

MAR ATHANASIOUS COLLEGE OF ENGINEERING
(Affiliated to APJ Abdul Kalam Technological University, TVM)
KOTHAMANGALAM



Department of Computer Applications

Mini Project Report

STAR-GALAXY CLASSIFICATION
USING DEEP LEARNING

Done by

Ajay Das M

Reg No : MAC22MCA-2014

Under the guidance of
Prof. Nisha Markose

2022-2024

MAR ATHANASIUS COLLEGE OF ENGINEERING
(Affiliated to APJ Abdul Kalam Technological University, TVM)
KOTHAMANGALAM

CERTIFICATE



Star-Galaxy Classification Using Deep Learning

Certified that this is the bonafide record of project work done by

Ajay Das M
Reg No: MAC22MCA-2014

during the third semester, in partial fulfilment of requirements for award of the
degree

Master of Computer Applications

of

APJ Abdul Kalam Technological University Thiruvananthapuram

Faculty Guide

Prof. Nisha Markose

Head of the Department

Prof. Biju Skaria

Project Coordinator

Prof. Sonia Abraham

Internal Examiners

ACKNOWLEDGEMENT

With heartfelt gratitude, I extend my deepest thanks to the Almighty for His unwavering grace and blessings that have made this journey possible. May His guidance continue to illuminate my path in the years ahead.

I am immensely thankful to Prof. Biju Skaria, Head of the Department of Computer Applications and my mini project guide, and Prof. Nisha Markose, our dedicated project coordinator, for their invaluable guidance and timely advice, which played a pivotal role in shaping this project. Their guidance, constant supervision, and provision of essential information were instrumental in the successful completion of the mini project.

I extend my profound thanks to all the professors in the department and the entire staff at MACE for their unwavering support and inspiration throughout my academic journey. My sincere appreciation goes to my beloved parents, whose guidance has been a beacon in every step of my path.

I am also grateful to my friends and individuals who generously shared their expertise and assistance, contributing significantly to the fulfillment of this endeavor.

ABSTRACT

The challenge of accurately classifying astronomical objects as stars or galaxies has been a fundamental task in astrophysics for centuries. Traditional methods relied heavily on visual inspection and morphological analysis, which were labour-intensive and limited by human subjectivity and the capacity to process large data volumes. With the advent of modern sky surveys like the Sloan Digital Sky Survey (SDSS), the volume of astronomical data has grown exponentially, rendering manual classification impractical.

The literature survey across the reviewed papers highlights three algorithms Convolution Neural Network (CNN), deep convolutional neural networks (ConvNets), ContextNet where taken into consideration.

The performance of deep learning architecture Convolution Neural Network (CNN) is used to classify stars and galaxies. Steps include rejecting data with errors, correcting for extinction, aligning images, and centring objects using nMontage and SExtractor.

The Dataset is taken from the Kaggle repository, the dataset contains 3986 data which 942 galaxy 3044 Star data.

Among the three Architecture, the Convolution Neural Network (CNN) is found to be best in terms of model building and computation. Thus, Star-Galaxy Classification Using Deep learning offers significant benefits for star-galaxy classification, including reduced human error, increased scalability, and efficient handling of vast data quantities.

LIST OF TABLES

Table 2.1.1. Summary of Paper 1

Table 2.1.2. Summary of Paper 1

Table 2.1.3. Summary of Paper 1

Table 2.1.4. Summary of all the reference papers

LIST OF FIGURES

CONTENTS

- 1. Introduction**
- 2. Supporting Literature**
 - 2.1 Literature Review
 - 2.1.1 Summary Table
 - 2.2 Findings and Proposals
- 3. System Analysis**
 - 3.1 Analysis of Dataset
 - 3.1.1 about the Dataset
 - 3.1.2 Explore the dataset
 - 3.2 Data Pre-processing
 - 3.3 Analysis of Algorithm
- 4. System Design**
- 5. Results and Discussion**
- 6. Model Deployment**
- 7. Git History**
- 8. Conclusion**
- 9. Future Work**
- 10. Appendix**
- 11. References**

1. Introduction

The challenge of accurately classifying astronomical objects as stars or galaxies has been a fundamental task in astrophysics for centuries. Traditional methods relied heavily on visual inspection and morphological analysis, which were labour-intensive and limited by human subjectivity and the capacity to process large data volumes. With the advent of modern sky surveys like the Sloan Digital Sky Survey (SDSS), the volume of astronomical data has grown exponentially, rendering manual classification impractical.

The literature survey across the reviewed papers highlights three algorithms Convolution Neural Network (CNN), deep convolutional neural networks (ConvNets), ContextNet where taken into consideration.

The performance of deep learning architecture Convolution Neural Network (CNN) is used to classify stars and galaxies. Steps include rejecting data with errors, correcting for extinction, aligning images, and centring objects using nMontage and SExtractor.

The Dataset is taken from the Kaggle repository, the dataset contains 3986 data which 942 galaxy 3044 Star data.

Among the three Architecture, the Convolution Neural Network (CNN) is found to be best in terms of model building and computation. Thus, Star-Galaxy Classification Using Deep learning offers significant benefits for star-galaxy classification, including reduced human error, increased scalability, and efficient handling of vast data quantities.

2. SUPPORTING LITERATURE

2.1 Literature Review

Paper 1: *Ganesh Ranganath Chandrasekar Iyer Krishna Chaithanya Vastare (2017). Deep Learning for Star-Galaxy Classification*

This project explores a CNN-based classifier to address these limitations. The paper "Deep Learning for Star-Galaxy Classification" (2017) demonstrates that Convolutional Neural Networks (CNNs) can effectively distinguish between stars and galaxies in astronomical images, achieving higher accuracy than traditional methods.

Table 2.1.1. Summary of Paper 1

Title of the paper	Ganesh Ranganath Chandrasekar Iyer Krishna Chaithanya Vastare (2017). Deep Learning for Star-Galaxy Classification
Area of work	Using deep learning, specifically Convolutional Neural Networks (CNNs), for classifying stars or galaxies.
Dataset	Dataset was taken from the Sloan Digital Sky Survey (SDSS). The dataset contains 30 million images.
Methodology / Strategy	CNN-based binary star-galaxy classifier involves collecting labelled image data from sources like the SDSS, pre-processing the data by normalizing and resizing images, and splitting it into training, validation, and test sets. A CNN is designed with convolutional and pooling layers for feature extraction, followed by fully connected layers for classification, with a sigmoid output layer for binary classification. The model is trained using binary cross-entropy loss and the Adam optimizer, then evaluated using accuracy, precision, recall, and F1-score metrics. Finally, the trained model is deployed to classify new astronomical data.

Architecture	Convolutional Neural Networks(CNN)
Result/Accuracy	CNN(Convolutional Neural Networks) – 99.19

Paper 2 : *Kim EJ, Brunner RJ. Star-galaxy classification using deep convolutional neural networks. Monthly Notices of the Royal Astronomical Society. 2016 Oct 17:stw2672.*

Kim and Brunner (2016) developed a deep CNN approach for classifying stars and galaxies in astronomical images. Their method improves accuracy by effectively learning from the features in the images, outperforming traditional classification techniques.

Table 2.1.2. Summary of Paper 2

Title of the paper	Kim EJ, Brunner RJ. Star-galaxy classification using deep convolutional neural networks. Monthly Notices of the Royal Astronomical Society. 2016 Oct 17:stw2672.
Area of work	Star-galaxy classification using deep convolutional neural networks.
Dataset	photometric and spectroscopic data sets with different characteristics and compositions. data sets and the image pre-processing steps for retrieving cutout images
Methodology / Strategy	The research uses deep convolutional neural networks (ConvNets) to classify astronomical objects from SDSS and CFHTLenS survey data. The ConvNet, with several convolutional and fully connected layers, employs data augmentation and dropout to reduce over fitting. The study compares ConvNet performance to the Trees for Probabilistic Classifications (TPC) algorithm, focusing on accuracy and probabilistic calibration.
Architecture	Convolutional Neural Networks (ConvNets)
Result/Accuracy	ConvNet - 99.48

Paper 3 : Kennamer N, Kirkby D, Ihler A, Sanchez-Lopez FJ. *ContextNet: Deep learning for star galaxy classification. In International conference on machine learning 2018 Jul 3 (pp. 2582-2590). PMLR.*

The paper titled "ContextNet: Deep Learning for Star Galaxy Classification" presents a framework for classifying stars and galaxies in astronomical images, specifically for data from the Large Synoptic Survey Telescope (LSST)

Table 2.1.3. Summary of Paper 3

Title of the paper	Kennamer N, Kirkby D, Ihler A, Sanchez-Lopez FJ. ContextNet: Deep learning for star galaxy classification. In International conference on machine learning 2018 Jul 3 (pp. 2582-2590). PMLR.
Area of work	The work applies ContextNet Architecture to classify stars and galaxies in astronomical images from ground-based surveys like the LSST
Dataset	The dataset used in the work consists of simulated images from the Large Synoptic Survey Telescope (LSST) observations, generated using the GalSim image simulation package.
Methodology / Strategy	The methodology uses ContextNet, a three-step neural network framework. It includes a local network for individual object features, a global network for comparing features across objects to capture context, and a prediction network that combines these features for classification. This approach handles non-IID data and improves accuracy by leveraging neural network weight replication for variable object numbers in each exposure.
Architecture	Local Network: Convolutional Neural Networks (CNNs) Global Network: Recurrent Neural Networks (RNNs) Prediction Network: Fully Connected Neural Networks (FCNs)
Result/Accuracy	ContextNet - 95%

2.1.4 SUMMARY TABLE

Table 2.1.4. Summary of all the reference papers

REVIEW PAPER	ARCHITECTURE	ACCURACY
Deep Learning for Star-Galaxy Classification	Convolutional Neural Networks(CNN)	99.19
Star-galaxy classification using deep convolutional neural networks	Convolutional Neural Networks (ConvNets)	99.48
ContextNet: Deep Learning for Star Galaxy Classification	ContextNet	95

2.2 Findings and Proposals

From the above three papers, we get to know that different models were used for the classification of Stars and Galaxies. The initial project report on star-galaxy classification using deep learning explores three key research papers that leverage different neural network architectures for this task. The first paper, "Deep Learning for Star-Galaxy Classification" (2017), focuses on using Convolutional Neural Networks (CNNs) to classify astronomical objects. This study utilized a large dataset from the Sloan Digital Sky Survey (SDSS) and demonstrated that CNNs could achieve high accuracy in distinguishing between stars and galaxies, with the model reaching an accuracy of 99.19%. The CNN-based approach was found to be highly effective, emphasizing the strength of deep learning in handling complex classification tasks.

The second paper, "Star-Galaxy Classification Using Deep Convolutional Neural Networks" (2016), by Kim EJ and Brunner RJ, further advanced the use of deep learning by employing deep convolutional neural networks (ConvNets). This study worked with photometric and spectroscopic datasets from the SDSS and CFHTLenS surveys and incorporated techniques like data augmentation and dropout to enhance model performance. The ConvNet model outperformed traditional classification methods, achieving a remarkable accuracy of 99.48%. This research highlighted the potential of deep learning to improve the precision and reliability of astronomical classifications.

The third paper, "ContextNet: Deep Learning for Star-Galaxy Classification" (2018), introduced a more complex architecture known as ContextNet, designed to handle data from the Large Synoptic Survey Telescope (LSST). ContextNet integrates CNNs, Recurrent Neural Networks (RNNs), and Fully Connected Neural Networks (FCNs) to capture both local and global features of astronomical images. Although this model achieved a slightly lower accuracy of 95%, it offered a sophisticated approach to addressing the challenges posed by non-independent and identically distributed (non-IID) data in astronomical surveys. Together, these studies underscore the effectiveness of deep learning, particularly CNNs, in advancing star-galaxy classification.

3. SYSTEM ANALYSIS

3.1. Analysis of Dataset

3.1.1. About the Dataset

The dataset is taken from the Kaggle repository. The dataset contains 3986 sample observations with 942 Galaxies and 3044 Stars photometric data

The dataset contains a collection of astronomical images captured using a 1.3-meter telescope located in Nainital, India. These images feature stars, galaxies, and other celestial objects. Researchers and data scientists can utilize this dataset for various tasks, including star-galaxy classification, object detection, and image analysis. The dataset provides a valuable resource for exploring the cosmos through machine learning and computer vision techniques.

Dataset: <https://www.kaggle.com/datasets/divyansh22/dummy-astronomy-data>

3.1.2. Explore the Dataset

The dataset contains 3986 sample observations with 942 Galaxies and 3044 Stars photometric data

Fig 3.1 Snapshot of Galaxy class from the dataset

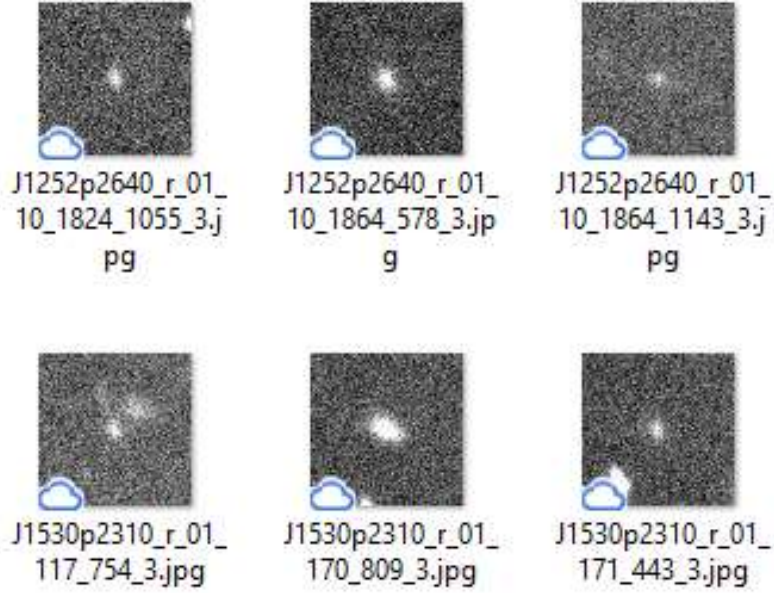


Fig 3.2 Snapshot of Star class from the dataset



3.2. Data Preprocessing

Resizing Image

Uniform Image Size: Since CNNs require fixed-size input images, all images in the dataset must be resized to a uniform size. A common choice for this type of classification task is 64x64 or 128x128 pixels, although the size can be adjusted based on the computational resources available and the complexity of the objects in the images.

Aspect Ratio Consideration: Ensure that resizing doesn't distort the images, particularly if the original images have different aspect ratios. In some cases, padding the images to maintain aspect ratios might be necessary.

Normalize

Pixel Value Scaling: CNNs perform better when input data is normalized. Typically, image pixel values are scaled from their original range (0-255 for 8-bit images) to a range of 0-1 or -1 to 1. This is done by dividing the pixel values by 255. Normalization helps in speeding up the convergence during training by ensuring that the input features have a similar scale.

Data Augmentation

Data augmentation artificially increases the size of the training dataset by creating modified versions of images in the dataset. This helps the model generalize better and become more robust to variations.

Technique:

Rotation: Randomly rotate images within a certain range to simulate different orientations of celestial objects.

Flipping: Horizontally or vertically flip the images to introduce symmetry variations.

Zooming: Randomly zoom in on images to simulate different scales.

Brightness/Contrast Adjustments: Modify the brightness and contrast of the images to account for different lighting conditions in the data.

Translation: Shift images horizontally or vertically to simulate positional variance.

Splitting the Database

Training Set: 80% of the dataset is used for training. This is the subset of data the model will learn from.

Test Set: The remaining 20% is reserved for testing the model after training to evaluate its performance on unseen data.

3.3. Analysis of Algorithm

3.3.1 Network Architecture of CNN

CNNs are a class of Deep Neural Networks that can recognize and classify particular features from images and are widely used for analyzing visual images. Their applications range from image and video recognition, image classification, medical image analysis, computer vision and natural language processing.

Convolutional Neural Networks (CNNs) are deep learning models that extract features from images using convolutional layers, followed by pooling and fully connected layers for tasks like image classification.

The main layers of CNN are:

- Input Layer
- Convolution Layer
- Pooling Layer
- Fully-Connected (dense) Layers
- Output Layer

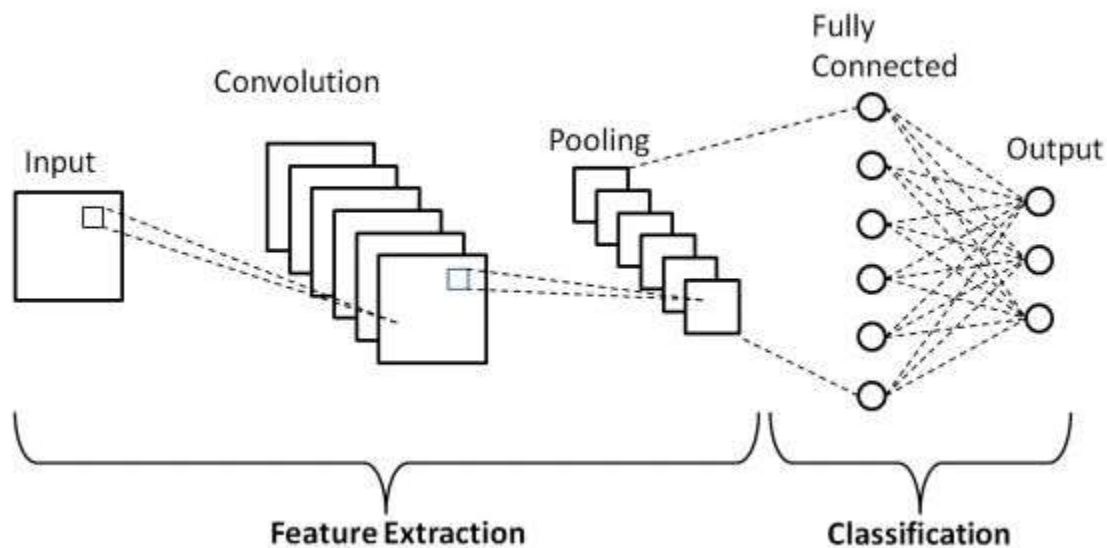


Fig 3.3 Architecture Diagram

Layers in CNN Architecture

Input Layer

This layer accepts the raw input images, which is in this case 64 x 64 pixel images in five photometric bands (u, g, r, i, z). This layer provides the initial data (images) to the network, which will be processed and analyzed to distinguish between stars and galaxies.

Convolution Layer

This layer Applies convolution operations to the input data, using a set of filters (kernels) to extract features such as edges, textures, and shapes. These layers detect various features at different levels of abstraction. Early layers might detect basic features like edges, while deeper layers detect more complex structures relevant to differentiating stars from galaxies.

Activation Function(Leaky ReLU)

This is Applies a non-linear transformation to the output of each convolutional layer. Leaky ReLU helps in avoiding the problem of dead neurons by allowing a small, non-zero gradient when the unit is not active. Introduces non-linearity to the model, enabling it to learn from complex data and to improve feature detection and classification.

Pooling Layer

This layer Reduces the spatial dimensions (width and height) of the feature maps, retaining the most critical information while reducing the computational load and controlling overfitting. By reducing the dimensionality, these layers help in abstracting the features detected by convolutional layers and make the network more computationally efficient.

Fully-Connected (Dense) Layers

In this layer each neuron in these layers is connected to every neuron in the previous layer, which allows the network to combine the features extracted by the convolutional and pooling layers and make final predictions. These layers are responsible for the final classification, combining all learned features to distinguish whether an object in the image is a star or a galaxy.

Output Layer

This is the final Layer of the architecture this layer Produces the final output, typically using a softmax function in classification tasks to produce probabilities for each class. His layer outputs the probability of the image belonging to either the "star" or "galaxy" class, allowing for final decision-making in the classification task.

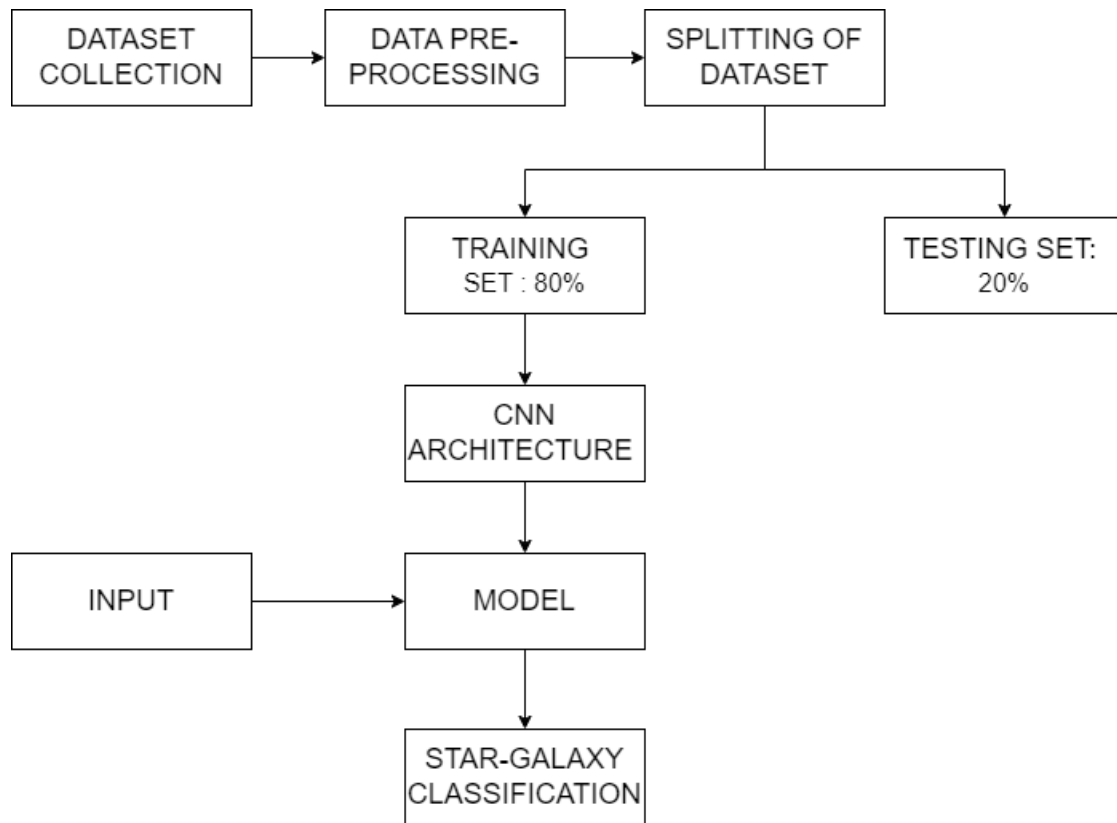
3.3.2 Dimension Table

Type	Filters	Filter Size	Padding	Non-linearity	Initial Weights	Initial Biases
Convolutional	32	5×5	-	Leaky ReLU	Orthogonal	0.1
Convolutional	32	3×3	1	Leaky ReLU	Orthogonal	0.1
Pooling	-	2×2	-	-	-	-
Convolutional	64	3×3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	64	3×3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	64	3×3	1	Leaky ReLU	Orthogonal	0.1
Pooling	-	2×2	-	-	-	-
Convolutional	128	3×3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	128	3×3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	128	3×3	1	Leaky ReLU	Orthogonal	0.1
Pooling	-	2×2	-	-	-	-
Fully-Connected	2048	-	-	Leaky ReLU	Orthogonal	0.01
Fully-Connected	2048	-	-	Leaky ReLU	Orthogonal	0.01
Fully-Connected	2	-	-	Softmax	Orthogonal	0.01

3.4. Project Plan

3.4.1. Project Pipeline

Fig 3.4 Project Pipeline



3.4.2. Project Implementation Plan

- Submission of project synopsis with Journal Papers - 22.07.2024
- project proposal approval - 26.07.2024
- presenting project proposal before the Approval Committee - 29.07.2024 & 30.07.2024
- Initial report submission - 12.08.2024
- Analysis and design report submission - 16.08.2024
- First project presentation - 21.08.2024 & 23.08.2024
- Sprint Release I - 30.08.2024
- Sprint Release II - 26.09.2024
- Interim project presentation - 30.09.2024 & 01.10.2024
- Sprint Release III - 18.10.2024
- Submission of the project report to the guide - 28.10.2024
- Final project presentation - 28.10.2024 & 29.10.2024
- Submission of project report after corrections - 01.11.2024