DETECTION OF LSB GALAXIES

Using A Compact Convolutional Neural Network

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Motivation & Methods

- Detection of LSBGs (Low Surface Brightness Galaxies), UDGs (Ultra Diffuse Galaxies), and distant galaxies that are strongly dimmed due to Tolman effect
- New deep sky surveys like LSST and Euclid promise increased discovery of LSBGs
- Vast volume of available data poses a challenge for conventional source detection methods
- Machine learning can improve accuracy or efficiency of LSBG detection
- Convolutional Neural Networks (CCNs) can be used to improve established pipelines
- Use of efficient/small architectures with depthwise-separable convolution (DSC) and small number of layers (compact CNN)
- Our method:
  Apply a cCNN to filter detection results from Source Extractor in Python

Search for LSBGs

- Download *g*, *r*, *i* fits for one HSC-SSP tract
- Inverse-variance-weighted stacking of the different bands
- Source Extractor in Python [2] search in the image with low threshold
- Parameters: Threshold = 1.1, minarea= 10, mincont = 0.001
- CNN is used to filter the resulting catalog for LSBG candidates (2412 Objects)
- Automated photometry with Photutils
- Filtering by size and surface brightness (22 Objects remain)
- Visual inspection of Objects (15 Objects remain)
- Checking for Objects in NED (6 Objects not in NED)

Low Surface Brightness Galaxies

- **Properties: Effective surface brightness $\mu_{eff} \geq 24.3\ mag\ arcsec^{-2}$ [5]**
- **HSC 5σ $depth\ (g)$: 26.5 mag [1]**

CNN Structure

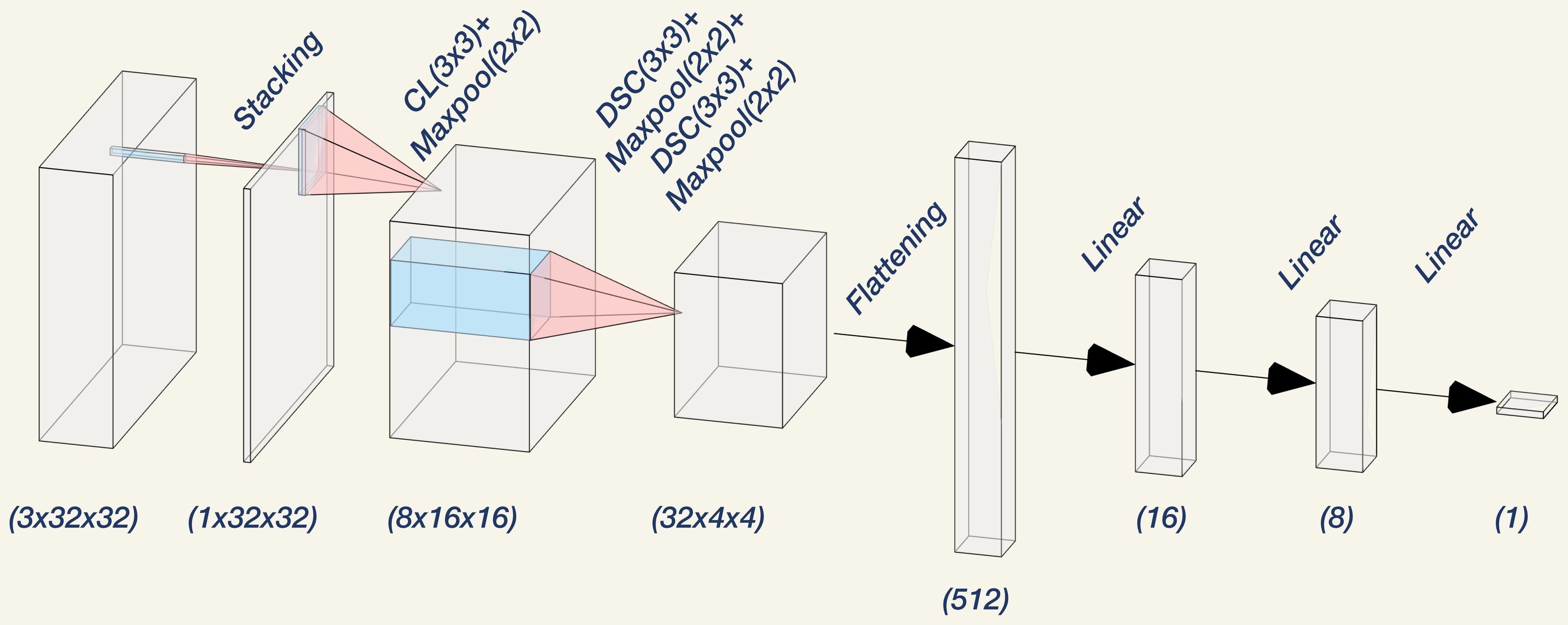


Fig 1. Final CNN using depth-wise separable convolution

Positive dataset

- 779 LSBGs from Greco et al. [5]

Negative dataset

- Objects from Morishita [6]
- Noise cutouts from Morishita [6]

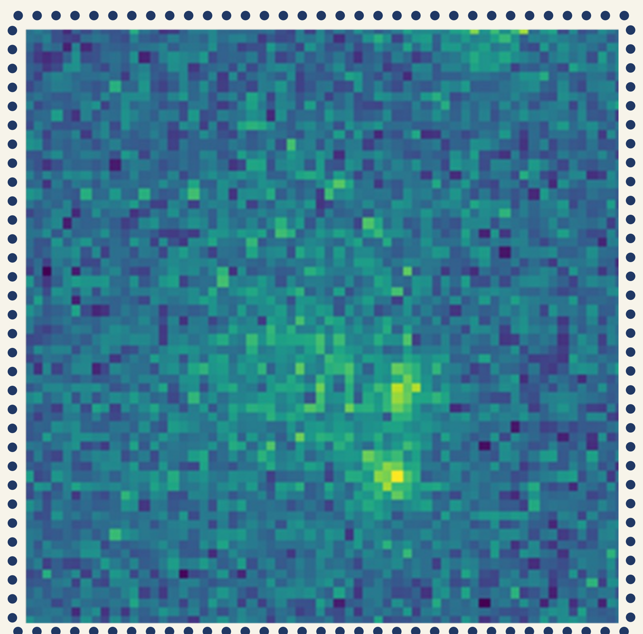
Training/Validation

- The data was divided into 3 splits:
  - Training dataset (70%)
  - Validation dataset (15%)
  - Test dataset (15%)
- Augmentation of the training data through transforms (rotating, flipping, inverting)
- Weight decay and early stopping were used for regularization
- Hyperparameters optimized
- Pos. Weight was calculated to alleviate the influence of class imbalance
- Optimizer: AdamW
- Start Learning Rate η = 1e-3
- Normalized Weight Decay λ = 2.537e-3
- Training was done for 100 epochs with a validation pass after every epoch
- the model with the best F1 score on the validation set was saved as final model

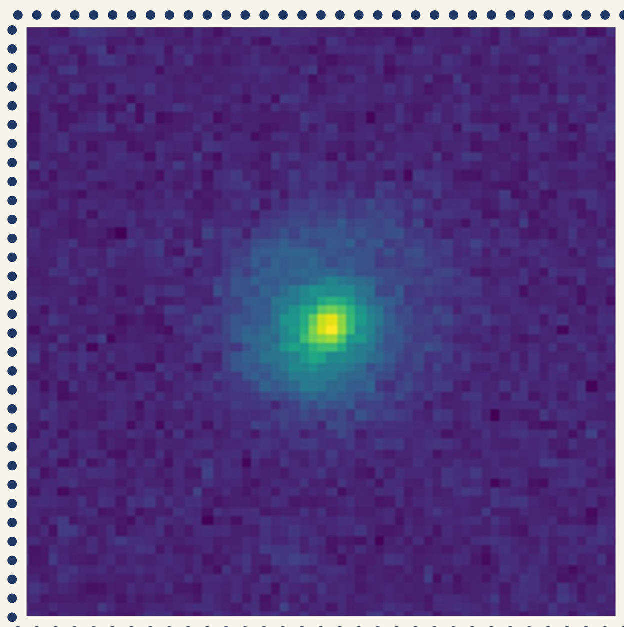
Testing

Metric	Result
TP	117
FN	0
FP	13
TN	1448
F1	94.74 %
MCC	94.45 %

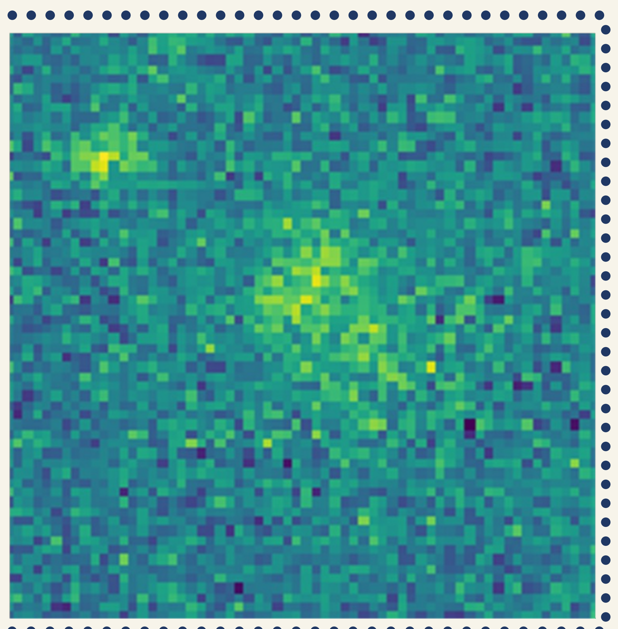
A few interesting objects (g-band)



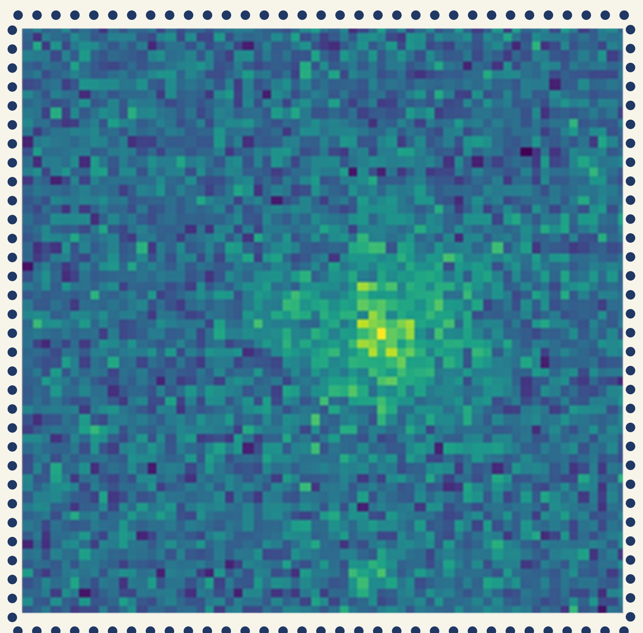
- $\mu_{eff} = 24.8\ mag\ arcsec^{-2}$
- $n \approx 0.5$
- $r_{eff} = 3.0\ arcsec$



- $\mu_{eff} = 24.4\ mag\ arcsec^{-2}$
- $n \approx 0.5$
- $r_{eff} = 3.5\ arcsec$

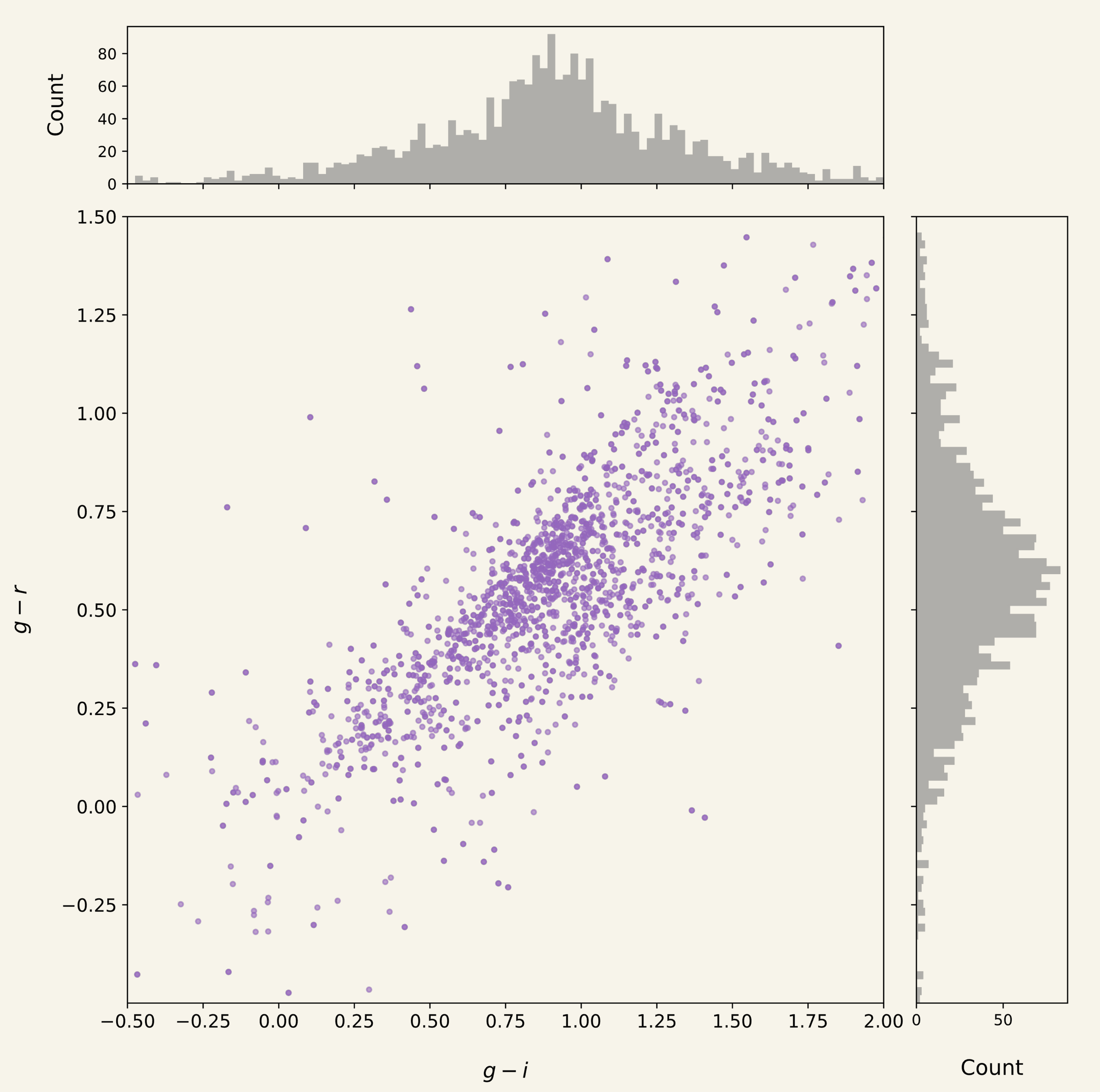


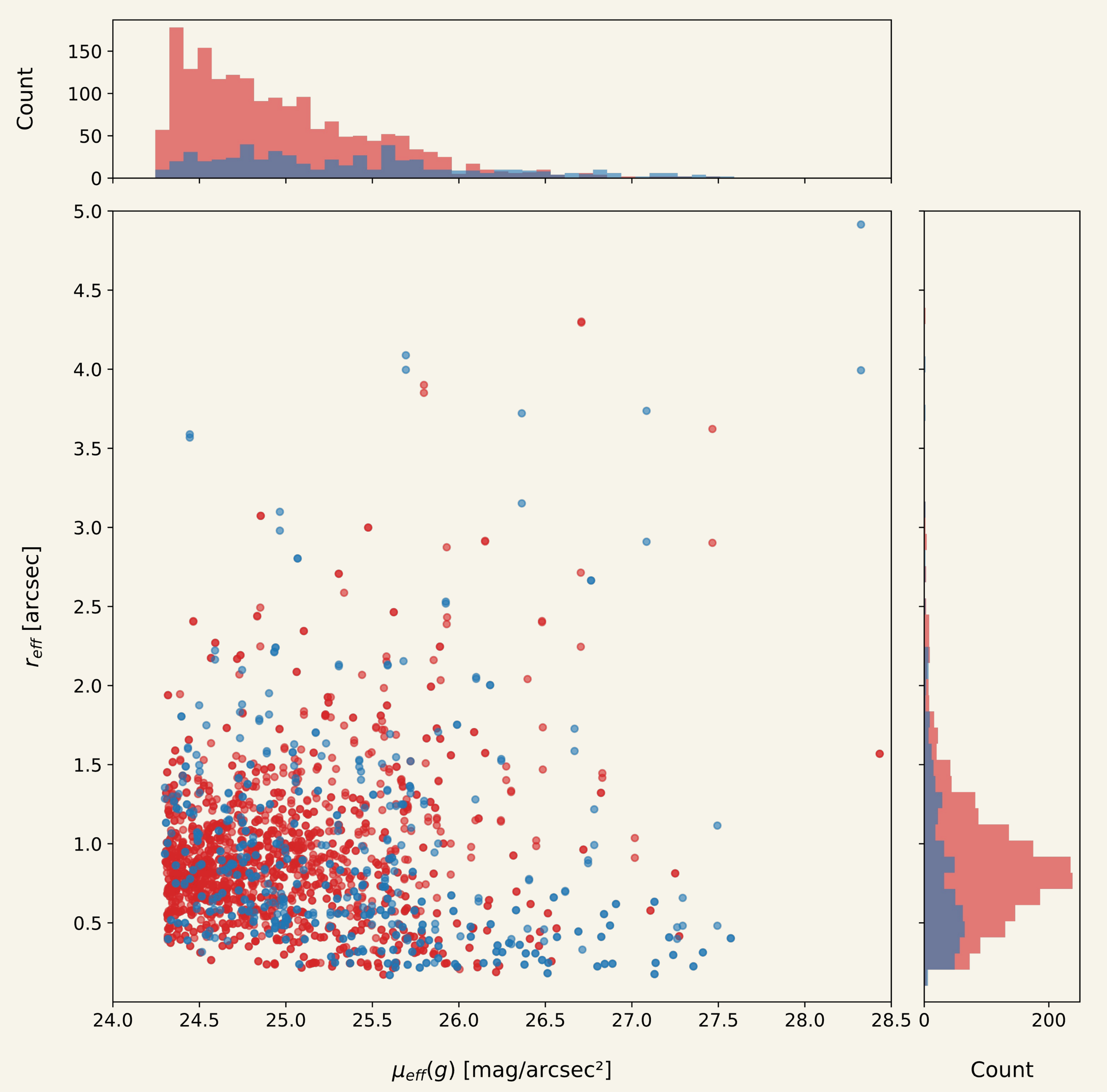
- $\mu_{eff} = 25.3\ mag\ arcsec^{-2}$
- $n \approx 0.5$
- $r_{eff} = 2.7\ arcsec$



- $\mu_{eff} = 26.7\ mag\ arcsec^{-2}$
- $n \approx 0.5$
- $r_{eff} = 4.3\ arcsec$

Distributions of all objects





References

[1] Aihara et al. 2022 PASJ 74 247-272 (10.1093/pasj/psab122)
[2] Barbary et al. 2016 JOSS 1 58 (10.21105/joss.00058)
[3] Bertin et al. 1996 A&AS 117 393-404 (10.1051/aas:1996164)
[4] Bradley et al. 2025 Zenodo (10.5281/zenodo.14889440)
[5] Greco et al. 2018 ApJ 857 104 (10.3847/1538-4357/aab842)
[6] Morishita et al. 2021 ApJS 253 4 (10.3847/1538-4365/abce67)
[7] Tanoglidis et al. 2021 ApJS 252 18 (10.3847/1538-4365/abc420)