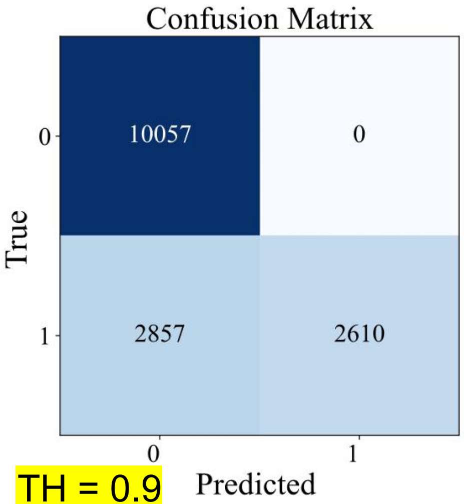



TH = 0.5




TH = 0.9

Li, ..., *NL** et al. 2024, arXiv:2404.01780

# Is It Possible to Compose Papers with AI?

How to Enhance the Impact of Your research? Inspired by Strong Lensing Clusters

Nan Li[1] †   ChatGPT[2] ‡

[1]National Astronomical Observatories, Beijing, 100101, People's Republic of China

[2] OpenAI, L.L.C., 3180 18th Street, San Francisco, CA, 94110, USA

‡The Corresponding Author

†Please go to **Acknowledgement** for author contribution statements.

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**Abstract**

The impact of one's research is often used to gauge the success of an academic career, and extraordinary impact can lead to student job opportunities, greater resources and tenured positions for early-career researchers, and more funding and reputations for established professors. Inspired by strong lensing clusters, we present a strategy to craft impactful papers by drawing parallels between the magnification of strongly lensed arcs and the citation counts of papers. Additionally, we introduce the H-index of strong lensing clusters as a measure of their visual significance and explore methods for junior and experienced researchers to enhance the impact of their published work. In conclusion, chasing or creating hotspots can elevate the impacts of your papers on some level. However, the intrinsic luminosity of the source galaxies determines the observability of strongly lensed arcs.

To summarize, while magnification can make lensed arcs visually striking, citation counts truly make a paper stand out. Similarly, the H-index of a strong lensing cluster can indicate its efficiency as a lens. At the same time, a researcher's H-index reflects their contributions to science on some level. Thus, if you gaze into strong lensing



clusters, you will understand what happiness is. Look, a new day has begun.

## Acknowlegement

NL, the primary author of this paper, initiated the manuscript, while ChatGPT, the corresponding author, provided the final editing. Please note that this is an April Fools Day Paper, so any mistaken ideas should be disregarded. In case of dissatisfaction with the English language used in this paper, please contact OpenAI[6] for further discussion (NL writes the above sentences). NL expresses sincere gratitude towards OpenAI for developing ChatGPT and making it publicly available to human beings, which is the most remarkable program NL has ever utilized. Chatgpt will undoubtedly revolutionize the world in the near future (ChatGPT writes this sentence).

*NL* and ChatGPT*, 2023/04/01, **Rejected by ArXiv**

# Take Home Points

## Galaxy Morphology Classification in the Era of Big Data

- Machine Learning
- Human-machine Cross-check
- Human-machine Cooperation

## One Model to Handle Them All

- An AI Model for Galaxy Vision Tasks
- An AI System for Astronomy
- An AI Toolkit for Astronomers