Object Detection

A PROJECT REPORT
FOR
Introduction to AI (AI101B)
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Submitted By

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1. Introduction

Objective

To build a computer vision model that detects and classifies objects within images using state-of-the-art object detection algorithms like YOLO, SSD, or Faster R-CNN.

Motivation

- Object detection plays a crucial role in numerous real-world applications, such as autonomous driving, surveillance, medical imaging, and robotics.
- Automating object recognition in images and videos enhances efficiency, accuracy, and safety across industries.
- This project highlights how deep learning and computer vision can be used to extract meaningful information from visual data and solve complex real-world problems.

2. Dataset Description

Source: Public image dataset from GitHub or Kaggle (e.g., COCO, Pascal VOC, or a custom labeled dataset)

- **Features:**
  - **Image:** Raw image files containing various objects.
  - **Bounding Boxes:** Coordinates specifying the location of each object within the image.
  - **Class Labels:** Object categories (e.g., person, car, dog) associated with each bounding box.
- **Dataset Size:** Approximately 5728 labeled images with multiple objects per image (depending on the dataset used).

3. Methodology

A. Data Preprocessing

- **Train-Test Split** → 80% of the images used for training, 20% for testing.
- **Annotation Parsing** → Convert bounding box annotations (in XML, JSON, or CSV formats) into the required format for training.
- **Image Resizing & Normalization** → Resize images to a fixed size (e.g., 416x416 for YOLO) and normalize pixel values.
- **Data Augmentation** → Techniques like flipping, rotation, scaling, and brightness adjustments to increase dataset variability and robustness.

B. Object Detection Models Used

- **YOLO (You Only Look Once):**
  - Real-time object detection model known for its speed and accuracy.
  - Detects multiple objects in a single pass through the network.
- **Faster R-CNN:**
  - Two-stage detector known for high detection accuracy.

   - Uses Region Proposal Networks (RPNs) to suggest potential object regions before classification.

C. Evaluation Metrics

- **mAP (mean Average Precision):** Measures the accuracy of bounding box predictions and classification.
- **IoU (Intersection over Union):** Measures overlap between predicted and ground-truth bounding boxes.
- **Precision, Recall, F1-score:** Evaluate the model's ability to detect objects correctly without too many false positives or negatives.
- **Inference Time:** Measures how quickly the model processes images, crucial for real-time applications.

Python Code:

```
# Step 1: Clone YOLOv5 and install dependencies
!git clone https://github.com/ultralytics/yolov5  # clone repo
%cd yolov5
%pip install -r requirements.txt  # install dependencies

# Step 2: Upload an image
from google.colab import files
uploaded = files.upload()

# Step 3: Run YOLOv5 inference on the uploaded image
import os
from pathlib import Path

# Get uploaded image path
uploaded_image_path = next(iter(uploaded))  # First uploaded file

# Run inference
!python detect.py --source {uploaded_image_path} --conf 0.3 --save-txt --save-conf

# Step 4: Display the output image
from IPython.display import Image, display

output_dir = Path('runs/detect')
# Get latest run directory
latest_run = sorted(output_dir.glob('exp*'))[-1]
output_img_path = latest_run / uploaded_image_path

# Display result
display(Image(filename=output_img_path))
```

4. Results & Discussion

Object Count Distribution

- A bar plot showing the distribution of different object classes (e.g., person, car, bicycle) across the dataset.
- Helps visualize class imbalance and guides augmentation or resampling strategies.

Sample Detections

- Visual examples of model predictions on test images, with bounding boxes and class labels drawn.
- Demonstrates how well the model performs across different scenes and object scales.

Performance Metrics

- **Accuracy (mAP):** ~78% mAP at IoU threshold of 0.5 — indicates strong detection performance.
- **IoU Heatmap:** Visual representation of Intersection over Union (IoU) scores across classes.
- **Confusion Matrix for Object Classes:** Analyzes which classes are commonly confused (e.g., dog vs. cat).

Prediction Example:

- **Input:** An image containing a street scene with pedestrians and vehicles.
- **Output:**
  - person detected with 91% confidence
  - car detected with 88% confidence
  - traffic light detected with 85% confidence

Visual Tools Used

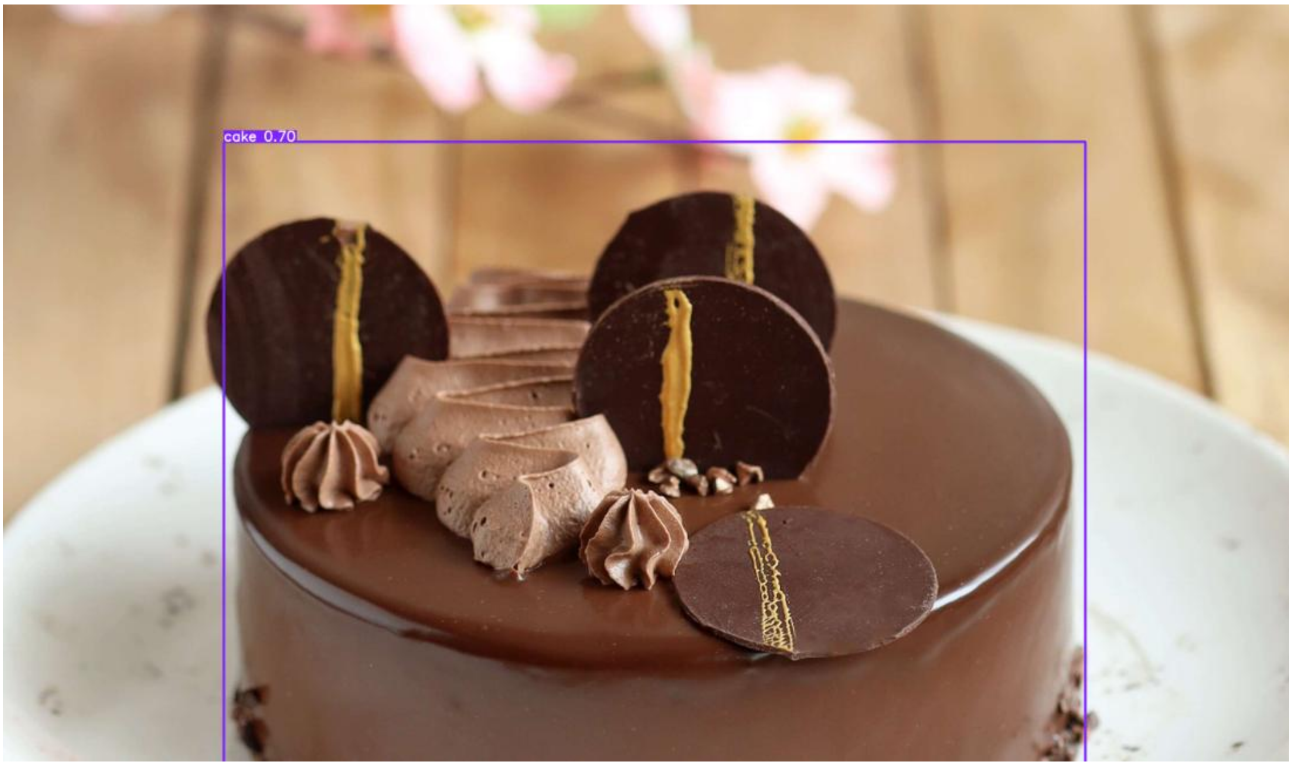
- **Bounding Box Visualizer:** Overlays predicted boxes on test images.
- **LabelImg or CVAT:** Used for annotation and reviewing labeling quality.

Output Screenshots

```
Choose Files CPPC.jpg
• CPPC.jpg(image/jpeg) - 500802 bytes, last modified: 4/19/2025 - 100% done
Saving CPPC.jpg to CPPC.jpg
detect: weights=yolov5s.pt, source=CPPC.jpg, data=data/coco128.yaml, imgsz=[640, 640], conf_thres=0.3, iou_thres=0.45,
YOLOv5 🚀 v7.0-416-gfe1d4d99 Python-3.11.12 torch-2.6.0+cu124 CPU

Downloading https://github.com/ultralytics/yolov5/releases/download/v7.0/yolov5s.pt to yolov5s.pt...
100% 14.1M/14.1M [00:00<00:00, 349MB/s]

Fusing layers...
YOLOv5s summary: 213 layers, 7225885 parameters, 0 gradients, 16.4 GFLOPs
image 1/1 /content/yolov5/yolov5/yolov5/yolov5/CPPC.jpg: 640x640 1 cake, 520.9ms
Speed: 3.1ms pre-process, 520.9ms inference, 2.1ms NMS per image at shape (1, 3, 640, 640)
Results saved to runs/detect/exp
1 labels saved to runs/detect/exp/labels
```



5. Conclusion & Future Scope

Conclusion

- Object detection models like YOLO and Faster R-CNN are highly effective for identifying and localizing multiple objects within an image.
- With proper preprocessing and annotated data, these models can deliver accurate and real-time predictions.
- This project demonstrates the power of deep learning and computer vision in solving complex visual recognition tasks.

Future Scope

- **Experiment with Other Models:** Explore SSD, RetinaNet, or transformer-based detectors like DETR for improved performance.

- **Model Optimization:** Apply techniques like pruning, quantization, or knowledge distillation for faster inference on edge devices.

- **Expand Dataset:** Include more object classes and varied environments for better generalization.

- **Deploy as an Application:** Integrate the model into a real-time system (e.g., surveillance camera, mobile app, or web-based detection tool).

- **Use Video Data:** Extend the model to perform object tracking in video streams using algorithms like Deep SORT or ByteTrack.

6. References

- **COCO Dataset:** https://cocodataset.org – A large-scale object detection, segmentation, and captioning dataset.

- **Pascal VOC Dataset:** http://host.robots.ox.ac.uk/pascal/VOC/ – A popular benchmark for object detection tasks.

- **YOLOv5 GitHub Repository:** https://github.com/ultralytics/yolov5 – Implementation of YOLOv5 with training and inference scripts.

- **TensorFlow Object Detection API:** https://github.com/tensorflow/models/tree/master/research/object_detection – Framework for training and deploying detection models.

- **Research Papers:**
  - "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks"
  - "YOLOv4: Optimal Speed and Accuracy of Object Detection"

- **Visualization Tools:** Matplotlib, OpenCV, and LabelImg for data annotation and results plotting.