Galaxy Morphology Classification using Deep Convolutional Networks

Shreyas Kalvankar, Hrushikesh Pandit, Pranav Parwate

***Abstract*---**The project presents a deep convolutional architecture for galaxy classification. The galaxies, based on their features, can be classified into three main categories Elliptical, Spiral and Irregular. The project tries to study various architectures used for a Convolutional model and determine the best architecture that classifies the galaxy image based on its shape and features. It is trained over 40,000 images and the results so far have shed light on some new concepts that will help us improve the accuracy currently achieved by the network.

Key words: galaxy classification, CNN, deep convolution, computational astrophysics.

I. Introduction

Properties of galaxies and its shape give important clues about the origin and the development of the universe. The classification of a particular galaxy is important in studying the formation that galaxy. Galaxy morphological classification is a system developed to segregate galaxies into different classes based on its shape and structure. It is usually done on a huge database for astrophysicists to test their theories and ideas on modeling the universe [1].

Prior to the modern age of technological advancement, galaxies were classified visually by inspecting a two-dimensional image and categorizing them. After the entire computer revolution, there has been an increase in the number of satellite and telescopes which provide extremely large databases, for example, the Sloan Digital Sky Survey (SDSS). The data achieved is too much to analyze manually. This classification was the means to classify the galaxies based on the shape and quality images have been provided that has made classification very challenging [2].

Galaxy classification system helps astronomers in the process of grouping galaxies per their visual shape. The most famous being the Hubble sequence Hubble sequence is considered one of the most used schemes in galaxy morphological classification. The Hubble sequence was created

by Edwin Hubble in 1926 [3]. In the past few years, advancements in computational tools and algorithms have started to allow automatic analysis of galaxy morphology. There are several machine learning methods are used to improve the classification of galaxy images.

Prior researchers do not achieve satisfying results. In [8], the authors perform automated morphological galaxy classification based on machine learning and image analysis. They depend on feed-forward neural network and locally weighted regression method for classification. The achieved accuracy was about 91%. In 2013, [9] used naive base classifier and Random Forest classifiers for the morphological galaxy classification. The achieved accuracy was about 91% for Random Forest classifiers and 79% for the Nave base classifier. The authors in [10] proposed a method using the supervised machine learning system based on Non-Negative matrix factorization for images of galaxies in the Zsolt frei Catalog. The achieved accuracy was about 93%. In 2017, [11] proposed a new automated machine supervised learning astronomical classification scheme based on the Nonnegative Matrix Factorization algorithm. The accuracy of this scheme was about 92%.
Convolution operation is well-known in the computer vision and signals processing community. The convolutional operation is frequently used by conventional computer vision, especially for noise reduction and edge detection [4]. The idea of a Convolutional Neural Network (CNN) is not recent. In 1998, CNN achieved great results for handwritten digit recognition [5]. However, they

dramatically drop down due to memory and hardware constraints, besides the absence of large training data. They were unable to scale to much larger images. With the huge increase in the processing power, memory size and the availability of powerful GPUs and large datasets, it was possible to train deeper, larger and more complex models [6]. The machine learning Researchers had been working on learning models which included learning and extracting features from images.
Deep Learning has achieved significant results and a huge improvement in visual detection and recognition with a lot of categories [7]. Raw data images are used be deep learning as input without the need of expert knowledge for optimization of segmentation parameter or feature design.

II. Problem Statement

Creating a Deep Convolutional Model using Tensorflow for morphological classification of the Galaxies.

III. Objectives

Objective of the project was to study the behavior of image recognition models based on their architecture and nature of input data.

IV. Outcomes

An analytical study was done to determine the best network architecture and the use of different architectures and effect of augmentation on an image fed into a network.

V. Software and Hardware

Python modules used:
TensorFlow
NumPy
Pandas
Keras
OpenCV
Matplotlib

Software/API:
Python
Jupyter notebook
CUDA
CUDNN

Hardware:
CPU:
Intel i7 7700HQ
Intel i7 8750H
Intel i7 9750H

GPU:
Nvidia GeForce GTX 1050ti
Nvidia GeForce GTX 1060
Nvidia GeForce GTX 1660

VI. Model

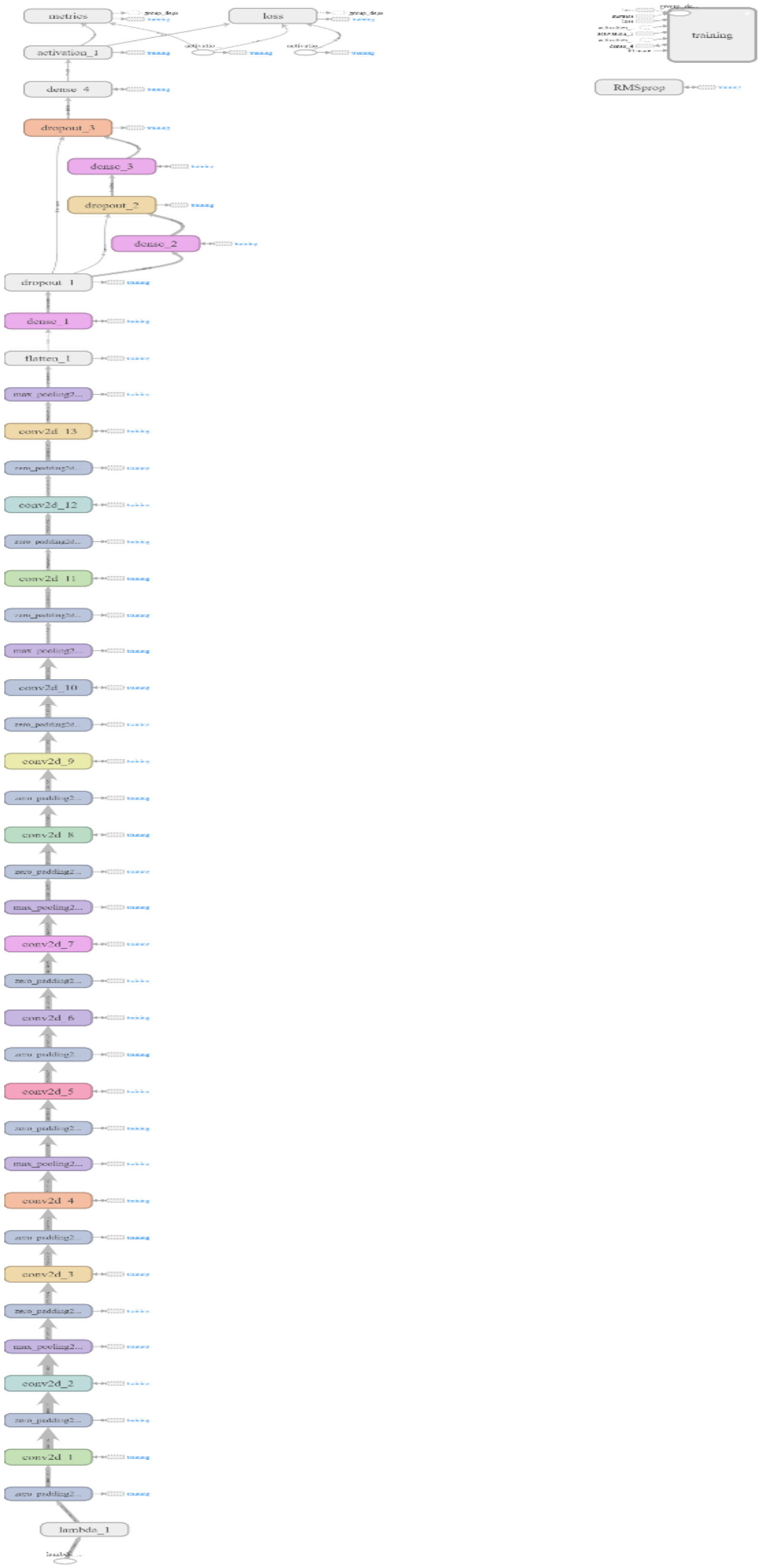

Figure 1: Model of ResNet used

VII. Dataset

GalaxyID	Class1.1	Class1.2	Class1.3	Class2.1	Class2.2	Class3.1	Class3.2	Class4.1	Class4.2	Class5.1	...	Class9.3	Class10.1	Class10.2	Class10.3	C
100008	0.383147	0.616853	0.000000	0.000000	0.616853	0.038452	0.578401	0.418398	0.198455	0.0	...	0.000000	0.279952	0.138445	0.000000	(
100023	0.327001	0.663777	0.009222	0.031178	0.632599	0.467370	0.165229	0.591328	0.041271	0.0	...	0.018764	0.000000	0.131378	0.459950	(
100053	0.765717	0.177352	0.056931	0.000000	0.177352	0.000000	0.177352	0.000000	0.177352	0.0	...	0.000000	0.000000	0.000000	0.000000	(
100078	0.693377	0.238564	0.068059	0.000000	0.238564	0.109493	0.129071	0.189098	0.049466	0.0	...	0.000000	0.094549	0.000000	0.094549	(
100090	0.933839	0.000000	0.066161	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	...	0.000000	0.000000	0.000000	0.000000	(

5 rows × 37 columns

Figure 2: Dataset

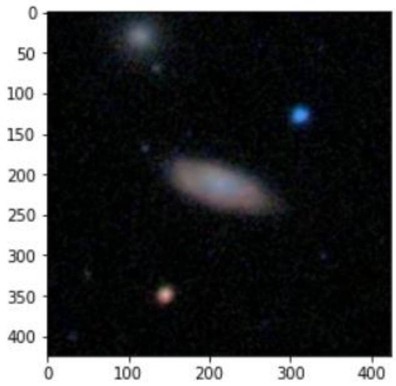

Figure 3: Input image Before processing

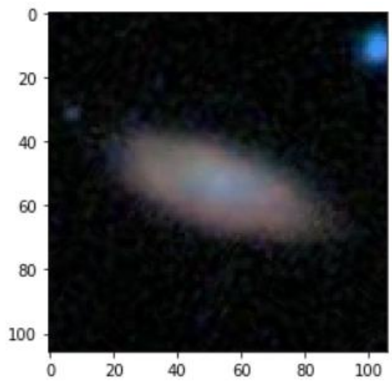

Figure 4: Input Image After processing

VIII. Methodology and Results

The first architecture tried is the VGG16 architecture that consists of 16 weighted layers.

Table 1: **ConvNet configurations** (shown in columns). The depth of the configurations increases from the left (A) to the right (E), as more layers are added (the added layers are shown in bold). The convolutional layer parameters are denoted as "conv⟨receptive field size⟩-⟨number of channels⟩". The ReLU activation function is not shown for brevity.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

The input to the network is a 3-dimensional tensor of shape (106,106,3).

The network was trained over such images and the problem here was the network loss was constant after a certain number of epochs.

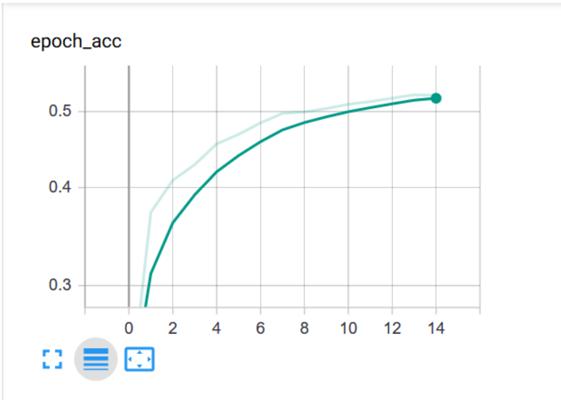

Figure 5: Epoch accuracy achieved with VGG16

The second architecture was the VGG19 architecture that didn't give us any promising results either.

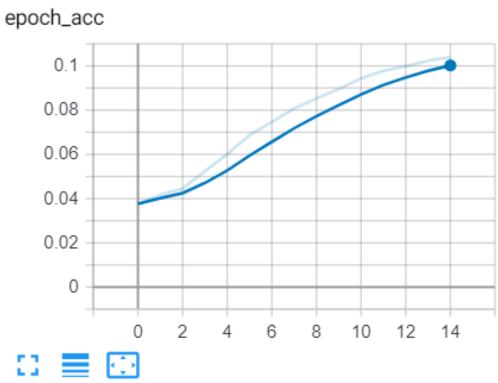

Figure 6: Epoch accuracy achieved with VGG19

The final architecture that we worked on was the ResNet50 with a convolution block and identity block. It gave promising results and bumped up the accuracy to about 56%.

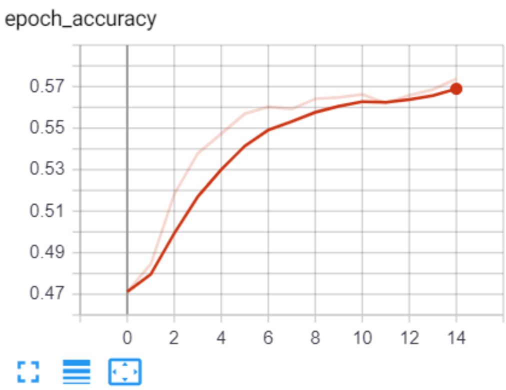

Figure 8: Epoch accuracy achieved with ResNet50

Figure 7: Epoch loss for ResNet50

The problem that we ran into was that out network wasn't able to minimize the cost funtion to an extent as to reduce the losses. The problem of local minimum that we're getting stuck at will be tackled with in the future. Results acvhieved were significantly improved when using a ReLu activation with a glorot uniform initializer.

IX. Conclusion

The project brought to light different aspects of deep convolutional networks and their scope in galaxies and image processing.

We conclude that the ResNet architecture works better at classification than a VGG network and improvements can be made in image preprocessing so that we can achieve better results in future.

X. References

Main papers:
Jia-Ming Dai, Jizhou Tong, Galaxy Morphology Classification with Deep Convolutional Neural Networks

Nour Eldeen M. Khalifa, Mohamed Hamed N. Taha, Aboul Ella Hassanien, I. M. Selim, Deep Galaxy: Classification of Galaxies based on Deep Convolutional Neural Networks

[1] M. Abd Elfattah, N. El-Bendary, M. A. Abu Elsoud, A. E. Hassanien, and M. F. Tolba, An intelligent approach for galaxies images classification, in 13th International Conference on Hybrid Intelligent Systems (HIS 2013), 2013, pp. 167172.
[2] M. Abd Elfattah, N. Elbendary, H. K. Elminir, M. A. Abu El-Soud, and A.E. Hassanien, Galaxies image classification using empirical mode decomposition and machine learning techniques, in 2014 International Conference on Engineering and Technology (ICET), 2014, pp. 15.
[3] A. Adams and A. Woolley, Hubble classification of galaxies using neural networks, Vistas Astron., vol. 38, pp. 273280, Jan. 1994.
[4] A. Dominguez, A History of the Convolution Operation [Retrospectroscope], IEEE Pulse, vol. 6, no. 1, pp. 3849, Jan. 2015.
[5] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE, vol. 86, no. 11, pp. 22782324, 1998.
[6] S. Srinivas, R. K. Sarvadevabhatla, K. R. Mopuri, N. Prabhu, S. S. S. Kruthiventi, and R. V. Babu, A Taxonomy of Deep Convolutional Neural Nets for Computer Vision, Front. Robot. AI, vol. 2, p. 36, 2016.
[7] H. Jiang and E. Learned-Miller, Face Detection with the Faster R-CNN, in 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017), 2017, pp. 650657.
[8] J. De La Calleja and O. Fuentes, Machine learning and image analysis for morphological galaxy classification, Mon. Not. R. Astron. Soc., vol. 349, no. 1, pp. 8793, 2004.
[9] M. Marin, L. E. Sucar, J. A. Gonzalez, and R. Diaz, A Hierarchical Model for Morphological Galaxy Classification, in Proceedings of the Twenty-Sixth International Florida Artificial Intelligence Research Society Conference, 2013, pp. 438443.
[10] I. M. Selim, A. E., and B. M.El, Galaxy Image Classification using Non-Negative Matrix Factorization, Int. J. Comput. Appl., vol. 137, no. 5, pp. 48, Mar. 2016.
[11] I. M. Selim and M. Abd El Aziz, Automated morphological classification of galaxies based on a projection gradient nonnegative matrix factorization algorithm, Exp. Astron., vol. 43, no. 2, pp. 131144, Apr. 2017.