Classifying Galaxy Morphologies Using Bayesian Neural Networks for LSST

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Code Repo:

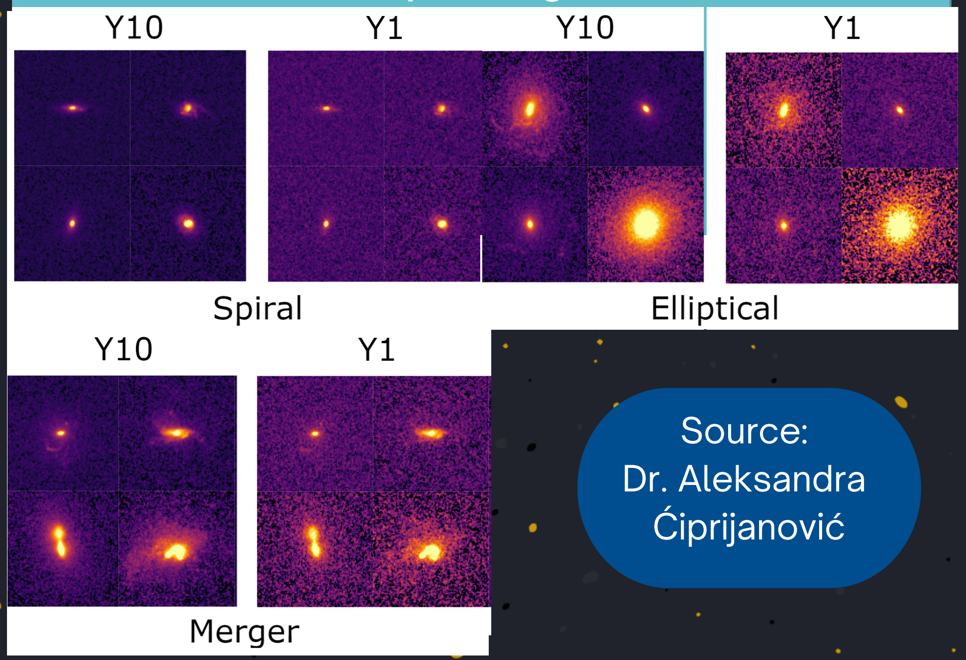
Introduction

Improving extraction and analysis techniques for big datasets is becoming increasingly necessary for astronomy. Many new observatories will come online over the next decade, generating massive and complex data, requiring creative and dependable methods for data storage and discovery.

This is critical to answering fundamental questions, especially in cosmology. We hope to uncover information about objects in the early universe, including galaxies, and determine their "morphologies", or structural formations, and understand how they have evolved over time

As part of the effort to prepare for these observations, we introduce a Deep Learning model for galaxy classification for simulated data for the upcoming Legacy Survey of Space and Time (LSST), which utilizes Bayesian Neural Networks (BNNs) to distinguish spiral, elliptical, and merging galaxies with quantified prediction confidences.

Example Images:



Source:
Dr. Aleksandra Ćiprijanović

Problem Definition

For 2 sets of images, both noisy and pristine, can we identify if the galaxy pictured is a spiral, elliptical, or merger with high accuracy? Can we improve the accuracy of the model by making use of techniques like Transfer Learning?

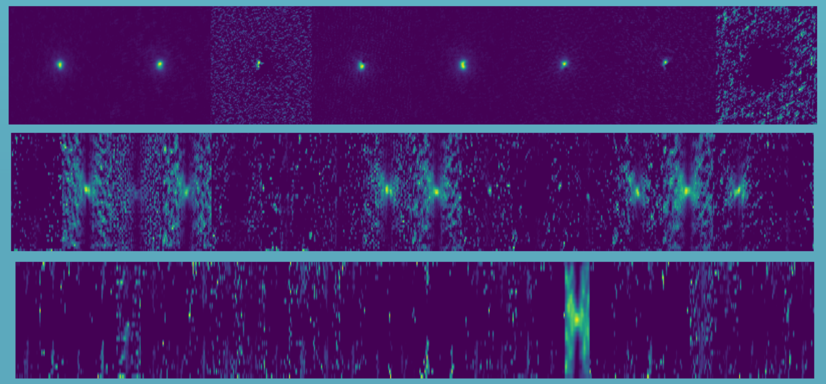
This project makes use of BNNs to obtain quantified uncertainties in the model's predictions when performing galaxy classification- which has not been done to date!

Related Work

Convolutional Neural Networks have been increasingly used for classifying galaxies, such as those with low surface brightness [3], galaxy mergers [4], and galaxy morphologies [2], with Barchi et al. 2019 being the first to compare Deep Learning & traditional ML methods for galaxy classification [1].

DeepMerge [4] is most closely related to this project, with the same data and a similar network architecture used as a starting point for model testing; however, this was used for binary classification to determine if an image was of a galaxy merger or not. This model achieved a classification accuracy of 76% for pristine, non-noisy images, and 79% for noisy images.

Feature Maps for Model 1



Proposed Methods

Standard deterministic Convolutional Neural Network was developed first to use as a baseline model. Methods used to try to prevent overfitting:

- Batch Normalization
- Dropout
- L2 regularization for kernel regularizers
- Early Stopping ModelCheckpoint, and ReduceLCOnPlateau callbacks

Loss function: Categorical Cross-Entropy
Activation function: Softmax

Improve accuracy:

- Image Augmentation
- Transfer Learning

A probabilistic model was then created from this to obtain the aleatoric uncertainty and visualize the prediction probabilities using the Negative Log-likelihood loss function

Finally, a Bayesian Neural Network model was created to obtain the epistemic uncertainty. This was done by:

- Changing regular convolutional layers to convolutional reparameterization layers
- Changing dense layers to dense variational layers.

Challenges:

- Computational power & RAM crashing
- M1 Mac TensorFlow package issues
- Kaggle TPU's issues

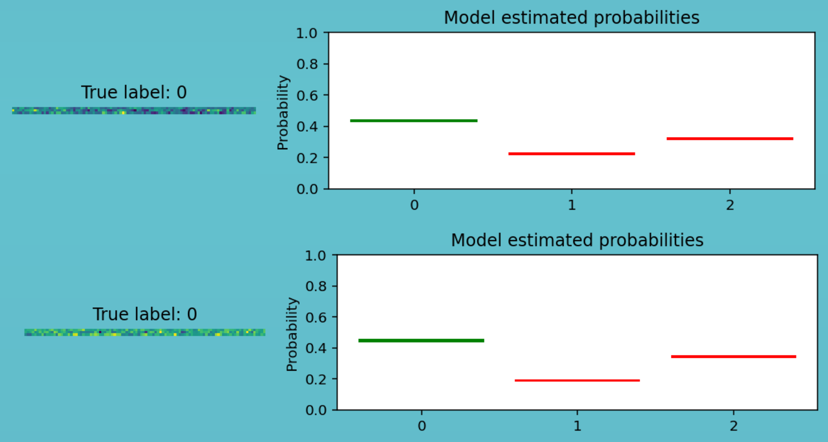
Resources Used:

Results

For the 3 different deterministic network architectures tested, the maximum validation accuracy achieved was ~42%.

1st model performed well on first runs but no longer does- still investigating. 2nd and 3rd models had image augmentation, deeper architectures that should have helped, but didn't improve by much.

Final BNN accuracy: ~35%



Example Probabilities

Conclusions

Despite implementing techniques to theoretically improve accuracy, additional hypertuning needs to be done to the deterministic models to help improve probabilistic and BNN models. Image Augmentation may not have helped.

Future considerations:

- Deepening networks (i.e. adding more Conv2D layers)
- Fine-tune elements like Dropout rate and batch size.
- Train separately on noisy data
- Look into using Gaussian Processes
- Other prior & posterior distributions

References:

[1] P.H. Barchi, R.R. de Carvalho,...and T.C. Moura. 2020. Machine and Deep Learning Applied to Galaxy Morphology - A Comparative Study. *Astronomy and Computing* 30 (Jan. 2020), 100334.
[2] T.Y. Cheng, C. J. Conselice,...and C To. 2021. Galaxy Morphological Classification Catalogue of the Dark Energy Survey Year 3 Data with Convolutional Neural Networks. *Monthly Notices of the Royal Astronomical Society* 507,3 (July 2021), 4425–4444.
[3] D. Tanoglidis, A. Ciprijanovic, and A. Drlica-Wagner. 2021. DeepShadows: Separating Low Surface Brightness Galaxies from Artifacts Using Deep Learning. *Astronomy and Computing* 35 (April 2021), 100469.
[4] A. Ciprijanovic, G. Snyder, B. Nord, and J. E. G. Peek. 2020. DeepMerge: Classifying High-Redshift Merging Galaxies with Deep Neural Networks. *Astronomy and Computing* 32 (May 2020).

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