Combining deep learning and citizen science for morphological analysis of galaxy images

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Abstract

Modern digital sky surveys can image and archive millions and sometimes billions of galaxies. Due to the large size of these databases, manual annota- tion of the morphological features of each galaxy is not practical, reinforcing the use of automation for that purpose. An earlier solution to the problem uti- lized the pattern recognition power of the human brain through citizen science campaigns, involving a large number of volunteers who annotated the galaxies manually. However, while citizen science has been proven to provide some accu- rate datasets, its throughput is far too low to perform an exhaustive annotation of all galaxies in digital sky surveys such as the Dark Energy Survey (DES) or the Large Synoptic Survey Telescope (LSST). Here we present a method of automatic annotations of galaxy morphology by using datasets annotated by citizen scien- tists to train a deep neural network. The annotations made by citizen scientists have different degrees of reliability based on the degree of agreement between the users who annotated them, and selecting a higher threshold of agreement leads to cleaner data, but reduces the number of samples that their annotation passes that threshold. Therefore, using citizen science annotations as training data re- quires the adjustment of the trade-off between the consistency of the training data and the size of the training set. Here we show that the accuracy can be improved when training the neural network by combining annotations of different agreement levels, and using the different agreement levels as weights to penalize the deep neural network based on the agreement level of each annotation. Experimental results show that the method outperform a deep neural network trained by adjusting the trade-off between the size of the training set and the agreement level threshold.

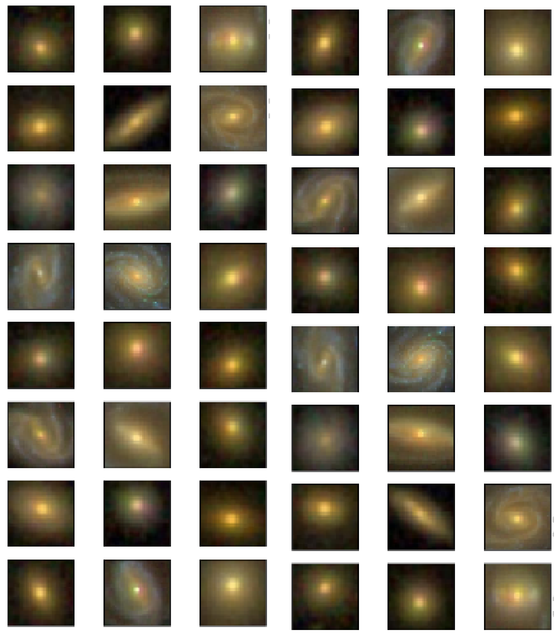


Figure 1: Examples of images in the dataset

1 Introduction

1.1 What is galaxy morphology?

Galaxy morphology is essentially *physical* descriptors of a galaxy. Some examples include:

- Spiral or Elliptical
- Tightness of spiral arms
- Number of spiral arms
- Edge on
- Bars
- Bulge prominence
- Round
- Bulge shape

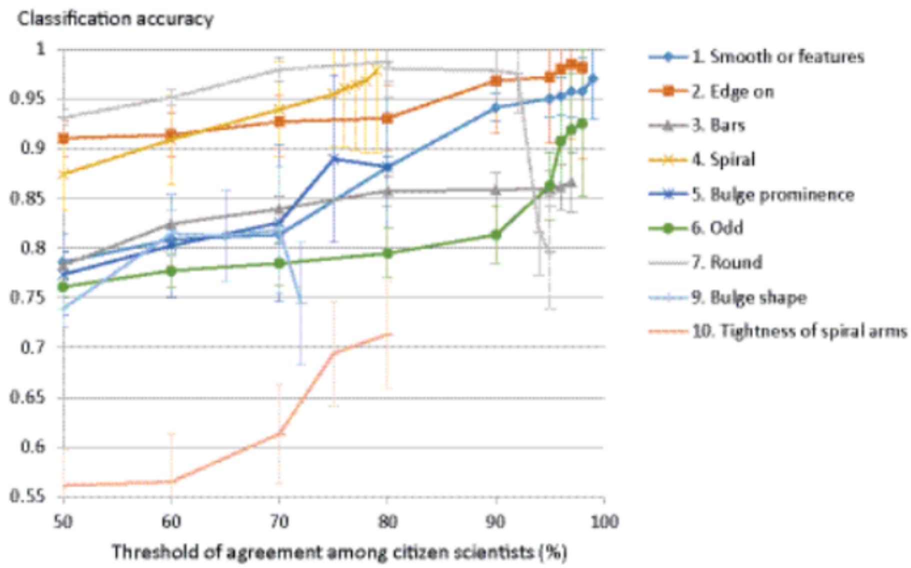


Figure 2: Examples of images in the dataset

1.2 How is morphology data acquired?

Telescopes that capture galaxy images, such as SDSS and LSST, are unable to automatically determine morphological features. Features classifications can not be easitly determined by looking at low level features like pixel data. Until recently, the only way to acquire morphology data is to do it manually or by using citizen scientists as was done is the Galaxy Zoo project.

1.3 Automatic Classification

Previous research used data provided by the Galaxy zoo project to train a machine learning classifier to predict morphology data. The results shown in figure 2 are fairly good. The classifier performs with $> 75\%$ accuracy in almost all cases.

2 Using deep learning to improve classification accuracy

This project focused primarily on improving classification accuracy of previous results. This was done by using a deep neural network with a custom loss function trained on citizen science data from the galaxy zoo project. All training samples were assigned a weight based on the highest agreement threshold among citizen scientists (See Fig 3). This means that training samples with a higher

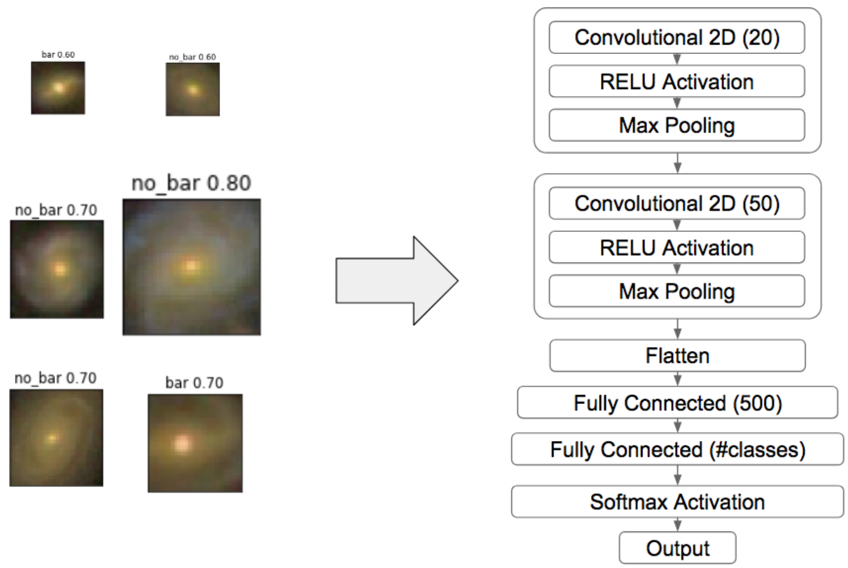


Figure 3: Examples of how weights are used to train the network

agreement level had higher influence on the network. The training samples were fed into an network similar to Lenet-5.

3 Results

As shown in Fig 4, the weighted network performs significantly better than previous methods. It is able to achieve $> 90\%$ accuracy for nearly all features. A galaxy image can be classified in approximately 0.18 seconds for all features making this solution robust for large amounts of incoming data.

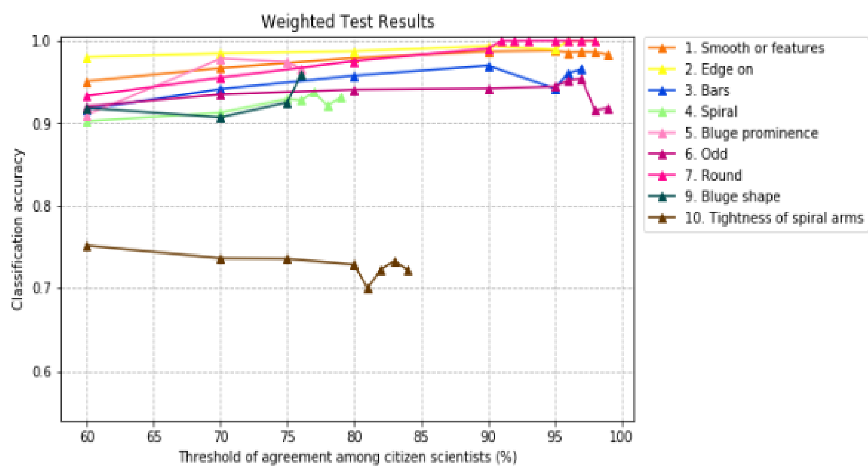
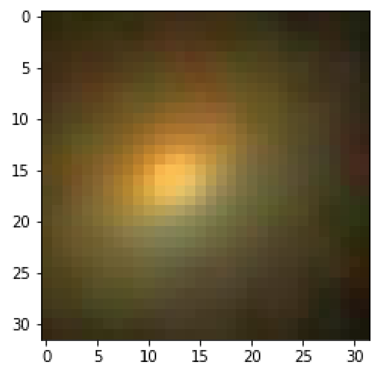


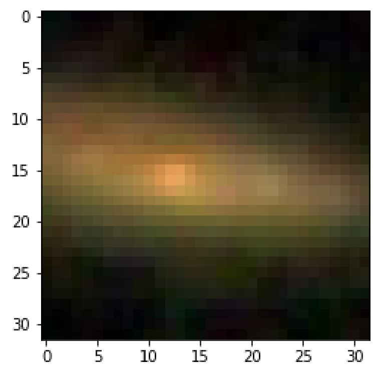
Figure 4: The weighted neural network performed significantly better than previous methods (Fig. 2)

3.1 Example 1



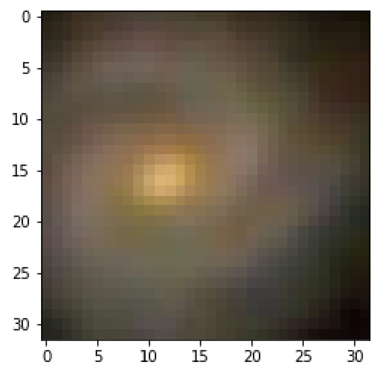
Feature	Prediction	Certainty
Round	completely_round	0.979339
Spiral or Eliptical	eliptical	0.999992
Tightness of spiral arms	medium	0.588440
Number of spiral arms	1_arm	0.966647
Odd	odd_yes	0.652618
Bluge prominence	obvious	0.993835
Smooth or features	smooth	0.999947
Edge on	edgeon_yes	0.937408
Arm Count	1	0.929233
Disturbed	other	0.841458
Bluge shape	bulge_rounded	0.997960
Spiral	no_spiral	0.995150
Bars	bar	0.816452

3.2 Example 2



Feature	Prediction	Certainty
Round	cigar_shaped	0.999952
Spiral or Eliptical	spiral	0.909629
Tightness of spiral arms	loose	0.917366
Number of spiral arms	1_arm	0.572123
Odd	odd_no	0.509861
Bluge prominence	just_noticeable	0.927303
Smooth or features	features_or_disk	0.852092
Edge on	edgeon_yes	0.999888
Arm Count	1	0.867311
Disturbed	dust_lane	0.563583
Bluge shape	no_bulge	0.620495
Spiral	no_spiral	0.916847
Bars	bar	0.837524

3.3 Example 3



Feature	Prediction	Certainty
Round	completely_round	0.987888
Spiral or Eliptical	spiral	0.986352
Tightness of spiral arms	tight	0.582286
Number of spiral arms	3_arms	0.356062
Odd	odd_no	0.841164
Bluge prominence	just_noticeable	0.808645
Smooth or features	features_or_disk	0.999660
Edge on	edgeon_no	0.999973
Arm Count	1	0.445723
Disturbed	merger	0.577173
Bluge shape	no_bulge	0.710448
Spiral	spiral	0.919897
Bars	bar	0.508351