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Μηχανική Μάθηση στην Αστροπληροφορική: Κατηγοροποίηση Γαλαξιών

Διπλωματική Εργασία

Σταματία-Δανάη Κραβαρίτη

Επιβλέπων: Δημήτριος Κατσαρός

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Machine Learning applied to Astroinformatics: Galaxy Classification

Diploma Thesis

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Ευχαριστίες ή Σχόλια

Θα ήθελα να ευχαριστήσω των κ. Κατσαρό για την βοήθεια του και την μητέρα μου, Ιφιγένεια, για την επιμονή της.

Διπλωματική Εργασία

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Περίληψη

Το διάστημα είναι ασύλλυπτα μεγάλο και ένα μυστήριο για τον άνθρωπο, το οποίο, μόλις τα τελευταία χρόνια έχει αρχίσει να ανακαλύπτει και να εξερευνά εξαιτίας της πολύτιμης βοήθειας την συνεχούς αναπτυσσόμενης τεχνολογίας αλλα και αυξανόμενης συλλογής δεδομένων.

Ο ορισμός της λέξης μορφολογία, για την αστρονομία, σημαίνει την μελέτη των δομικών ιδιοτήτων των γαλαξιών. Αναλύοντας την αρχιτεκτονική των γαλαξιών, ίσως να καταφέρουμε να καθορίσουμε τους μηχανισμούς που κρύβονται πίσω απο την δημιουργία και την ανάπτυξη ενός γαλαξία [1].

Ένας γαλαξίας δεν είναι κατι παραπάνω απο ενα σύμπλεγμα αμέτρητων αστεριών διατεταγμένα σε συστάδες. Οι γαλαξίες φαίνονται χρησιμοποιώντας τις εικόνες φωτονικής ζώνης τους και η μορφολογική τους δομή ταξινομείται οπτικά ανάλογα με την εκτίμηση του παρατηρητή για το πώς φαίνονται.

Αν μπορέσουμε να προβλέψουμε, πως ενας παρατηρητής θα χαρακτήριζε και κατιγοροποιούσε την μορφολογία ενός γαλαξία, θα λύσουμε το πρόβλημα της κατιγοροποίησης γαλαξιών.

Λέξεις-κλειδιά:

Αστροπληροφορική, Μηχανική Μάθηση, Βαθειά Μαθηση, Κατηγοροποίηση

Diploma Thesis

Machine Learning applied to Astroinformatics: Galaxy Classification

Stamatia-Danai Kravariti

Abstract

The universe is vast, and we only lately start to understand it with the help of the advancing technology and the data collected. As the data dramatically increase, so is the chance for the noise to increase so it is of the outmost importance that we treat them methodically.

The word morphology in context of astronomy means the study of structural properties of galaxies. By analyzing the architecture of galaxies, we may determine the physical mechanisms behind galaxy creation and development [1].

The galaxy is nothing more than a collection of countless stars arranged in clusters. Galaxies are seen using their photonic band pictures, and their morphological structure is classified visually depending on the observer's assessment of how they look.

If we predict, how the observer would classify a morphology of a galaxy, we could solve galaxy classification.

Keywords:

Astroinformatics; Machine learning; Deep learning; Classification; Convolutional networks

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CNN	Convolutional Neural Network
ViT	Vision Tranformer

Chapter 1 Introduction

The universe is vast, and we only lately start to understand it with the help of the advancing technology and the data collected. As the data dramatically increase, so is the chance for the noise to increase so it is of the outmost importance that we treat them methodically.

1.1 Subject

In this thesis, I will use the huge and impressive dataset containing more than 60.000 images of galaxies and classify them. I will interpret various methods used for computer vision to figure out what works best for the selected data and share the results.

I will experiment with different approaches to computer vision and deep learning. Some have been around for years, and some are slowing starting to gain some attention.

First, we'll check what results the classic solution to computer vision give us, which is CNNs. Of course, there are countless ways to model a CNN so I will experiment with different number of layers and different hyperparameters to see what fits the best.

Next, we will see how transfer learning works for this problem by trying a few viral pre-trained existing models with ImageNet.

Finally, I will try out Vision Transformers. Self-Supervised vision transformers attract more and more attention lately and show remarkable learning abilities.

1.1.1 Contribution

1. Data pruning
2. Testing of different CNN architectures
3. Use of several transfer learning algorithms
4. Use of Vision Transformers
5. Evaluation of results

1.2 Volume Organization

In Chapter 2, Astro informatics is discussed and its newest achievements.
In Chapter 3, we see machine learning theory with a focus on deep learning's CNNs, Transfer learning and Vision Transformers.
In Chapter 4, the subject of this thesis is presented. The data are being discussed and the overall process is developed.
In Chapter 5, we see graphs and further information of each experiment, as well as some comments and comparisons.
In Chapter 6, there is a conclusion regarding the whole process and the information I gathered from it. Some talk about further work is also involved.

Chapter 2 Astroinformatics

2.1 Introduction

To cope with the data streams and data sets created by a new generation of instruments, sensors, and computer simulations, a new field called Astroinformatics has emerged, although one with somewhat ill-defined limits. Astroinformatics is causing a genuine methodological change within the astronomical community, therefore there is at least one strong reason to evaluate it as a new subject rather than as a mere amalgam of issues and approaches acquired from other domains. Consideration of data volume and data complexity aids comprehension.

2.2 Definition

> "**Astroinformatics** is an interdisciplinary field of study involving the combination of astronomy, data science, machine learning, informatics, and information/communications technologies.", [7],[8]

Astroinformatics is largely focused on creating the tools, techniques, and applications of computer science, data science, machine learning, and statistics for study and teaching in data-oriented astronomy. In its most basic form, Astroinformatics may be seen as the application of data science to the field of astronomy. It is fundamentally a methodological discipline [8] much like Data Science in general, and it is built based on the theoretical, experimental, and practical features of other subjects, such as different domains of Computer Science and Engineering, Statistics, and so on. These shifts have led to the development of a new approach to data analysis in 21st century astronomy courses and laboratories known as Astroinformatics.

2.2 Related work

Like many other scientific fields, astronomy is experiencing a major data flood that will inevitably alter the routine and technique of scientific inquiry. While Astroinformatics may seem essential for meeting technical issues, it is also providing exciting new opportunities for astronomical discoveries by making use of cutting-edge data mining techniques. This team [9] creates and uses high-performance computing tools to simulate and analyze data from complicated astrophysical systems such turbulent fluids, the Sun, and interstellar stuff in galaxies. Tools for data analysis that make use of machine learning and tools for accelerating simulation using graphics processing units are among the ways that have been created.

Data-to-knowledge transformations, semantic data integration, information visualization, knowledge extraction, techniques for indexing the sky and astronomical catalogues, information retrieval methods, data mining and knowledge discovery methods, content- and context-based information representations, consensus semantic annotation tags, astronomical classification taxonomies, and astronomic ontologies are all subfields of astronomical informatics. These methods make science more productive by making it easier to combine, mine, find, retrieve, find new information, and help people make decisions. A robotic telescope can be used to choose places to look at. Galaxy classification is a task for convolutional neural networks built on TensorFlow. It is a multiclass picture classification problem that needs to be solved.

2.3 Limitations

To overcome the data-to-knowledge problems of huge data collections and to aid in the discovery of the unknown unknowns hidden within this data deluge, scientists will need to devote their time, energy, and resources to the creation and implementation of astronomy-specific data science algorithms. You can figure out how many of these kinds of resources are available by looking at things like the number of researchers on staff, the number of graduate student spots, and the amount of money from outside sources. Astronomers of the past, present, and future will need to be experts at data mining, analysis, visualization, and other similar techniques to make sense of huge amounts of data.

To better prepare students for jobs in astronomy and related fields, a new paradigm for graduate education in multidisciplinary astronomy is being made. Using this framework, students will not only get a solid foundation in data-intensive computing, data mining, statistics, time-series analysis, and information science, but also a thorough education in the basic astronomy and astrophysics topics that are essential to the success of their research.

2.3 Future work

When extremely large time-domain surveys, like the Enormous Synoptic Survey Telescope's (LSST) sky survey, begin in the next decade, astronomers will have a pressing need for the discovery of new information from enormous data sets. Due to their importance to the scientific community, these Astroinformatics techniques should be developed and refined with the highest priority. This will allow astronomers to sift through the astronomy community’s massive data archives more rapidly and effectively in search of the countless scientific discoveries that lie inside them.

Chapter 3 Machine Learning

3.1 Introduction

Machine Learning (ML) is a type of Artificial Intelligence (AI) that is used by software applications to achieve more accurate predictions without following precise instructions to do so. ML uses algorithms to learn patters and behaviour based on historical input data to be able to predict new output values.

There are four different types but for the purposes of this project, only supervised learning is used. In supervised learning, the data scientist trains the model using both labelled inputs and desired outputs.

ML has different types and different models. Choosing a model for a specific problem can be tricky and time consuming so it needs to be approaches strategically.

On our case, it is straightforward since Convolutional neural networks (CNNs), which is a type of deep learning, are widely used for image/object recognition and classification.

3.2 Deep Learning

Deep learning is a hot domain and widely used for classification purposes. Deep learning models are also used for and perform well on unstructured data like images data, audio data, video data etc. currently the researchers only have images data of galaxies so deep learning is a suitable choice for prediction purposes.

Each model of deep learning mostly consists of three layers. The input layer, hidden layers, and the output layer.

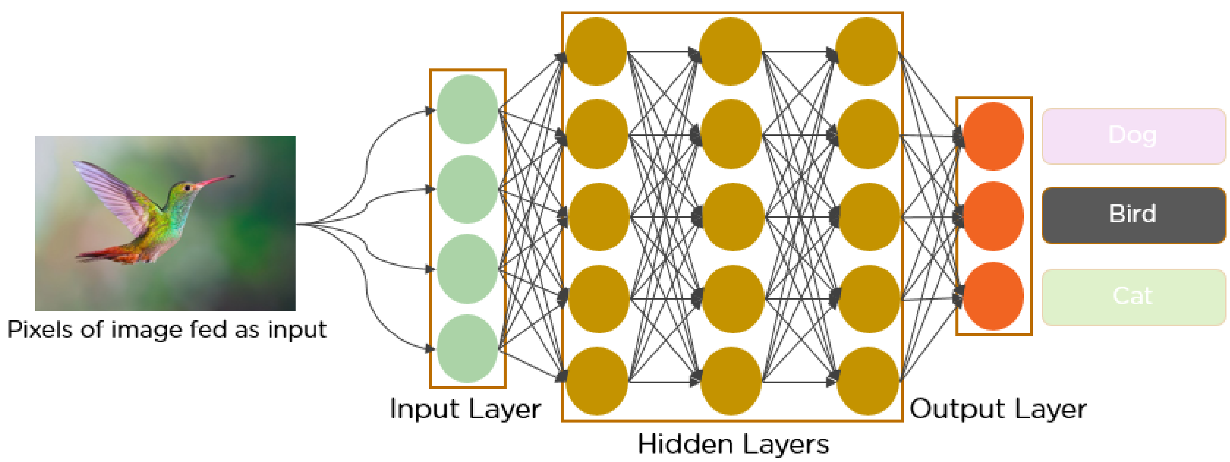


Figure 1: Deep Neural Network

The input layer is the first layer that provide input to the model. The deep learning model take input, structure the input, and provide the output of input layer as input to the hidden layers. The hidden layer consists of one or more layers and process the input data. The hidden layers provide output to output layers. The output layers get data from hidden layers and presents in the form of output of the model. Each layer of the deep learning model has their corresponding activation function that helps in generating the output for next layer.

3.2 CNNs

Deep learning has a wide range of algorithms. One of the most used ones is Convolutional Neural Network (CNN). A CNN usually takes an image as an input and assign values for the weight and biases which determine the importance of specific features in the image with a result of being able to differentiate one from another.

Being a type of deep learning, CNNs have the same structure as we observed earlier but consists of specific kinds of layers, such as the Convolution layer, the pooling layer, and the Fully Connected layer.

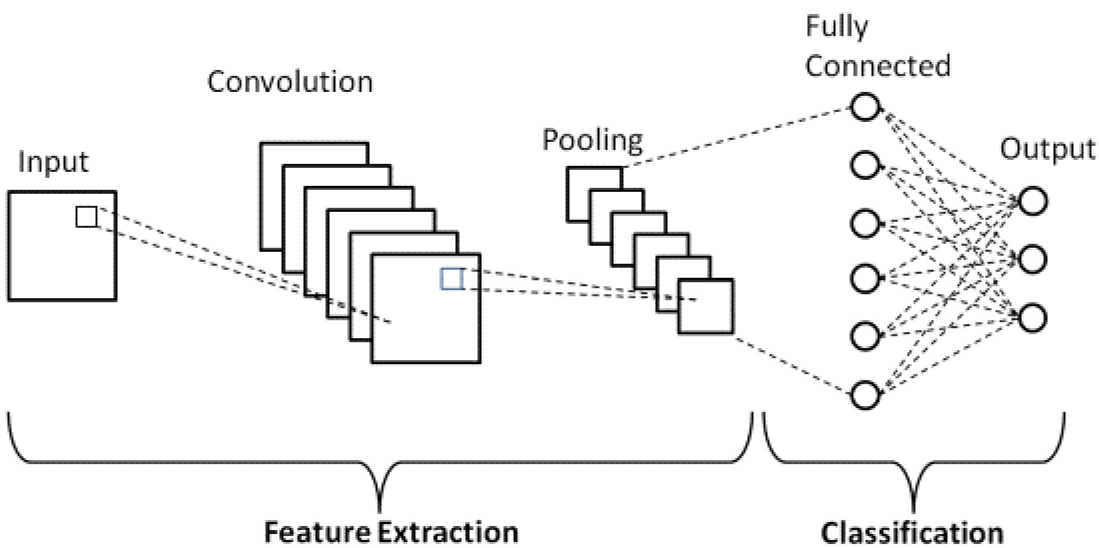


Figure 2: Convolutional Network Structure

The convolutional layer comes first and perform a mathematical operation between the input and a chosen filter, which results to an output called feature map. Later, the feature map is fed to the next layer and in most cases this layer is the pooling layer. The goal od this layer is to make the size of the feature map smaller by decreasing the connections between layers. Later, the now resized feature map is fed to the fully connected layer which performs the connection of neurons between two different layers. At this point, the classification takes place.

Usually, a dropout layer is also added to prevent overfitting by reducing the number of neurons which results in a smaller model.
Finally, activation functions play a very important role in the CNN model since they learn the complex relationships between variables and choose what to left behind depending on the importance of such values.
There are countless combinations of these layers that can be used to find the most suiting model for a problem.

3.3 Transfer Learning

Transfer learning for deep learning is a method that takes a previously developed model for one task and reuses it as a starting point for another task.

> *"Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned."*
> - Chapter 11: Transfer Learning, Handbook of Research on Machine Learning Applications, 2009.

It's not uncommon to use transfer learning when the input is image data. In these cases, a deep learning model is used pre-trained for a large and usually challenging task as image classification is. A famous pre-trained model is ImageNet with as much as 1000 different classes. That means that a training for a new task can be resource-intensive instead of starting from scratch and use it to identify previously categorized objects.

3.4 Vision Transformer

When Transformer Network came out, initially it became the go to model for Natural Language Processing (NLP) tasks. [6] In 2021, we saw how Transformer can be implemented for Computer Vision tasks and outperform CNN in image classification tasks.
A Vision Transformer, or ViT, uses patches of an image and through a transformer-like architecture performs image classification. It's a relatively new method for computer vision without the use of convolution but is becoming more and more dominating in the field by achieving top performing results.

As said earlier, vision transformer takes an image and split it into patches. Later, it flattens them so lower-dimensional linear embeddings can be produced. After that, positional embeddings are added, and the sequence is ready to be fed to the transformer encoder as an input.

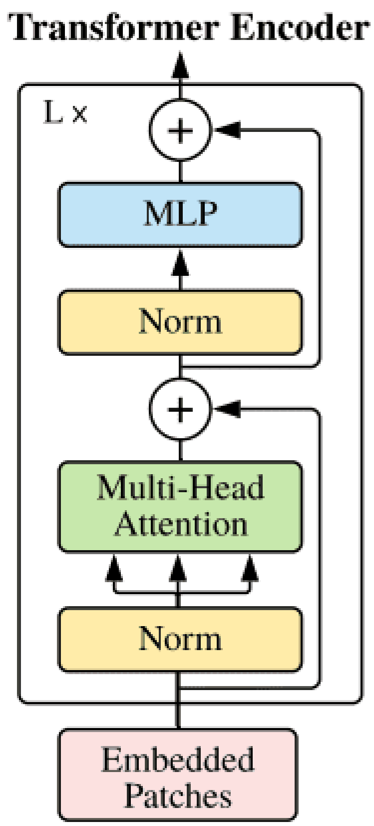


Figure 3: Transformer Encoder.

Image by Alexey Dosovitskiy et al 2020.

Source: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

Now, the pretraining of the model can be done and finally the classification is performed by finetuning on the downstream dataset.

Basically, the transformer uses the patches as tokens similarly to how language processing uses words.

In this work, an implementation from TensorFlow is used, which applies the transformer with self-attention.

Chapter 4 Galaxy Classification

4.1 Introduction

The word morphology in context of astronomy means the study of structural properties of galaxies. By analyzing the architecture of galaxies, we may determine the physical mechanisms behind galaxy creation and development [1]. The galaxy is nothing more than a collection of countless stars arranged in clusters. Galaxies are seen using their photonic band pictures, and their morphological structure is classified visually depending on the observer's assessment of how they look. Based on the kinds of stars that are present in a galaxy's celestial population, it has a variety of various colors. Younger, hotter stars make up most of the light coming from spirals and irregular style galaxies, hence cooler stars seem red and hot stars are often blue in color.

There are different techniques that are used for classification of galaxies based on their structural form. The online citizen initiative Galaxy Zoo has recently been coordinated effort to categorize a substantial proportion of galaxies [2]. Classifying galaxy clusters at greater redshifts is difficult.

The researchers [3] uses deep convolutional neural network for the classification and feature prediction of morphology of the galaxy. Based on the properties of the galaxy, ten morphological classifications are identified. The architecture has two phases, in 1^{st} phase the output class is identified while in 2^{nd} phase the features of the galaxy are predicted. The authors have put the astronomical objects in categories like, quasars, stars, and galaxies.

The researcher [4] proposed a novel approach CyMorph that is based on machine learning and deep learning. For experimentation and modeling purposes, the data set is obtained from Sloan Digital Sky Survey Data Release 7 (SDSS-DR7). All the models are evaluated by finding the overall accuracy for each model. The results shows that all models have achieved minimum accuracy of 94.5% and average accuracy of deep learning models is 99% for two class classification while 82% for three class classification.

4.2 Aim of the project

The aim of this project is to classify the 37 different morphologies as identified by crowdsourced volunteer classifications. That means, the goal it to predict how the people would classify these images. These morphologies are related to probabilities for each category; a high number (close to 1) indicates that many users identified this morphology category for the galaxy with a high level of confidence. Low numbers for a category (close to 0) indicate the feature is likely not present.

We can observe the asked questions below:

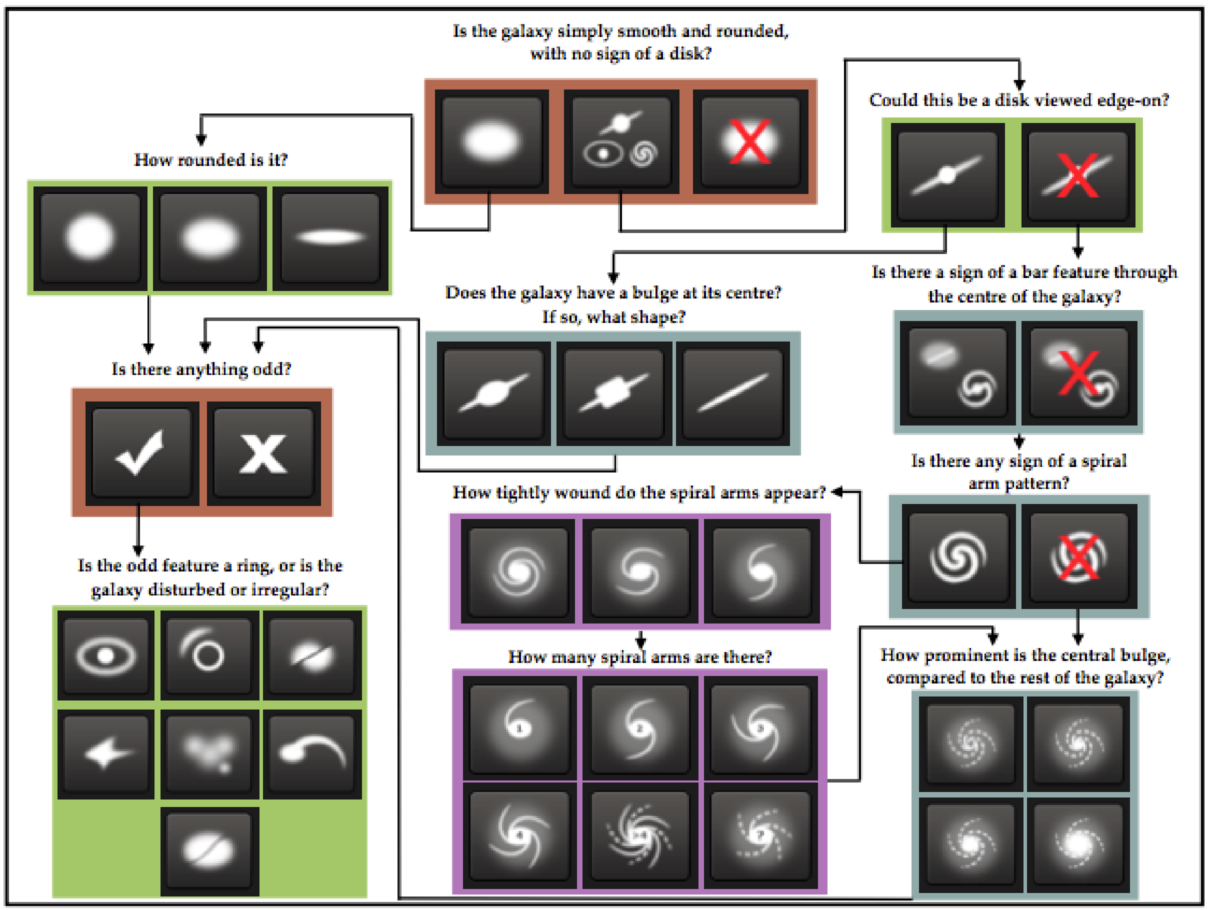


Figure 1. Flowchart of the classification tasks for GZ2, beginning at the top centre. Tasks are colour-coded by their relative depths in the decision tree. Tasks outlined in brown are asked of every galaxy. Tasks outlined in green, blue, and purple are (respectively) one, two or three steps below branching points in the decision tree. Table 2 describes the responses that correspond to the icons in this diagram.

Figure 5: Decision tree

4.3 The Dataset

The data set utilized in this task is obtained online and available on Kaggle website [5]. The original data set contain 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. The csv file contains 38 columns and 61578 rows. The first column is the ID of each galaxy image, the remaining 37 columns are different features of each image. The value of each feature is in between 0 and 1. Each image in the data set is preprocessed and its shape is reduced. The original shape of each image is (424, 424) while taking advantage of the fact that the point of interest is at the center, I just crop and down sample the images. The final shape of the image is (60, 60). The figure 5a shows original image of a galaxy while figure 5b shows cropped image.

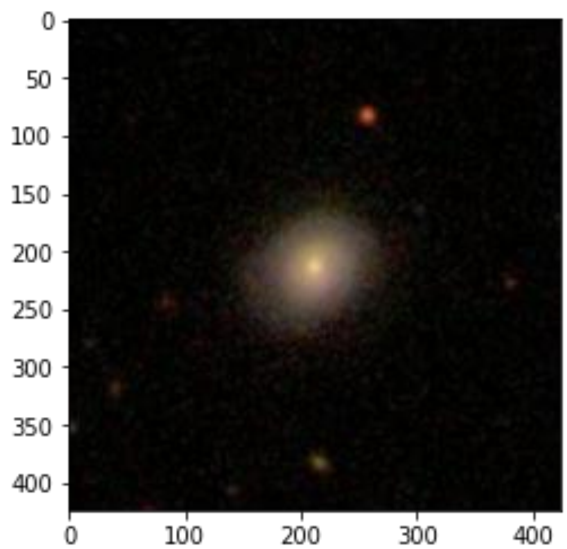


Figure 5a: Original Image of Galaxy

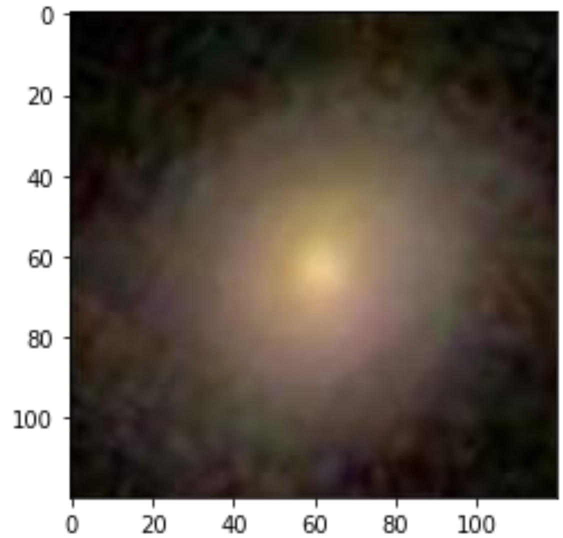


Figure 5b: Cropped Image of Galaxy

Chapter 5 Experiments

As discussed in this paper, there are a lot of combinations of layers that we can use in a CNN architecture. In this report, eight models of neural network (deep learning) are applied on the galaxy data set.

Method

I started by exploring different architecture to choose, as a base model, the one with the best accuracy. I tried three basic architectures, Lenet5, Conv-Pool- Conv-Pool and VGG.
Using binary cross entropy and Adam optimizer with learning rate of 0.001 we train with 25 each architecture to get accuracy values as shown below.

Lenet5:	`val_loss: 0.2897 - val_accuracy: 0.5974`
Conv-Pool-Conv-Pool:	`val_loss: 0.3019 - val_accuracy: 0.5747`
VGG:	`val_loss: 0.2804 - val_accuracy: 0.6169`

The VGG Architecture seems to have a slighter better accuracy, so I choose this one as my base model.

VGG Deep Learning Model

VGG is architecture of deep learning. VGG accepts an RGB picture. VGG's convolutional layers employ a 3x3 receptive field that is incredibly tiny. Additionally, there are 1x1 convolution filters that alter the input linearly before passing it on to the ReLU function. There are also two fully connected layers. VGG model uses Relu activation function in their hidden layers. Generally, the VGG model does not use Local Response Normalization (LRN) as it takes more time during training and does not put an increase in the accuracy of the model.

The VGG model used in this task has total four convolutional layers with 3x3 kernel filters, two 2D pooling layers with 2x2 kernel filters, and two fully connected layers. The activation function throughout the hidden layer is Relu, in first fully connected layer, the activation function is Relu while in second layer the activation function is SoftMax. The figure 6 shows architecture of VGG model.

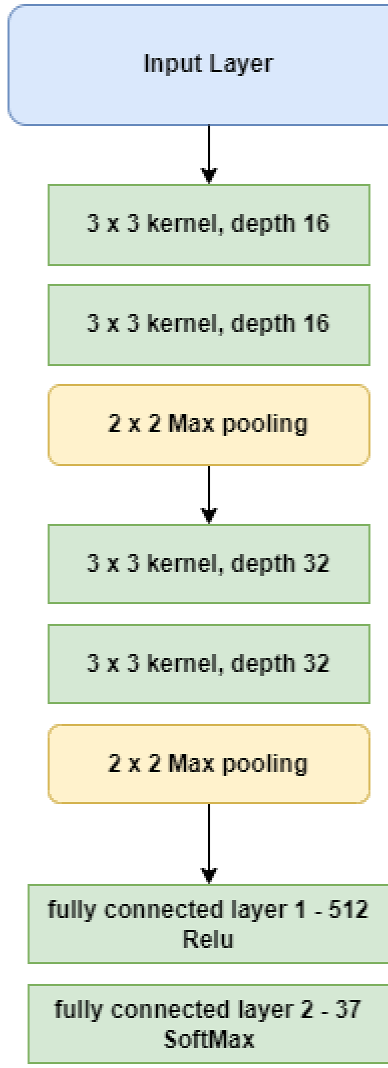
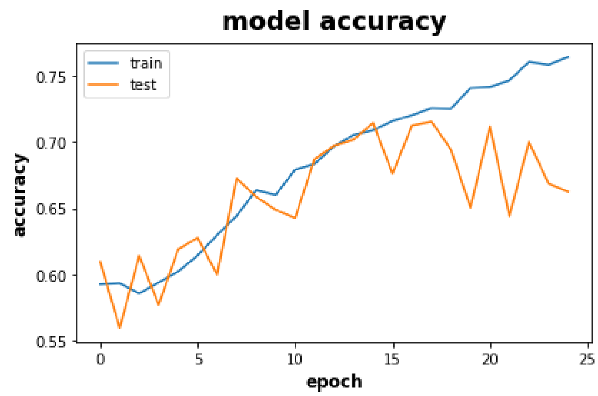
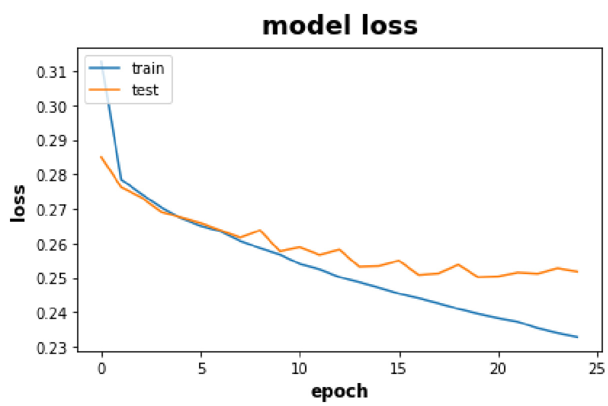


Figure 6: Architecture of VGG Model

After training the VGG model with above architecture and evaluated, the loss value of model is 25.2% and accuracy value of 66.7%.



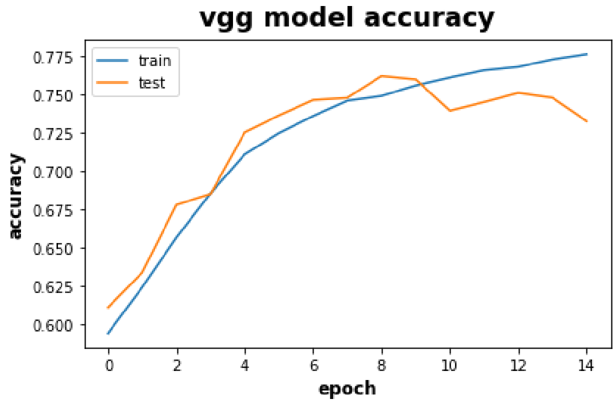
Graph 1a: VGG Model Accuracy



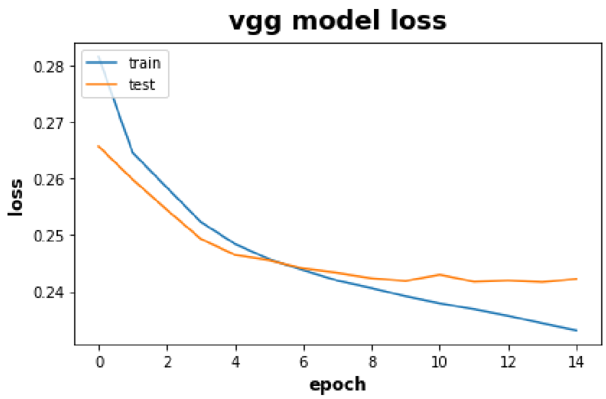
Graph 1b: VGG Model loss

We observe a fall from 15th epoch and on, so an early stopping function is added, which uses callbacks to stop earlier in case not further improvement is made.

After 120 minutes and an early stopping at the 15th epoch, we observe an improvement of 24.6% for loss and accuracy value of 72.5%.



Graph 2a: VGG Model Accuracy



Graph 2b: VGG Model Loss

AlexNet

Next, I used an alteration of a famous model called AlexNet. I used the original model but made changes at the sizes because the images of this project have a size of 60x60 and a addition of a dropout to result in a 37 sized output was necessary. One for each category. The figure 7 shows architecture of the AlexNet model.

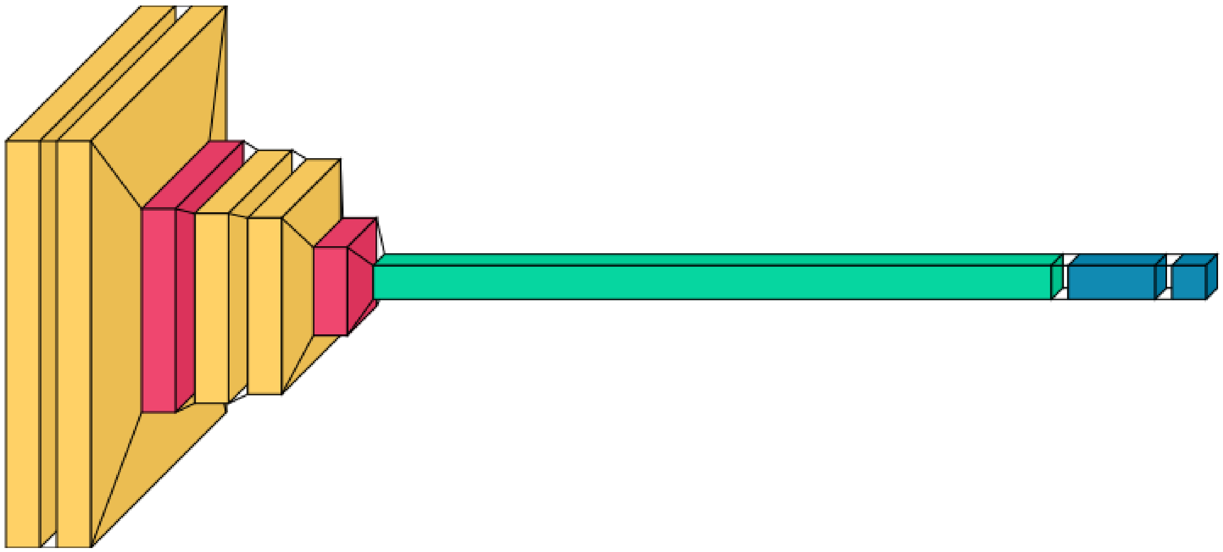
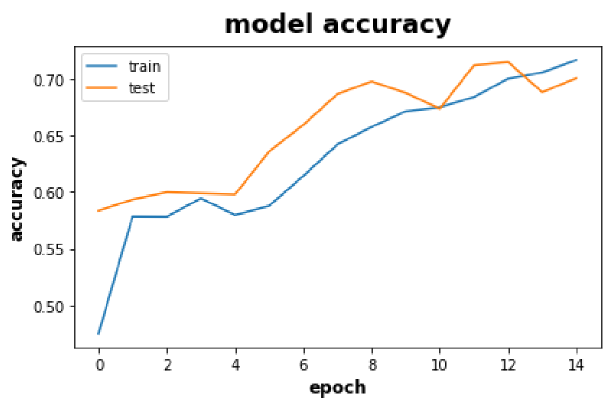
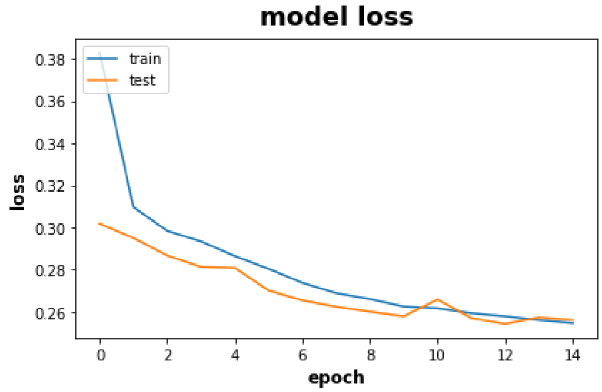


Figure 7: Architecture of alternative AlexNet Model

After training the AlexNet model with above architecture and evaluated, the loss value of model is 25.2% and accuracy value of 69.7%.



Graph 3a: AlexNet Model Accuracy



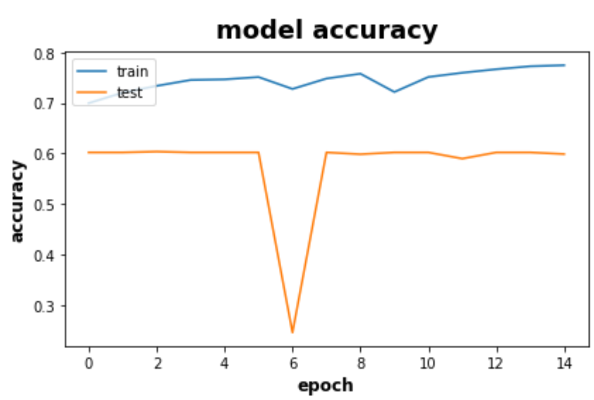
Graph 3b: AlexNet Model Loss

It took much more time – 480 minutes – and it didn't show any promising behaviour or better performance.

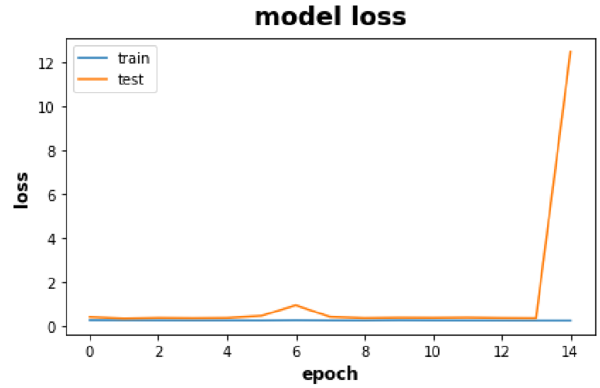
Pre-trained Models

Next, I tried the transfer learning approach. I used a pre-trained model called EffientNetB3 use as the first part of my model. We then Flatten the result and add a single Dense layer with 512 units. The output layer is still the same Dense layer with 37 units. One for each category.

After training the model for 560 minutes and evaluated, the loss value of model is 25.2% and accuracy value of 66.7%.



Graph 4a: EfficientNetB3 Model Accuracy

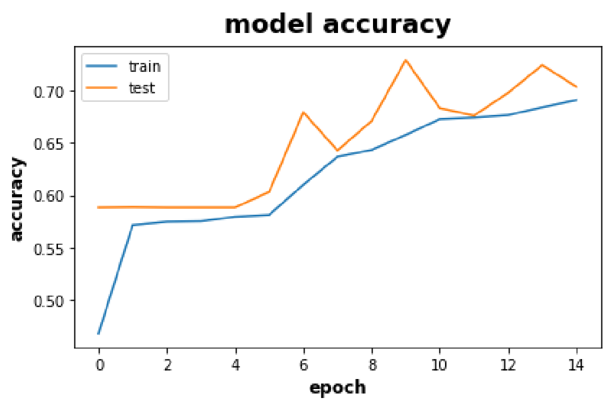


Graph 4b: EfficientNetB3 Model Loss

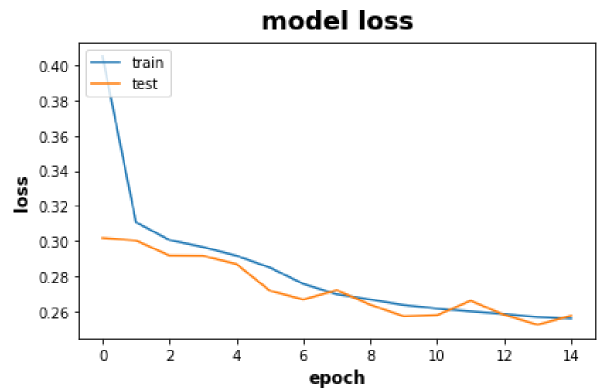
We observe the issue of overfitting as the train and test accuracy difference is quite big.

Another pre-trained model that was used is VGG16. Similarly, as before, the model is used for the first part, then the result is getting flattened and finally, the output layer is a Dense layer with 37 units.

After training the model for 908 minutes and evaluated, the loss value of model is 26.1% and accuracy value of 68.7%. It doesn't seem to have overfitting and we observe a promising behaviour.



Graph 5a: VGG16 Model Accuracy



Graph 5b: VGG16 Model Accuracy

The pre-trained models didn't work as well as expected, probably because of the nature of the dataset.

Vision Transformer

To use this alternative to convolution is necessary to perform data augmentations first. After this, each image was turned into patches as we see at the following figure.

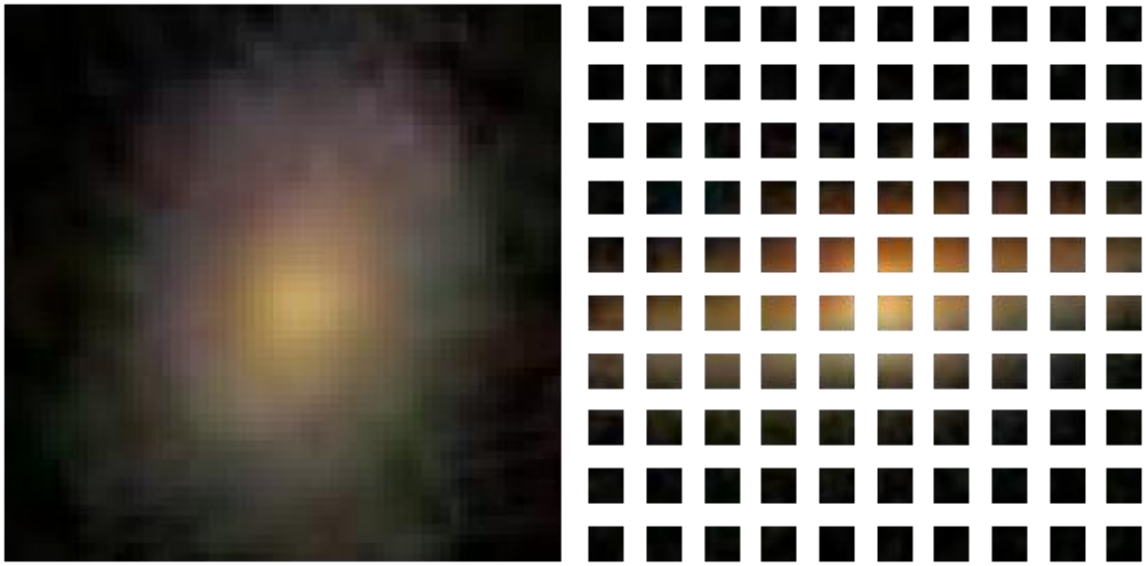


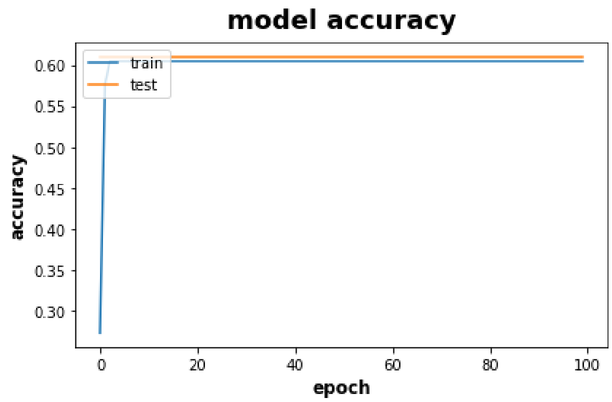
Figure 8: Image turned into patches

The architecture is designed as base model in which all the hyperparameters are defined. The table 1 shows all the hyperparameters and their values.

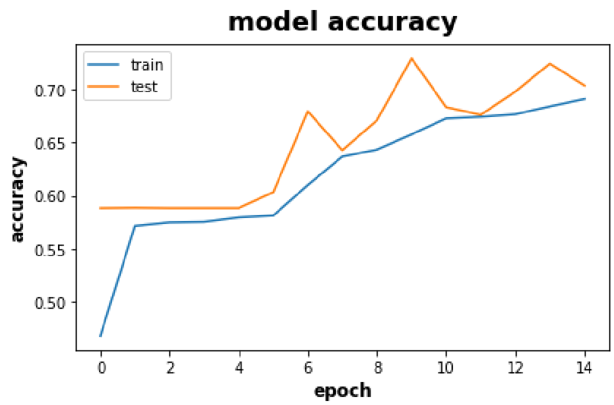
Table 1: Hyperparameters of Tranformer

Hyperparameter	**value**
learning_rate	0.001
weight_decay	0.0001
batch_size	128
num_epochs	100
image_size	60
Projection_dim	64
Num_heads	4
Transformer_layers	8

Running the TensorFlow implementation and 100 epochs later, the ViT model achieves around 60% accuracy.



Graph 6a: ViT Model Accuracy



Graph 6b: ViT Model Loss

These are not competitive results on the dataset but can be improved by experiment with the hyperparameters.

Chapter 6 Conclusion

The analysis in this paper demonstrated that there is still room for improvement when it comes to complex and vast datasets

6.1 Summary and conclusions

The VGG model had the best performance and especially with the early stopping function, achieving a 72% accuracy.

AlexNet had similar results, but the training lasted 3 times as long.

The pretrained models didn't performed as I would expect, having mediocre performance and lasting an extreme amount of time. My interpretation of this, is that the ImageNet didn't fit this dataset.

Lastly, the vision transformer showed promising results and can be further explored for improvement.

6.2 Future work

Additional performance improvements and wider use of ML solutions can be achieved by:

1. Increase parameter sharing
2. Further data augmentation
3. Use Hypers for hyperparameter tuning
4. Explore different architectures having the VGG model as a base
5. Experiment with the number of patches and hyperparameters for Vit

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