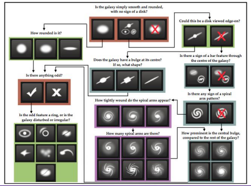
End-to-End Soft-Target Galaxy Image Classification Using CNN-FCNs Architectures in the Galaxy Zoo Dataset

Classifying galaxies is a fundamental problem in astrophysics. Manual classification is slow and limited by human bias. We leverage deep learning - specifically Convolutional Neural Networks (CNNs), to automate and improve galaxy classification. By modeling the probability distributions over 37 answer categories for Galaxy Zoo questions, our approach supports insights into galaxy morphology, formation, and evolution.

Dataset: We use the Galaxy Zoo dataset, designed for automated galaxy morphology classification using supervised learning.

- **Training Set (1GB)**
  - • 61,578 galaxy images (424×424 RGB JPGs)
  - • Each image is labeled with a **37-dimensional probability vector** derived from aggregated human classifications
  - • Labels encode responses to morphological questions (e.g., spiral arms, bulge, bar)
- **Test Set (0.8GB)**
  - • 79,975 unlabeled galaxy images (424×424 RGB)
  - • Model predictions must output a **37-class probability distribution** for each image
- **Benchmarks Provided**
  - • **All-Ones / All-Zeros**: Naive baselines with uniform label outputs
  - • **Central Pixel Benchmark**: Uses k-means clustering on the central pixel color to assign label priors from visually similar training galaxies.

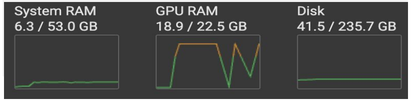


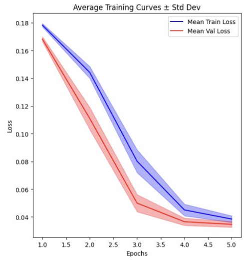
Methodology

1. Normalize images and augment training set (rotations, zoom, flipping).
2. Pass input through deep CNN feature extractor.
3. ~~Apply custom FCN head to produce 37 probability scores grouped into 11 softmaxed questions.~~ Assume MSE loss and sigmoid outputs.
4. Minimize RMSE between predicted and ground truth soft labels.
5. Evaluate per-question accuracy and aggregate performance.
6. Optuna evaluates the results and tweaks the hyperparameters and trains everything again.

Setup

Training was conducted across multiple platforms: from a local M1 MacBook to Google Colab's T4 GPU, then to the HYAK cluster, and finally on Colab Pro's L4 GPU for optimized compute performance. The modeling pipeline followed an iterative refinement process: starting with VGG11, then VGG16, followed by ResNet50, and ultimately a custom 7-block VGG-inspired CNN tailored for the task.





Findings

The custom VGG-inspired 7-block model outperformed deeper architectures like ResNet50 or VGG 16, achieving sub-0.079 RMSE with fewer parameters and lower overfitting risk. Built with stacked 3×3 convolutions, ReLU, max pooling, batch normalization and dropout, it balanced depth and regularization effectively.

Its simplicity enabled faster convergence and more stable training on limited hardware, while also allowing more efficient hyperparameter tuning. In contrast, VGG16+ (or custom prediction heads instead of sigmoid) required more aggressive regularization and was less robust under constrained compute resources.

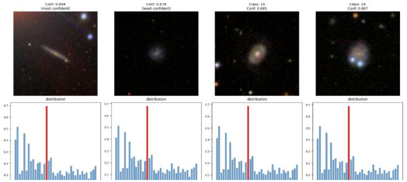
Simplicity Performed Better Than Complexity!

Goal

The primary objective was to outperform the winning RMSE (~0.079) achieved by Sander Dieleman on the Galaxy Zoo v2 dataset. This benchmark set a high standard for galaxy morphology prediction using deep learning, motivating a fresh approach combining architectural experimentation and iterative refinement.

Summary

An iterative deep learning approach using progressively more complex architectures allowed for improved galaxy morphology predictions. Leveraging varied compute resources and continuous model tuning was critical in achieving competitive performance and surpassing the central pixel baseline.



References

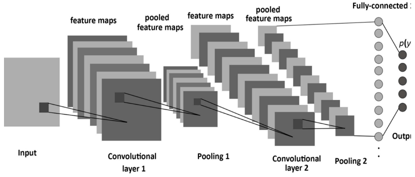
1. Willett, K. W., Lintott, C. J., Bamford, S. P., Masters, K. L., Simmons, B. D., Casteels, K. R. V., ... & Thomas, D. (2013). Galaxy Zoo 2: Detailed morphological classifications for 304,122 galaxies from the Sloan Digital Sky Survey. *Monthly Notices of the Royal Astronomical Society, 435*(4), 2835–2860. https://arxiv.org/pdf/1308.3496
2. Dieleman, S., Willett, K. W., & Dambre, J. (2015). Rotation-invariant convolutional neural networks for galaxy morphology prediction. Monthly Notices of the Royal Astronomical Society, 450(2), 1441–1459.
3. Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556.

Motivation

- Manual labeling of galaxies is bottlenecked by scale and subjectivity.
- Understanding galactic morphologies enables testing of cosmological models.
- Deep learning offers a scalable, reproducible alternative to human classification with high fidelity.

Model Architecture

Base Model: VGG style model with batch normalization
Modifications:
Custom fully connected tail
Sigmoid-activated output layer
RMSE loss over all 37 output dimensions
Alternative: Pretrained ResNet-50 fintuned with lora + custom FCN
Optimizer: Adam
Dataloader: per batch load & memory cleanup + probabilistic augmentation
Tuning: Optuna-based hyperparameter search



Trained through cross validation, partial precision, JIT, scheduler LR, custom data loader.

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