Galaxy Morphology Classification with Deep Learning

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Abstract

One of the significant problems in cosmology is the morphological classification of galaxies in order to gain insights about the origin and evolution of our Cosmos. Here, we investigate the classification accuracy of several modern convolutional neural network architectures (some of them pretrained on non-astronomical data and others trained from scratch to galaxy data), and of transformers with primary goal to understand their performance on conditions of fast training (i.e., in a few rounds). We experimented with Transfer Learning, and Vision Transformers (ViT). We contrasted their performance with that of traditional Convolutional Neural Networks (CNN) methods, i.e., AlexNet, and VGG. Our results show a 75% classification accuracy (by the ViT and VGG), beating the rest of the competitors. Moreover, one pretrained VGG model showed also excellent performance.

CCS Concepts

• Computing methodologies → Machine learning; **Machine learning approaches**; **Neural networks**; **• Applied computing → Physical sciences and engineering**; **Astronomy**;

Keywords

Galaxies, morphological classification, astrophysics, cosmology, vision transformers, convolutional neural networks, pretrained neural networks, deep learning.

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1 Introduction

During the past decade the world of astrophysics/cosmology witnessed tremendous advances with respect to our ability to observe the Cosmos and subsequently to collect and process huge amounts of data. The operation of new scientific instruments such as the JWST pose new challenges to our ability to extract knowledge from unprecedented vast volumes of collected data. The *Astroinformatics* discipline, which employs Deep Learning (DL), big data management and distributed computing for serving astronomy's goals, has emerged as a result of this wave of scientific evolution.

In cosmology, the creation of galaxy catalogs is a significant goal related to questions concerning the origin, age and evolution of the Cosmos. Morphological classification of galaxies is maybe the most basic information when creating these catalogs and comprises an important steps to study the formation, structure and evolution of galaxies. Starting from the famous Hubble classification system [5] to more detailed classification systems e.g., de Vaucouleurs, the aim of these efforts is to classify galaxies into one of (sub)categories

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2 Evaluated neural networks

We implemented and evaluated several convolutional neural networks (CNNs); some baseline ones, namely the *AlexNet* [4], more advanced ones, namely a *VGG* family member, some pretrained models and a transformer. *AlexNet* is comprised by eight layers: the first five are convolutional layers, some of them followed by max-pooling layers, and the last three are fully connected layers. Our *VGG* variant has a total of four convolutional layers with 3×3 kernel filters, two 2D pooling layers with 2×2 kernel filters, and two fully connected layers. The pretrained model is a pretrained *VGG-16* model. *VGG16* has thirteen convolutional layers, five Max Pooling layers, and three Dense layers, which sum up to 21 layers, but it has only sixteen weight layers, i.e., learnable parameters layers. Our pretrained model is trained on the ImageNet dataset. Our deployed Vision Transformer (ViT) is the classic one [2].

3 Dataset and evaluation setting

The Galaxy Zoo (GZ) project invited volunteers to classify galaxies from the Sloan Digital Sky Survey based on the morphology of the given color images [6]. Subsequently, a Kaggle competition centered around the GZ was developed. This paper uses the dataset from the GZ project available on the Kaggle platform, which has been used by other studies as well, e.g., [1, 7]. In particular, our dataset contains 61578 images of JPG format for training, and 79975 images of JPG format for testing purposes. There is a solution file of training images that shows the probability distribution for each image.

We used as loss function the Binary Cross Entropy and the Adam optimizer with learning rate equal to 0.001.

4 Experimental results

The experimental results are reported in Figure 1–5. We show only the accuracy achieved by the competitors on the classification task.

Our first observation is that the accuracy climbs up very fast for all competitors, even after a few training epochs. This is a very encouraging fact, implying that we can get very good classification accuracy early in training, which is a necessity when dealing with massive datasets.

Our second observation concerns issues of overfitting. As it can be observed in Figure 2 and 3 which concern the same neural model

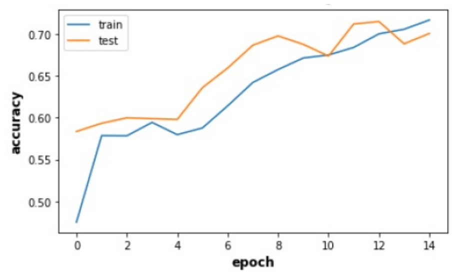

Figure 1: AlexNets' accuracy.

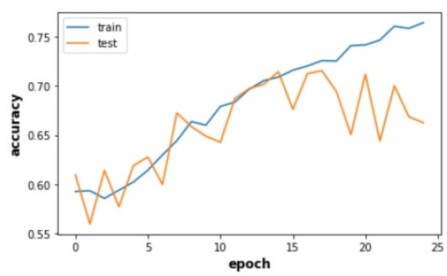

Figure 2: VGG's accuracy without early stopping.

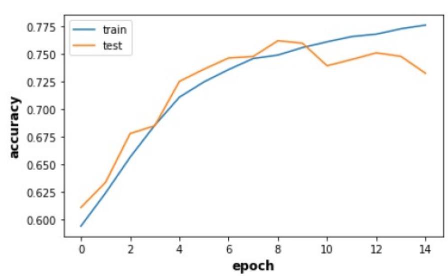

Figure 3: VGG's accuracy with early stopping.

but without early stopping in the former figure and with early stopping in the latter, the technique of *early stopping* is very beneficial by improving the test accuracy and on the other hand improving convergence. Additionally, we can see that the pretrained model, namely VGG16 (see Figure 4) it achieves a testing accuracy which is clearly superior to its training accuracy, even though it was trained in an "irrelevant" dataset.

As far as the accuracy is concerned, we observe in Figure 1, and Figures 2 – Figure 5 that with only a dozen training rounds, the examined methods are able to achieve around 75% accuracy, and the percentage keeps growing for some methods in subsequent rounds. Among the competitors, the Vision Transformer, achieves this performance from the very first few rounds.

5 Conclusions

Neural networks are very effective computational mechanisms for addressing significant problems in astronomy and astrophysics. Here we investigated the question of whether their deployment can reap

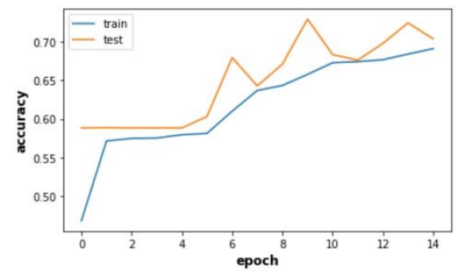

Figure 4: Pretrained VGG16's accuracy.

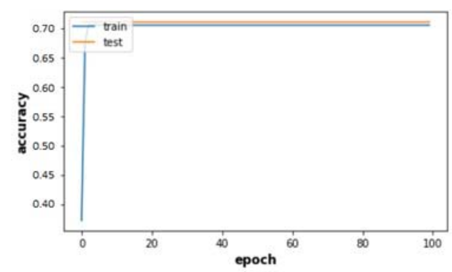

Figure 5: Vision Transformer's accuracy.

performance gains with minimal training in the context of morphological galaxy classification. Our results strongly suggest that this is feasible.

The surprising and unexpected result is the performance of the pretrained VGG architecture, which – even though it has been trained on a dataset of different nature – showed almost identical performance to that of the top performers. This maybe implies that *transfer learning*, which can alleviate the burden of tremendous dataset sizes in astronomy/astrophysics, needs to be thoroughly investigated. We plan to extend our investigation along the lines of federated learning [3], so as to allow for training using geographically dispersed dataset repositories.

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