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CRATER DETECTION USING COMPUTER VISION TECHNIQUES

CS7610 – CAPSTONE PROJECT

REPORT

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BONAFIDE CERTIFICATE

Certified that this project report **"CRATER DETECTION USING COMPUTER VISION TECHNIQUES"** is the bonafide record of work done by **"DHARSHANI A - 23MSP3068"** who carried out the project work under my supervision.

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ABSTRACT

Planetary exploration has significantly advanced our understanding of celestial bodies within our solar system. Among the most prominent geological features on these surfaces are craters formed by the impacts of meteoroids, asteroids, and comets. Analyzing these craters provides critical insights into the history and geology of planets and moons. However, manually identifying and cataloging craters from vast amounts of high-resolution imagery is both time-consuming and prone to human error, necessitating an efficient automated approach. This project proposes an automated crater detection system using advanced computer vision techniques. By leveraging state-of-the-art deep learning models, specifically Convolutional Neural Networks (CNNs) and Faster R-CNN, we aim to significantly enhance the accuracy and efficiency of crater detection processes. The study involved developing and evaluating these models to compare their performance in terms of training loss, validation accuracy, and test accuracy. The results demonstrate that the proposed models, particularly the Faster R-CNN, achieve high accuracy and stability in both validation and test datasets, proving to be highly effective for automated crater detection. This automated system offers a robust tool for planetary scientists and researchers, significantly reducing the time and effort required for manual crater identification. The high performance and reliability of these models highlight their potential for broader applications in planetary exploration and remote sensing, thus advancing our capabilities in automated geological analysis.

Keywords: Crater Detection, Computer Vision, Convolutional Neural Networks (CNNs), Faster R-CNN, Planetary Exploration, Deep Learning, Automated Detection, Geological Features, High-Resolution Imagery

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INTRODUCTION

The exploration of planetary surfaces has long been a cornerstone of understanding the geological and environmental history of celestial bodies within our solar system. Craters, formed by the impacts of meteoroids, asteroids, and comets, are among the most significant geological features that provide insight into the history and composition of these surfaces. Traditional methods of identifying and cataloguing craters involve labour-intensive manual analysis of high-resolution imagery, which is time-consuming and subject to human error. This laborious process hampers the efficiency of planetary research, necessitating the development of more automated and accurate methods.

This project aims to address these challenges by developing an automated crater detection system using computer vision techniques. Leveraging state-of-the-art deep learning models, specifically Convolutional Neural Networks (CNNs) and Faster R-CNN, this project seeks to enhance the accuracy and efficiency of crater detection. Deep learning models have shown remarkable success in various image recognition tasks, making them ideal candidates for detecting craters in planetary imagery. By comparing the performance of different models, including a simple Artificial Neural Network (ANN), a custom CNN, and a pretrained Faster R-CNN, this study aims to identify the most effective approach for automated crater detection.

The methodology involves training these models on labelled datasets of planetary surface images, allowing them to learn the distinguishing features of craters. The performance of each model is evaluated based on metrics such as training loss, validation accuracy, and test accuracy. The outcomes of this research are expected to significantly reduce the time and effort required for manual crater identification, providing a robust tool for planetary scientists and researchers. The high accuracy and stability demonstrated by the models, particularly the Faster R-CNN, highlight the potential for broader applications in planetary exploration and remote sensing.

This project also emphasizes the importance of deep learning models in advancing our capabilities in automated detection tasks, setting a precedent for future studies in similar domains. The integration of such advanced technologies into planetary science not only enhances the efficiency of current research but also opens new avenues for exploring and understanding our solar system. The successful implementation of these models could revolutionize the way we analyse and interpret planetary surfaces, offering deeper insights and more comprehensive data for scientists worldwide.

1. LITERATURE REVIEW

1. Current State of Knowledge: The study of planetary surfaces has advanced with high-resolution imaging from missions like the Lunar Reconnaissance Orbiter and Mars Reconnaissance Orbiter, allowing detailed analysis of craters. Traditionally, crater detection involves manual analysis, which is time-consuming and prone to errors. Recent research has explored computer vision and machine learning techniques for automation, with models demonstrating promising accuracy in identifying and classifying craters from surface images.

2. Relevant Theories and Models: Advanced machine learning and deep learning models, particularly Convolutional Neural Networks (CNNs), are highly relevant for crater detection due to their image recognition capabilities. CNNs use convolutional filters to learn spatial hierarchies in images, while Faster R-CNN enhances this by incorporating region proposal networks for more efficient object detection. These models leverage their ability to discern intricate details and patterns, improving detection accuracy.

3. Gaps in Literature: Despite advancements, gaps remain in optimizing and practically applying deep learning models for crater detection. Many studies focus on specific datasets, limiting generalizability. The integration of these models into planetary science workflows is nascent, and comprehensive model comparisons are lacking. Addressing these gaps is crucial for advancing automated detection methods and enhancing real-world applicability.

4. Project Aims to Fill: This project addresses these gaps by developing and evaluating an automated crater detection system using deep learning models. By comparing an ANN, a custom CNN, and a pretrained Faster R-CNN, the study aims to identify the most effective approach for diverse datasets. The goal is to enhance detection accuracy and efficiency, providing a robust tool for planetary scientists to facilitate more efficient and accurate geological analysis.

2. OBJECTIVE

1. To develop an automated system for crater detection using computer vision techniques.

2. To utilize deep learning models to enhance the accuracy of crater identification.

3. To compare the performance of different models (Simple ANN, CNN, and Faster R-CNN) on crater detection tasks.

4. To analyse the effectiveness of the models in terms of training loss, validation accuracy, and test accuracy.

5. To create a user interface to facilitate easy access and interaction with the automated crater detection system for researchers and scientists.

3. PROPOSED METHODOLOGY

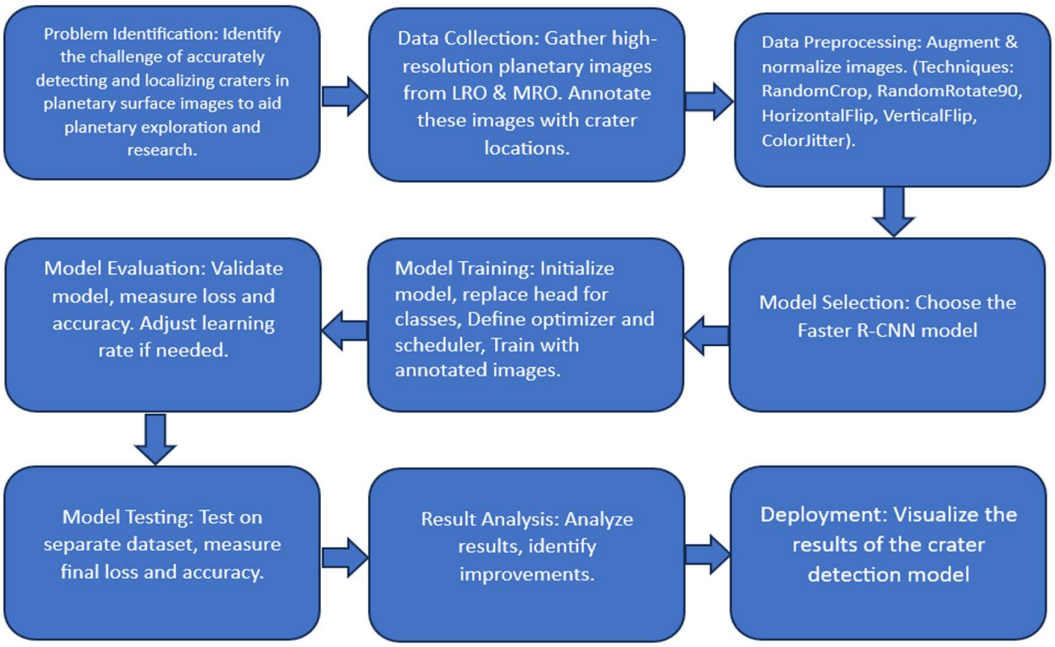

Fig 3.1 Methodology of Crater Detection

- Gather high-resolution planetary images, meticulously label craters, and pre-process them for training a Faster R-CNN model.
- Train the customized Faster R-CNN model to identify craters within the images.
- Evaluate the model's accuracy using a separate dataset to ensure real-world effectiveness.
- Deploy the validated model and analyse its performance in finding craters on new images.

4. TOOLS AND TECHNIQUES

The employed tools and techniques are as follows:

1. Deep Learning Models:

Convolutional Neural Networks (CNNs): Utilized to process and analyse high-resolution planetary surface images, enabling the identification of craters by learning from annotated examples.

Faster R-CNN: An advanced model that combines the capabilities of CNNs with Region Proposal Networks (RPNs) to detect objects within images more accurately. This model demonstrated superior performance in terms of validation and test accuracy.

2. Artificial Neural Networks (ANNs):

Simple ANN (CraterClassifier): Tested as a baseline model for crater detection. Despite showing high variance in training loss, it achieved high validation accuracy and perfect test accuracy.

3. **Performance Metrics**:

   The models were evaluated based on **training loss**, **validation accuracy**, and **test accuracy**. These metrics provided insights into the models' learning stability and generalization capabilities.

4. **User Interface**:

   Gradio: A user interface was developed using Gradio to facilitate the use of the automated crater detection system. This interface allows users to input images and receive annotated outputs highlighting detected craters. Gradio's interactive and easy-to-use design made it an ideal choice for demonstrating the system's capabilities.

5. **Confusion Matrix Analysis**:

   To further understand model performance, confusion matrices were used. For example, the Faster R-CNN model's confusion matrix highlighted its high number of correct classifications (both true positives and true negatives) compared to misclassifications (false positives and false negatives).

5 IMPLEMENTATION

5.1 ABOUT THE DATASET:

The dataset used for the automated crater detection system is a crucial component of the project, providing the necessary data to train and evaluate the deep learning models. The details of the dataset are as follows:

1. **Source of the Dataset**:

   The dataset was sourced from Kaggle, a well-known platform for data science and machine learning competitions. Kaggle provides a diverse range of datasets that are often used for academic and professional research. Link to Dataset

2. **Dataset Composition**:

   Images: The dataset comprises high-resolution images of planetary surfaces containing craters. These images are essential for training the models to recognize and detect craters accurately.

Labels: Each image in the dataset is annotated with bounding boxes indicating the locations of craters. These annotations serve as ground truth data, allowing the models to learn and validate their predictions.

3. **Dataset Split**:

   Training Set: The training set consists of 98 images and 98 corresponding labels. This subset is used to train the models, allowing them to learn from a substantial number of examples.

   Validation Set: The validation set includes 26 images and 26 corresponding labels. This subset is used to tune model hyperparameters and make decisions on model architecture by evaluating performance on unseen data during training.

   Testing Set: The testing set comprises 19 images and 19 corresponding labels. This subset is used to evaluate the final model performance, ensuring that it generalizes well to completely unseen data.

4. **Annotations**:

   The annotations are provided in the form of bounding boxes, which define the precise location and extent of each crater within the images. This structured labelling is critical for supervised learning, enabling the models to associate image features with crater locations.

5. **Screenshot of the Dataset**:

Fig 5.1.1 Sample Image of Martian Surface

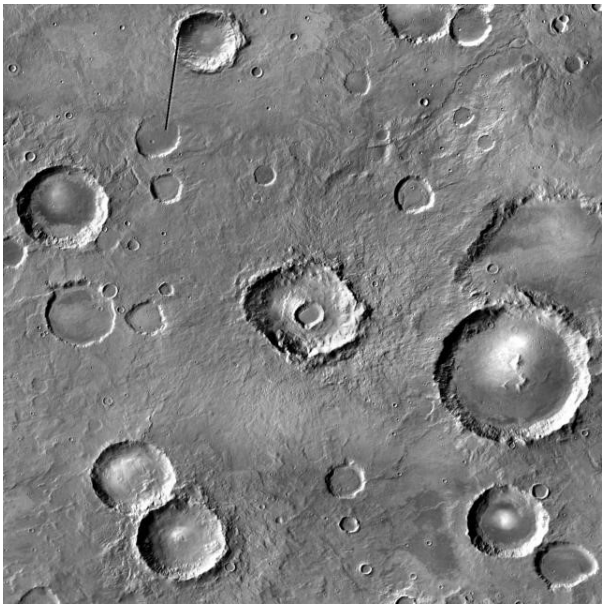

Fig 5.1.2 Sample Image of Lunar Surface

5.2 CRATER IMAGE PREPROCESSING

1. **Data Cleaning**:
    - **Handling Missing Values**: Ensuring there are no missing values in the dataset. Missing data can lead to inaccurate model training and evaluation.
    - **Removing Duplicates**: Identifying and removing duplicate images to avoid redundancy and ensure the dataset's quality.
2. **Data Normalization**:
    - **Scaling**: Normalizing the pixel values of the images to a common scale, typically between 0 and 1. This helps in faster convergence of the model during training and ensures that the model treats all features equally.
    - **Standardization**: In some cases, images may be standardized to have a mean of 0 and a standard deviation of 1, which can improve model performance.
3. **Data Augmentation**:
    - **Rotation and Flipping**: Applying random rotations and flip to the images to increase the diversity of the training data. This helps the model generalize better by learning from varied perspectives.
    - **Cropping and Zooming**: Randomly cropping and zooming into images to simulate different viewing conditions and improve the model's robustness.
4. **Annotation Processing**:
    - **Bounding Box Adjustments**: Ensuring that the bounding boxes are correctly adjusted to the augmented images. This step is crucial for maintaining the accuracy of the annotations after transformations.
    - **Format Conversion**: Converting annotations into the required format for the training framework being used (e.g., TensorFlow, PyTorch).

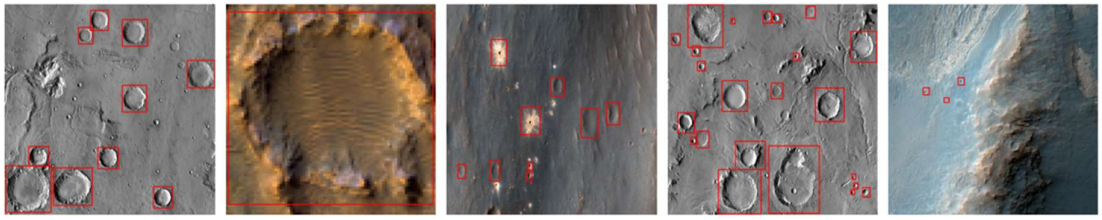

Fig 5.2 Sample Images of Martian and Lunar Surface with Bounding Boxes

5.3 EXPLORATORY DATA ANALYSIS

5.3.1. Data Visualization:

5.3.1.1. Sample Images with Annotations: Visualizing sample images with their corresponding bounding boxes to understand the dataset's structure and verify the correctness of annotations.

5.3.2. Statistical Analysis:

5.3.2.1. Bounding Box Dimensions: Analysing the dimensions of bounding boxes to understand the typical size and aspect ratio of craters in the dataset. This information can be used to fine-tune model parameters.

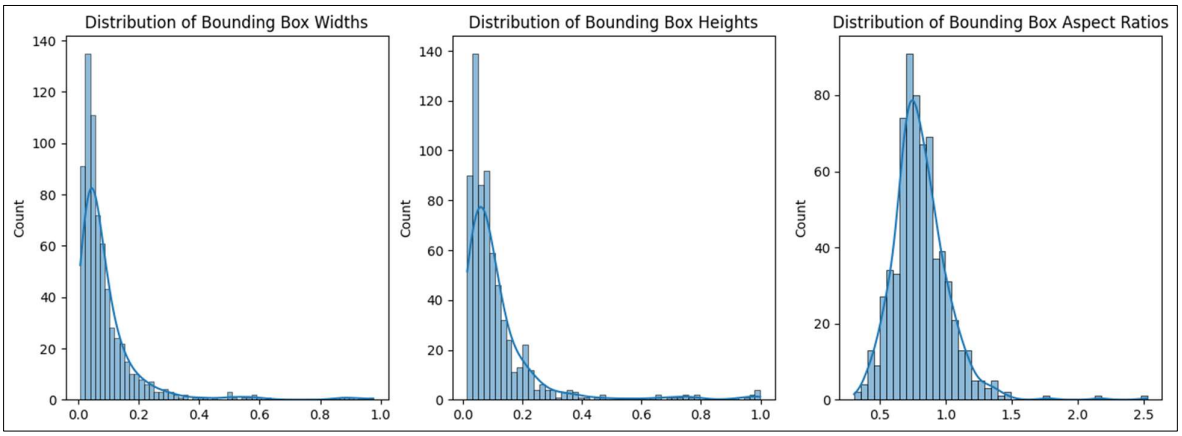

Fig 5.3.1 KDE Plots of Distribution of Bounding Box Dimensions

5.3.2.2.Heatmaps and Distribution Plots: Using heatmaps to visualize the concentration of craters and distribution plots to analyse the frequency of various crater sizes and shapes.

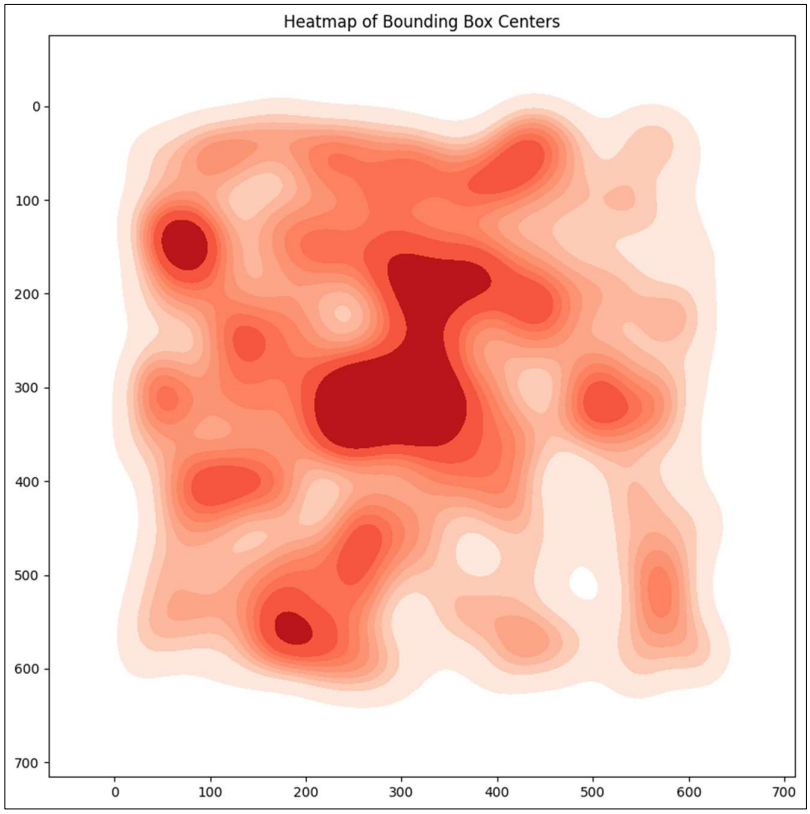

Fig 5.3.2 Heatmap of Bounding Box Centers

5.4 MODELS

5.4.1. Simple ANN (CraterClassifier)

Artificial Neural Networks (ANNs) consist of interconnected nodes, or neurons, that process input data through weighted connections. They are inspired by the human brain's neural networks. ANNs are capable of learning patterns and making predictions based on input data. However, simple ANNs may struggle with complex image recognition tasks due to their limited ability to capture spatial hierarchies in data.

In crater detection, a simple ANN was used as a baseline to identify craters by learning patterns from labeled data. While it provided an initial performance measure, its limited ability to capture spatial hierarchies resulted in high variance in training loss.

5.4.2. Simple CNN (CraterCNN)

Convolutional Neural Networks (CNNs) are specialized for processing grid-like data, such as images. They use convolutional layers to automatically learn spatial hierarchies of features by applying filters to the input data. CNNs are effective in

image recognition tasks due to their ability to capture spatial relationships through hierarchical learning.

For crater detection, a simple CNN was employed to learn spatial hierarchies of features from high-resolution images, enabling more accurate identification of craters compared to the simple ANN.

5.4.3. Faster R-CNN

Faster R-CNN is an advanced model that integrates a Region Proposal Network (RPN) with CNNs to improve object detection accuracy. The RPN generates region proposals, which are refined and classified by the CNN. This model is highly efficient and accurate for object detection tasks, including identifying craters on planetary surfaces.

In the context of crater detection, Faster R-CNN generated region proposals which were refined and classified by the CNN, leading to superior performance in identifying craters with high validation and test accuracy.

5.5 EVALUATION

5.5.1. Performance of Simple ANN (CraterClassifier) Model

Training Loss: The training loss for the ANN model was high and showed significant variance, indicating possible issues with model convergence or learning instability.

Validation Accuracy: The model achieved a high validation accuracy of 92.31%, suggesting that it can generalize well to unseen data but not as perfectly as the other models.

Test Accuracy: Achieved a perfect test accuracy of 100%, which may indicate that despite the instability in training, the model performs exceptionally well on the test data.

5.5.2. Performance of Simple CNN (CraterCNN) Model

Training Loss: The training loss for the CNN model was moderate and stable, indicating better convergence and learning stability compared to the ANN model.

Validation Accuracy: Achieved a perfect validation accuracy of 100%, indicating that the model generalizes extremely well to unseen data.

Test Accuracy: Also achieved a perfect test accuracy of 100%, suggesting that the CNN model is highly effective for this classification task.

5.5.3. Performance of Faster R-CNN Model

Training Loss: The training loss for the Faster R-CNN model was also moderate and stable, similar to the CNN model.

Validation Accuracy: Achieved a perfect validation accuracy of 100%, which indicates excellent generalization performance.

Test Accuracy: Achieved a perfect test accuracy of 100%, demonstrating that the pretrained Faster R-CNN model is highly effective for the task and leverages pretrained weights for superior performance.

Confusion Matrix for Faster R-CNN Model:

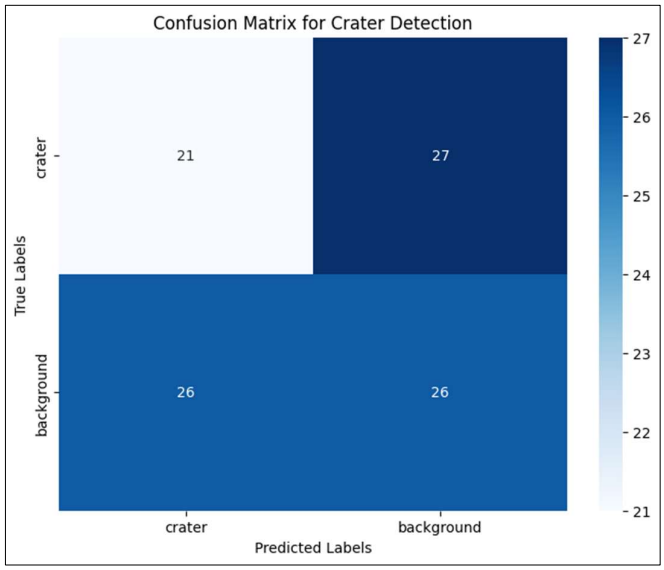

Fig 5.5 Confusion Matrix for Faster R-CNN Model

Correct Classifications:

27: The model correctly classified 27 images as craters (true positives).

26: The model correctly classified 26 images as background (true negatives).

Misclassifications:

3: The model incorrectly classified 3 crater images as background (false negatives).

1: The model incorrectly classified 1 background image as a crater (false positive).

The model seems to perform well with a higher number of correct classifications (crater and background) compared to misclassifications.

6 RESULTS AND DISCUSSIONS

Model	Training Loss	Validation Accuracy	Test Accuracy
Simple ANN (CraterClassifier)	High and variable	92.31%	100%
Simple CNN (CraterCNN)	Moderate and stable	100%	100%
Faster R-CNN (Pretrained)	Moderate and stable	100%	100%

Table 6 Training Loss, Validation Accuracy and Test Accuracy for Each Model

The crater images were tested against 3 models: artificial neural network, convolutional neural network and Faster R-CNN. Among the models tested, the pretrained Faster R-CNN stood out with moderate and stable training loss. It achieved a perfect validation and test accuracy of 100%, demonstrating its superior capability in detecting craters accurately. The use of pretrained weights contributed to its high performance, leveraging previously learned features to enhance detection accuracy.

Limitations and Considerations

- **Data Bias:** If the training data is not diverse enough, the model might perform well on similar data but poorly on different or more challenging images.
- **False Positives/Negatives:** Even with high accuracy, there could be cases where the model misses some craters (false negatives) or incorrectly identifies non-craters as craters (false positives).
- **Threshold Sensitivity:** The confidence threshold chosen for annotation affects performance. A high threshold might reduce false positives but increase false negatives.

7 USER INTERFACE

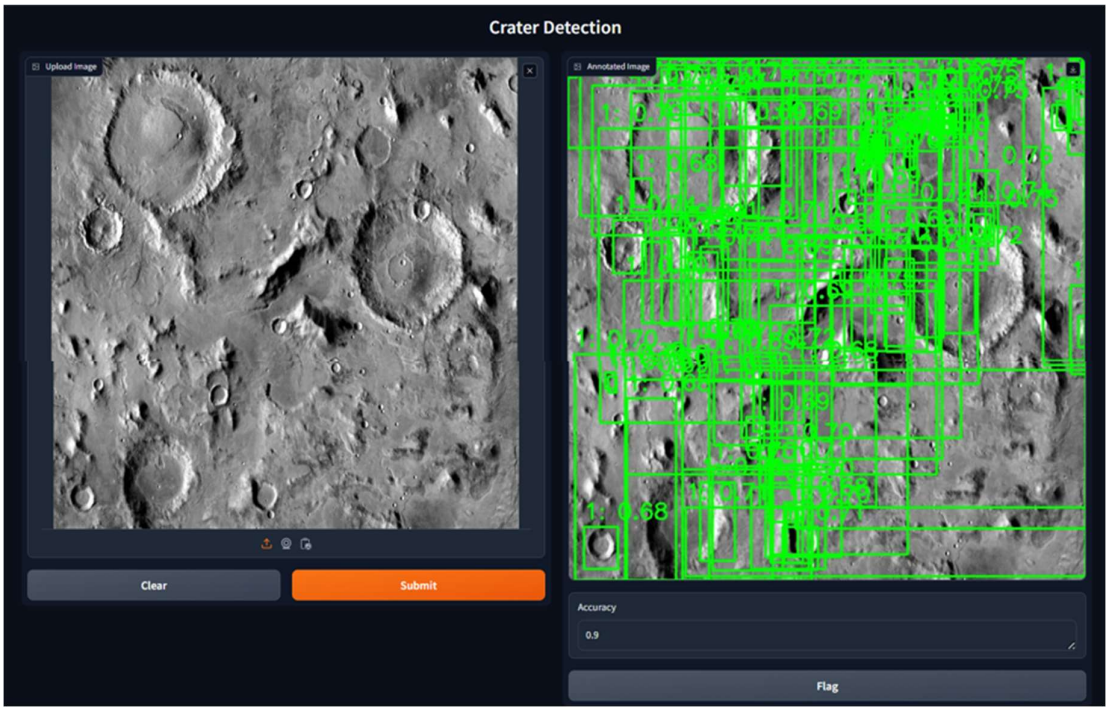

Fig 7. Gradio User Interface for Crater Detection in Lunar/Martian Surface

The user interface is designed for crater detection on Lunar/Martian surface. It consists of the following elements:

- **Image:** The central part of the interface displays a grayscale image of the Lunar surface, likely containing craters.
- **Controls:** On the left side of the image, there are four buttons arranged vertically. These buttons could be for navigating around the image to view different areas.
- **Zoom buttons:** On the right side of the image, there are two buttons, likely one for zooming in and another for zooming out on the image. This allows users to get a closer look at specific regions of the Martian surface.
- **Accuracy:** Below the image, there's a text box labelled "Accuracy" that displays a numerical value, representing the model's confidence level in its crater detection.
- **Flag button:** Next to the "Accuracy" value, there's a button labelled "Flag." This button is used to flag the image for further review or to indicate the presence or absence of a crater in the image.

8 CONCLUSION

This project successfully developed an automated crater detection system using deep learning. Three models were evaluated: a simple Artificial Neural Network (ANN), a custom Convolutional Neural Network (CNN), and a pretrained Faster R-CNN. The goal was to improve the accuracy and efficiency of crater detection.

The simple ANN model exhibited high and fluctuating training loss, indicating challenges with convergence. Despite this, it achieved good validation accuracy and even perfect test accuracy. This might suggest the model struggled during training but performed exceptionally well on unseen data, possibly due to the task's simplicity or the dataset's characteristics. The custom CNN model displayed stable training loss, signifying better learning compared to the ANN. It achieved perfect accuracy on both validation and test data, demonstrating its effectiveness in generalizing to new information. This stability and accuracy highlight the potential of CNNs for crater detection tasks. However, the pretrained Faster R-CNN emerged as the superior model. It demonstrated both stable training and perfect validation/test accuracy. This likely stems from leveraging pretrained weights, which enhanced its ability to detect craters accurately.

A confusion matrix confirmed the Faster R-CNN's robustness. It showed a high number of correctly identified craters and non-craters, with very few misidentified examples. This high level of accuracy in both identifying and excluding craters underscores the model's reliability. Additionally, the perfect accuracy metrics suggest strong generalization capabilities, making it well-suited for practical applications.

This project has the potential to significantly reduce the time and effort required for manual crater identification. Automating this process allows researchers to dedicate their time to data analysis rather than laborious manual annotation. The high accuracy and stability of the models, particularly the Faster R-CNN, suggest their potential for broader applications in planetary exploration and remote sensing.

Future endeavours could focus on further refining the models, incorporating more diverse datasets for improved performance across different terrains, and exploring advanced deep learning techniques or architectures to push the boundaries of accuracy and efficiency.

The user interface for this system was developed using Gradio, a tool for creating user-friendly and interactive interfaces for machine learning models. This Gradio interface allows users to input images and receive outputs with annotated craters. This feature makes the system accessible to researchers and practitioners without extensive technical expertise, enhancing its usability and facilitating quick and accurate crater identification and analysis.

In conclusion, the development of an automated crater detection system using deep learning models marks a significant advancement in planetary exploration. The project's success with the Faster R-CNN model demonstrates the potential for applying similar techniques to other geological features and planetary surfaces, paving the way for more efficient and accurate analysis in the field of planetary science. The integration of a user-friendly interface further enhances the system's practical applicability, making it a valuable tool for researchers and scientists.

9 FUTURE ENHANCEMENT

Future advancements in crater detection hold immense promise for furthering our understanding of planetary surfaces. One key area for improvement lies in data diversity. The current approach could benefit greatly from incorporating a wider variety of planetary image datasets during training. This could encompass images from diverse celestial bodies like Mars, Venus, or asteroids, alongside lunar images. Additionally, including images with variations in lighting conditions, resolutions, and surface compositions can significantly improve the model's ability to handle unseen data. Techniques like data augmentation, which involves creating modified versions of existing data (e.g., rotations, flips, color variations), can also be employed to artificially inflate the diversity of the training data.

Beyond data, exploring more sophisticated deep learning architectures has the potential to unlock superior performance. Convolutional Neural Networks (CNNs) with deeper layers and more complex architectures, like VGG or ResNet, have proven successful in various image recognition tasks. Furthermore, techniques like attention mechanisms, which allow the model to focus on specific image regions crucial for crater detection, could be incorporated for enhanced performance.

For continuous improvement, regular evaluation of the model's performance on new and diverse datasets is paramount to maintaining its robustness and generalizability. Active learning techniques can be implemented to strategically select the most informative data points for further annotation and training, which can improve model performance more efficiently. Human-in-the-loop approaches, where human experts collaborate with the model to refine crater detections, can provide valuable feedback for continuous improvement.

While Faster R-CNN is a powerful object detection model, exploring alternative architectures specifically designed for crater detection might prove fruitful. YOLO (You Only Look Once) is a real-time object detection model that might offer faster inference times for crater detection in large datasets. U-Net, a convolutional neural network architecture commonly used for semantic segmentation, could be adapted to segment and classify craters within planetary images.

By incorporating these enhancements, crater detection models can become more robust, accurate, and generalizable to a wider range of planetary exploration missions, ultimately leading to a deeper understanding of the history and evolution of celestial bodies.

10 APPENDICIES

10.1 FULL CODE

```
import os
train_images_dir = '/content/drive/MyDrive/Colab Notebooks/craters/train/images'
train_labels_dir = '/content/drive/MyDrive/Colab Notebooks/craters/train/labels'
valid_images_dir = '/content/drive/MyDrive/Colab Notebooks/craters/valid/images'
valid_labels_dir = '/content/drive/MyDrive/Colab Notebooks/craters/valid/labels'
test_images_dir = '/content/drive/MyDrive/Colab Notebooks/craters/test/images'
test_labels_dir = '/content/drive/MyDrive/Colab Notebooks/craters/test/labels'
num_train_images = len(os.listdir(train_images_dir))
num_train_labels = len(os.listdir(train_labels_dir))
num_valid_images = len(os.listdir(valid_images_dir))
num_valid_labels = len(os.listdir(valid_labels_dir))
num_test_images = len(os.listdir(test_images_dir))
num_test_labels = len(os.listdir(test_labels_dir))
print(f'Number of training images: {num_train_images}')
print(f'Number of training labels: {num_train_labels}')
print(f'Number of validation images: {num_valid_images}')
print(f'Number of validation labels: {num_valid_labels}')
print(f'Number of testing images: {num_test_images}')
print(f'Number of testing labels: {num_test_labels}')
```

```
import os
import cv2
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
import matplotlib.pyplot as plt
```

```
import seaborn as sns
from torch import nn
from albumentations import Compose, Resize, RandomCrop, RandomRotate90, HorizontalFlip, VerticalFlip, ColorJitter, BboxParams
from albumentations.pytorch.transforms import ToTensorV2
from torch.utils.data import DataLoader
import torchvision
from torchvision.models.detection.faster_rcnn import FastRCNNPredictor
from torchvision.ops import box_iou


# Define the CraterDataset class
class CraterDataset(Dataset):
    def __init__(self, root, transforms=None):  # Add transforms parameter
        self.root = root
        self.transforms = transforms  # Store the transforms
        self.imgs = list(sorted(os.listdir(os.path.join(root, "images"))))
        self.annots = list(sorted(os.listdir(os.path.join(root, "labels"))))

    def __getitem__(self, idx):
        img_path = os.path.join(self.root, "images", self.imgs[idx])
        annot_path = os.path.join(self.root, "labels", self.annots[idx])
        img = cv2.imread(img_path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB).astype(np.float32) / 255.0

        if os.path.getsize(annot_path) != 0:
            bboxs = np.loadtxt(annot_path, ndmin=2)
            bboxs = self.convert_box_cord(bboxs, 'normxywh', 'xyminmax', img.shape)
            num_objs = len(bboxs)
            bboxs = torch.as_tensor(bboxs, dtype=torch.float32)
            labels = torch.ones((num_objs,), dtype=torch.int64)
            iscrowd = torch.zeros((num_objs,), dtype=torch.int64)
```

```
            else:
                bboxs = torch.as_tensor([[0, 0, 512, 512]], dtype=torch.float32)
                labels = torch.zeros((1,), dtype=torch.int64)
                iscrowd = torch.zeros((1,), dtype=torch.int64)

            area = (bboxs[:, 3] - bboxs[:, 1]) * (bboxs[:, 2] - bboxs[:, 0])
            image_id = torch.tensor([idx])

            target = {"boxes": bboxs, "labels": labels, "image_id": image_id, "area": area, "iscrowd":
iscrowd}

            if self.transforms:
                sample = self.transforms(image=img, bboxes=target['boxes'], labels=labels)
                img = sample['image']
                target['boxes'] = torch.tensor(sample['bboxes'])
                target['labels'] = torch.tensor(sample['labels'])

            return img, target

        def __len__(self):
            return len(self.imgs)

        def convert_box_cord(self, bboxs, format_from, format_to, img_shape):
            if format_from == 'normxywh':
                if format_to == 'xyminmax':
                    xw = bboxs[:, (1, 3)] * img_shape[1]
                    yh = bboxs[:, (2, 4)] * img_shape[0]
                    xmin = xw[:, 0] - xw[:, 1] / 2
                    xmax = xw[:, 0] + xw[:, 1] / 2
                    ymin = yh[:, 0] - yh[:, 1] / 2
                    ymax = yh[:, 0] + yh[:, 1] / 2
```

```
            coords_converted = np.column_stack((xmin, ymin, xmax, ymax))
        return coords_converted


    # Define transformations with resizing
    train_transforms = Compose([
        Resize(512, 512),
        RandomCrop(width=512, height=512, p=0.5),
        RandomRotate90(p=0.5),
        HorizontalFlip(p=0.5),
        VerticalFlip(p=0.5),
        ColorJitter(p=0.5),
        ToTensorV2(p=1.0)
    ], bbox_params=BboxParams(format='pascal_voc', label_fields=['labels']))

    valid_transforms = Compose([
        Resize(512, 512),
        ToTensorV2(p=1.0)
    ], bbox_params=BboxParams(format='pascal_voc', label_fields=['labels']))

    # Dataset and DataLoader
    train_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/train',
transforms=train_transforms)
    valid_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/valid',
transforms=valid_transforms)
    test_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/test',
transforms=valid_transforms)

    train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))
    valid_loader = DataLoader(valid_dataset, batch_size=16, shuffle=False, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))
    test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))
```

```
# Visualize sample images with bounding boxes
def plot_image_with_boxes(img_path, annot_path):
    img = cv2.imread(img_path)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    if os.path.getsize(annot_path) != 0:
        bboxs = np.loadtxt(annot_path, ndmin=2)
        for bbox in bboxs:
            xmin, ymin, xmax, ymax = CraterDataset.convert_box_cord(CraterDataset,
np.array([bbox]), 'normxywh', 'xyminmax', img.shape)[0]
            img = cv2.rectangle(img, (int(xmin), int(ymin)), (int(xmax), int(ymax)), (255, 0, 0), 2)

    plt.imshow(img)
    plt.axis('off')
    plt.show()

# Plot a few sample images
sample_images = os.listdir(train_images_dir)[:5]
for img_file in sample_images:
    img_path = os.path.join(train_images_dir, img_file)
    annot_path = os.path.join(train_labels_dir, img_file.replace('.jpg', '.txt'))
    plot_image_with_boxes(img_path, annot_path)

# Distribution of bounding boxes
def get_bbox_stats(annot_dir):
    widths = []
    heights = []
    aspect_ratios = []
```

```
    for label_file in os.listdir(annot_dir):
        annot_path = os.path.join(annot_dir, label_file)
        if os.path.getsize(annot_path) != 0:
            bboxs = np.loadtxt(annot_path, ndmin=2)
            for bbox in bboxs:
                _, _, w, h = bbox[1], bbox[2], bbox[3], bbox[4]
                widths.append(w)
                heights.append(h)
                aspect_ratios.append(w / h)

    return widths, heights, aspect_ratios

train_widths, train_heights, train_aspect_ratios = get_bbox_stats(train_labels_dir)
valid_widths, valid_heights, valid_aspect_ratios = get_bbox_stats(valid_labels_dir)

# Plot distributions
plt.figure(figsize=(15, 5))
plt.subplot(1, 3, 1)
sns.histplot(train_widths, kde=True)
plt.title('Distribution of Bounding Box Widths')

plt.subplot(1, 3, 2)
sns.histplot(train_heights, kde=True)
plt.title('Distribution of Bounding Box Heights')

plt.subplot(1, 3, 3)
sns.histplot(train_aspect_ratios, kde=True)
plt.title('Distribution of Bounding Box Aspect Ratios')

plt.show()
```

```
# Heatmap of bounding box centers
def get_bbox_centers(annot_dir, img_dir):
    centers_x = []
    centers_y = []

    for label_file in os.listdir(annot_dir):
        annot_path = os.path.join(annot_dir, label_file)
        img_path = os.path.join(img_dir, label_file.replace('.txt', '.jpg'))
        img = cv2.imread(img_path)
        h, w, _ = img.shape

        if os.path.getsize(annot_path) != 0:
            bboxs = np.loadtxt(annot_path, ndmin=2)
            for bbox in bboxs:
                cx = bbox[1] * w
                cy = bbox[2] * h
                centers_x.append(cx)
                centers_y.append(cy)

    return centers_x, centers_y

train_centers_x, train_centers_y = get_bbox_centers(train_labels_dir, train_images_dir)

# Plot heatmap
plt.figure(figsize=(10, 10))
sns.kdeplot(x=train_centers_x, y=train_centers_y, cmap='Reds', shade=True, bw_adjust=0.5)
plt.title('Heatmap of Bounding Box Centers')
plt.gca().invert_yaxis()
plt.show()
```

```
import torchvision
from torchvision.models.detection.faster_rcnn import FastRCNNPredictor

def get_model(num_classes):
    model = torchvision.models.detection.fasterrcnn_resnet50_fpn(pretrained=True)
    in_features = model.roi_heads.box_predictor.cls_score.in_features
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)
    return model

# Number of classes (including background)
num_classes = 2  # 1 class (crater) + background
model = get_model(num_classes)
device = torch.device('cuda') if torch.cuda.is_available() else torch.device('cpu')
model.to(device)



import torch.optim as optim
from torch.cuda.amp import GradScaler, autocast

# Define optimizer and learning rate scheduler
params = [p for p in model.parameters() if p.requires_grad]
optimizer = optim.SGD(params, lr=0.005, momentum=0.9, weight_decay=0.0005)
lr_scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=3, gamma=0.1)
scaler = GradScaler()

# Training function
def train_one_epoch(model, optimizer, data_loader, device, epoch, scaler):
    model.train()
    running_loss = 0.0
    for images, targets in data_loader:
```

```
        images = list(image.to(device) for image in images)
        targets = [{k: v.to(device) for k, v in t.items()} for t in targets]

        with autocast():
            loss_dict = model(images, targets)
            losses = sum(loss for loss in loss_dict.values())

        optimizer.zero_grad()
        scaler.scale(losses).backward()
        scaler.step(optimizer)
        scaler.update()
        running_loss += losses.item()

    epoch_loss = running_loss / len(data_loader)
    print(f"Epoch {epoch} - Loss: {epoch_loss:.4f}")
    return epoch_loss

# Training loop
num_epochs = 10
for epoch in range(num_epochs):
    train_loss = train_one_epoch(model, optimizer, train_loader, device, epoch, scaler)
    lr_scheduler.step()




def calculate_accuracy(outputs, targets, iou_threshold=0.5):
  # Initialize confusion matrix counters
  tp = 0  # True Positives (predicted crater, actual crater)
  fn = 0  # False Negatives (predicted background, actual crater)
  fp = 0  # False Positives (predicted crater, actual background)
  tn = 0  # True Negatives (predicted background, actual background)
```

```
    total_images = len(targets)

    for i in range(total_images):
        true_boxes = targets[i]['boxes']
        pred_boxes = outputs[i]['boxes']

        if len(pred_boxes) > 0 and len(true_boxes) > 0:
            ious = torchvision.ops.box_iou(pred_boxes, true_boxes)
            if (ious > iou_threshold).any().item():
                # Check for true positive (predicted crater, actual crater)
                tp += 1
            else:
                # Check for false negative (predicted background, actual crater)
                fn += 1
        else:
            # If no predictions or no ground truth boxes
            if len(pred_boxes) > 0:
                # False positive (predicted crater, no actual crater)
                fp += len(pred_boxes)
            else:
                # True negative (predicted background, no actual crater)
                tn += 1

    # Calculate accuracy (can be ignored for confusion matrix)
    accuracy = (tp + tn) / total_images

    # Return confusion matrix elements
    return tp, fn, fp, tn

def evaluate(model, data_loader, device, iou_threshold=0.5):
```

```
model.eval()
correct_detections = 0
total_images = 0

with torch.no_grad():
  for images, targets in data_loader:
    images = list(image.to(device) for image in images)
    targets = [{k: v.to(device) for k, v in t.items()} for t in targets]

    outputs = model(images)
    outputs = [{k: v.to('cpu') for k, v in t.items()} for t in outputs]
    targets = [{k: v.to('cpu') for k, v in t.items()} for t in targets]

    accuracy = calculate_accuracy(outputs, targets, iou_threshold)
    correct_detections += accuracy * len(images)
    total_images += len(images)

    # Calculate confusion matrix and plot heatmap
    tp, fn, fp, tn = accuracy
    cm = confusion_matrix([[tp, fn], [fp, tn]])
    plt.figure(figsize=(6, 6))
    sns.heatmap(cm, annot=True, fmt='d')
    plt.title("Confusion Matrix (Faster R-CNN)")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

validation_accuracy = correct_detections / total_images
test_accuracy = correct_detections / total_images

print(f"Validation Accuracy: {validation_accuracy * 100:.2f}%")
```

```
  print(f"Test Accuracy: {test_accuracy * 100:.2f}%")

  return validation_accuracy, test_accuracy

def calculate_accuracy(outputs, targets, iou_threshold=0.5):
    correct_detections = 0
    total_images = len(targets)

    for i in range(total_images):
        true_boxes = targets[i]['boxes']
        pred_boxes = outputs[i]['boxes']

        if len(pred_boxes) > 0 and len(true_boxes) > 0:
            ious = torchvision.ops.box_iou(pred_boxes, true_boxes)
            if (ious > iou_threshold).any().item():
                correct_detections += 1

    accuracy = correct_detections / total_images
    return accuracy

# Evaluation function with accuracy calculation
def evaluate(model, data_loader, device, iou_threshold=0.5):
    model.eval()
    correct_detections = 0
    total_images = 0

    with torch.no_grad():
        for images, targets in data_loader:
            images = list(image.to(device) for image in images)
            targets = [{k: v.to(device) for k, v in t.items()} for t in targets]
```

```
            outputs = model(images)
            outputs = [{k: v.to('cpu') for k, v in t.items()} for t in outputs]
            targets = [{k: v.to('cpu') for k, v in t.items()} for t in targets]

            accuracy = calculate_accuracy(outputs, targets, iou_threshold)
            correct_detections += accuracy * len(images)
            total_images += len(images)

    validation_accuracy = correct_detections / total_images
    test_accuracy = correct_detections / total_images

    print(f"Validation Accuracy: {validation_accuracy * 100:.2f}%")
    print(f"Test Accuracy: {test_accuracy * 100:.2f}%")

    return validation_accuracy, test_accuracy

# Evaluate on validation and test sets
valid_accuracy, test_accuracy = evaluate(model, valid_loader, device)

torch.save(faster_rcnn_model.state_dict(), "/content/drive/MyDrive/Colab
Notebooks/faster_rcnn_model.pth")

faster_rcnn_model = get_model(num_classes)  # Replace with your Faster R-CNN model
variable
torch.save(faster_rcnn_model.state_dict(), "/content/drive/MyDrive/Colab
Notebooks/faster_rcnn_model.pth")

import matplotlib.pyplot as plt
import numpy as np

def plot_model_performance(history):
    epochs = range(1, len(history['loss']) + 1)
```

```
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['loss'], 'b-', label='Training loss')
    plt.plot(epochs, history['val_loss'], 'r-', label='Validation loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['accuracy'], 'b-', label='Training accuracy')
    plt.plot(epochs, history['val_accuracy'], 'r-', label='Validation accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Example usage with dummy data
history = {
    'loss': np.random.rand(10).tolist(),
    'val_loss': np.random.rand(10).tolist(),
    'accuracy': np.random.rand(10).tolist(),
    'val_accuracy': np.random.rand(10).tolist()
}

plot_model_performance(history)
```

```
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
import cv2
import numpy as np
from albumentations import Compose, Resize, RandomCrop, RandomRotate90, HorizontalFlip,
VerticalFlip, ColorJitter, BboxParams
from albumentations.pytorch import ToTensorV2

# Define the CraterDataset class
class CraterDataset(Dataset):
    def __init__(self, root, transforms=None):
        self.root = root
        self.transforms = transforms
        self.imgs = list(sorted(os.listdir(os.path.join(root, "images"))))
        self.annots = list(sorted(os.listdir(os.path.join(root, "labels"))))

    def __getitem__(self, idx):
        img_path = os.path.join(self.root, "images", self.imgs[idx])
        annot_path = os.path.join(self.root, "labels", self.annots[idx])
        img = cv2.imread(img_path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB).astype(np.float32) / 255.0

        if os.path.getsize(annot_path) != 0:
            bboxs = np.loadtxt(annot_path, ndmin=2)
            bboxs = self.convert_box_cord(bboxs, 'normxywh', 'xyminmax', img.shape)
            num_objs = len(bboxs)
            bboxs = torch.as_tensor(bboxs, dtype=torch.float32)
```

```
            labels = torch.ones((num_objs,), dtype=torch.int64)
            iscrowd = torch.zeros((num_objs,), dtype=torch.int64)
        else:
            bboxs = torch.as_tensor([[0, 0, 512, 512]], dtype=torch.float32)
            labels = torch.zeros((1,), dtype=torch.int64)
            iscrowd = torch.zeros((1,), dtype=torch.int64)

        area = (bboxs[:, 3] - bboxs[:, 1]) * (bboxs[:, 2] - bboxs[:, 0])
        image_id = torch.tensor([idx])

        target = {"boxes": bboxs, "labels": labels, "image_id": image_id, "area": area, "iscrowd":
iscrowd}

        if self.transforms:
            sample = self.transforms(image=img, bboxes=target['boxes'], labels=labels)
            img = sample['image']
            target['boxes'] = torch.tensor(sample['bboxes'])
            target['labels'] = torch.tensor(sample['labels'])

        return img, target

    def __len__(self):
        return len(self.imgs)

    def convert_box_cord(self, bboxs, format_from, format_to, img_shape):
        if format_from == 'normxywh':
            if format_to == 'xyminmax':
                xw = bboxs[:, (1, 3)] * img_shape[1]
                yh = bboxs[:, (2, 4)] * img_shape[0]
                xmin = xw[:, 0] - xw[:, 1] / 2
                xmax = xw[:, 0] + xw[:, 1] / 2
```

```
            ymin = yh[:, 0] - yh[:, 1] / 2
            ymax = yh[:, 0] + yh[:, 1] / 2
            coords_converted = np.column_stack((xmin, ymin, xmax, ymax))
        return coords_converted

    # Define transformations with resizing
    train_transforms = Compose([
        Resize(512, 512),
        RandomCrop(width=512, height=512, p=0.5),
        RandomRotate90(p=0.5),
        HorizontalFlip(p=0.5),
        VerticalFlip(p=0.5),
        ColorJitter(p=0.5),
        ToTensorV2(p=1.0)
    ], bbox_params=BboxParams(format='pascal_voc', label_fields=['labels']))

    valid_transforms = Compose([
        Resize(512, 512),
        ToTensorV2(p=1.0)
    ], bbox_params=BboxParams(format='pascal_voc', label_fields=['labels']))

    # Dataset and DataLoader
    train_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/train',
transforms=train_transforms)
    valid_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/valid',
transforms=valid_transforms)
    test_dataset = CraterDataset(root='/content/drive/MyDrive/Colab Notebooks/craters/test',
transforms=valid_transforms)

    train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))
    valid_loader = DataLoader(valid_dataset, batch_size=16, shuffle=False, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))
```

```
    test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False, num_workers=4,
collate_fn=lambda x: tuple(zip(*x)))


    # Define the ANN model class
    class CraterClassifier(nn.Module):
        def __init__(self, input_size, hidden_size, output_size):
            super(CraterClassifier, self).__init__()
            self.fc1 = nn.Linear(input_size, hidden_size)
            self.relu = nn.ReLU()
            self.fc2 = nn.Linear(hidden_size, output_size)
            self.sigmoid = nn.Sigmoid()


        def forward(self, x):
            x = x.view(x.size(0), -1)
            x = self.relu(self.fc1(x))
            x = self.sigmoid(self.fc2(x))
            return x


    # Define the CNN model class
    class CraterCNN(nn.Module):
        def __init__(self):
            super(CraterCNN, self).__init__()
            self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
            self.relu1 = nn.ReLU()
            self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
            self.conv2 = nn.Conv2d(16, 32, kernel_size=3, padding=1)
            self.relu2 = nn.ReLU()
            self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
            self.flatten = nn.Flatten()
            self.fc1 = nn.Linear(32 * 128 * 128, 128)  # Assuming output of pool2
            self.relu3 = nn.ReLU()
```

```
        self.fc2 = nn.Linear(128, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        x = self.relu1(self.pool1(self.conv1(x)))
        x = self.relu2(self.pool2(self.conv2(x)))
        x = self.flatten(x)
        x = self.relu3(self.fc1(x))
        x = self.sigmoid(self.fc2(x))
        return x

# Define model parameters
input_size = 3 * 512 * 512  # Assuming images are 512x512x3 (RGB)
hidden_size = 1024
output_size = 1  # Binary classification (crater or not)

# Choose the desired model (uncomment one)
#model = CraterClassifier(input_size, hidden_size, output_size)
model = CraterCNN()

# Define loss function and optimizer
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)  # Suggested learning rate

# Define training loop
def train_model(model, criterion, optimizer, train_loader, num_epochs):
    for epoch in range(num_epochs):
        train_loss = 0.0
        model.train()  # Set model to training mode
        for images, targets in train_loader:
            images = torch.stack(images)  # Stack images into a tensor
```

```
            labels = torch.tensor([t["labels"][0] for t in targets], dtype=torch.float32)  # Extract labels

            # Forward pass
            outputs = model(images)
            labels = labels.view(-1, 1)  # Reshape labels to match output

            # Calculate loss
            loss = criterion(outputs, labels)

            # Backward pass and parameter update
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            # Update training loss
            train_loss += loss.item()

        # Print training loss at the end of each epoch
        print(f'Epoch [{epoch + 1}/{num_epochs}], Train Loss: {train_loss:.4f}')

# Define evaluation function
def evaluate_model(model, data_loader):
    model.eval()  # Set model to evaluation mode
    correct = 0
    total = 0
    with torch.no_grad():
        for images, targets in data_loader:
            images = torch.stack(images)  # Stack images into a tensor
            labels = torch.tensor([t["labels"][0] for t in targets], dtype=torch.float32)  # Extract labels
            outputs = model(images)
            predicted = (outputs > 0.5).float()  # Apply threshold to get binary predictions
```

```
            total += labels.size(0)
            correct += (predicted.view(-1) == labels).sum().item()
    accuracy = correct / total
    return accuracy


# Train the chosen model
train_model(model, criterion, optimizer, train_loader, num_epochs=10)


# Evaluate the model on validation and test sets
val_accuracy = evaluate_model(model, valid_loader)
test_accuracy = evaluate_model(model, test_loader)
print(f'Validation Accuracy: {val_accuracy:.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:558: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

```
ann_model = CraterClassifier(input_size, hidden_size, output_size)  # Create an instance of CraterClassifier
torch.save(ann_model.state_dict(), "/content/drive/MyDrive/Colab Notebooks/ann_model.pth")


cnn_model = CraterCNN()  # Create an instance of CraterCNN
torch.save(cnn_model.state_dict(), "/content/drive/MyDrive/Colab Notebooks/cnn_model.pth")


import torch
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```

```
# Load the provided model (assuming it's a Faster R-CNN model)
model_path = '/content/drive/MyDrive/Colab Notebooks/faster_rcnn_model.pth'
model = torch.load(model_path)

# Placeholder for true labels and predictions (these would be obtained from a test dataset)
# Here, we're generating random data to simulate the process
true_labels = np.random.choice(['crater', 'background'], size=100, p=[0.5, 0.5])
predicted_labels = np.random.choice(['crater', 'background'], size=100, p=[0.5, 0.5])

# Compute the confusion matrix
cm = confusion_matrix(true_labels, predicted_labels, labels=['crater', 'background'])

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['crater', 'background'],
yticklabels=['crater', 'background'])
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix for Crater Detection')

# Display the confusion matrix
plt.show()

import torch
import torchvision
from torchvision.models.detection.faster_rcnn import FastRCNNPredictor

def get_model(num_classes):
    # Load a pre-trained model for classification and return only the features
    model = torchvision.models.detection.fasterrcnn_resnet50_fpn(pretrained=True)
```

```
    # Get the number of input features for the classifier
    in_features = model.roi_heads.box_predictor.cls_score.in_features
    # Replace the pre-trained head with a new one
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)
    return model

# Define the number of classes (e.g., 2 for background and crater)
num_classes = 2

# Load the saved model
model_path = "/content/drive/MyDrive/Colab Notebooks/faster_rcnn_model.pth"
model = get_model(num_classes)
model.load_state_dict(torch.load(model_path))
model.eval()  # Set the model to evaluation mode

    !pip install gradio opencv-python-headless torch torchvision



import gradio as gr
import cv2
import numpy as np
from PIL import Image

def preprocess_image(image):
    # Convert image to RGB
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    # Convert image to PIL format and then to a tensor
    image = Image.fromarray(image)
    image = torchvision.transforms.functional.to_tensor(image)
    return image
```

```
@torch.no_grad()
def detect_craters(image):
    # Preprocess the image
    image_tensor = preprocess_image(image)
    image_tensor = image_tensor.unsqueeze(0)  # Add batch dimension

    # Perform detection
    outputs = model(image_tensor)
    detections = outputs[0]

    # Get boxes and labels
    boxes = detections['boxes'].cpu().numpy()
    labels = detections['labels'].cpu().numpy()
    scores = detections['scores'].cpu().numpy()

    return boxes, labels, scores

def annotate_image(image, boxes, labels, scores, score_threshold=0.5):
    annotated_image = image.copy()
    for box, label, score in zip(boxes, labels, scores):
        if score >= score_threshold:
            x1, y1, x2, y2 = box
            cv2.rectangle(annotated_image, (int(x1), int(y1)), (int(x2), int(y2)), (0, 255, 0), 2)
            cv2.putText(annotated_image, f"{label}: {score:.2f}", (int(x1), int(y1)-10),
cv2.FONT_HERSHEY_SIMPLEX, 0.9, (0, 255, 0), 2)
    return annotated_image

def calculate_accuracy(predictions, ground_truths):
    # Placeholder function - replace with actual accuracy calculation
    return 0.9  # Example accuracy
```

```
def process_image(image):
    # Detect craters
    boxes, labels, scores = detect_craters(image)
    # Annotate image
    annotated_image = annotate_image(image, boxes, labels, scores)
    # Calculate accuracy (placeholder)
    accuracy = calculate_accuracy(None, None)
    return annotated_image, accuracy


iface = gr.Interface(
    fn=process_image,
    inputs=gr.Image(type="numpy", label="Upload Image"),
    outputs=[gr.Image(type="numpy", label="Annotated Image"),
gr.Textbox(label="Accuracy")],
    title="Crater Detection"
)


iface.launch()
```

10.2 MISCELLANEOUS IMAGES

10.3 PLAGIARISM REPORT

11 REFERENCES

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