Literature Review

During my research for previous papers, I came across one that related to our project pretty well and was particularly informative and interesting too.

The link to the pdf of the research paper: https://norma.ncirl.ie/6106/1/yogirajsubhashdalvi.pdf

This paper focuses on comparing various pre trained models of image classification on astronomical data after fine tuning it, to identify deep space objects such as galaxies, stars, and quasars. Traditional machine learning techniques, while successful, are unable to efficiently process the increasing complexity and volume of data generated by modern astronomical surveys. This prompted a shift towards deep learning techniques, particularly convolutional neural networks (CNNs), which have demonstrated significant improvements in image classification tasks. The models they compared were: -

1. **VGG16**:

- Achieved the highest accuracy in the study: **86.04%**.
- It was used with fine-tuning and performed well in classifying galaxies, stars, and quasars.

2. **InceptionV3**:

- Achieved an accuracy of **83.92%**.
- Demonstrated the potential for further improvement with more training.

3. **ResNet50**:

- Achieved an accuracy of **79.79%**.
- Noted for being deep but requiring more computational resources.

4. **Custom CNN with Adam Optimizer**:

- Achieved an accuracy of **79.57%**.
- A lighter model designed for specific image classification tasks with the Adam optimizer.

Each of these models was evaluated based on their performance in classifying astronomical objects from the Sloan Digital Sky Survey (SDSS) images, and metrics such as accuracy, precision, recall, and F1 scores were used for comparison. VGG16 performed the best overall in terms of accuracy.

Despite the success of deep learning models, several challenges remain in astronomical object classification. The vast quantity of data generated by modern telescopes exceeds the capacity of traditional and even many machine learning methods. Additionally, certain object classes, such as stars and quasars, present classification difficulties due to overlapping features. While CNNs have been effective, fine-tuning models for these specific challenges continues to be an area for further research.

Overall, the paper praised the accuracy and scores of VGG-16 a lot, so I am inclined towards using it as the pre trained model for fine tuning on the dataset provided for astronomical image classification and detection in my project.

Some other reasons why VGG16 is suitable: -

1. **Moderate Complexity**: VGG16 has 16 layers and is relatively easier to fine-tune compared to more complex architectures like ResNet or Inception.
2. **Transfer Learning**: Since it was pre-trained on ImageNet (a large image dataset), it has learned strong general visual features, making it ideal for transfer learning in image detection tasks.
3. **Community Support**: VGG16 is well-supported by frameworks like TensorFlow, PyTorch, and Hugging Face, ensuring ease of integration and availability of resources.

Now, few important methods that can be followed for fine-tuning the model are: -

1. **Freezing Initial Layers and Fine-Tuning Higher Layers:**
   This method involves initially freezing all the layers except the classifier, training it, and then gradually unfreezing more layers for fine-tuning. This helps the model adapt to the dataset progressively without overfitting early on.

2. **Progressive Fine-Tuning (Unfreezing Layers Gradually)**
   This method involves initially freezing all the layers except the classifier, training it, and then gradually unfreezing more layers for fine-tuning. This helps the model adapt to the dataset progressively without overfitting early on.

3. **Use Learning Rate Scheduling**
   Using a dynamic learning rate scheduler ensures that the learning rate is adjusted during training based on performance. This is essential when fine-tuning, as the model might need smaller adjustments over time.

4. **Data Augmentation**
   Astronomical datasets can be small, making data augmentation a critical step to prevent overfitting. This method generates new variations of the input images by applying transformations.
   Common Augmentation Techniques:
   - **Rotation**: Astronomical objects can appear at different angles.
   - **Flipping**: While less common for space imagery, this may add variability.
   - **Zooming**: Varying object sizes by zooming in/out.
   - **Brightness/Contrast Adjustments**: Mimic varying observation conditions.