MAR ATHANASIUS 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

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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

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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.

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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.

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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

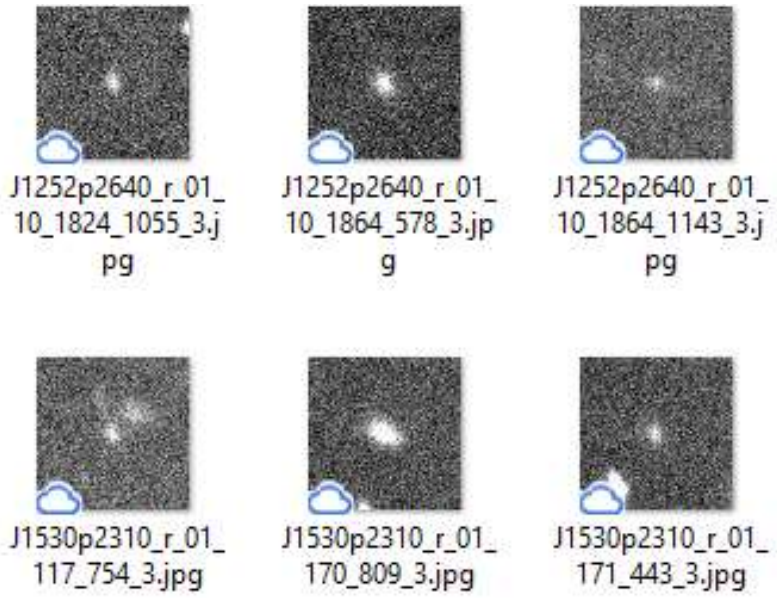
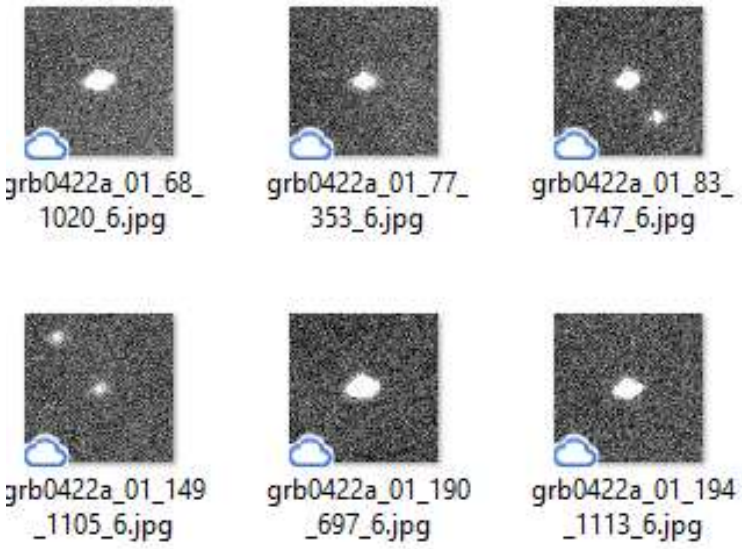


Fig 3.2 Snapshot of Star class from the dataset



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

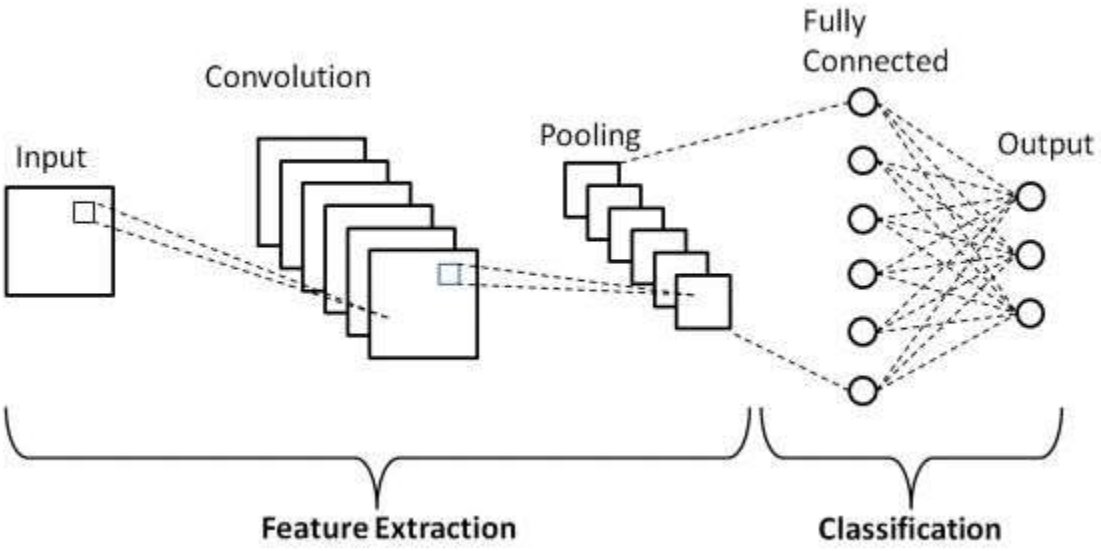


Fig 3.3 *Architecture Diagram*

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. This 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

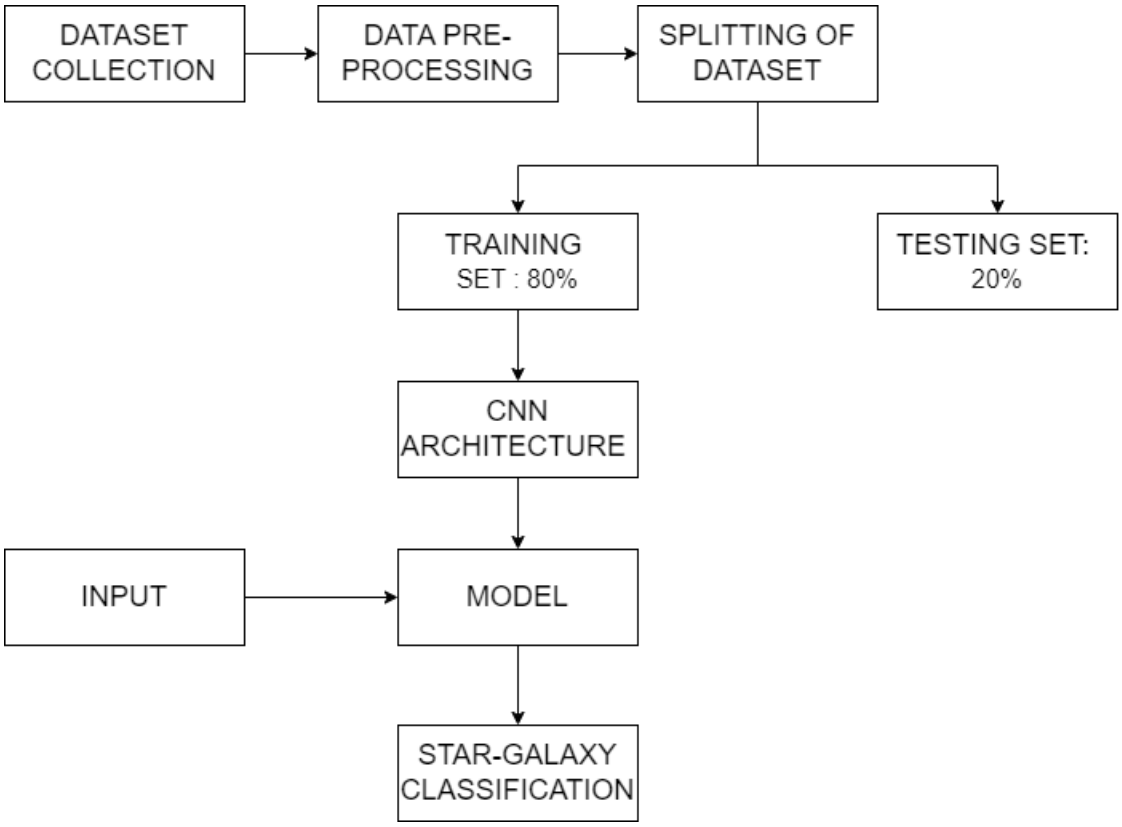
Table 3.1 Dimension Table of CNN

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 x 2	-	-	-	-
Convolutional	64	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	64	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	64	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Pooling	-	2 x 2	-	-	-	-
Convolutional	128	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	128	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Convolutional	128	3 x 3	1	Leaky ReLU	Orthogonal	0.1
Pooling	-	2 x 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

4. SYSTEM DESIGN

4.1. Model Building

4.1.1. Model Planning

The primary aim of the model planning phase in the star-galaxy classification project is to establish a comprehensive framework that guides subsequent model-building activities. This phase involves defining the scope, selecting appropriate algorithms, and outlining the overall strategy for accurately classifying astronomical objects as stars or galaxies using deep learning techniques.

1. Objective:
Develop a star-galaxy classification system using Convolutional Neural Network (CNN) to classify astronomical objects based on their photometric data

2. Approach:
Utilize CNN architecture, which has proven effective for image classification tasks. The model will be trained on a dataset containing images of stars and galaxies, preprocessing the data for improved accuracy.

2. Approach:
Utilize CNN architecture, which has proven effective for image classification tasks. The model will be trained on a dataset containing images of stars and galaxies, preprocessing the data for improved accuracy.

3. Data Preparation:
Import and preprocess the astronomical images. Handle any errors in the data, correct for extinction, align images, and center the objects using tools like nMontage and SExtractor. Rescale images, apply random transformations for data augmentation to enhance model robustness

4.1.2 Training

The Convolutional Neural Network (CNN) model is constructed using a deep learning approach to extract features from images and classify them accordingly. Below are the detailed steps involved in the model-building process, including model architecture and training procedure using the training dataset.

Step 1: Importing Required Libraries

To commence the model-building process, it is essential to import all necessary libraries, such as TensorFlow and Keras. These libraries are fundamental for constructing and training the CNN model, offering extensive functionalities and support for deep learning applications.

Step 2: Convolutional Neural Network Model Architecture

The CNN model is meticulously designed using a structured sequence of layers, each contributing to the overall functionality and performance of the model:

1. **Input Layer**: This layer receives the input images, setting the stage for subsequent layers to process the data.

2. **Convolution Layer 1**: This layer consists of 32 filters, each with a 3x3 kernel, and employs the ReLU activation function to introduce non-linearity.

3. **MaxPooling Layer 1**: This layer utilizes a 2x2 pool size to reduce the spatial dimensions of the feature maps, thereby minimizing computational complexity.

4. **Convolution Layer 2**: This layer is composed of 64 filters, each with a 3x3 kernel, and also employs the ReLU activation function for enhanced feature extraction.

5. **MaxPooling Layer 2**: This layer again uses a 2x2 pool size to further reduce the spatial dimensions of the feature maps.

6. **Convolution Layer 3**: This layer includes 128 filters, each with a 3x3 kernel, and employs the ReLU activation function to capture more complex features.

7. **MaxPooling Layer 3**: This layer uses a 2x2 pool size to provide additional dimensionality reduction.

8. **Flatten Layer**: This layer converts the 2D feature maps into a 1D vector, facilitating the transition from convolutional layers to fully connected layers.

9. **Dense Layer 1**: This layer contains 128 units and employs the ReLU activation function to learn intricate patterns and representations.

10. **Dropout Layer 1**: Operating with a 50% dropout rate, this layer helps prevent overfitting by randomly deactivating neurons during training.

11. **Dense Layer 2**: This layer comprises 64 units and employs the ReLU activation function, further refining the learned patterns.

12. **Dropout Layer 2**: Similar to the previous dropout layer, this one also operates with a 50% dropout rate to mitigate overfitting risks.

13. **Output Layer**: This final layer consists of 2 units with the Softmax activation function, providing the classification output as probabilities for each class.

Step 3: Model Compilation and Class Weights

Upon completion of the model architecture, the next step is to compile the model. This is achieved using the Adam optimizer, which is known for its efficiency and adaptability in deep learning applications. A learning rate schedule is implemented to gradually decrease the learning rate during training, thereby enhancing the optimization process. The loss function utilized is categorical cross-entropy, which is suitable for multi-class classification tasks. Additionally, class weights are

computed to address any imbalance present within the dataset, ensuring that each class is appropriately represented during the training process..

- **Learning Rate Schedule**: Helps in gradually decreasing the learning rate during training.

- **Class Weights**: Computed to balance the influence of different classes during training.

Step 4: Model Training

The model undergoes training utilizing the dataset, with validation loss monitoring to avert overfitting through early stopping mechanisms..

- **Early Stopping**: A callback is used to stop training when validation loss does not improve for a specified number of epochs.

4.1.3 Testing

Model Performance

The Convolutional Neural Network model was evaluated using a test dataset to classify images into two categories: Star and Galaxy. The testing phase evaluates the model's performance and its ability to generalize to unseen data, which is crucial for understanding the model's effectiveness in real-world applications. The following are the key metrics and results obtained from this evaluation

Testing Metrics

- **Test Accuracy:** The model achieved an accuracy of 88.59% on the test dataset, indicating its reliability in distinguishing between stars and galaxies**.**

- **Test Loss**: The test loss was recorded at 28.75%, which is reflective of the model's performance during the testing phase.

Training Metrics

- **Training Accuracy**: During the training phase, the model achieved an accuracy of 87.72%. This demonstrates the model's ability to learn from the training data effectively.

- **Training Loss**: The training loss was measured at 29.91%, providing insight into the error rate during the model's training.

Evaluation Matrix:

The model's performance was further assessed using various evaluation metrics, as detailed in the table below

Table 4.1 Evaluation Matrix

Metric	Galaxy	Star	Accuracy	Macro Average	Weighted Average
Precision	0.24	0.76		0.50	0.64

Recall	0.21	0.79		0.50	0.66
F1-Score	0.23	0.78	0.66	0.50	0.65
Support	189	609	798	798	798

Analysis

Precision: The precision for the "Galaxy" class is 0.24, and for the "Star" class, it is 0.76. This indicates the model's ability to correctly identify positive instances of each class.

Recall: The recall for the "Galaxy" class is 0.21, and for the "Star" class, it is 0.79, showing the model's ability to capture the relevant instances of each class.

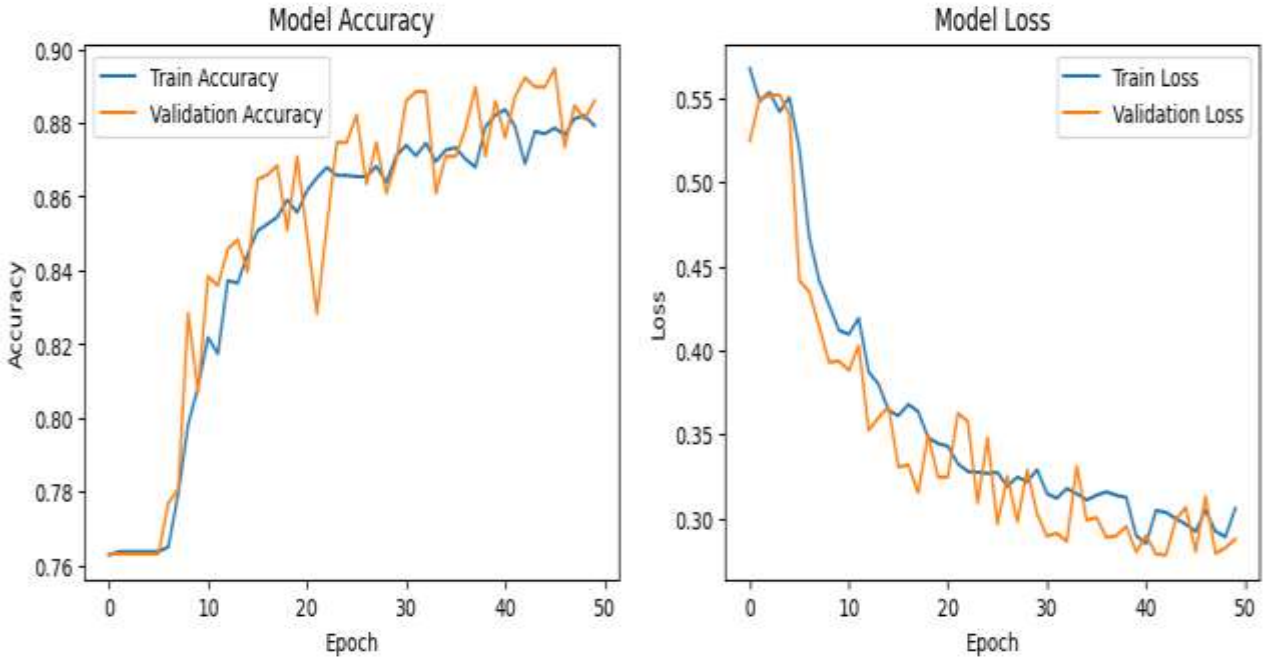
F1-Score: The F1-Score for the "Galaxy" class is 0.23, while for the "Star" class, it is 0.78. This metric provides a balance between precision and recall.

Support: The support values indicate the number of actual instances for each class: 189 for "Galaxy" and 609 for "Star."

Learning Curves:

The learning curves for the model accuracy and model loss over the training and validation datasets are depicted in Figure 4.2. These curves provide a visual representation of how the model's performance evolved during the training process.

Fig 4.2 Model Accuracy and Model Loss Curves



5. RESULTS AND DISCUSSION

The following code demonstrates the process of loading a pre-trained Convolutional Neural Network (CNN) model and utilizing it to classify astronomical images into two categories: stars and galaxies. The code encompasses essential steps, including model loading, image preprocessing, prediction, and result visualization.

In the initial phase, the necessary libraries are imported, including *NumPy* for numerical operations, *Matplotlib* for plotting, and *TensorFlow/Keras* for deep learning functionalities. The trained CNN model is then loaded using the *load_model* function, which retrieves the saved model from the specified file path.

Fig 5.1 Source code loading the model

```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import load_model

# Load your trained model
model = load_model('star_galaxy_classifier.h5')
```

The *load_and_preprocess_image* function is defined to load and preprocess the input image for prediction. The image is resized to the target dimensions (64x64 pixels) and converted to grayscale. The image is then transformed into an array, expanded to create a batch of size one, and rescaled by dividing by 255.0 to normalize the pixel values.

Fig 5.2 Source code load_and_preprocess_image function

```
def load_and_preprocess_image(img_path):
    """Load and preprocess the image for prediction."""
    img = image.load_img(img_path, target_size=(64, 64), color_mode='grayscale')
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)  # Create a batch of size 1
    img_array /= 255.0  # Rescale the image
    return img_array
```

The *predict_image* function is responsible for predicting the class of the input image. It preprocesses the image using the previously defined function, makes predictions using the loaded model, and determines the predicted class by selecting the class with the highest probability

Fig 5.3 Source code for predict_image function

```
def predict_image(img_path):
    """Predict the class of the input image."""
    preprocessed_image = load_and_preprocess_image(img_path)
    predictions = model.predict(preprocessed_image)
    predicted_class = np.argmax(predictions, axis=1)
    return predicted_class, predictions
```

In this section, an example image path is specified, and the *predict_image* function is utilized to predict the class of the specified image. The prediction results, including the predicted class and the associated probabilities, are printed to the console.

Fig 5.4 Source code printing the output

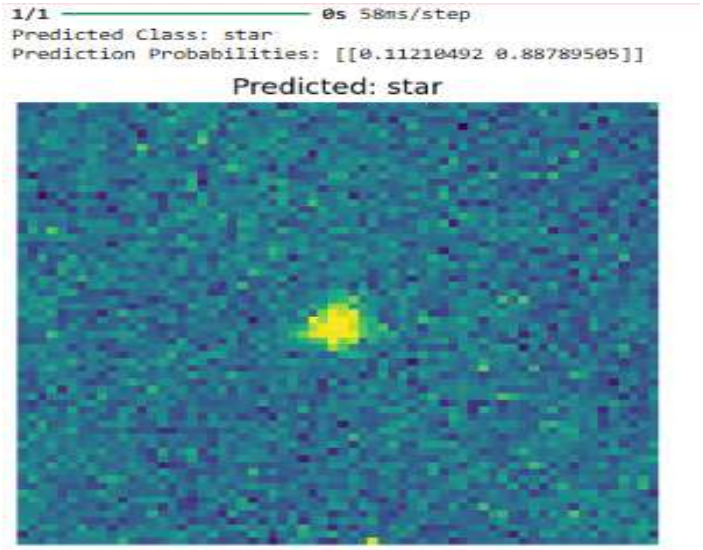
```
# Example of using the prediction function
img_path = 'dataset1/test/star/grb0422a_01_1465_1314_6.jpg'
predicted_class, predictions = predict_image(img_path)

# Display the prediction results
class_labels = list(train_generator.class_indices.keys())
print(f"Predicted Class: {class_labels[predicted_class[0]]}")
print(f"Prediction Probabilities: {predictions}")
```

Finally, the optional code block displays the input image along with the predicted class. The image is loaded and displayed using Matplotlib, with the title indicating the predicted class.

Fig 5.1 Source code printing the image in the output

```
# Optional: Display the input image
plt.imshow(image.load_img(img_path, color_mode='grayscale'))
plt.title(f"Predicted: {class_labels[predicted_class[0]]}")
plt.axis('off')
plt.show()
```

The output is:
Upon running the prediction code, the model processed the input image to classify it into one of the two categories: star or galaxy. The model's inference step resulted in the following output:



This output indicates that the model successfully processed the image within 58 milliseconds per step. The results show that the predicted class for the input image is "star," with a prediction probability of approximately 88.79% for the star class and 11.21% for the galaxy class. This high probability value suggests that the model is confident in its prediction for this particular instance.

6. MODEL DEPLOYMENT

The principal objective of model deployment in this project is to seamlessly integrate the star-galaxy classification models, which were meticulously developed, into a production environment. This critical transition enables end-users to access and utilize the classification system, thereby making informed decisions based on the model's predictions.

Model deployment is a crucial phase that effectively bridges the gap between the theoretical development of the model and its practical, real-world application. By deploying the classification models, this project aims to provide a tangible, accessible, and reliable solution that meets the needs and preferences of its target users. The deployment process ensures that the sophisticated algorithms developed during the project are fully operational and can be leveraged to their full potential by end-users.

To facilitate the deployment process, the project employs various frameworks and libraries, such as Flask for creating web applications and TensorFlow/Keras for managing the deep learning models. These tools are instrumental in ensuring the smooth and efficient integration of the models into the production environment. They contribute significantly to the overall effectiveness of the deployment, ensuring that the system is robust, scalable, and user-friendly.

By leveraging these frameworks and libraries, the deployment process is streamlined, allowing the star-galaxy classification system to be accessed seamlessly by end-users. This approach guarantees that the theoretical advancements and model optimizations translate into practical tools that can handle real-world data effectively. The deployment phase ensures that the developed models are not just theoretical constructs but are practical solutions providing meaningful insights and accurate classifications, thereby fulfilling the project's objectives and serving the end-users' requirements comprehensively.

User Interface (UI):

The star-galaxy classification system is meticulously integrated into the user interface, ensuring a seamless and user-friendly experience for its users. The system is designed to provide easy navigation and interaction with the classification tool through an intuitive web interface.

Upon accessing the application, users are greeted with a clean and user-friendly introduction page titled 'Star-Galaxy Classification System'. This introduction page provides a brief yet comprehensive overview of the system’s capabilities, guiding users on how to proceed with the classification process.

Main Interface

The main interface is thoughtfully designed with several key elements to facilitate straightforward interaction. Initially, users are presented with the primary page, where they have the option to upload their image for classification. To proceed, users need to select the image file from their device using the provided file upload input.

Classification Process

Once the image file is selected, users simply need to click on the "Classify" button to initiate the classification process. The application promptly processes the uploaded image utilizing the pre-trained Convolutional Neural Network (CNN) model, and subsequently, the classification results are displayed to the user.

Result Page

The result page is designed to present the classification results in an accessible and informative manner. It showcases the predicted class of the image, indicating whether the image is classified as a star or a galaxy. Additionally, the actual image itself is displayed on this page, allowing users to visually verify the classification result.

Interactive Features

To enhance user interaction, the result page includes a convenient button labeled "Upload Another Image". This button allows users to return to the upload page, where they can repeat the classification process with a new image. This feature ensures continuous engagement and provides flexibility for users who wish to classify multiple images.

Visual and Functional Design

The overall design of the user interface is simple and easy to understand, ensuring that users, regardless of their technical expertise, can effortlessly navigate and utilize the star-galaxy classification system. The straightforward interaction design begins with the clean introduction page, leading users through a smooth workflow from image upload to result visualization.

Fig 6.1 Star-Galaxy Classification interface Home page

Fig 6.2 Star-Galaxy Classification interface Result page

11. REFERENCES

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