

Deep Convolution Neural Networks for Galaxy Morphology Classification

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Abstract - An neural network architecture for galaxies classification is presented. The galaxy can be classified based on its features into the main three categories Elliptical, Spiral, and Irregular. This paper presents an new approach for an automatic detection of the galaxy morphology from datasets based on the image-retrieval approach. Currently, there are several classification methods proposed to detect the galaxy types within the image. However, in some situations, an aim is not only to determine a type of the galaxy within the queried image, but also to determine the most similar images for the query image. The galaxy can be classified based on its features into the main three categories Elliptical, Spiral, and the Irregular.

Key Words: galaxies classification, Deep Convolutional Neural Networks, Computational astrophysics.

1. INTRODUCTION

Studying the types and properties of an galaxies are important as it offers important clues about the origin and a development of an universe. The classification of the galaxy is an important role in studying an formation of the galaxies and an evaluation of our universe. Galaxy morphological classification is an system used to divide the galaxies into the groups based on their visual appearance. There are several schemes in the use by which the galaxies can be classified according to their morphologies. Galaxy classification is used to help an astrophysicists in facing this challenge. It is done on an huge databases of information to help the astrophysicists in testing theories and finding the new conclusions for explaining the physics of processes governing galaxies, star-formation, and an evaluation of universe. Historically, galaxies classification is an matter of the visually inspecting two-dimensional images of an galaxies and then categorizing them as they appear. Even though expert human classification is somewhat reliable, as it is simply too time consuming for the huge amounts of the astronomical database taken recently because of a increase in the size of an telescopes and the CCD camera have has produced extremely the large datasets of images, for example, an Sloan Digital Sky Survey (SDSS). These data is too much to analyze an manually feasible. Galaxy classification is based on an images and spectra. This classification was considered an long-term goal for the astrophysicists. However, the complicated nature of an galaxies and the quality of images have made the classification of a galaxies challenging and not so accurate.

Galaxy classification system helps the astronomers in an process of grouping the galaxies per their visual shape. The most famous being an Hubble sequence Hubble sequence is considered one of the most used schemes in tan galaxy morphological classification. The Hubble sequence was created by an Edwin Hubble in 1926. In the past few years, advancements in an computational tools and the algorithms have started to allow the automatic analysis of the galaxy morphology. There is several machine learning methods are used to improve an classification of the galaxy images. Prior researchers do not achieve the satisfying results. In this paper, an authors perform automated morphological galaxy classification based on the machine learning and the image analysis. They depend on the feed-forward neural network and an locally weighted regression method for the classification. With a huge increase in the processing power, an memory size and the availability of the powerful GPUs and the large datasets, it was possible to train a deeper, the larger and the more complex models. The machine learning Researchers had been working on the learning models which included learning and extracting features from the images. Deep Learning has achieved significant results and an huge improvement in visual detection and the recognition with an lot of categories. Raw data images are used as deep learning as input without the need of the expert knowledge for an optimization of the segmentation parameter or feature design.

1.1 Objective

The goal of deep galaxy detection is to detect all the instances of galaxy from a known class, such as color, shape in an image. Implementation System which is useful for galaxy research technique. In python where galaxy shape will be extracted from image.

1.2 Literature survey

Huertas-Company et al. (2011) used as system based on the colors, shapes and concentration to train an support vector machine to classify the 700k galaxies from the SDSS DR7 spectroscopic sample. For each galaxy, they estimate the probabilities of being E, S0, Sab, or Scd. It is not an pure morphometric classification, since it includes the colors. Scarlata et al. (2007) analyzed 56,000 COSMOS galaxies with a ZEST algorithm, using the five non-parametric diagnostics (A, C1, G, M20, q) and Sérsic index n. They perform the principal component analysis (PCA) and classify galaxies

with the three principal components. They find the contamination between the galaxy classes in the parameter space (see their Figure 10), although they do not state clearly an success rate of the classification.

Andrae et al. (2011) present an detailed analysis of the several critical issues when dealing with the galaxy morphology and the classification. Several morphological features are intertwined and cannot be estimated independently. They show the dependence between the C and n, which is also presented here in an different form in Appendix C. The authors claim that the parameter based approaches are better for the classification, and state that an system such as CASGM has the serious problems. However, they do not show it in the practice.

Dieleman et al. (2015) present an Neural Network machine to reproduce the Galaxy Zoo classification. They work directly in the pixel space, using a rotation invariant convolution that minimizes the sensitiveness to changes in the scale, rotation, translation and sampling of the image; however, since a human classification is also the error prone, as discussed in Section 1, their algorithm also reproduces an errors in the human classification. Freeman et al. (2013) introduced MID (multimode, intensity and deviation) statistics designed to detect the disturbed morphologies, and then classified in 1639 galaxies observed with an Hubble Space Telescope WFPC3 with a random forest. It is one of the few works that state an detailed classifier performance, in terms of the confusion matrix coefficients.

2. Existing system

Several machine learning methods for the star/galaxy separation based on the photometric analysis from an cal catalogs. The experiments revealed that in the terms of accuracy, most of the analyzed and the explored methods outperformed the baseline method ZeroR. Among them, both the NN and an RF achieved good performance.

2.1 Disadvantages of Existing System

- 1) Prior researchers do not achieve the satisfying results using the automated morphological galaxy classification based on the machine learning and an image analysis.
- 2) Many challenges also emerge to identify and classify the shape of galaxy.
- 3) Over fitting the problem.

2.2 Proposed System

Galaxies to be classified based on their morphological features as one of the three types: Elliptical, Spiral, and Irregular. The proposed architecture convolutional layer for the features extraction with some filters and an two principles fully connected layers for the classification. Image

augmentation techniques were applied to an training data and included the rotation, reflection, cropping and Gaussian noise.

2.3 Advantages of Proposed System

- Augmentation techniques decreased the over fitting problem of an proposed architecture.
- The deep learning network do the classification network learns discriminative features of the extracted them.
- Develop an strong classifier which will able to handle the components of different shapes.

3. Algorithm used

An Convolutional Neural Networks Introduction .

- Step 1: Convolution Operation

The first building block in our plan is convolution operation. In this step, we will focus on the feature detectors, which can basically serve as the neural network's filters. We have also discussed the feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

- Step 1: ReLU Layer

The second part of this step will involve an Rectified Linear Unit or ReLU. We have also discussed ReLU layers and explore how the linearity functions in the context of Convolutional Neural Networks.

It is not necessary for understanding the CNN's, but there is no harm in an quick lesson to improve your skills.

- Step 2: Pooling

In this part, will cover the pooling and will understand exactly how generally it works. Our nexus here, however, will be an specific type of pooling; max pooling. We'll cover an various approaches, though, including a mean (or sum) pooling. This part will be end with an demonstration made using an visual interactive tool that will definitely sort out the whole concept.

- Step 3: Flattening

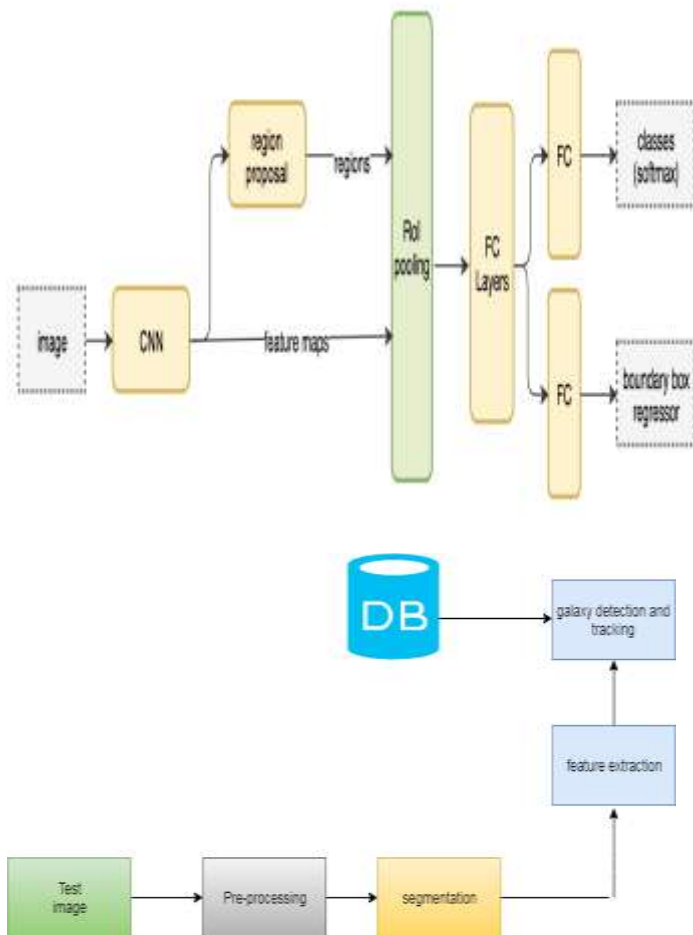
This will be an brief breakdown of the flattening process and how we move from pooled to the flattened layers when working with the Convolutional Neural Networks.

- Step 4: Full Connection

In this part, everything that is covered throughout the section will be merged together. By learning this, the envision to a fuller picture of how Convolutional Neural

Networks operate and how the "neurons" that are finally produced to learn the classification of images.

4. SYSTEM ARCHITECTURE



In the image preprocessing, image data is been recorded by the sensors on an satellite restrain errors related to the geometry and brightness values of an pixels. These errors are corrected by using the appropriate mathematical models which are either definite or statistical models. Image enhancement is an modification of the image by changing an pixel brightness values to improve its visual impact. Image enhancement involves an collection of the techniques that are used to improve the visual appearance of an image, or to convert an image to a form which is better suited for the human or machine interpretation. Sometimes images are obtained from a satellites, conventional and an digital cameras lack in contrast and brightness because of the limitations of an imaging sub systems and illumination conditions while capturing an image. Images may have different types of noise. In image enhancement, the main goal is to accentuate specific image features for subsequent analysis or for image display. Examples include the contrast and edge enhancement, pseudo-coloring, noise filtering, sharpening, and magnifying. Image enhancement is very useful in feature extraction, image analysis and an image

display. The enhancement process itself does not increase a inherent information content in the data. It simply emphasizes certain specified image characteristics. Enhancement algorithms are generally interactive and very application dependent. Some of the enhancement techniques are:

- a. Contrast Stretching
- b. Noise Filtering
- c. Histogram modification

Image Segmentation:

Image segmentation is an process of partitioning the image into parts or regions. This division into parts is often based on an characteristics of the pixels in the image. For example, one way to find the regions in an image is to look for abrupt discontinuities in the pixel values, which typically indicate edges. These edges can define the regions. Other methods divide the image into an regions based on color values or texture.

Feature extraction:

Feature extraction is an type of the dimensionality reduction that efficiently represents an interesting parts of an image as a compact feature vector. This approach is useful when the image sizes are large and an reduced feature representation is required to quickly complete the tasks such as image matching and the retrieval. Feature detection, feature extraction, and matching are often combined to solve the common computer vision problems such as the object detection and an recognition, content-based image retrieval, the face detection and recognition, and an texture classification.

5. CONCLUSION

An deep learning approach led to the powerful shape detection system for the galaxy that performs better than an state-of-the- art systems. Extend our system by using the deep learning and correctly process an extracted features. The galaxy can be classified based on its features into the three main categories Elliptical, Spiral, and Irregular. A robust deep convolutional neural network architecture for the galaxy morphology classification will develop here.

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