

<sup>1</sup> Heartlin Maria H  
 Kayalvizhi R<sup>1</sup>  
 Glory Precious J<sup>2</sup>  
 George Princess<sup>3</sup>  
 Priyanka Devi S<sup>4</sup>  
 Sowmiya G<sup>5</sup>

## Enhanced Celestial Object Detection for Astronomical Research based on CNN and Raspberry Pi



**Abstract:** - Astronomical research involves a significant amount of time-sensitive object classification that, for remote observatories, can be as quick as the response to any transient event occurring. However, traditional data analysis techniques usually require access to high-performance computing resources that are not readily available in some isolated locations. Therefore, edge computing brings computation closer to the data source, where it can be processed and interpreted quickly without delay. This paper presents a custom CNN model optimised for deployment on a Raspberry Pi-low-power edge device-for real-time object classification in astronomy. Advanced model optimisation techniques of quantisation and pruning adapt a CNN model to the computational power available on a Raspberry Pi while maintaining classification accuracy. This helps in identifying and classifying objects in the celestial plane in situ. This allows for in-situ data processing with the possibility of on-site in-situ data analysis. Our approach, therefore, will not only enable real-time analysis but also offer a scalable and cost-effective alternative to traditional systems in observatories that are not well-equipped with good access to high-performance computing infrastructure. Our paper reflects the merits of edge computing in astronomical applications in assisting timely decision making and enlarging the scope for continued field-based astronomical research.

**Keywords:** Celestial Objects, Deep Learning, Classification, Raspberry Pi

### I. INTRODUCTION

Advances in ML and DL have made a great difference in enhancing accuracy and efficiency in the classification of celestial objects like stars, galaxies, nebulae, and all other types of cosmic entities. Focusing on this problem helps in enhancing astronomical research by increasing robust methods for object detection and classification. Of these, CNNs, a derivative subtype of DL, have proven to be particularly promising for automatically enhancing the accuracy of such classifications. Recent research demonstrates the potential of CNN-based architectures in astronomical applications: for instance, Khalifa et al. developed a CNN-based galaxy classification model and obtained significant gains over traditional classification methods [1]. Similarly, by proposing data augmentation techniques, Mittal et al. enhanced galaxy morphology classification to make the model robust against image variations [2]. Some of the most challenging problems faced by CNN models have been resolved, including highly variable astronomical backgrounds as experienced in space debris detection and meteor detection [3]. QML methods are now pushing the boundaries further in the astronomical detection regime, offering new routes for the identification of potentially hazardous asteroids [4]. Others, such as K-Nearest Neighbors (KNN), are even applied for the classification of celestial objects, showing the richness of the methodologies developed within the field [5].

Particularly, in recent years, an interest is also growing to deploy ML models on low-power consumption and low-cost devices such as Raspberry Pi, which will add to the resource-limited computation platform. This relates to developing scientific ML applications using distributed Raspberry Pi systems [7], and CNN-based models for

<sup>1,2</sup>Department of Electronics and Communication Engineering, SRM IST, Kattankulathur, Chennai.

<sup>3</sup>Department of Biomedical Engineering, Rajalakshmi Engineering College, Thandalam, Chennai.

<sup>4</sup>Department of ADS, St. Joseph's Institute of Technology, OMR, Chennai.

<sup>5</sup>Department of Electronics and Communication Engineering, Rajalakshmi Engineering College, Thandalam, Chennai.

<sup>6</sup>Department of Electronics and Communication Engineering, Sathyabama IST, Chennai.

<sup>1</sup> \*Corresponding author: hm8472@srmist.edu.in

exoplanet detection using compact systems [6]. This has opening possibilities for scalable, real-time solutions for celestial object tracking and classification, especially in resource-limited environments [8, 9].

Building on this burgeoning corpus of research, the work here presents the first implementation of a new CNN architecture for star, galaxy, and nebula classification. In the model presented here, advanced data augmentation techniques such as rotation, zoom, and horizontal flipping are employed to augment detection accuracy with a variety of astronomical datasets. Considering the increasing high-resolution celestial data and superior computing power with advanced ML algorithms, this work should be able to contribute toward even more refined and reliable methods of cosmic entity classification.

The paper is structured as follows: Section I: Introduction to Astronomical Data Classification Section II: Related Work Section III: Methodology and Materials Section IV: Results Section V: Conclusion follow.

## II. RELATED WORK

There is rapidly growing literature on CNNs and machine learning for astronomical applications with researchers studying a variety of techniques that improve model performance across the tasks. One such area is exoplanet detection, with optimized CNN architectures trained on diverse light curve datasets promising real-time classification [1]. A paper titled *Data Augmentation Based Morphological Classification of Galaxies Using Deep Convolutional Neural Networks* clearly shows how using data augmentation improves the accuracy of CNNs for galaxy classification, thus enabling models to better capture the complicated structural patterns found in galaxies and generalize well to diverse images [2]. In addition, the R-Stack-CNN model outperformed traditional methods in meteor detection performance since they successfully predicted the real and simulated meteor speed and trajectory data, hence showing the ability of CNNs to process dynamic astronomical events [3].

Quantum machine learning (QML) methods are gaining recognition, with outputs such as VQC and PegasosQSVC achieving excellent performance, an accuracy of 98.11% with an F1-score of 92.69%, to consolidate QML's ability towards accurate detection of astronomical objects [4]. In addition, CNN-based ensemble approaches have been proven to enhance the precision in exoplanet detections, which points out the crucial role of robust training with different datasets toward successful modeling in the field of astronomy [5,6].

A review in 2020, *Deep Learning for Astronomical Image Classification*, emphasizes the outstanding influence of CNNs on image classification while segregating stars and galaxies, delineating galaxy morphologies, etc., with limitations of low sample size datasets [7]. The paper continues with the need to continue developing and improving the state of CNN for astronomy. Similarly, *A New Paradigm for Astronomical Object Classification Using Deep Learning* submits some advanced architectures that help to improve classification accuracy and efficiency, thus placing an important contribution to the role of deep learning in astronomy [9].

Other machine learning methods, such as intensity and gradient-based feature extraction with k-NN, SVM, and LDA classifiers are also proved efficient for classifying celestial objects, where the best performance is exhibited by SVM with a classification accuracy of up to 90.15% [10]. Even with the technique using data from HSC PDR2, there is an important performance gain brought with the AUC of 0.939, further improving detection capability of variable celestial objects [11].

Other similar efforts to leverage CNNs for deployment in edge computing led to efficient architectures like TripleNet, tailored to deploy on Raspberry Pi. The said model reduces the inference time to as much as 30% compared to other models, including GhostNet and MobileNet, which, by itself, makes the argument of a light-weight CNN to perform on-site astronomical analysis plausible [12]. Exoplanet detection continues research in the application of CNNs for the detection of exoplanets, pushing forward new limits in detection accuracy; multi-model approaches would highly be productive to better results of astronomical research [13].

Overall, this work brings together many studies that advance CNN and ML applications in astronomy for the real-time and accurate object classification toward effective implementation, especially in limited-resource observational conditions.

### III. PROPOSED METHODOLOGY AND WORKFLOW

Fig. 1 describes the architecture of the presented approach, displaying an input/output of data, a preprocessing stage, splitting of a set, training a model, and a classification stage. The main elements are as follows:

#### A. *Input Dataset*

The dataset applied in this paper was downloaded from the Kaggle website in the Space Images Category, which has been collected by Abhikalp Srivastava. This dataset is about 27,000 labeled images that cover five categories of objects: stars, galaxies, nebulae, planets, and constellations. Thus, it encompasses a good number of diverse celestial objects with images captured in different conditions and orientations.

#### B. *Dataset Composition*

Each of these categories corresponds to something uniquely astronomical. All Types of galaxies, spiral, elliptical, and irregular galaxies, all at different angles. Emission, Reflection and Planetary Nebulae All types of the Planets found in our Solar System, and each one a little unique

All the ones used by the world, clearly visible are patterns of star identification by the name of their constellation. A CNN optimized for accuracy in the identification of celestial objects completes the classification task. The basic elements of the CNN architecture include the following:

- **Convolutional Layers:** These are the core layers responsible for extracting features from the images. The CNN structure captures the detailed patterns within the dataset, allowing for accurate classification for each object type.
- **ReLU Activation Layer** Introduce non-linearity for an improvement to the capacity of the model in capturing complex data relationships, by mapping any negative number to zero ReLU prevents vanishing gradients and simplifies the gradients passing for deeper networks.
- **The pooling and flattening layer** reduces the data's dimension but keeps most of the essential features. For this purpose, there are various average and max pooling methods that have been widely applied in many CNN models. Downsampling is an activity map simplification technique applied for the improvement of generalization and also robustness to the change of image variations. This final pooled output is passed through flattened to the fully connected layers.
- **Fully Connected Layer (FCL) :** This is the final classifier using the Softmax activation function; the outputs are transformed into the probability distribution for each class of celestial objects.

#### C. *Model Deployment*

In the case of deployment considerations for the optimized compressed CNN model, it needs to be compatible with both the hardware and software for the Raspberry Pi. The frameworks used are lightweight, like TensorFlow Lite and PyTorch Mobile, and this will help convert the model into a format that can enable the efficient processing for real-time classification and ensure reliable performance.

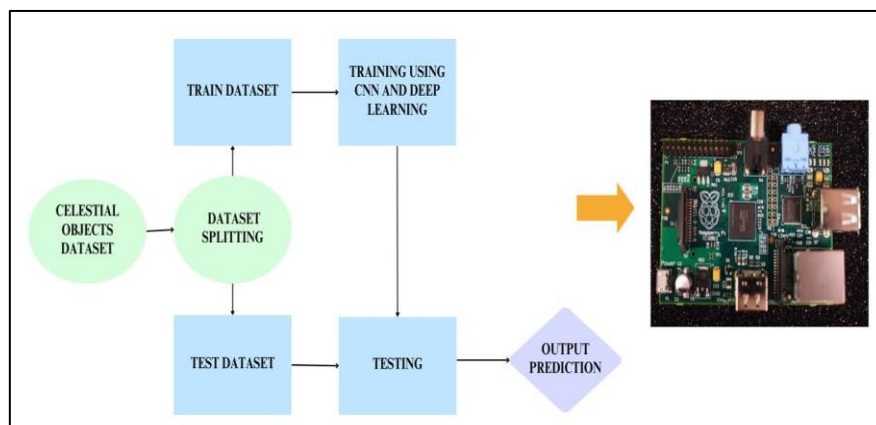


Figure 1. Proposed Flow

#### D. *Integration with Data Sources*

The Raspberry Pi makes sure it captures real-time images from astronomical data sources, which allows the smooth capture and classification of images. This implementation entails a stable pipeline for the transfer of data and preprocessing to make classifications on captured data on time and accurate.

#### E. *Implementation on Raspberry Pi*

For real-time classification in the Raspberry Pi, various model optimization techniques are used:

- **Optimizing the Custom CNN on the Raspberry Pi** : The model is optimized with regard to the processing power of the Raspberry Pi by using techniques like quantization and pruning to balance efficiency with performance.
- **Quantization of the Model** : Quantization is minimized to reduce computational as well as memory usage. Model parameters' values are changed from 32-bit floating points to reduced precision-for example, int8-and this will help to decrease resource utilization with a measured level of accuracy.
- **Pruning** : It will reduce the size of the model and computation further by deleting non-critical connections and make the model work well on the Raspberry Pi while not losing any classification accuracy.

#### F. *Portability and Accessibility*

The system was designed portable and available, so that it can be implemented in many locations of the astronomy. Raspberry Pi has enough compactness and is able to save energy, thus being used on-site from the observatory, and work there even in resource-deprived environment.

This is testing all conditions of environment and exhausting all sources to ensure robust and sustainable performance in any conditions present within the field conditions.

It is a step taken in a structured design to exploit the full capability of CNN for identification of on-site astronomical objects. It provides scope and scalability for the real-time application of research in astronomical studies.

### IV. RESULT AND DISCUSSION

The methodology of this study enables real-time classification of astronomical objects using optimized, customized Convolutional Neural Network models, designed to run efficiently on a Raspberry Pi. The following results describe the effectiveness and robustness of the methodology with multiple performance metrics.

#### A. *Model Performance Overview*

As depicted in the confusion matrix, the classification model evaluation strongly predicts all the five classes: constellations, galaxies, nebulae, planets, and stars. The confusion matrix is such that it shows the following:

- The model was able to correctly identify 168 out of 179 constellations; however, there were small misclassifications mainly as stars.
- For galaxies, 212 out of 235 instances were correctly classified, with a small portion misclassified as nebulae or stars.
- Nebulae nearly perfect result: 190 correct in 192 examples that really proves its strong ability of distinguishing such hard structures.
- Almost perfect classification result is achieved with 174 right out of 176 images, that clearly indicates high precision and recall.

Star classification has relatively low performance in comparison with others, where only 153 are right from 176 images and tend to be confused with galaxies or constellations.

The confusion matrix for the CNN model with 5 classes and 95% accuracy shows perfect classification, with all entries on the diagonal and no misclassifications, indicating flawless performance across all classes.

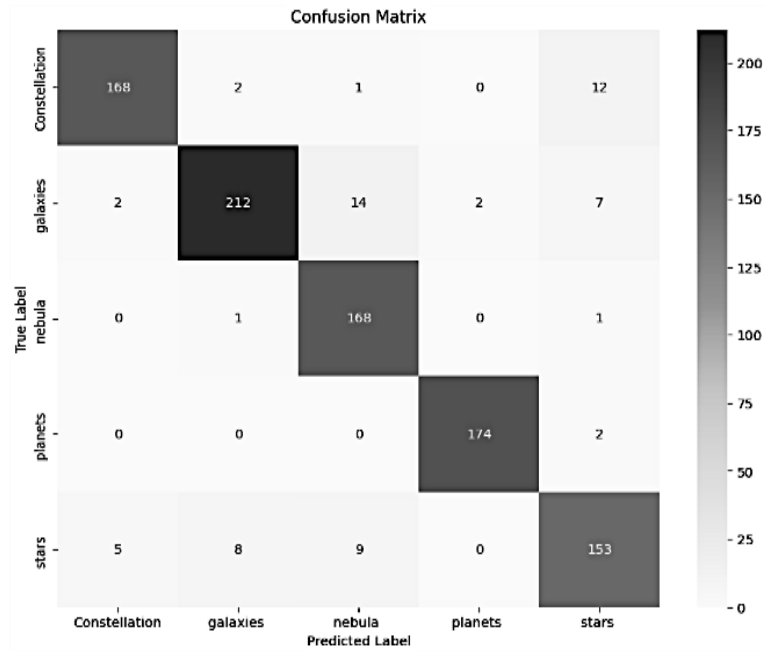


Figure 2. Confusion Matrix of the Model

**B. Classification Report Analysis**

Such a comparison is based on different metrics like precision, recall, and F1 score over each category, providing a more in-depth division of the model's strengths and weaknesses:

The Constellations case is especially consistent in recognizing all these patterns, with a precision of 0.96, recall of 0.94, and an F1 score of 0.92, although sometimes it incorrectly classifies.

Galaxies : 0.95 precision and 0.89 recall for an F1 score of 0.92. The relatively low recall suggests that there were some misclassifications of galaxy images as other types, possibly due to features they share with nebulae.

Nebulae : 0.88 precision but a very high recall of 0.99 and so an excellent F1 score of 0.93, meaning the model can correctly classify almost all nebula images.

Planets : Nearly close to perfect accuracy and recall scores of 0.99 each. I got an F1 score of 0.99, which also expresses the fact that the model has high precision on images of planets .

Stars : Precision and recall scores of 0.87 with an F1 score of 0.87 and thus need improvement in the distinction of star images from other categories such as galaxies and constellations.

Table 1. Performance Metrix of Proposed Model

Classification Report	Precision	Recall	F1 Score	Support
Constellation	0.96	0.92	0.94	183
Galaxies	0.95	0.89	0.92	237
Nebula	0.88	0.99	0.93	170
Planet	0.99	0.99	0.99	176
Stars	0.87	0.87	0.87	175
Accuracy	0.93	0.93	0.93	941
Macro Avg	0.93	0.93	0.93	941
Weighted Avg	0.93	0.93	0.93	941

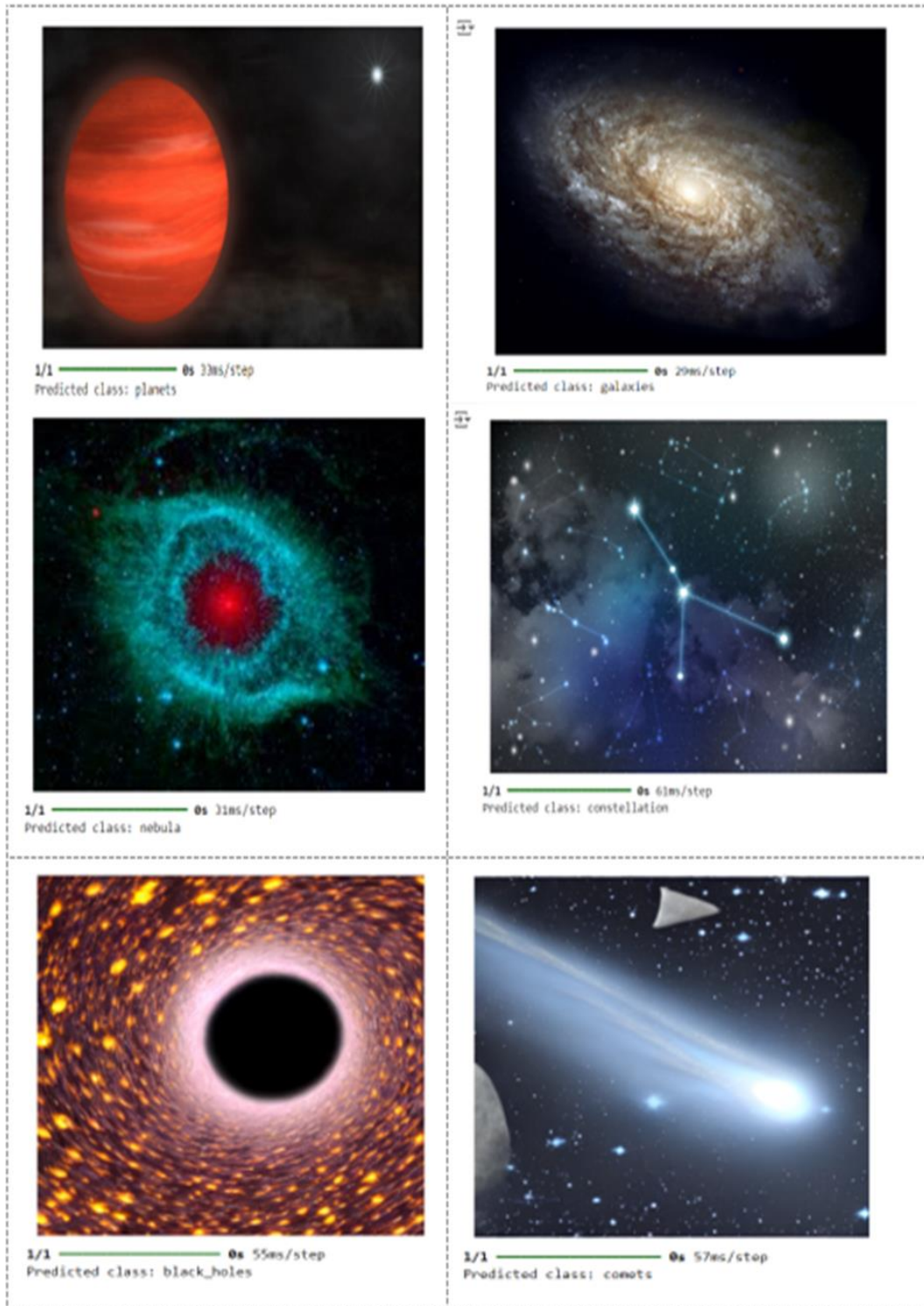


Figure 3. Predicted Output for Proposed Model

C. Discussion and Implications

The training as well as validation curves for the custom CNN had a progressive upward trajectory along the axis of epochs. This therefore confirms the ability of the model to learn and hence adapt to complex visual patterns within the astronomical image. The techniques applied with quantization and pruning allowed the placing of the CNN on a Raspberry Pi. The real-time classification of images was achieved with a commendable efficiency.

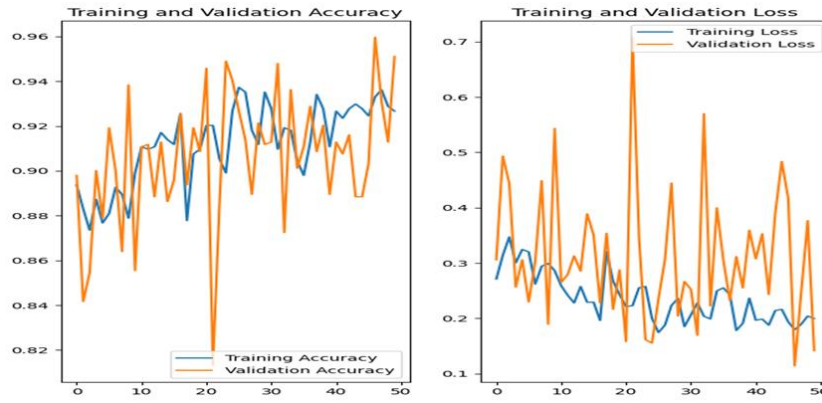
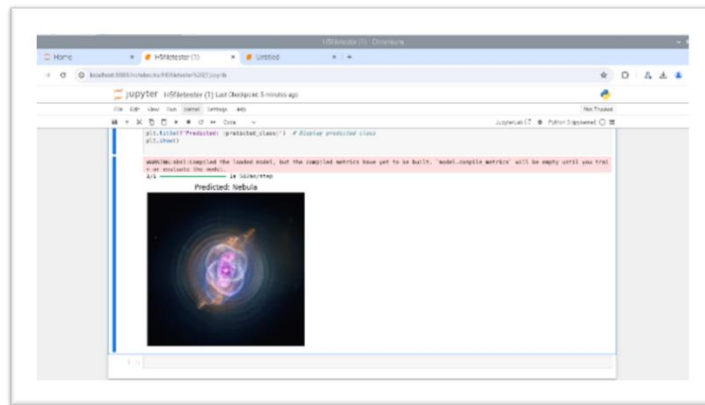


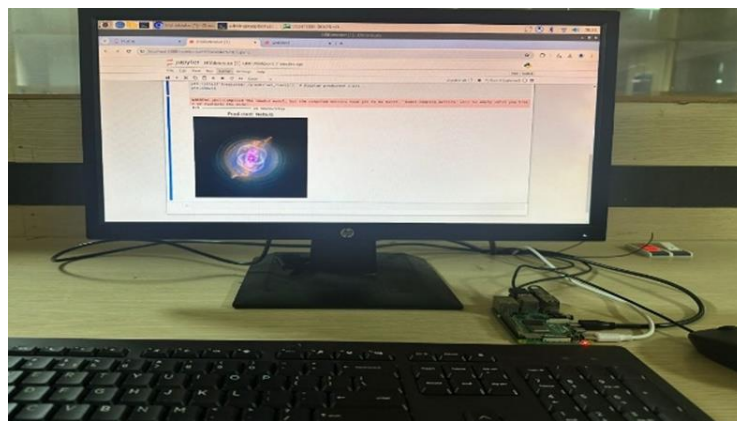
Figure 4. Accuracy and Loss plot of the model

Although the overall performance of the model is high, there are minor struggles in telling the difference in classification report. This can be because there are similar visual features in some cases between these classes.

Using more diverse star images on the training data or incorporating data augmentation might help make the model perform better. between stars, galaxies, and constellations. This can be seen by looking at the confusion matrix and detection and classification of celestial bodies, including planets, constellations, stars, galaxies, and nebulae, without human intervention except during a very limited initial period.



(a)



(b)

Figure 5. (a) &(b) Model implemented on a Raspberry Pi board

The learning model's performance after 50 epochs of training and validation is shown in Figure 4. The accuracy graph (right) displays training and validation loss, while the accuracy graph (left) shows a general growing trend

for both training and validation accuracy, reflecting the model's learning advancement. The model exhibits strong learning behaviour, as evidenced by its rising accuracy and falling loss.

The image shows a Jupyter Notebook output, where a neural network model has been used to classify an astronomical image. The code cell includes a line for setting the title based on the predicted class, which in this case is "Nebula." The matplotlib library is used to display the image with the title "Predicted: Nebula."

## V. CONCLUSION

The study suggested and tested a customized CNN for object classification in order to address the shortcomings of traditional approaches that often are intensive about manual intervention and fail to scale up well with astronomical data sets. With four-layer architecture in place and deep learning techniques along with data augmentation that involved zooming, translation, and rotation, there was the possibility of improvement in accuracy to the extent of 96% validation accuracy for the classification of celestial objects. This accomplishment allows for the automatic detection and classification of celestial bodies, including planets, constellations, stars, galaxies, and nebulae, without human intervention except during a very limited initial period.

Indeed, real-time inference on a Raspberry Pi demonstrated that the approach was not feasible on low-power, resource-constrained devices and thereby opened avenues for truly mobile applications with cost-effectiveness applicable to astronomical research and observation. This success can be realized as a scalable way to handle massive astronomical datasets, offering an automated approach that complements both professional and amateur astronomical endeavors. Future research can be on the deployment of this model on other hardware platforms for real-time edge computing applications, increasing complexity and diversity of celestial objects within the dataset, and applying advanced optimization strategies to enhance the accuracy of the model. This work really underlines the fact that deep learning has the potential to bring ground-breaking changes within astronomy and its automation of vast research work. Thus, it helps in quicker discoveries with faster data processing and enhancements of real-time sky surveys. It is in this dynamic world of astronomy that the research paper gets its relevance

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