Dynamics and Morphology of Galaxies And Convolutional Neural Networks

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Plan of the talk

<u>Part 1:</u> Identifying the Dynamical Parameters of an Interacting Galaxy Pairs

Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

- **Motivation**
- **Methodology**
- **Training, Hyper-parameters for the Network Architecture**
- **Performance Metrics**
- **Results**
- **Summary**

<u>Part 2:</u> Classification of spirals into Flocculents and Grand-designs using machine learning

Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

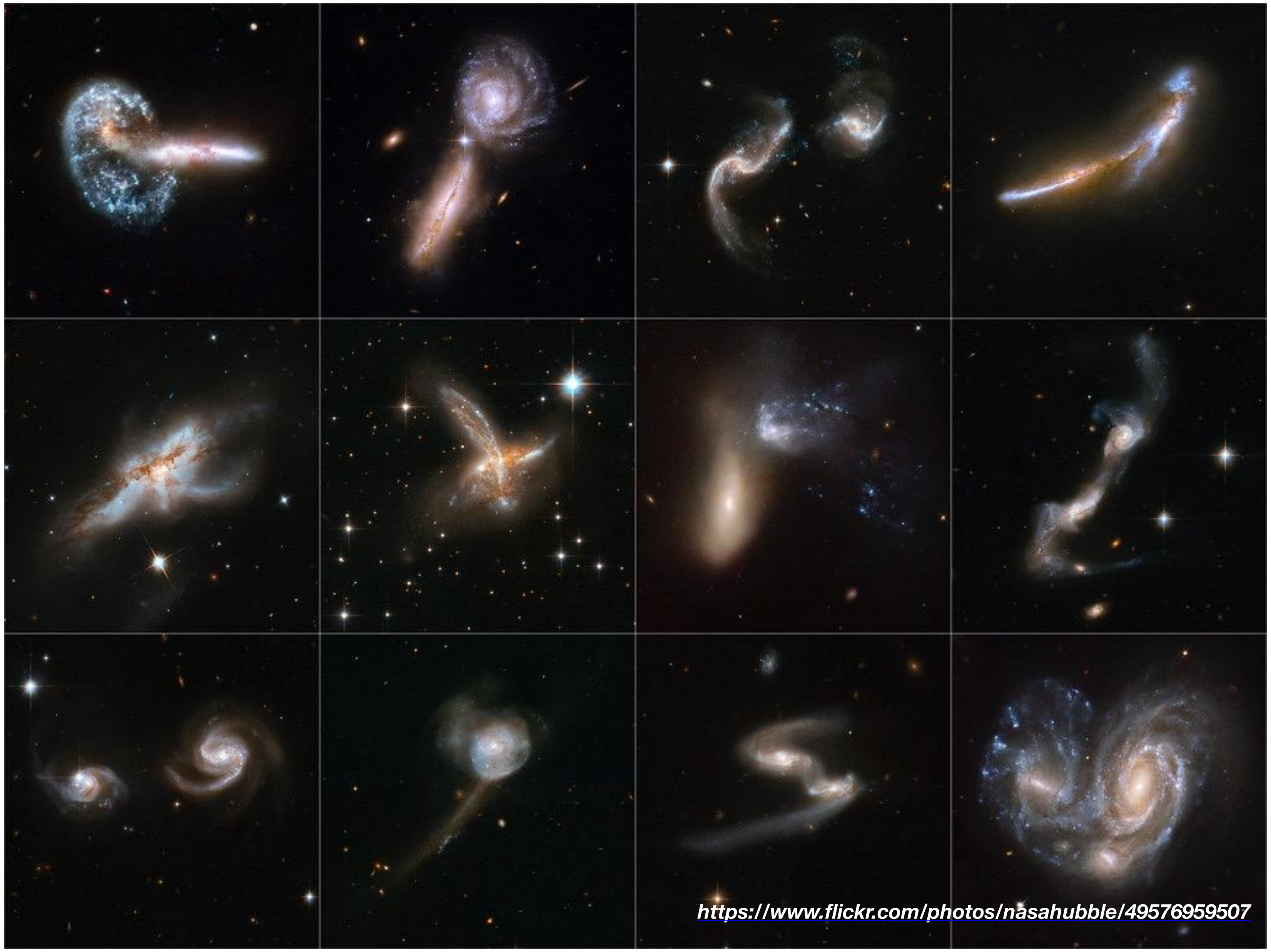
Part 1

Identifying the Dynamical Parameters of an Interacting Galaxy Pairs

Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3
(arXiv:2002.01238)

Motivation

An HST view of interacting galaxy pairs



- **Basic building blocks in a hierarchical universe**
- **Drives dynamical evolution: Morphological transformation, Bulge/Halo formation, Starbursts**

Barnes & Hernquist 1992, ARAA, 30, 705

Dynamical parameters of an interacting galaxy pair

- **Orbital Parameters**

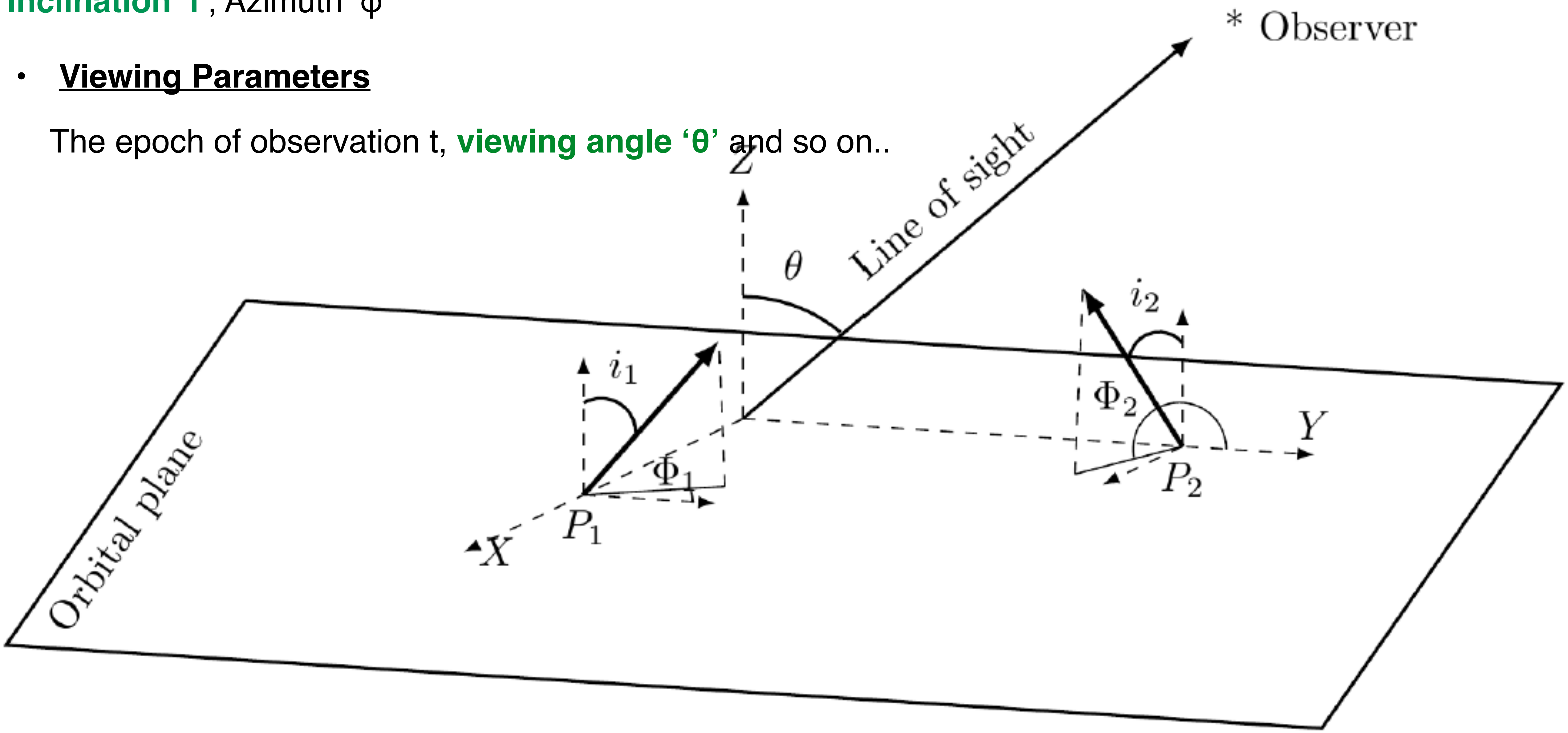
Peri-centric distance, galactic mass ratio, orbital eccentricity

- **Disc Orientations**

Inclination 'i', Azimuth 'ϕ'

- **Viewing Parameters**

The epoch of observation t, **viewing angle 'θ'** and so on..



Dynamical model constructed by guessing 16 parameters, followed by N-body + hydrodynamical simulations, over successive iterations

Barnes & Hibbard 2009, AN, 137, 3071

How it all started?

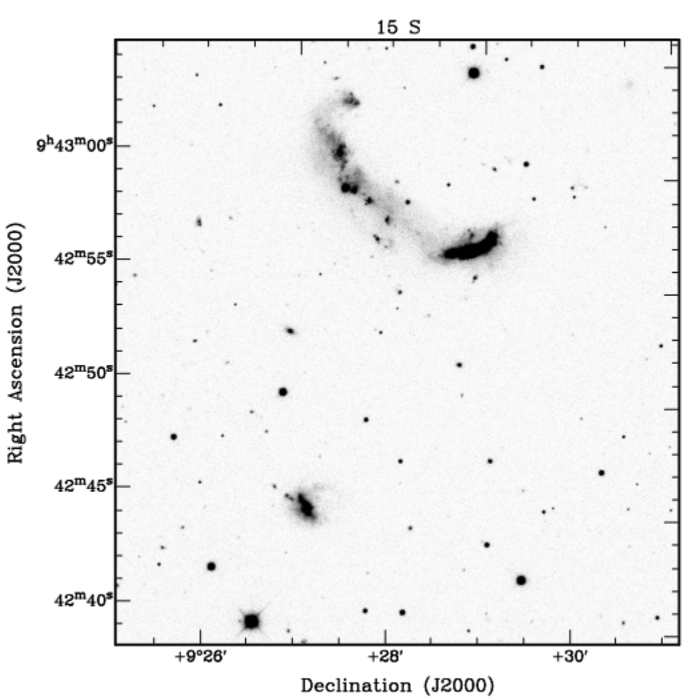
Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY
MNRAS **477,** 894–903 (2018) doi:10.1093/mnras/sty627
Advance Access publication 2018 March 8

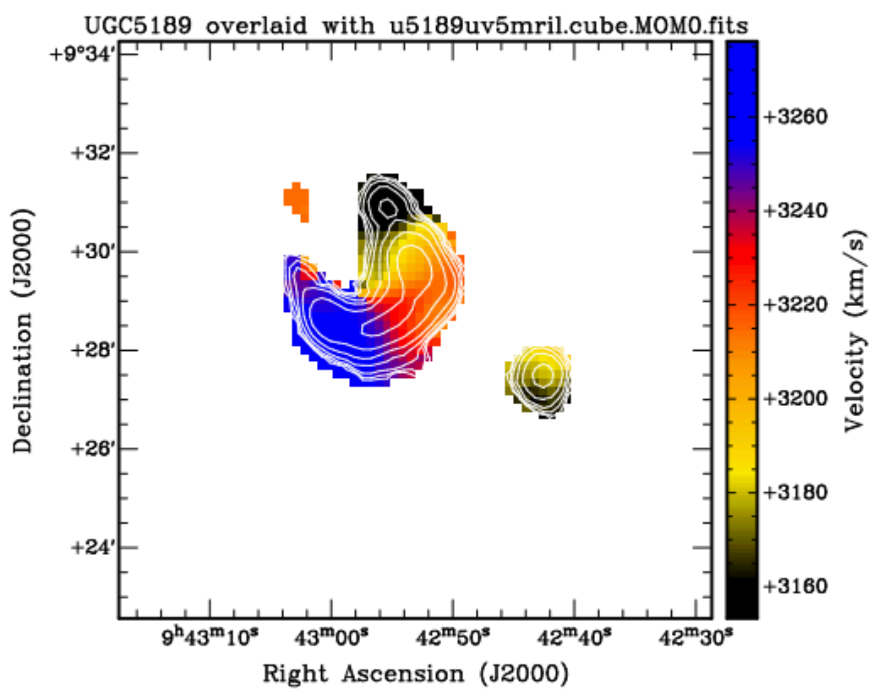
Detection of bars in galaxies using a deep convolutional neural network

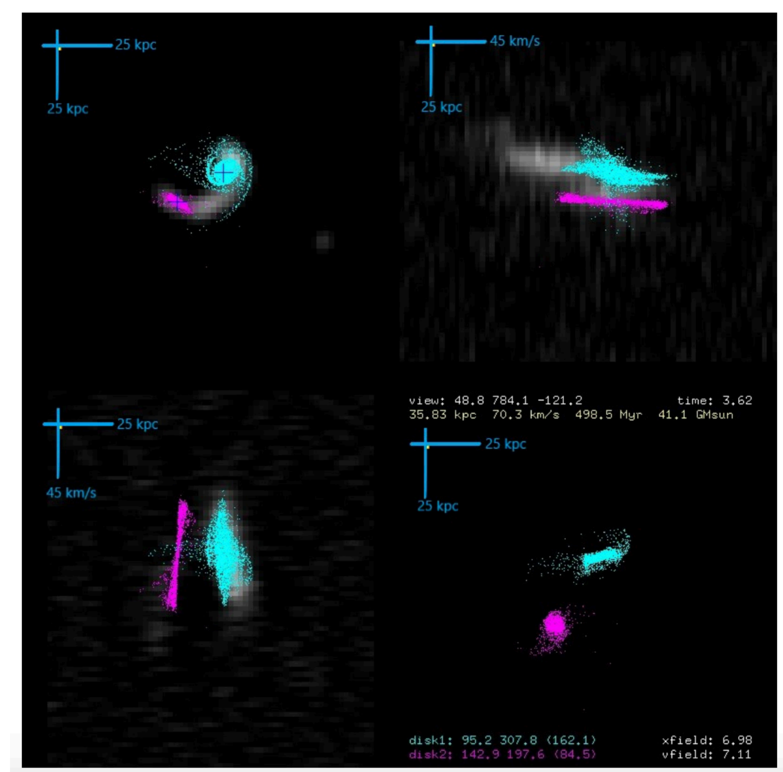
Sheelu Abraham,[1★] A. K. Aniyan,[2,3★] Ajit K. Kembhavi,[1★] N. S. Philip[4] and Kaustubh Vaghmare[1]
[1] *Inter-University Centre for Astronomy and Astrophysics, IUCAA Pune 411007, India*
[2] *Department of Physics and Electronics, Rhodes University, Grahamstown 6139, South Africa*
[3] *SKA South Africa, Pinelands,Cape Town 7405, South Africa*
[4] *Department of Physics, St Thomas College, Kozhencherry 689641, Kerala, India*

Accepted 2018 March 3. Received 2018 March 3; in original form 2017 October 9

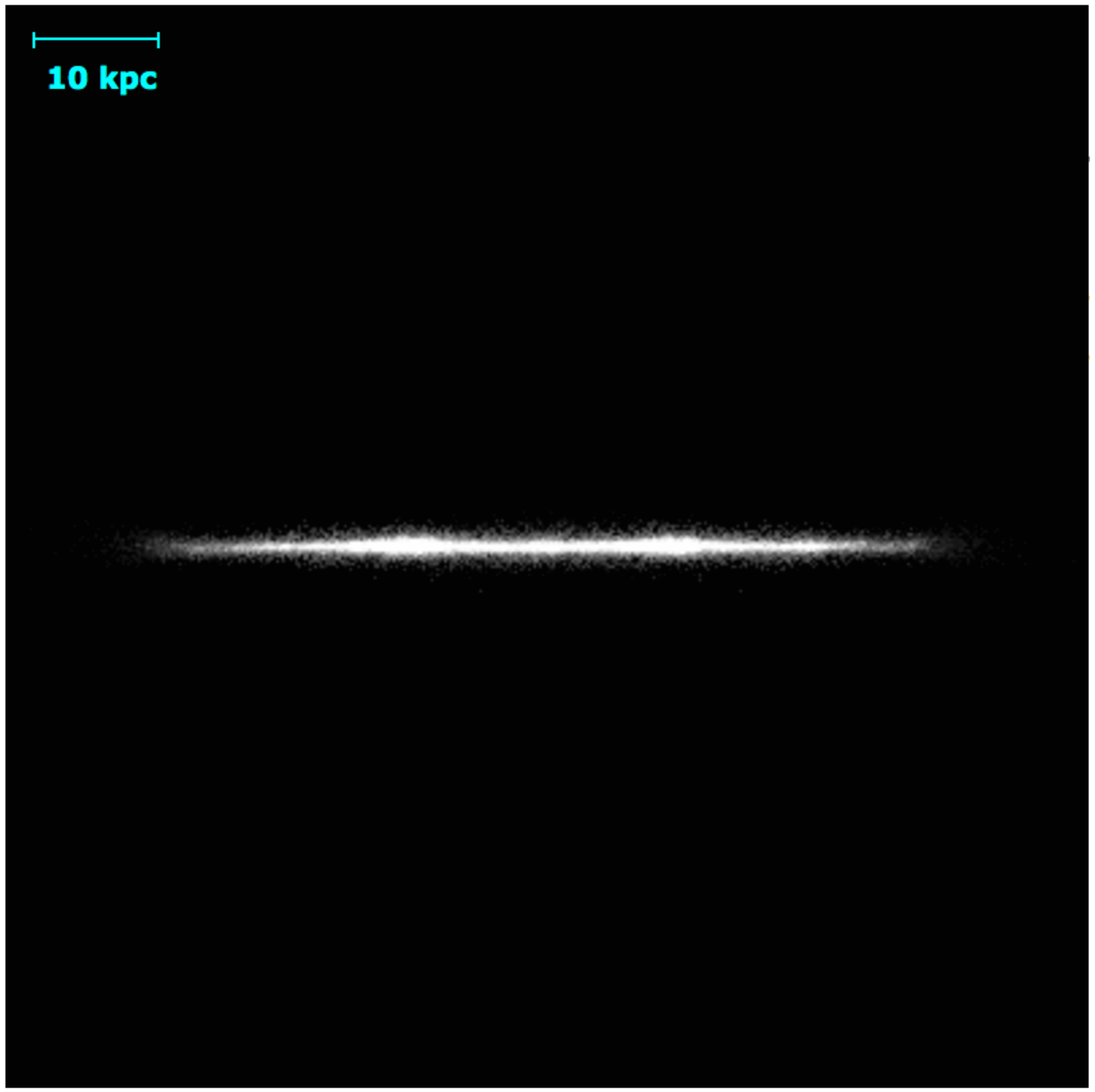
A Dynamical Model for the Interacting Dwarf Galaxies in UGC5189 using Identikit

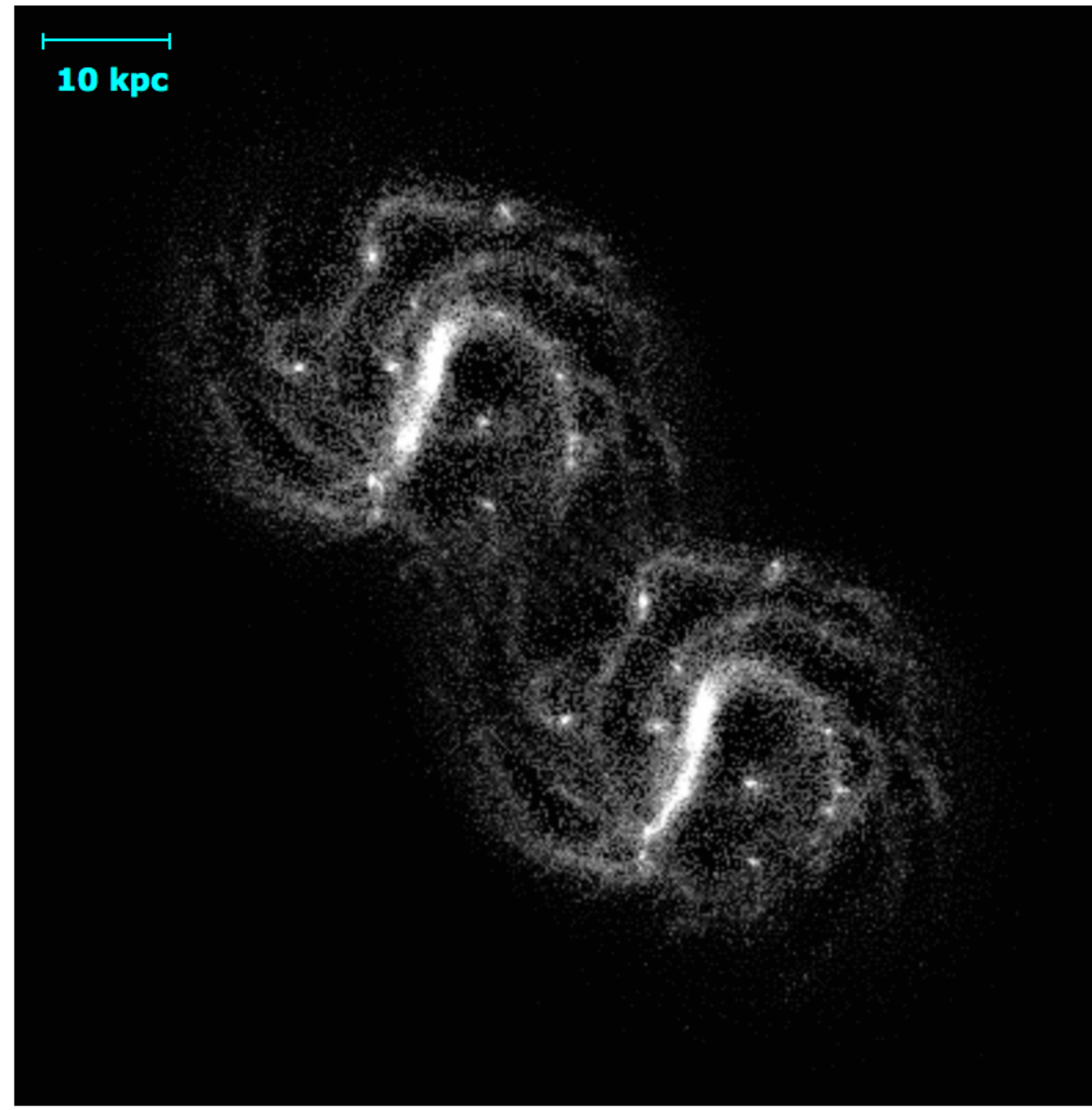






Dynamical Parameters: Morphological Signatures



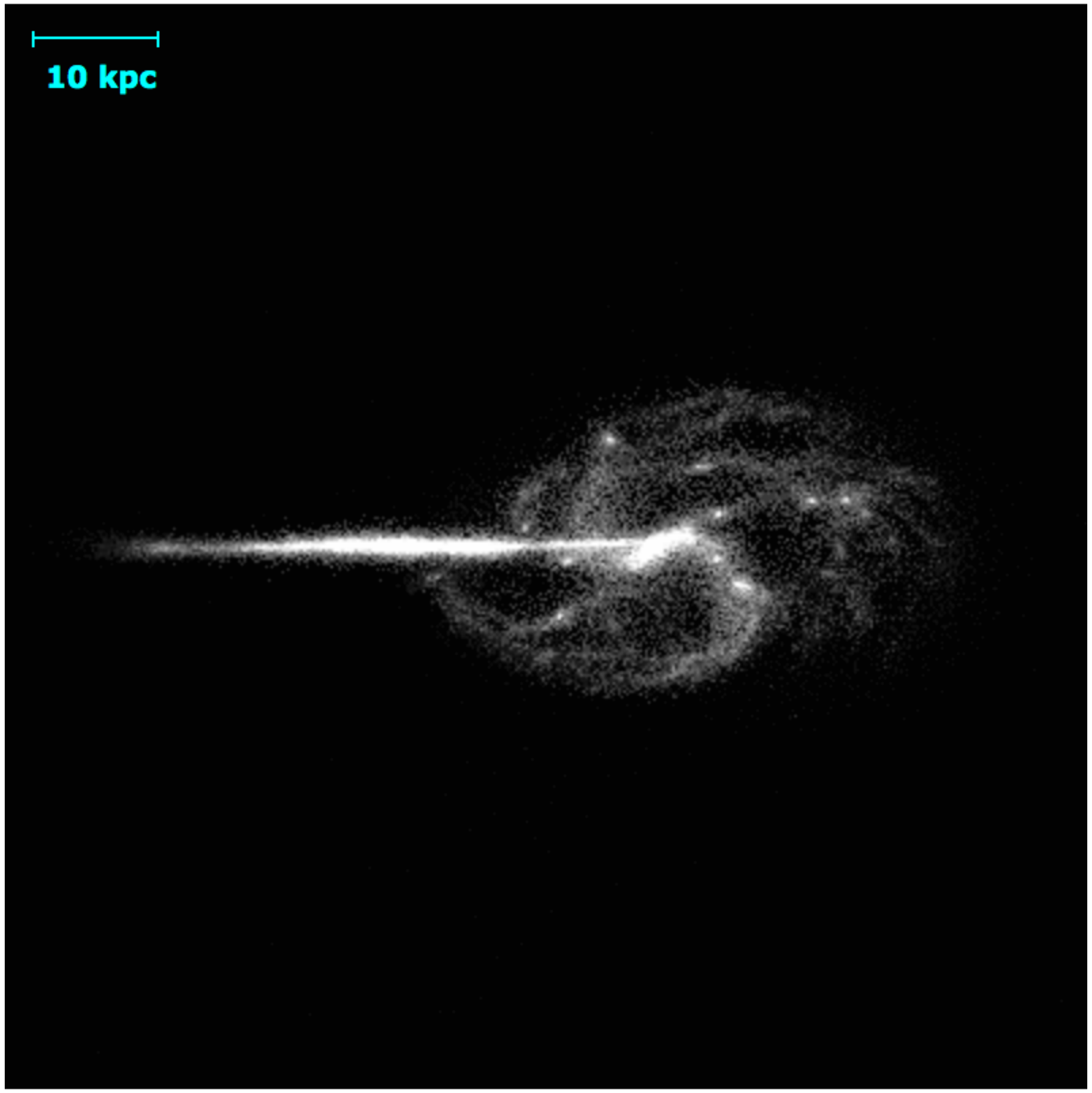


$i = 0$, $\theta = 90$

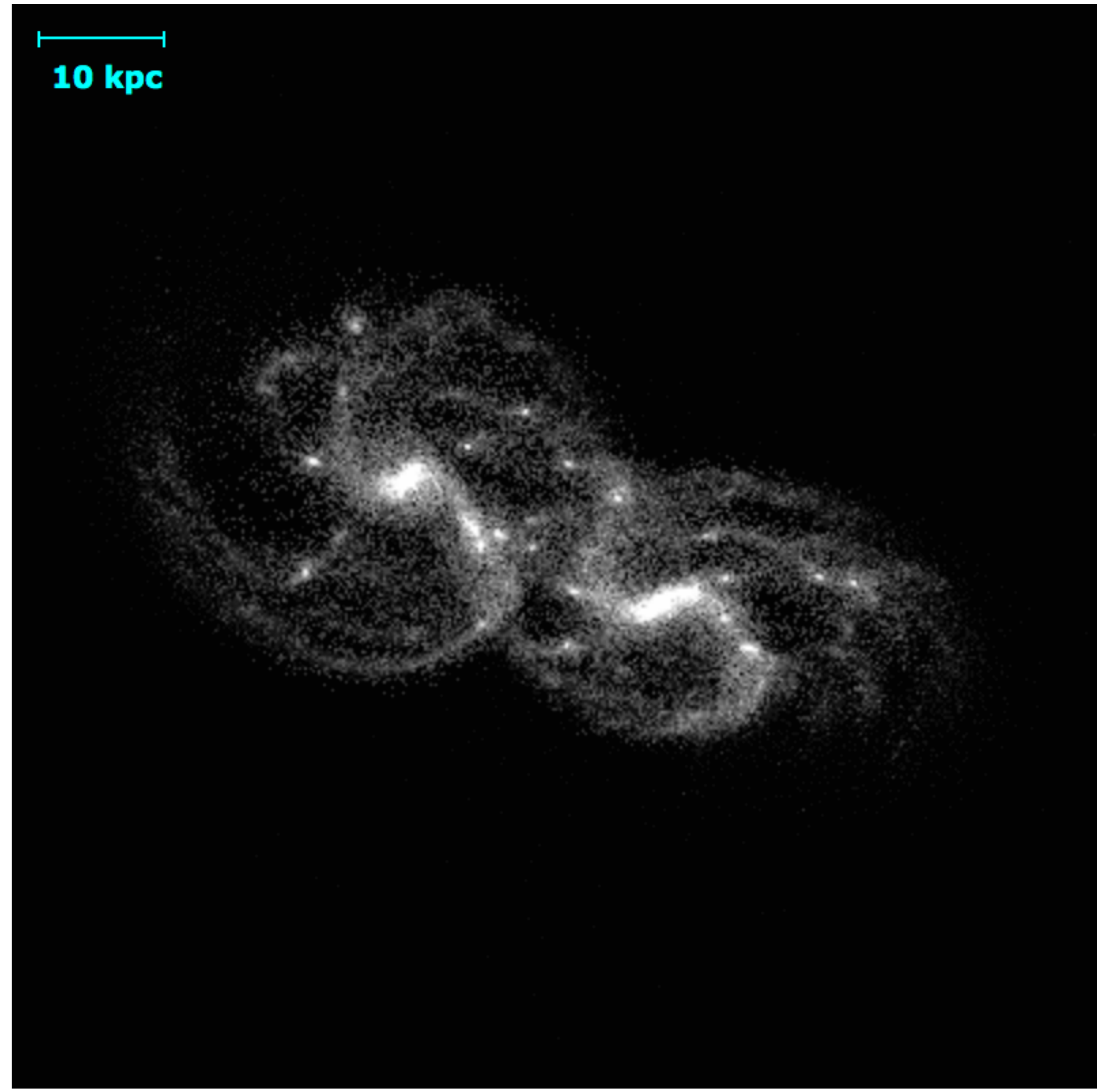
$i = 0$, $\theta = 0$

www.galmer.obsfm.fr

Dynamical parameters: Morphological Signatures



i = 45, θ = 90



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www.galmer.obsfm.fr

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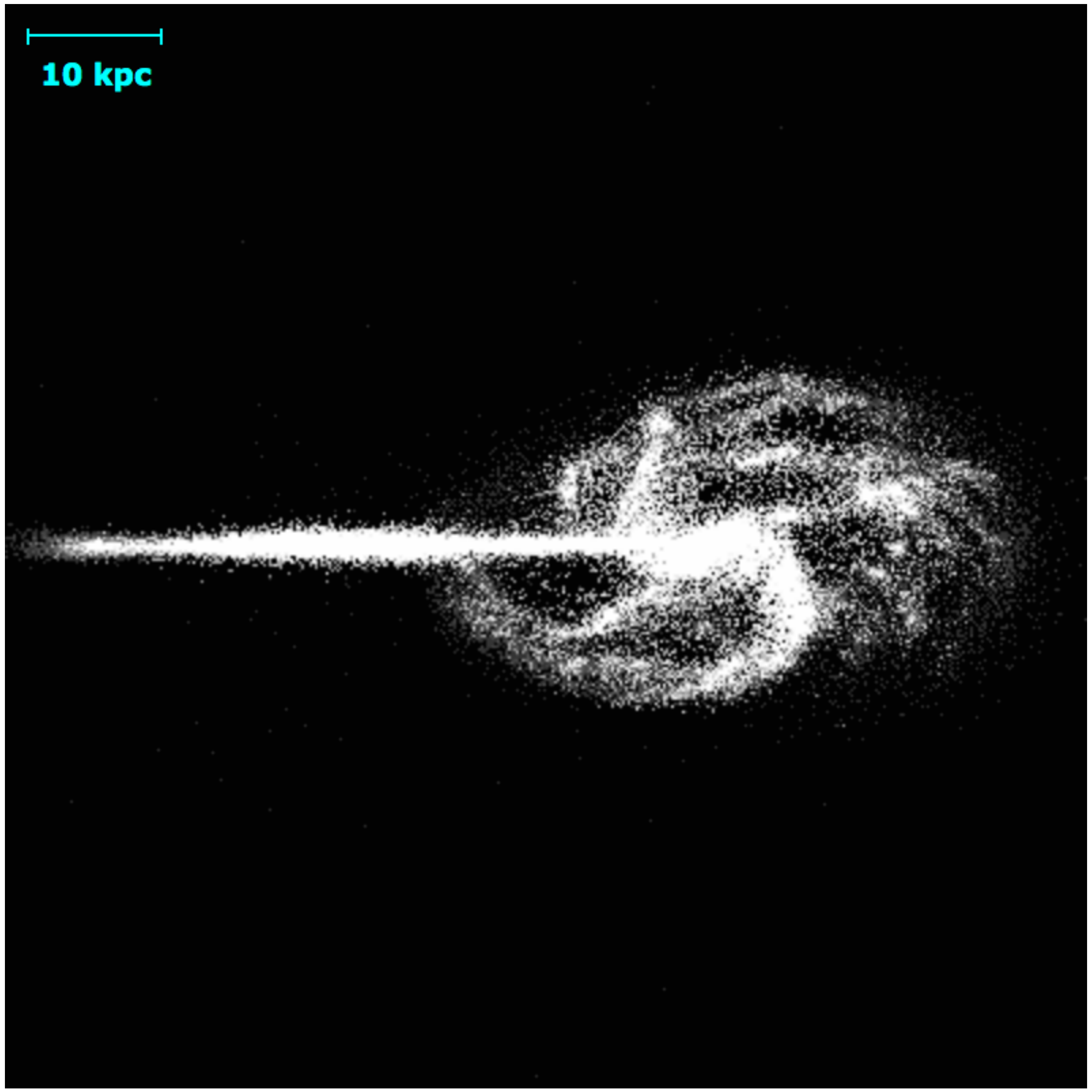
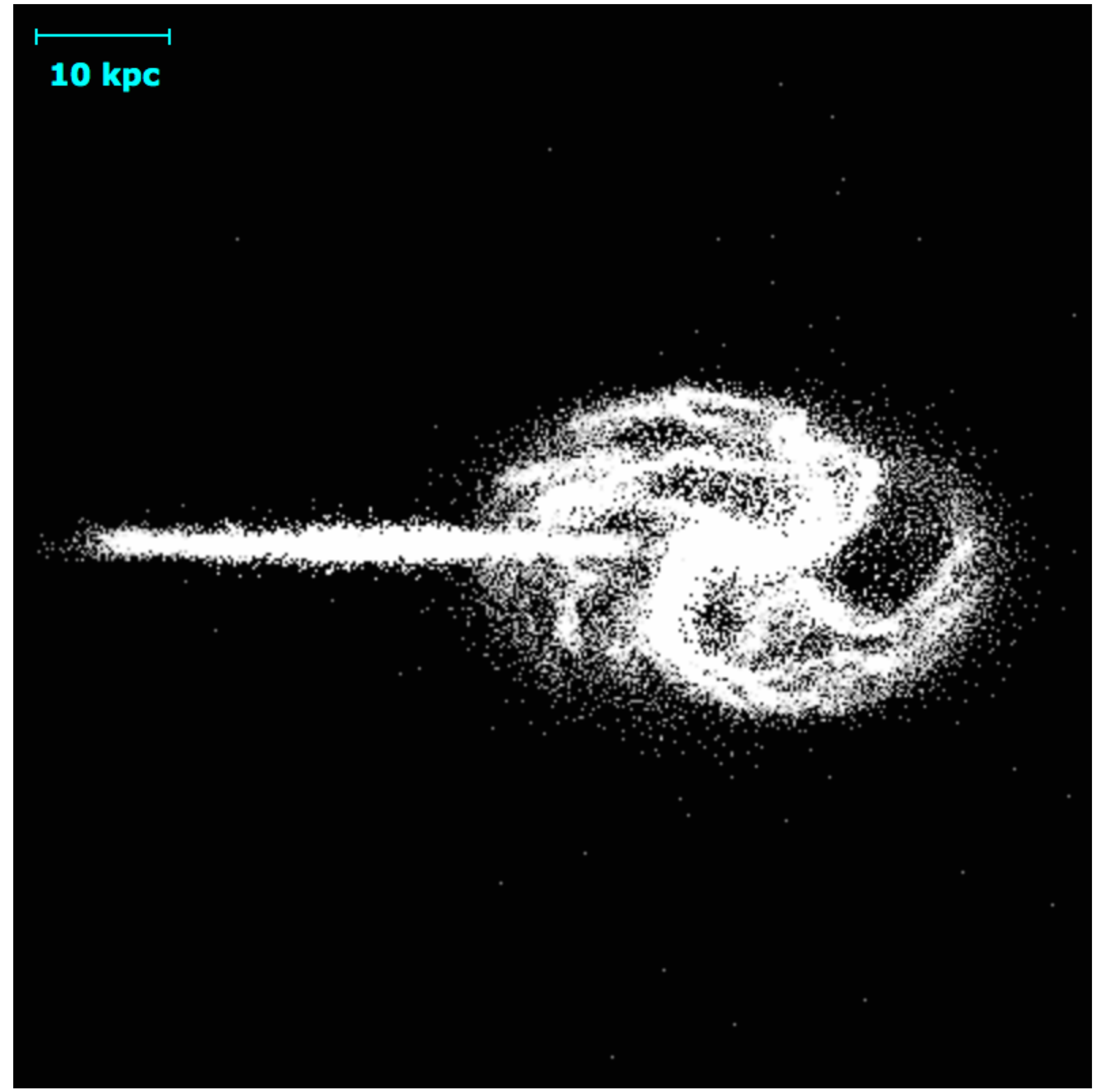


i = 45, θ = 0
Pericentre:24, Energy: 0 , Spin: Prograde



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www.galmer.obsfm.fr

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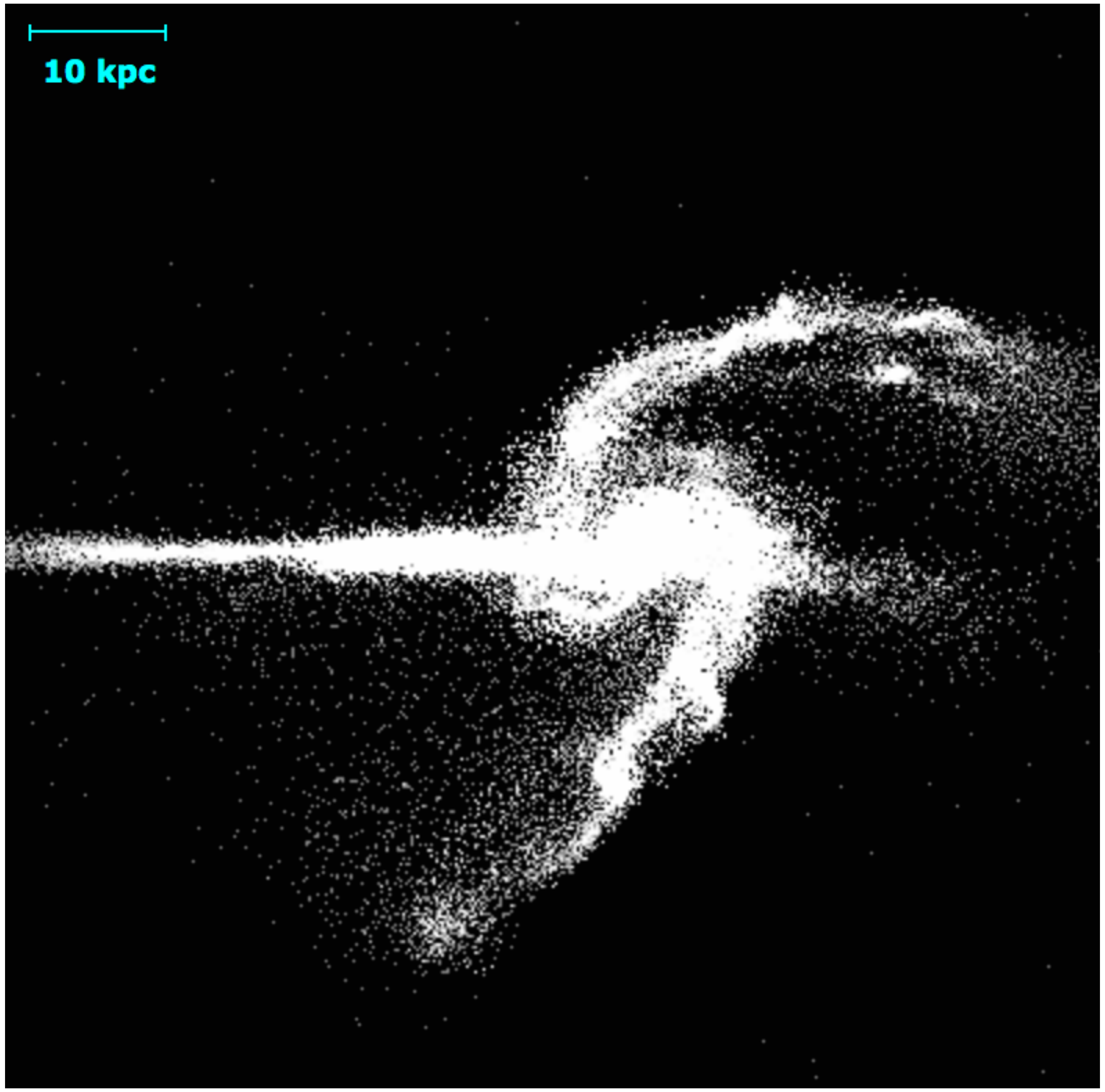
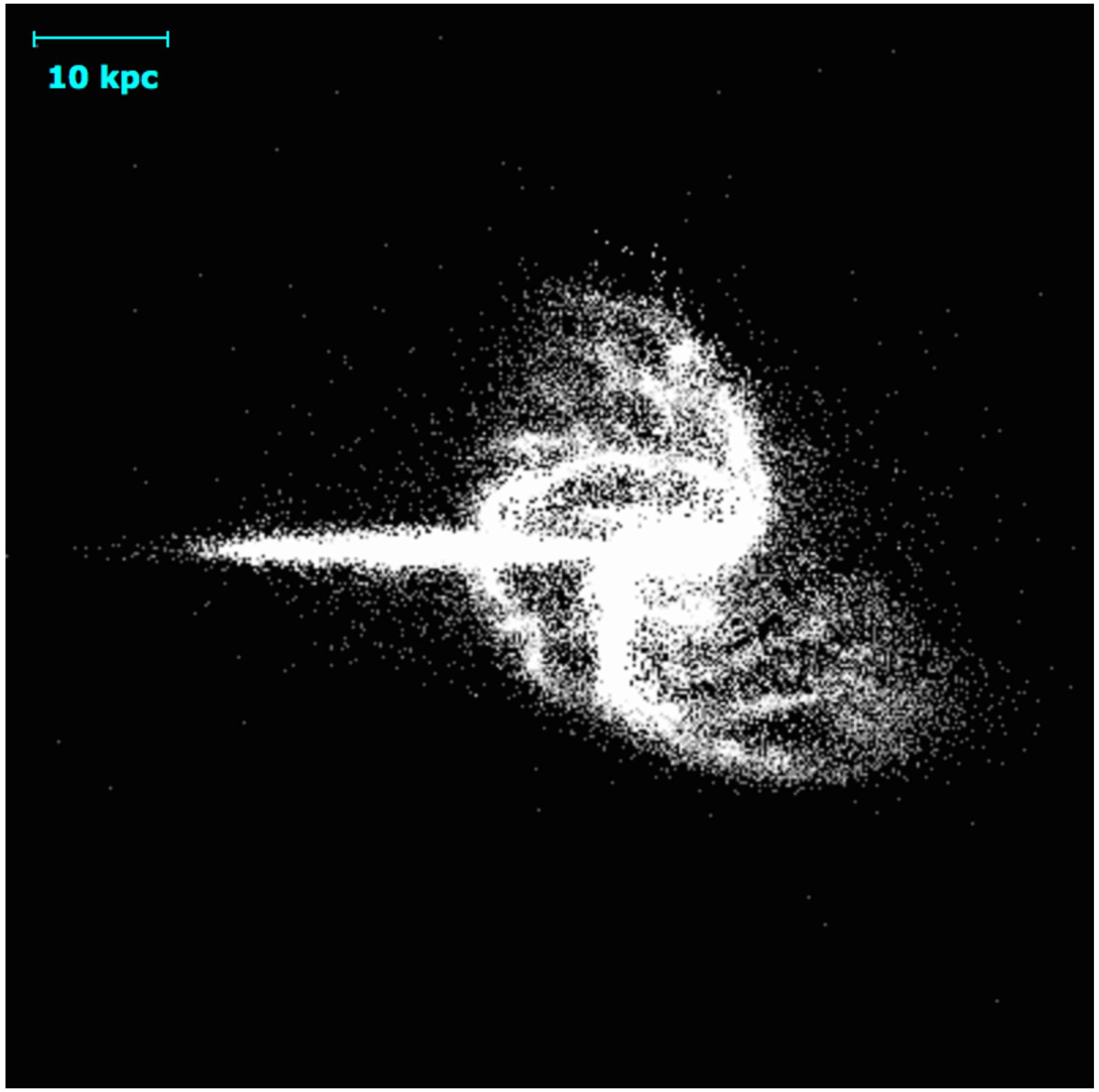


i = 45, θ = 0
Pericentre:24, <u>Energy: 15</u> , Spin: Prograde



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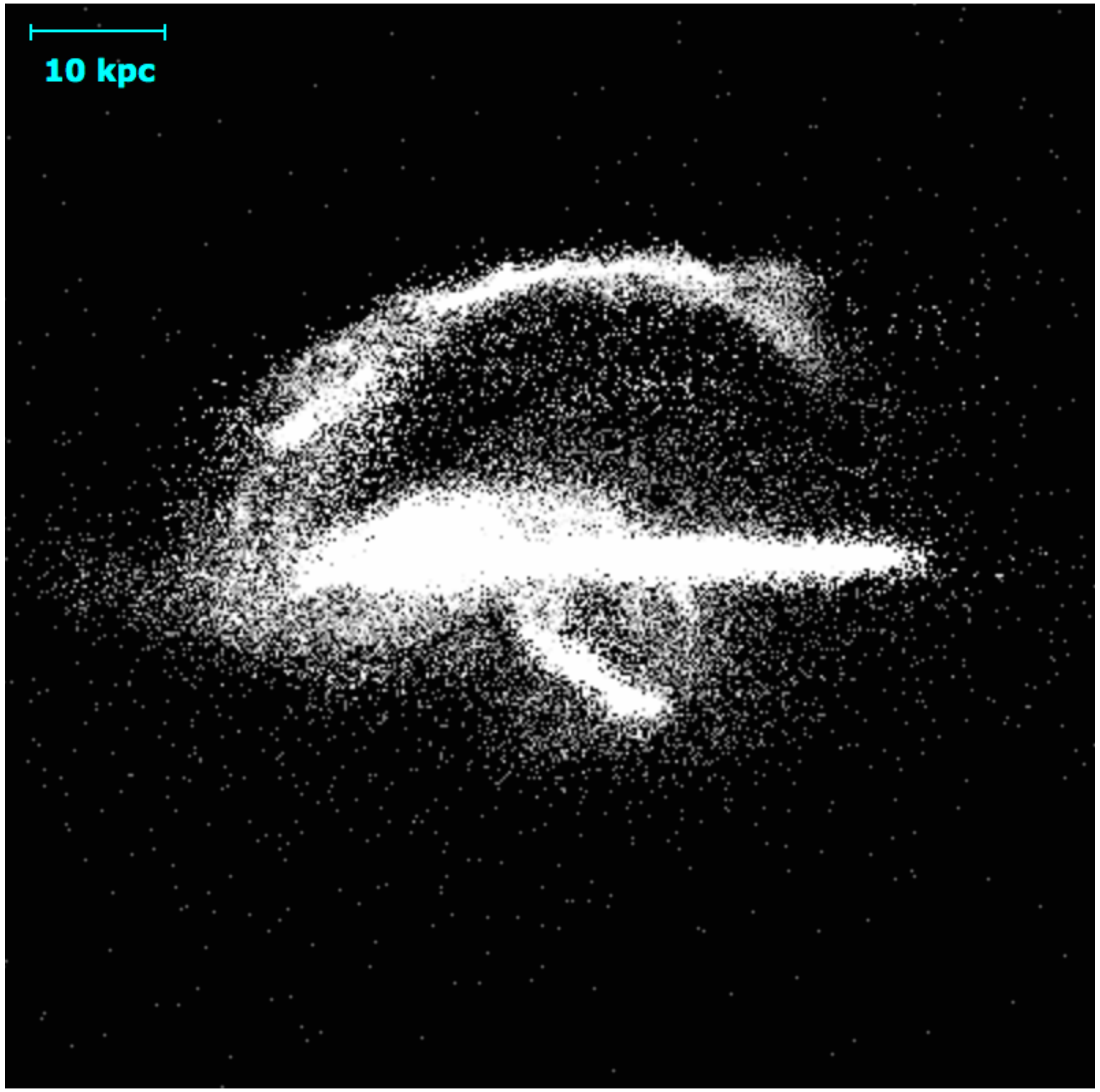
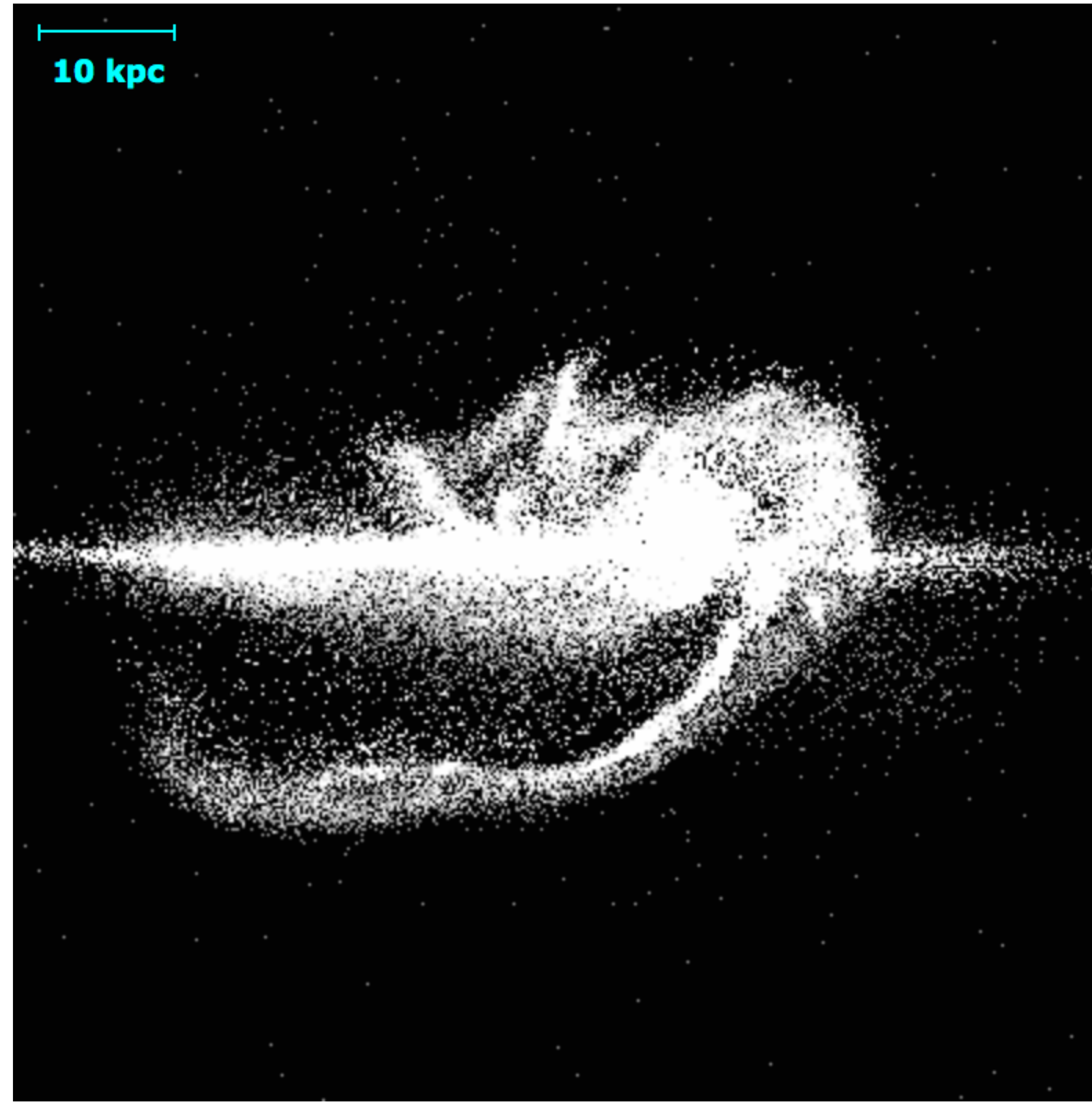
www.galmer.obsfm.fr

Dynamical parameters: Morphological Signatures

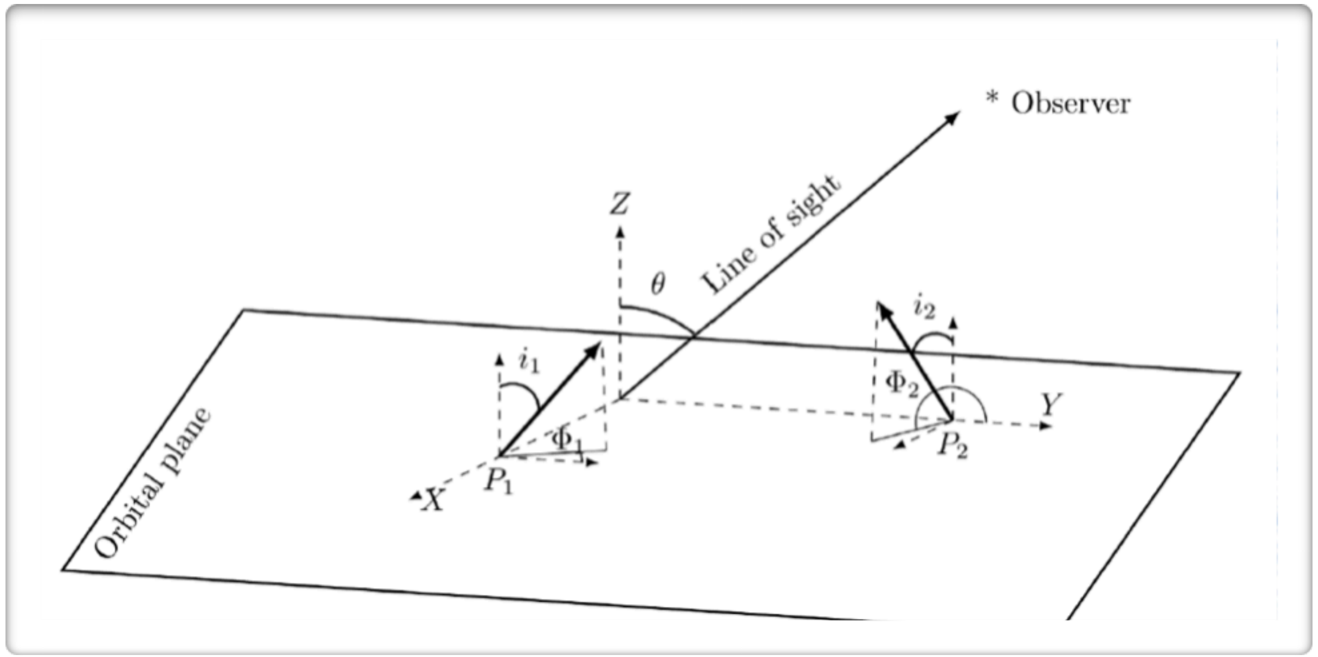




i = 45, θ = 0
Pericentre:8, Energy: 15 , Spin: Prograde

i = 45, θ = 0
Pericentre:8, Energy: 15 , Spin: Retrograde

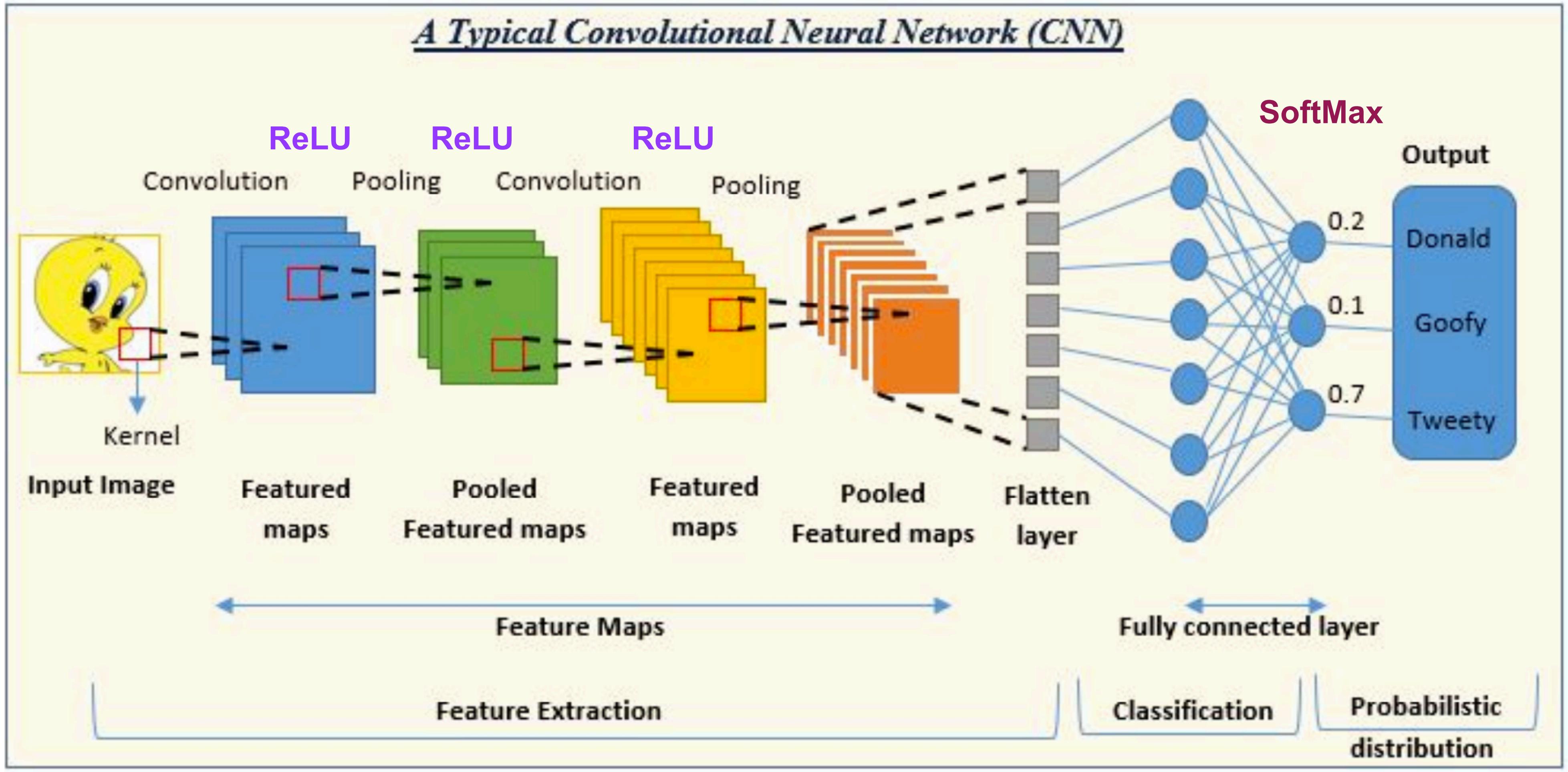
Dynamical parameters: Morphological Signatures



Could morphological signatures serve as diagnostic tracers of the dynamical parameters?

Methodology

Deep Convolutional Neural Networks



We use **ALEXNET**

ReLU: rectified linear unit, is a non-linear activation function

SoftMax: Last activation function of a neural network to normalize the output of a network to a probability distribution over

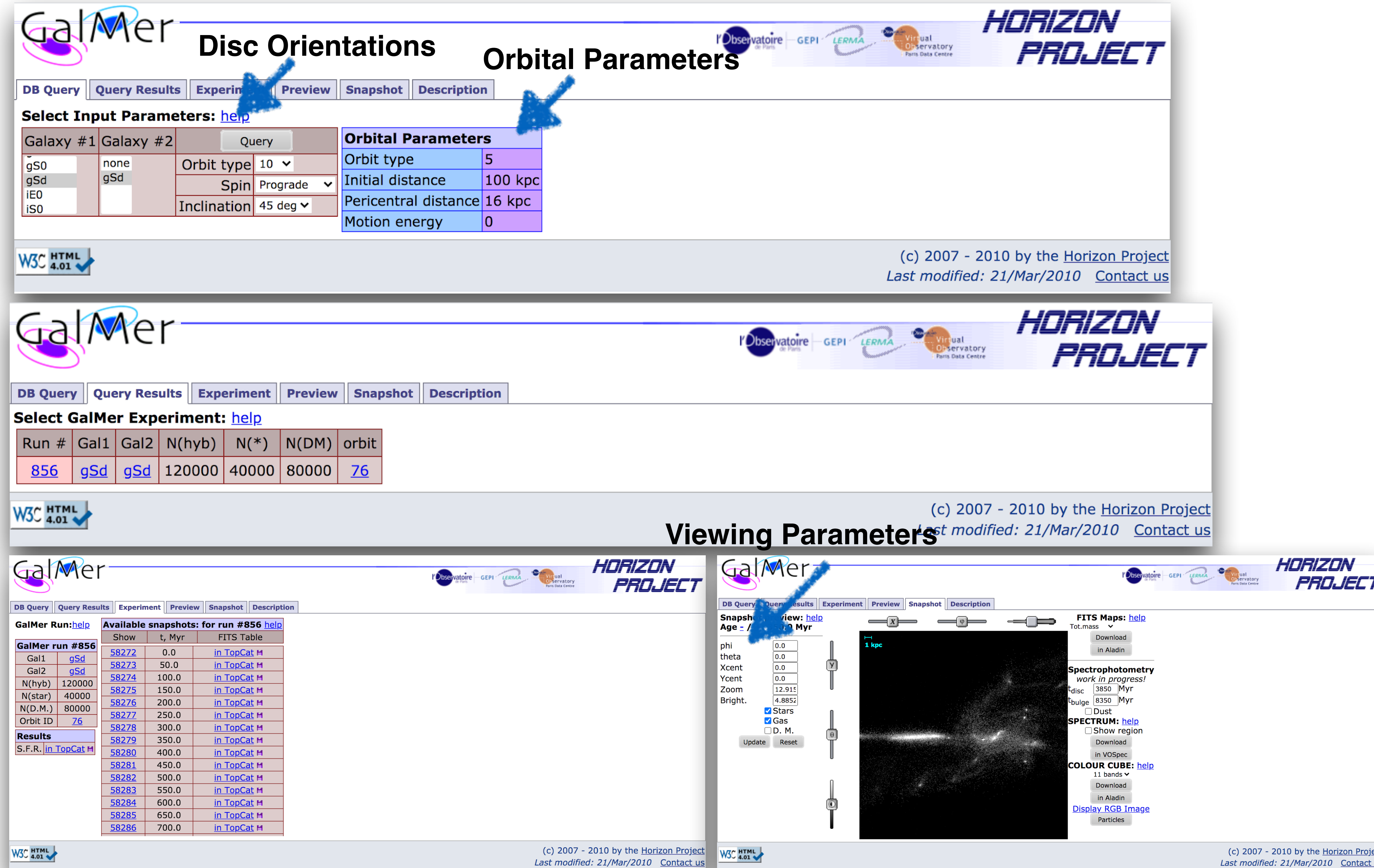
(See, for example, Krizhevsky et al. 2012, Advances in Neural Information Processing system)

Applications of DCNN in Astronomy

- **Abraham, Aniyan, Kembhavi, Philip & Vaghmare 2018, MNRAS, 477, 894**
- **Sharma, Kembhavi, Kembhavi, Sivarani, Abraham & Vaghmare 2020, MNRAS, 491, 2280**

Training Data Set: GalMer Horizon Project

http://galmer.obspm.fr/



Chilingarian, I. V.; Di Matteo, P.; Combes, F.; Melchior, A. -L.; Semelin, B. 2010, A&A, 518, A61

Training Data Set: GalMer Horizon Project

- **Orbital Parameters**

  Mass ratio: 1:1

  Orbit Type: 12 different types

- **Disc Orientations**

  Relative inclination i: 0, 45, 90

  Spin: Prograde/Retrograde

- **Viewing Angle**

  Viewing angle θ: -90 to 90

  Azimuthal angle: 0 to 360

No of images in each class before augmentation ~ 100

No of images after augmentation ~ 1000

9-Class Classification

**[{0º,15º}, {0º, 45º}, {0º, 75º},
{45º,15º}, {45º, 45º}, {45º, 75º},
{90º,15º}, {90º, 45º}, {90º, 75º}]**

Network design details

- Loss function: Cross Entropy
- Learning Rate: 0.01
- Decay Rate: 1%
- No. of epochs: 44 epochs
- Steps per epoch: 16000
- Rejection threshold: 70%
- Time taken to run 1 epoch: 8 - 10 hours

[Intel(R) Corei7-7700 processor with 3.60 GHz Frequency and 16GB RAM

Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

Network Performance Diagnostics [While Training]

(Quiz!)

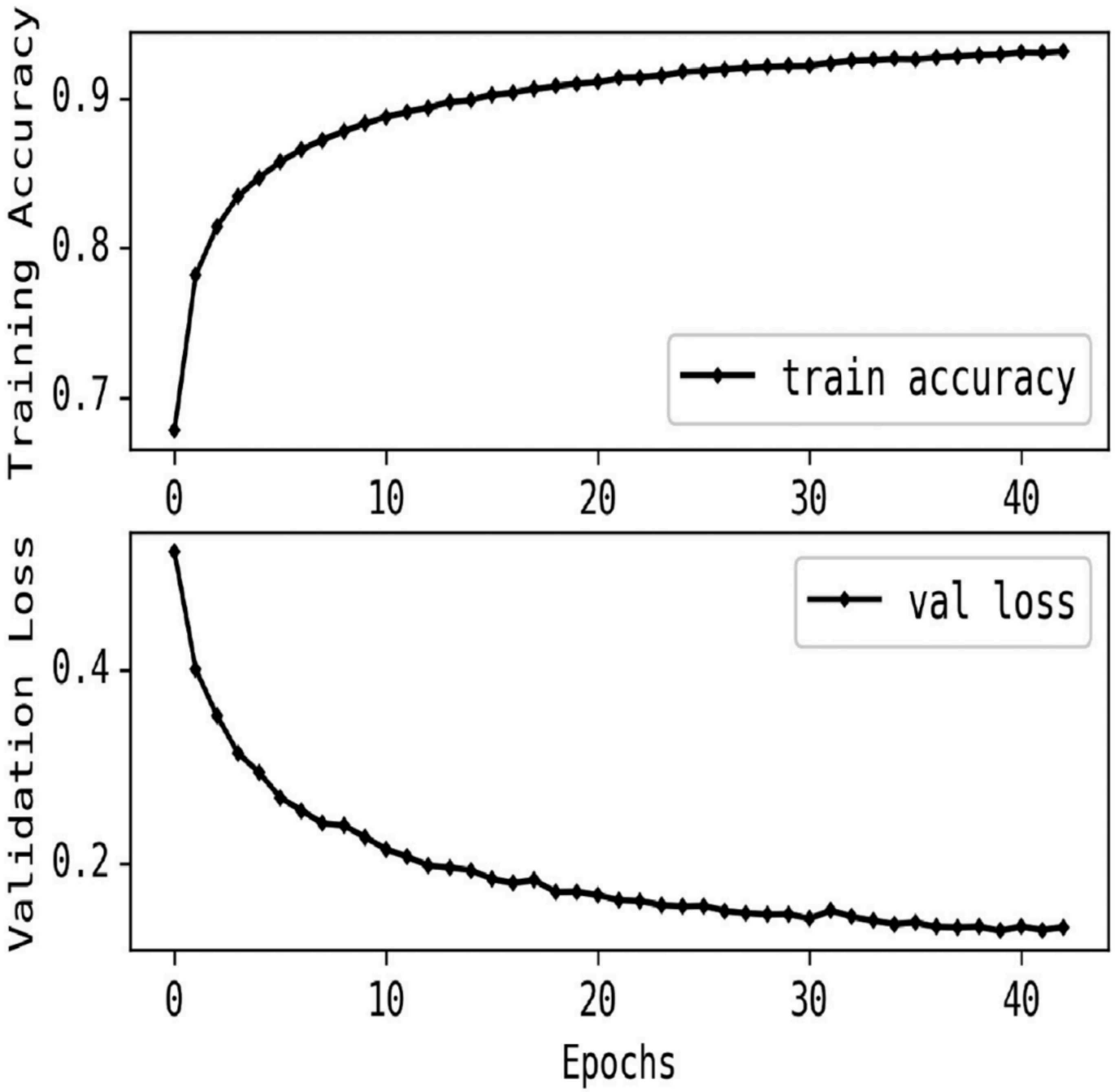
1. Training Accuracy/Validation Loss

Training Accuracy

= Number of correct predictions by the total number of predictions

Validation Loss

= Number of correct predictions by the total number of predictions



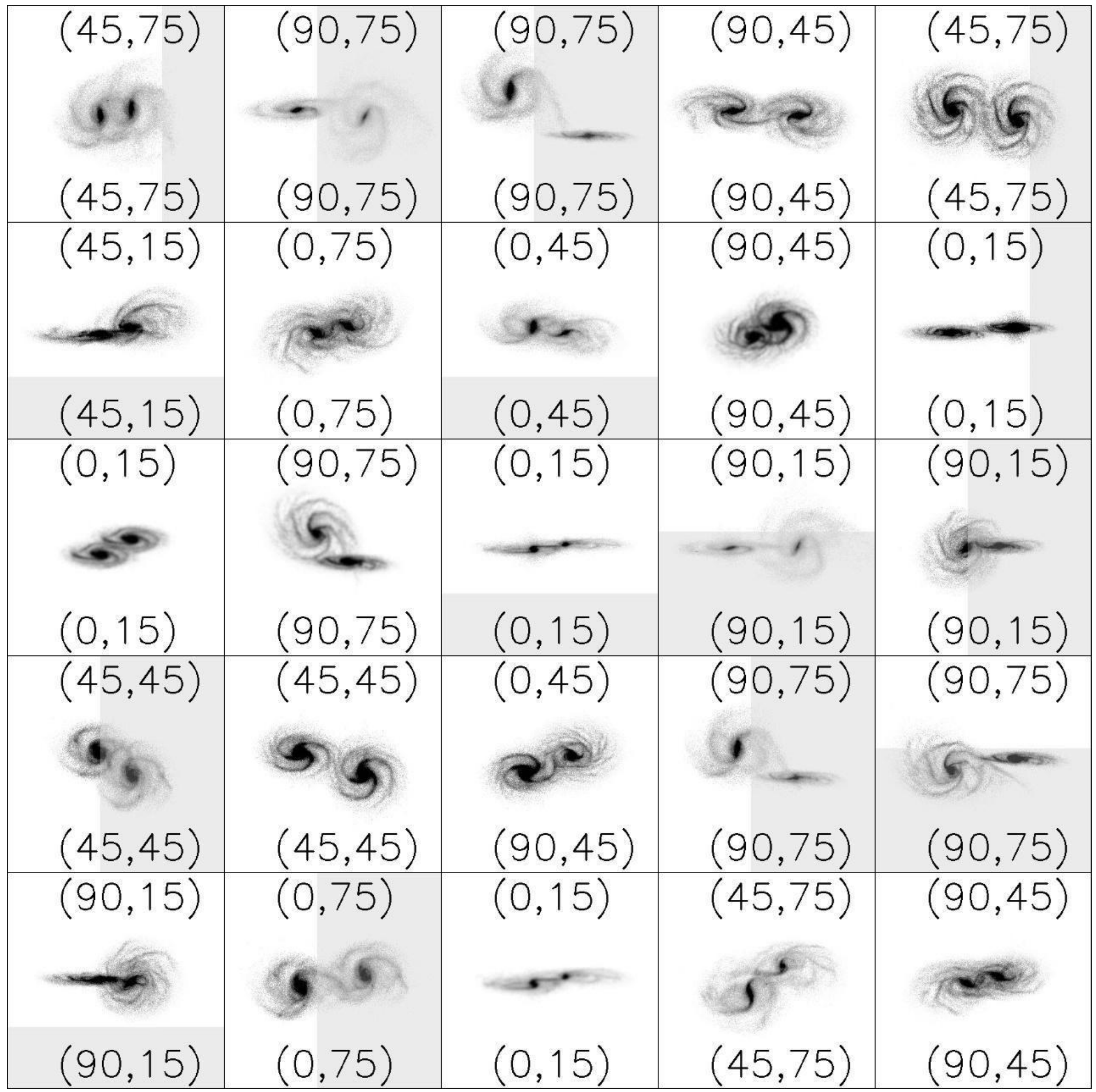
Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

Network Performance [after training]

A snapshot

Actual Label

Predicted Label

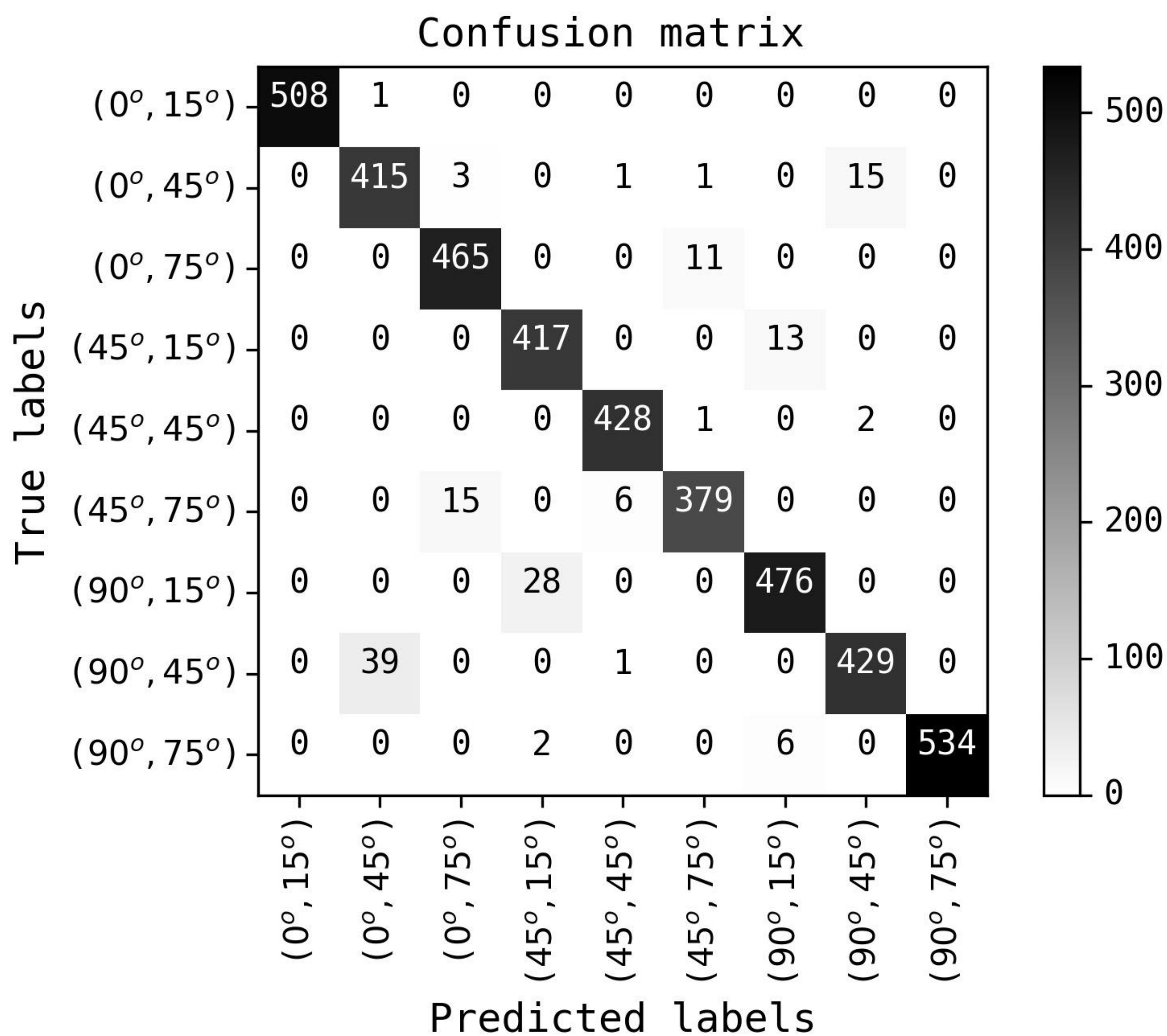


Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

Network Performance [after training]

(End-Semester Exam!)

Confusion Matrix



Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

Network Performance [after training]

Precision, Recall & F1 Measures

- **Precision = True Positive/Predicated Positive**

Precision is a good measure to determine, when the costs of False Positive is high. **[Eg. Positive: Spam Email]**

	Precision (%)	**Recall (%)**	**F_1-Score (%)**	**Total**
(0^o, 15^o)	1.00	1.00	1.00	509
(0^o, 45^o)	0.91	0.95	0.93	435
(0^o, 75^o)	0.96	0.98	0.97	476
(45^o, 15^o)	0.93	0.97	0.95	430
(45^o, 45^o)	0.98	0.99	0.99	431
(45^o, 75^o)	0.97	0.95	0.96	400
(90^o, 15^o)	0.96	0.94	0.95	504
(90^o, 45^o)	0.96	0.91	0.94	469
(90^o, 75^o)	1.00	0.99	0.99	542
Overall	0.97	0.97	0.97	4196

- **Recall = True Positive/Actual Positive**

a high cost associated with False Negative.
[Eg. Positive: Sick/Fraudulent Transaction]

- **F1 = Harmonic Mean of Precision and Recall**

[Eg. Class Imbalance]

https://towardsdatascience.com/accuracy-precision-recall-or-f1-331fb37c5cb9

Results

Feature Maps

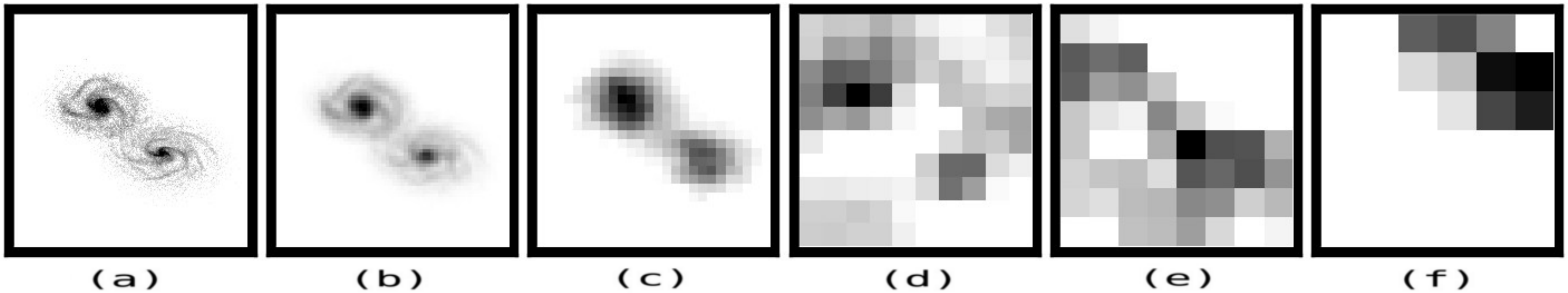
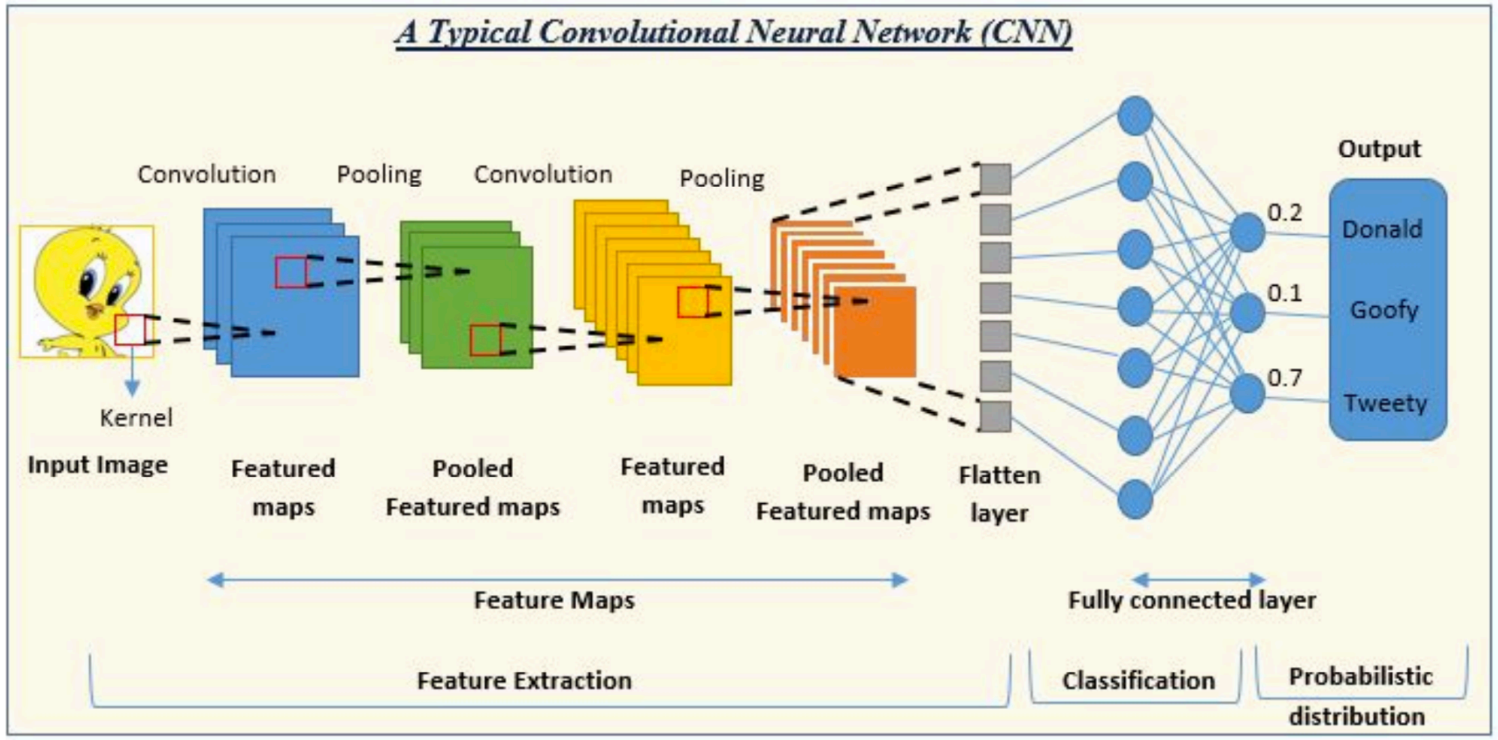


Figure 2. CNN automated feature extraction. (a) Input Image (b)-(f) Feature maps obtained for (a) using one kernel window from each of the five convolutional layers

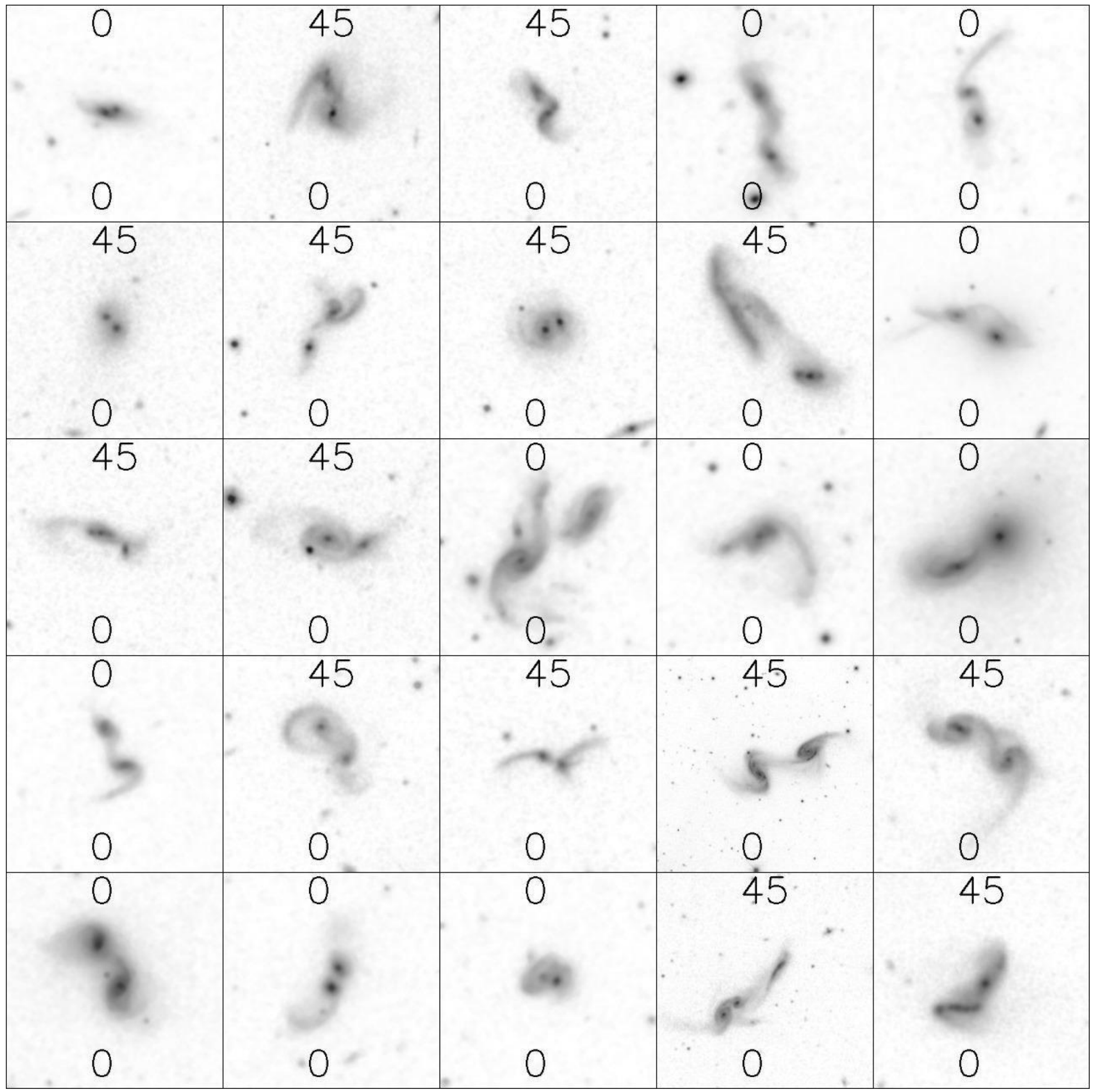
Prakash[1], Banerjee & Perepu 2020, MNRAS, 497, 3



Our DCNN as tested on SDSS data

Actual Label

Predicted Label



Prakash, Banerjee & Perepu 2020, MNRAS, 497, 3

Summary of Part 1

- Interacting galaxy pairs are the basic building blocks of a hierarchical universe and are also the primary drivers of dynamical evolution.

- We construct DCNN models to classify interacting galaxy pairs based on the value of two of their dynamical parameters: (1) relative inclination (2) viewing angle. For a 9-class classification, our DCNN model has an F1 score of 97%

- We tested our DCNN model on real data from Sloan Digital Sky Survey

- Our DCNN models could be extended to determine additional dynamical parameters, currently determined by trial and error method.

Part 2

Identification of Grand-design and Flocculent spirals from SDSS using deep convolutional neural network

Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

Motivation

Galactic Spiral Arms

An Overview

- Spiral galaxies: 30% of all massive galaxies

Lintott, C., Schawinski, K., Bamford, S., Slosar, A.,Land, K., Thomas, D., Edmondson, E., Masters, K.,Nichol, R. C., Raddick, M. J., Szalay, A., Andreescu,D., Murray, P., & Vandenberg, J. 2011, MNRAS, 410,166

- Non-axisymmetric feature: Angular momentum transport

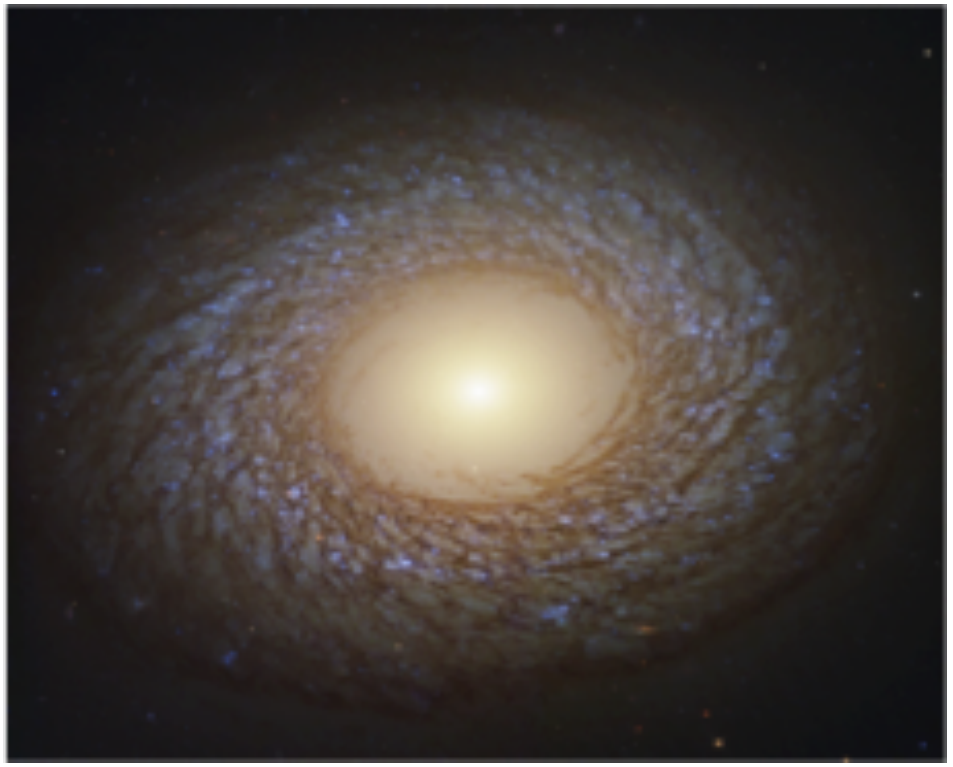
Binney, J. Tremaine, S. 1987, Galactic Dynamics. Princeton Univ. Press, Princeton, NJ

- Spiral arms are the primary sites of star formation

C. Dobbs, “Star formation in galaxies: the role of spiral arms,” inIAU Symposium, 2013, vol. 298.

Grand Design Spiral: M 51

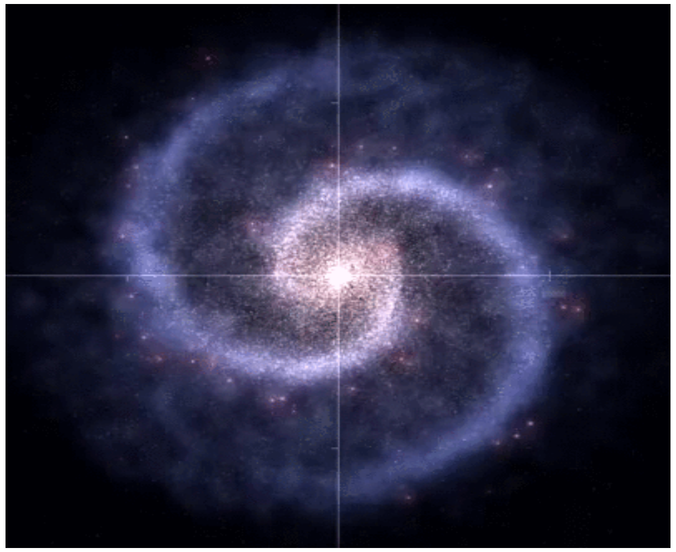
Flocculent Spiral: NGC 2775



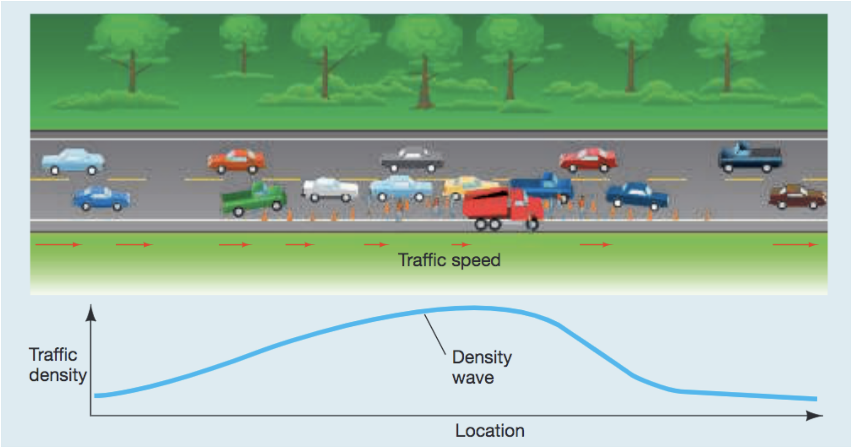
Credit: European Space Agency/Hubble/NASA.

Galactic Spiral Arms
Theories

Density wave theory



Credit : https://imgur.com/dtb8WrD



Credit : Eric Chaisson's Astronomy: A Beginner's guide

Galactic Spiral Arms

Open Questions

- Simulations fail to produce a stationary spiral pattern with a constant pattern speed

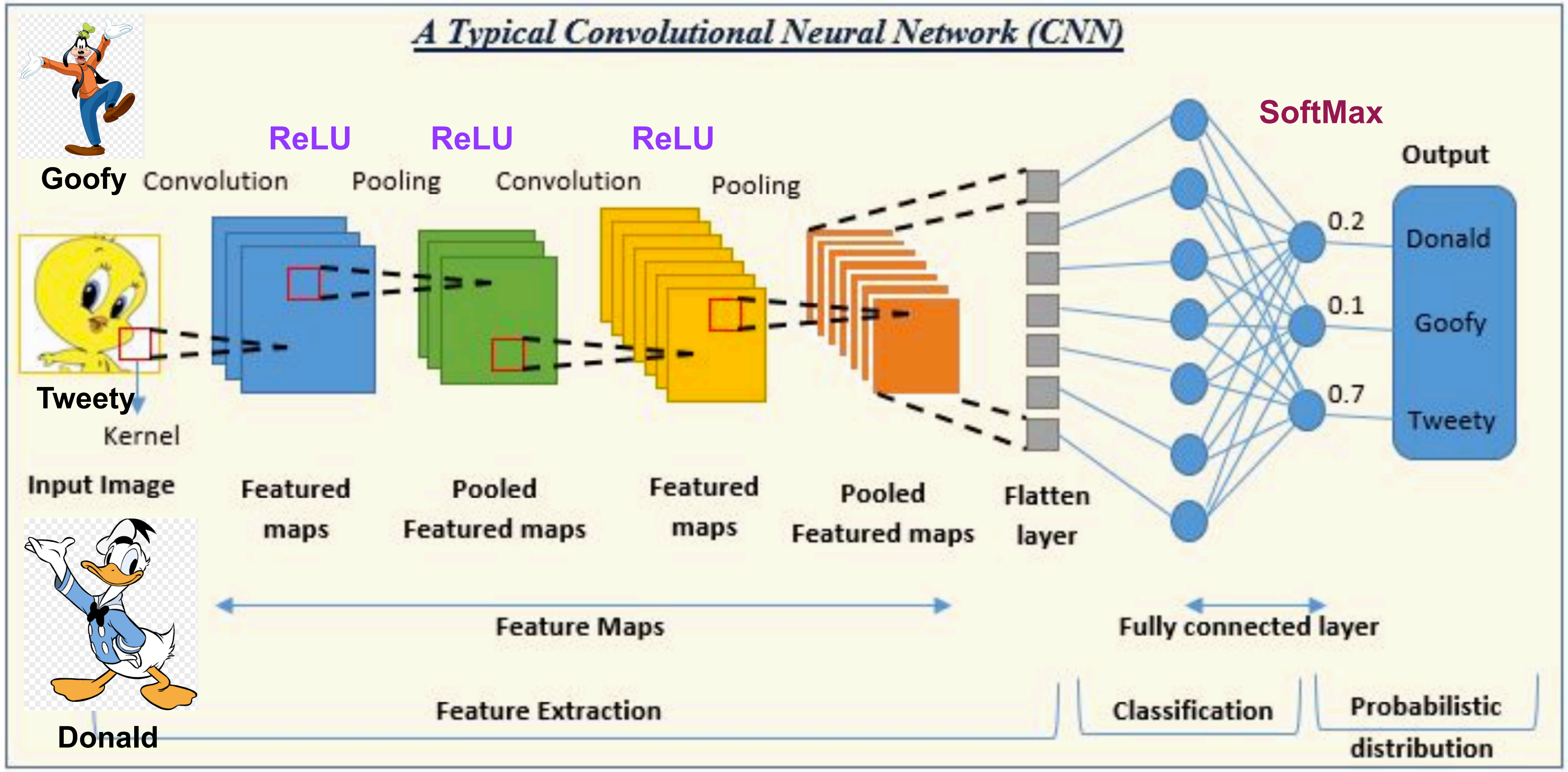
- Lack of theory-predicted correlation between the properties of bars and spiral arms in barred-spiral galaxies

- Inspite of the same atomic hydrogen content, Grand-designs are bluer than Flocculents

- Why do low surface brightness galaxies mostly host flocculent spiral arms?

Methodology

Deep Convolutional Neural Networks



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- Sharma, Kembhavi, Kembhavi, Sivarani, Abraham & Vaghmare 2020, MNRAS, 491, 2280

DCNN: AlexNet Architecture for Classification

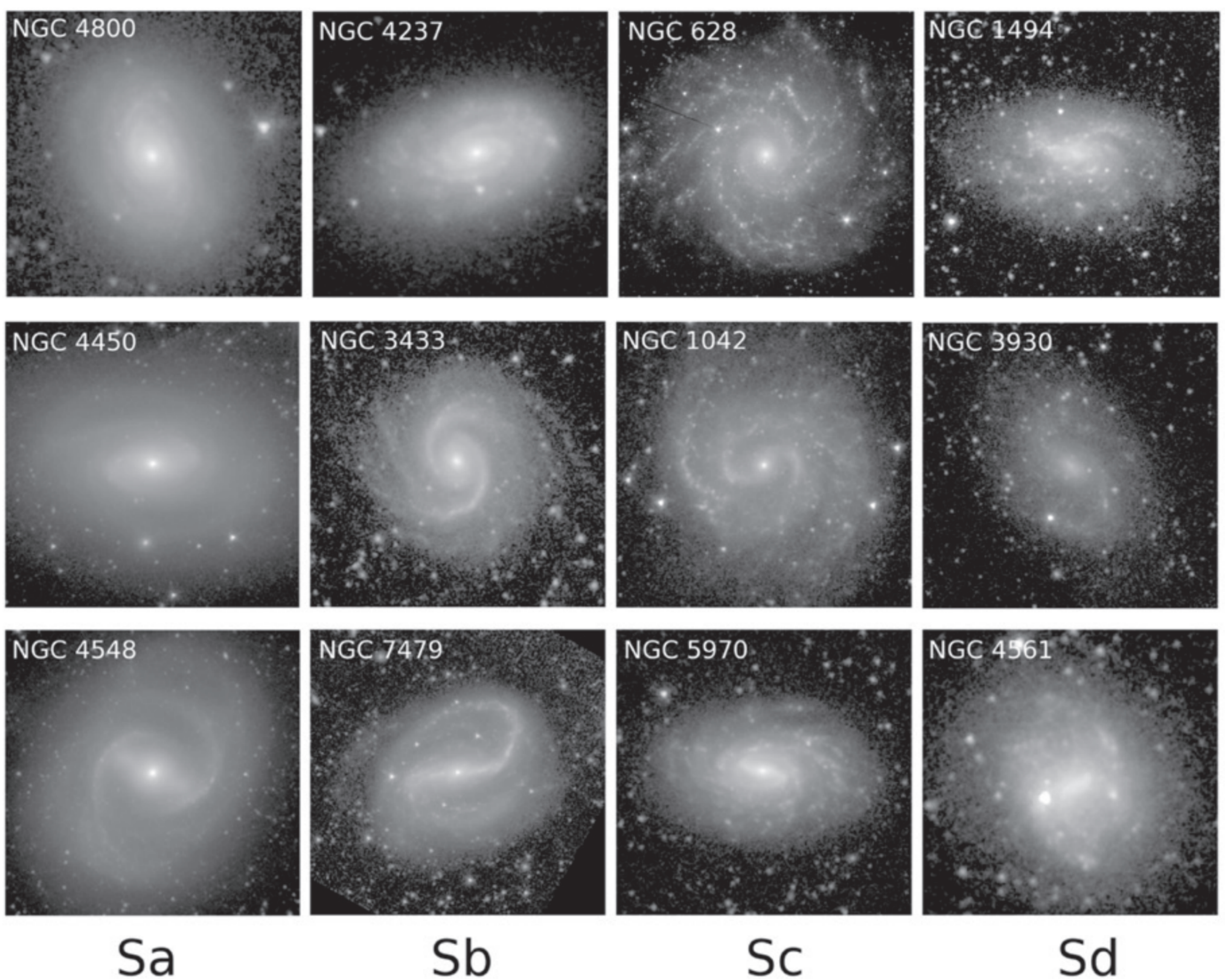
Layer number	Layer type	No. of Kernels/Pooling windows	Kernel/ Pooling window size	Parameters
1	Convolutional	96	11 x 11	34944
2	Pooling	96	3 x 3	34944
3	Convolutional	256	5 x 5	614656
4	Pooling	256	3 x 3	614656
5	Convolutional	384	3 x 3	885120
6	Convolutional	384	3 x 3	1327488
7	Convolutional	256	3 x 3	884992
8	Pooling	256	3 x 3	884992
9	Fully Connected	4096	NA	4198400
10	Fully Connected	4096	NA	16781312
11	Fully Connected	4096 x 2	NA	8194
12	Softmax	2/3/9 (based on number of classes)		

Training Data Set: Buta et al. (2015)

The Astrophysical Journal Supplement Series, 217:32 (46pp), 2015 April doi:10.1088/0067-0049/217/2/32

A CLASSICAL MORPHOLOGICAL ANALYSIS OF GALAXIES IN THE *SPITZER* SURVEY OF STELLAR STRUCTURE IN GALAXIES (S^4G)

Ronald J. Buta[1], Kartik Sheth[2], E. Athanassoula[3], A. Bosma[3], Johan H. Knapen[4,5], Eija Laurikainen[6,7], Heikki Salo[6], Debra Elmegreen[8], Luis C. Ho[9,10,11], Dennis Zaritsky[12], Helene Courtois[13,14], Joannah L. Hinz[12], Juan-Carlos Muñoz-Mateos[2,15], Taehyun Kim[2,15,16], Michael W. Regan[17], Dimitri A. Gadotti[15], Armando Gil de Paz[18], Jarkko Laine[6], Karín Menéndez-Delmestre[19], Sébastien Comerón[6,7], Santiago Erroz Ferrer[4,5], Mark Seibert[20], Trisha Mizusawa[2,21], Benne Holwerda[22], and Barry F. Madore[20]



Buta et al. (2015):

- Grand-designs: 201
- Flocculents: 553

After cross-matching with SDSS DR17:

- Grand-designs: 123
- Flocculents: 321

Final Sample:

- Grand-designs: 90
- Flocculents: 270

York et al. 2000

Network design details

- Loss Function: Binary Cross Entropy
- Learning Rate: 5×10^{-5}
- Decay Rate: 2×10^{-4}
  - No. of epochs: 100 [saturates at 60]
  - Steps per epoch: NA
  - Rejection threshold: NA
  - Time taken to run 1 epoch: 1 hour

[Intel(R) Corei7-7700 processor with 3.60 GHz Frequency and 16GB RAM]

Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

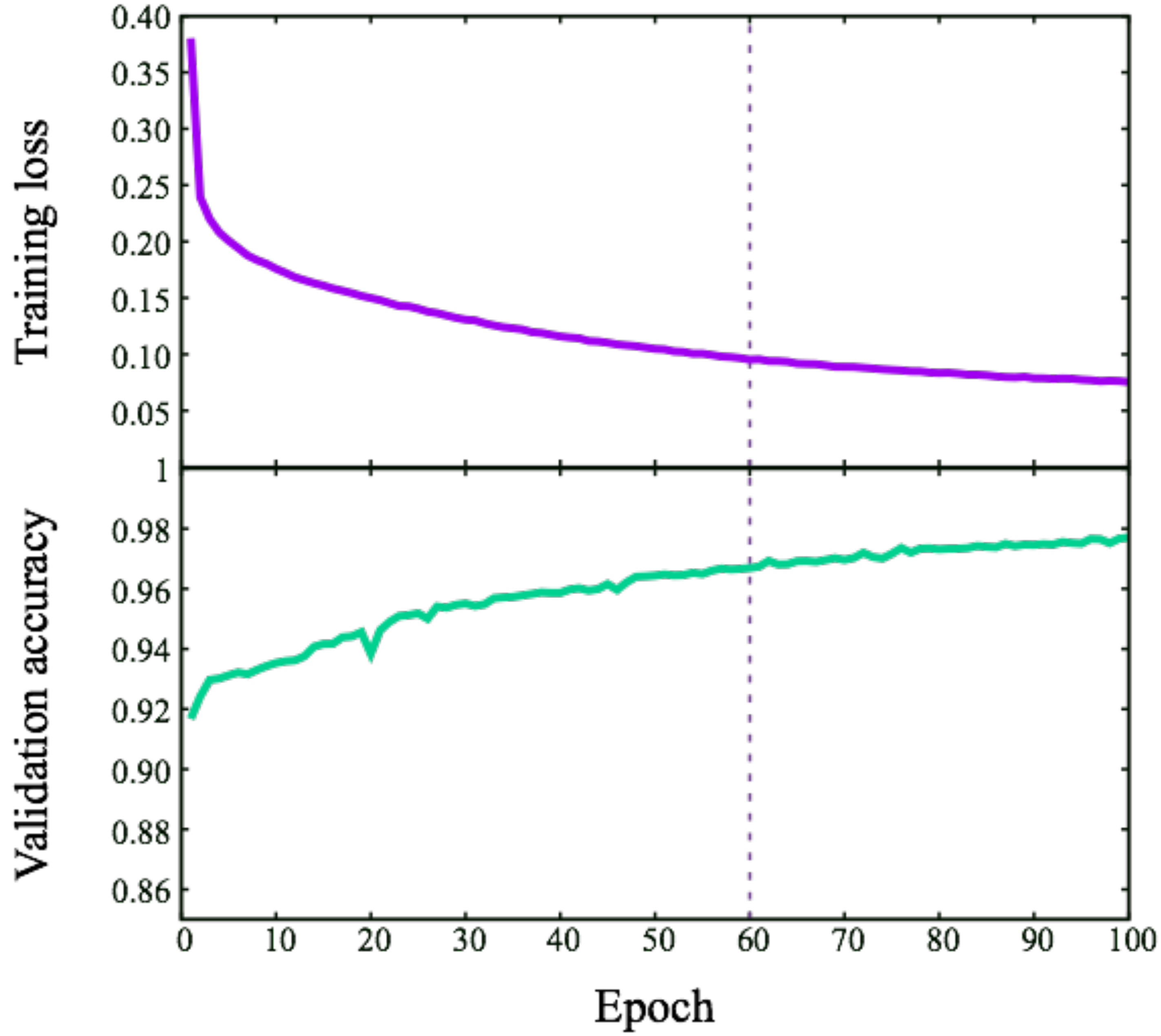
Network Performance [while training]

(Class Test!)

Learning Curves

Training Accuracy

= Number of correct predictions by the total number of predictions

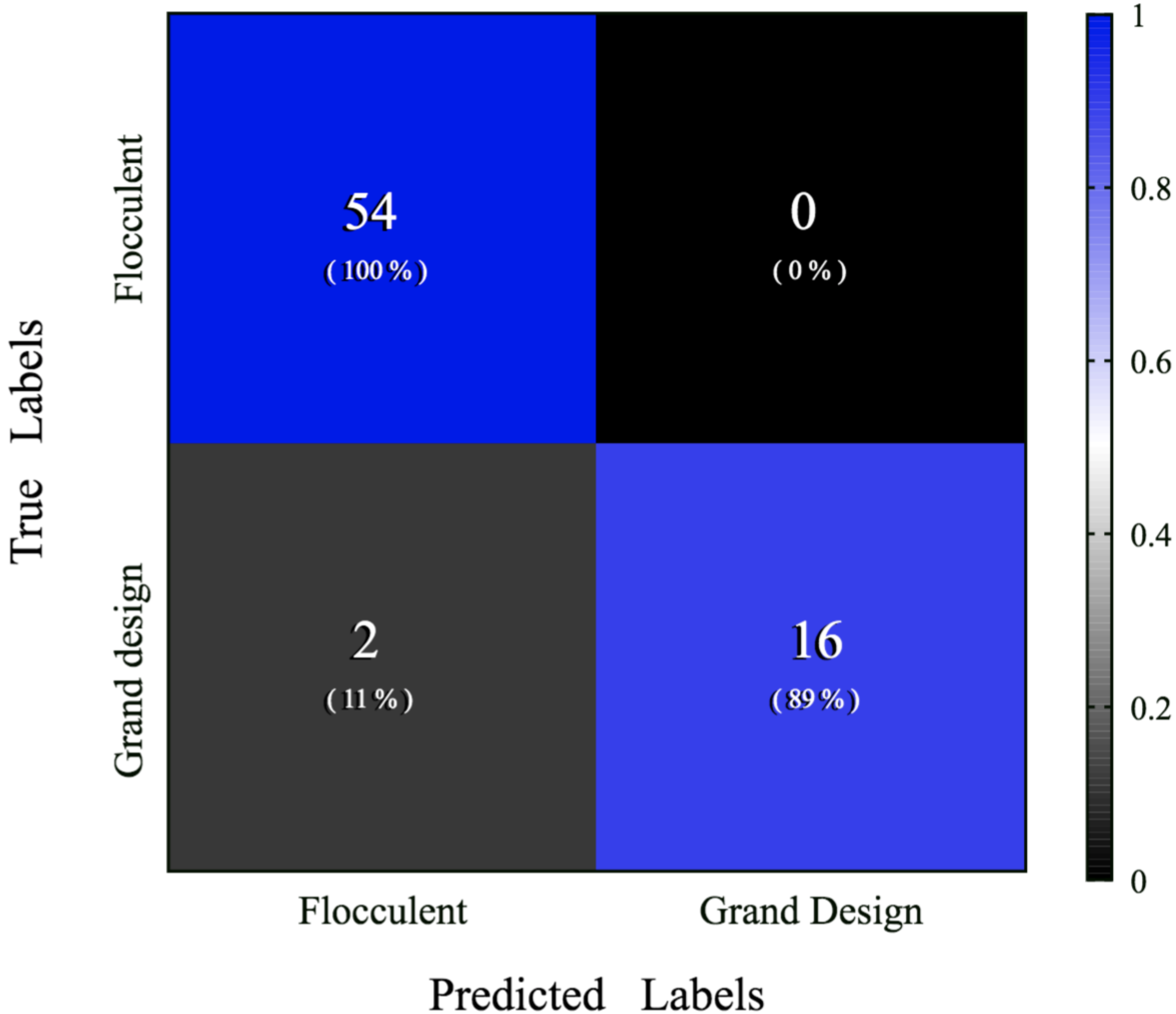


Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

Network Performance [after training]

(End-Semester Exam!)

Confusion Matrix



Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

Network Performance [after training]

Precision, Recall & F1 Measures

- **Precision = True Positive/Predicated Positive**

Precision is a good measure to determine, when the costs of False Positive is high. **[Eg. Positive: Spam Email]**

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a high cost associated with False Negative.
[Eg. Positive: Sick/Fraudulent Transaction]

- **F1 = Harmonic Mean of Precision and Recall**

[Eg. Class Imbalance]

Prediction accuracy for the testing set from our CNN model

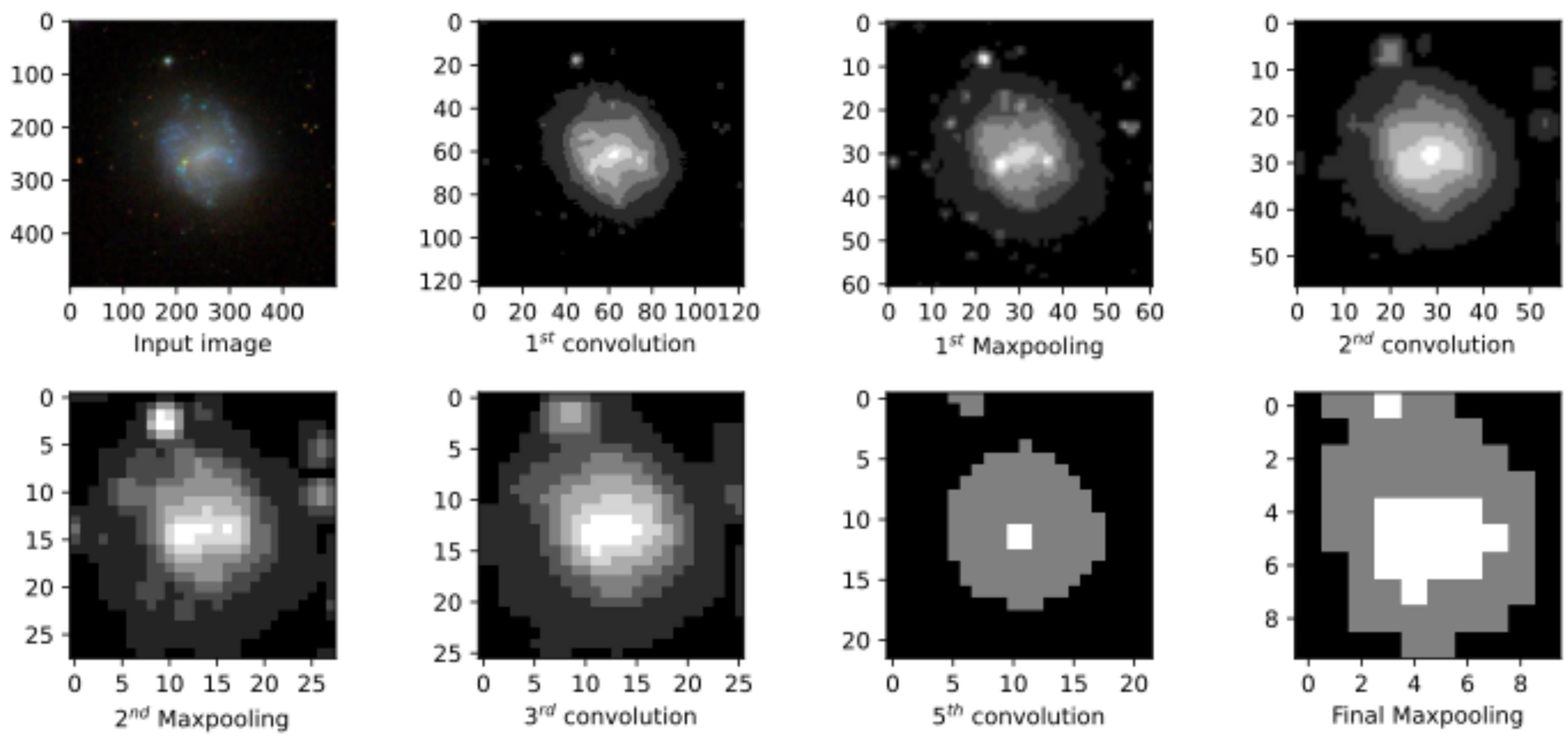
	True labels	Predicted as Flocculent	Predicted as Grand-design	Precision	Recall	f_1-score
Flocculent	54	54	0	0.96	1.00	0.98
Grand-design	18	2	16	1.00	0.89	0.94
Accuracy			**97.22 %**			

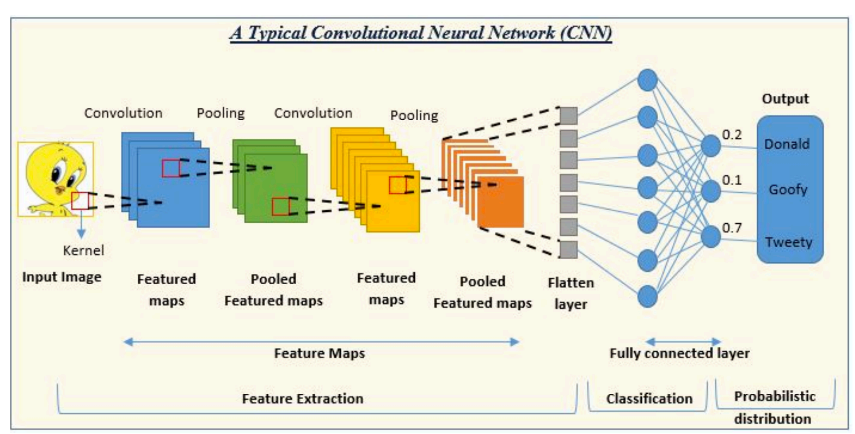
Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

New Results

Feature Maps

NGC4561: Flocculent

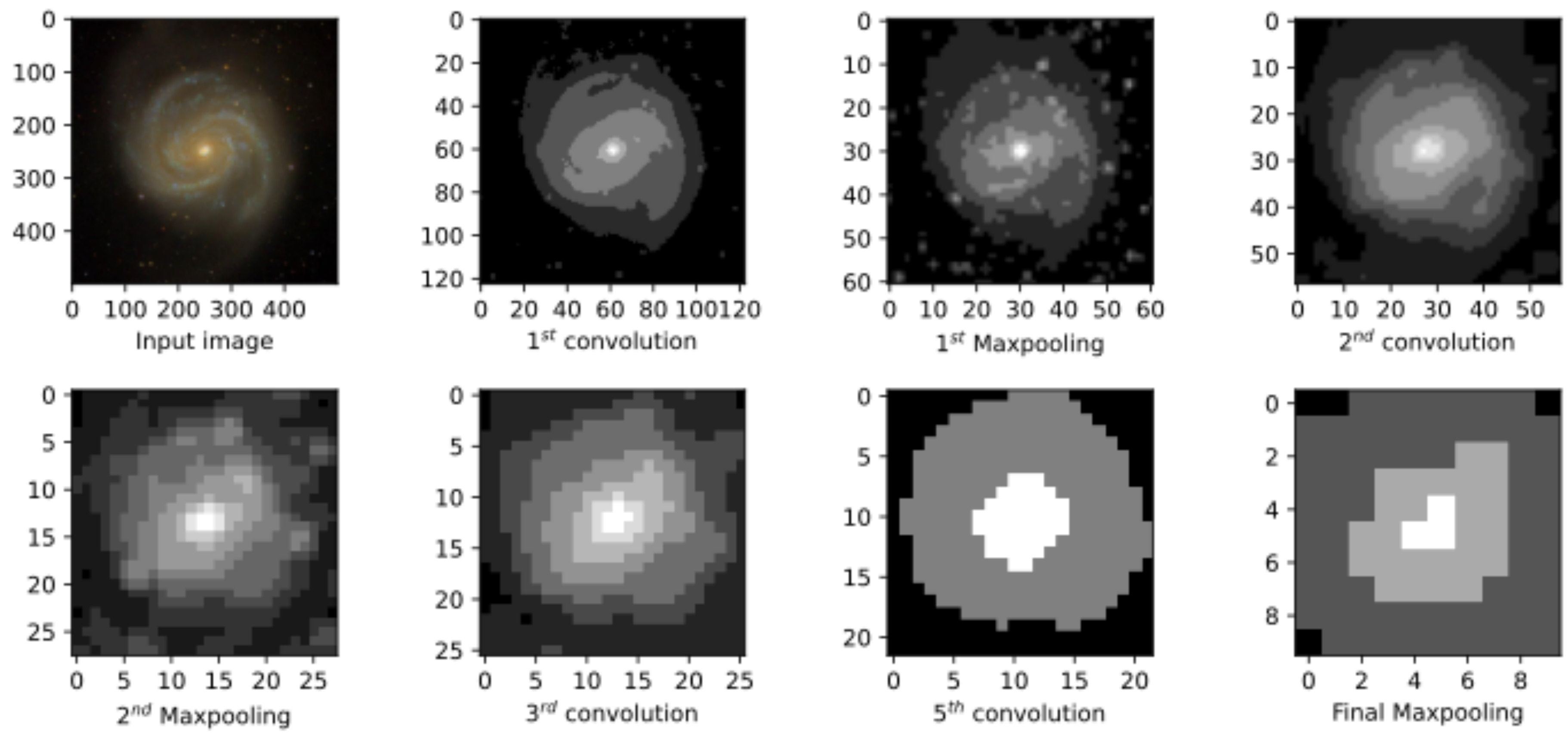


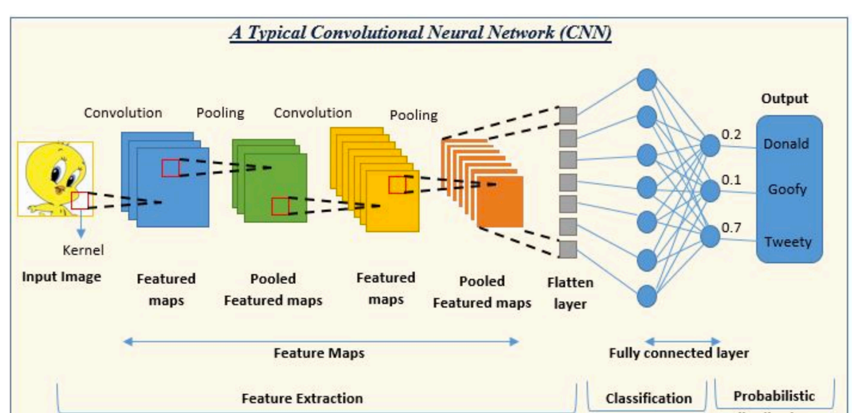


Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

New Results
Feature Maps

NGC 4321: Grand-design





Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

New Results
New Classifications

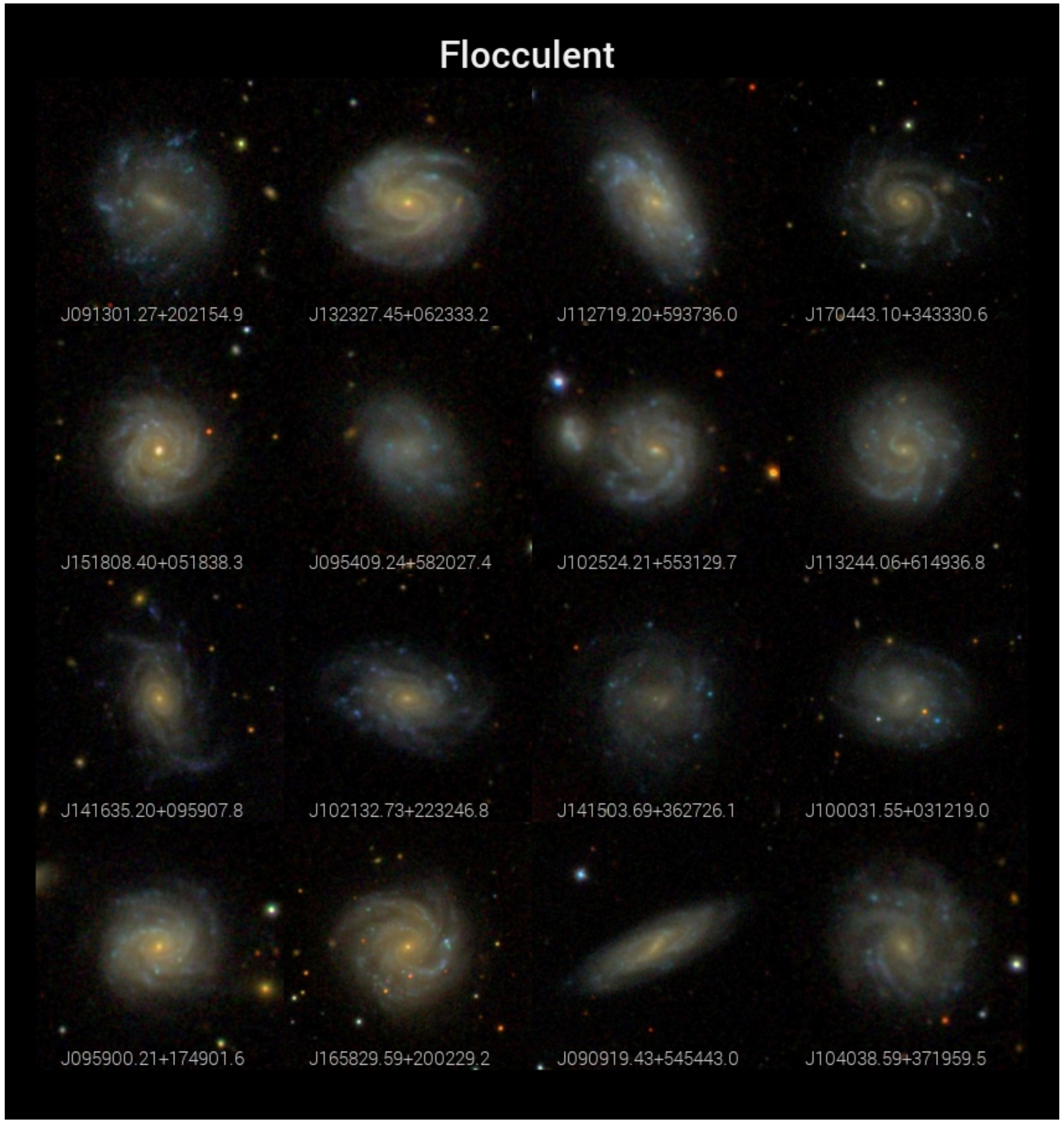
Willett et al. 2013

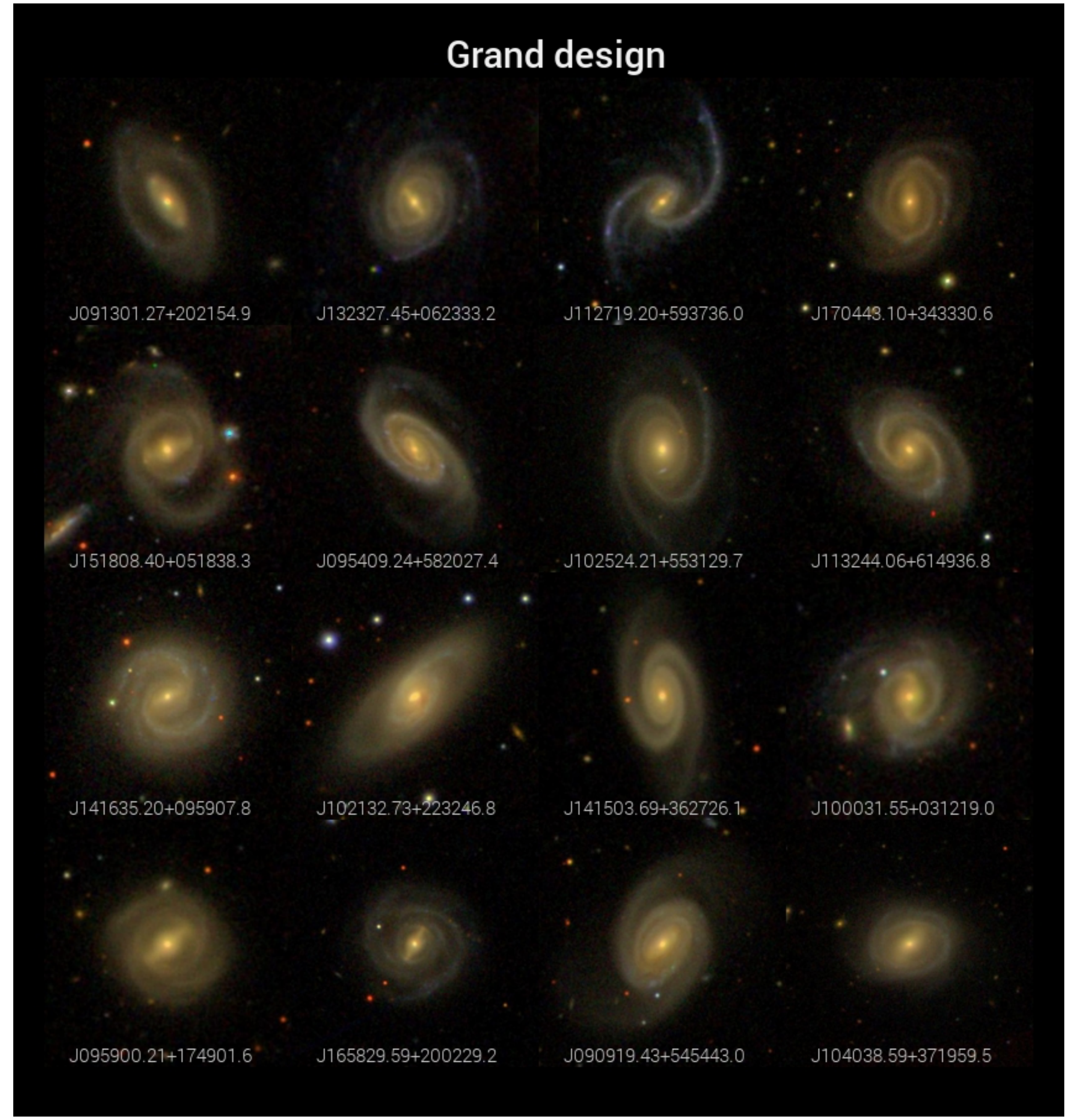
1354 spiral galaxies
(unclassified!)

York et al. 2000

New Results

New Classifications





New Classifications: Flocculents ~500 and Grand-designs ~700

Sarkar, Narayanan, Banerjee & Prakash 2023, MNRAS, 518, 1022

Summary of Part 2

- Galactic spiral arms play a crucial role in angular momentum transfer and hence drive the secular evolution of galaxies

- We developed a DCNN model to classify spiral galaxies into Grand-designs and Flocculents with more than 90% accuracy.

- Using this trained DCNN, we carried out 1200 new classifications from SDSS: Grand-designs ~700 and Flocculents ~500

- DCNN models could also be trained to classify spiral galaxies into other morphological types (For example, **Identifying lopsidedness in galaxies using a Deep Convolutional Neural Network** by **Biju Saha** at **3.30 P.M today**)

Thank you!