CMP3753M Project Proposal

Luke Roberts

University of Lincoln
25722923@students.lincoln.ac.uk

1 Introduction

Understanding the universe has been a pursuit of humanity for thousands of years. Because of the increasing effectiveness of deep learning image classification models, categorising distant objects in space has become much easier. Therefore, this rapid development in deep learning will allow astrophysicists to further their research into the early universe.

Advances in observational technology such as the James Webb Space Telescope (JWST) [1] push the bounds of galaxy observations further into deep space. The time taken for the light of distant galaxies to reach the earth means that our night sky is a window into the past, which allows astrophysicists to understand the evolution of our universe in more depth. Photographs such as the Hubble Ultra-Deep field show an ancient universe full of developing galaxies [2], and the amount of observed galaxies in astronomy databases continues to increase.

By identifying how the structure of galaxies, or galaxy morphology, changes over time, astrophysicists have a clearer picture of changes the universe has undergone. However, it is extremely time-consuming for astrophysicists to categorise galaxies in their research. A study in 2016 [3] calculated that there are 2.0×10^{12} galaxies in the observable universe. While it would be unnecessary to categorise every galaxy, automation accelerates research as the distance of observations continues increasing. One powerful method for automation of images is to train and deploy a deep learning model.

Deep Learning has recently revolutionised both scientific research and modern life in a profound way. From automated X-ray and MRI classification; machine translation such as Google Translate and large language models such as ChatGPT, deep learning has become the best way to categorise, analyse and generate unstructured data [4]. To perform many of these tasks, machine learning engineers create deep learning models which utilises a dataset that learns patterns about that data.

Image classification is a form of deep learning that uses images as input data and is used for a wide variety of applications in scientific research. Like all forms of deep learning, image processing models are trained so that they more accurately categorise

new input data by analysing how the model output differs from the expected output. All models are have some innacuracies but choosing the correct model minimises error. Popular models for image classification are deep neural networks (DNNs) and convoluted neural networks (CNNs). New deep learning models are also being developed. One promising new model is ConvXGB which was shown to be more acurate when compared to other deep learning models for certain datasets [6].

Recent studies such as (José A. de Diego et. al) [7] concluded that using a DNN "outperforms" other adopted models for galaxy classification. However, to extend this research which deep learning neural network is most effective at classifying the morphology of distant galaxies will be evaluated.

2 Aims and Objectives

2.1 Aim

The aim of this project is to train and test deep learning models in order to determine which is more suitable to classify the morphology of galaxies from astronomy databases. The project will compare DNN, CNN and ConvXGB models. Each model will be implemented in python using machine learning libraries and trained on GPU accelerated hardware.

2.2 Objectives

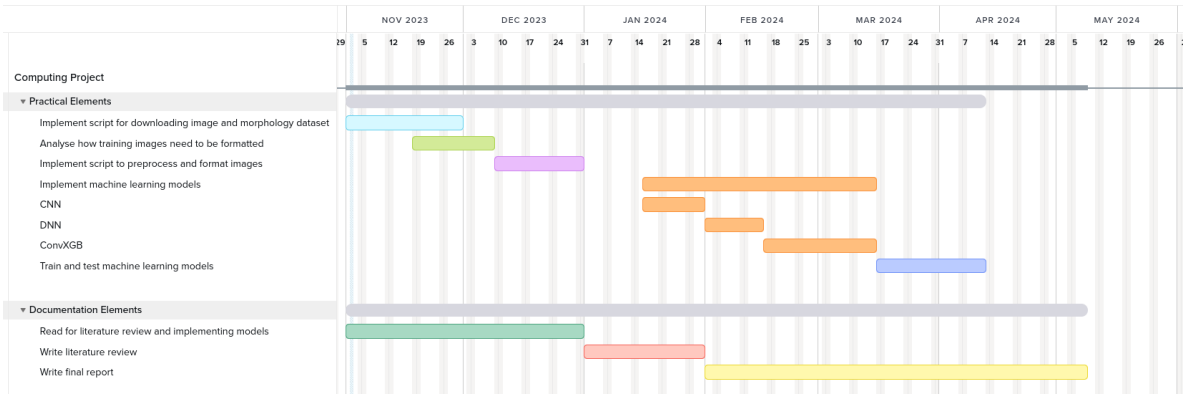
1. Collect a dataset of galaxy images, coupled with their morphological type using ESA astronomy archives [8] with the astropy library [9].
2. Analyse the formatting and structure of the dataset images so that preprocessing can be implemented.
3. Implement image preprocessing for training in python through an image processing library called Pillow [10] to training images. The rest of the dataset will also need to be cleaned before training.
4. Implement deep learning models (DNN, CNN, ConvXGB) for predicting the categorisation of images of galaxies. The real type of morphology associated with that image will be used in backpropergation the of the model to train it. The model implementations will be built using the python libraries Sci-kit Learn [11], TensorFlow [12] and XGBoost [13].
5. Deploy on hardware and train the models with the training dataset. Models will be tested and performance heuristics will determine which model is better at categorising galaxy morphology.

3 Project Plan and Risk Analysis

3.1 Project Plan

Practical implementations and dissertation writing will be worked on concurrently. Each stage of the implementation will be carried out in the order stated above in Objectives and an appropriate amount of time is given to each task depending on the complexity.

Fig. 1. Gant Chart of project



3.2 Risk Analysis

Table 1. Table of risks, their impacts and mitigations.

Risk	Occurance	Impact	Explenation	Mitigation
Missing Values	Very Likely	Low	Often, databases have missing values, which either affect model performance or prevent model training entirely.	Depending on the needs of the model, any rows of the dataset that have missing values could be removed or imputed.
Biassed Dataset	Very Likely	Medium - Low	Datasets sometimes overrepresent certain classifications or clusters of data, known as bias. This means the model is trained with biassed data which when tested, leads to biassed output.	Several techniques can be used to reduce bias. Resampling can be used to artificially overrepresent smaller classes and underrepresent larger classes. Applying data transformations can also reduce bias.
Performance Issues	Likely	High	Depending on the complexity of a machine or deep learning model, the computational resources needed to train the model may be quite high. This is especially true for neural network based models that require matrix multiplication and back-propagation calculations which are expensive for processors and memory.	GPU parallelisation will be necessary in order to train the models in a much shorter amount of time. The deep learning models will then be trained on a high-end GPU.
External Database Unavailable	Unlikely	High	If external databases used for training the model are either extremely slow or unavailable, data preprocessing and training models will not be available.	The database being down will be investigated to ascertain when it will be available again. If it remains down or will be down for a longer duration, alternative databases will be used instead.

References

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