DETR Fine-tuning Pipeline: Technical Report

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1. Introduction

This report details the technical approach, implementation, and rationale for fine-tuning a DETR (DEtection TRansformer) model for object detection on a custom dataset. The pipeline covers data ingestion, preprocessing, model adaptation, training, evaluation, and analysis of results, with a focus on reproducibility and extensibility.

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2. Dataset Construction

2.1 Annotation Format

- **File Structure:** Each image is paired with a `.txt` annotation file in a dedicated directory.

- **Annotation Content:** Each line in an annotation file encodes a single object as:

  ```
  <class_id> <x_center> <y_center> <width> <height>
  ```

  - All coordinates are normalized to [0, 1] relative to image dimensions.
  - Example:

    ```
    0 0.512 0.433 0.120 0.210
    2 0.700 0.600 0.100 0.150
    ```

- **Assumptions:** All annotation files are present, correctly formatted, and correspond to existing images.

2.2 Dataset Preparation and Splitting

- **Discovery:** The pipeline recursively scans the annotation directory for `.txt` files.
- **Integrity Check:** Ensures each annotation file has a corresponding image.
- **Splitting:** Dataset is split into training and validation subsets using a configurable ratio (e.g., 80/20) and a fixed random seed for reproducibility.
- **Development Subset:** For rapid prototyping, a small subset (e.g., first 10 files) can be used.

2.3 Custom Dataset Class

- **Class:** `MovedObjectDataset`
- **Responsibilities:**
  - Loads image-annotation pairs.
  - Applies preprocessing (including image diffs, see 3.2).
  - Integrates with HuggingFace image processor for normalization and resizing.
  - Returns data in the format expected by DETR (image tensor, target dict with boxes and labels).
- **Design Note:** Manual resizing is avoided; the image processor handles all resizing and normalization.

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3. Preprocessing Pipeline

3.1 Image Processor

- **Library:** HuggingFace Transformers
- **Model:** `facebook/detr-resnet-50`
- **Functionality:**
  - Converts PIL images to normalized tensors.
  - Resizes images to the input size expected by DETR.
  - Applies mean/std normalization as per pre-trained model requirements.
- **Initialization:** Loaded once at pipeline start for efficiency.

3.2 Image Diff Strategy

- **Motivation:** To enhance detection of moved objects, the pipeline computes the pixel-wise difference between "before" and "after" images.
- **Implementation:**
    - Both images are loaded and aligned.
    - The absolute difference is computed per channel.
    - The resulting diff image is passed to the image processor.
- **Rationale:** Image diffs provide a richer representation for detecting object movement compared to feature diffs, as they directly highlight changes in the scene.

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4. Model Architecture and Selection

4.1 DETR Overview

- **Architecture:** DETR combines a CNN backbone (ResNet-50) with a transformer encoder-decoder and a set-based global loss for direct set prediction of bounding boxes and class labels.
- **Advantages:**
    - End-to-end object detection without anchor boxes or NMS.
    - Strong performance on standard benchmarks.

4.2 Model Loading and Configuration

- **Loading:** Model is loaded via a `load_model()` utility, which:
    - Loads pre-trained weights (`facebook/detr-resnet-50`).
    - Adapts the classification head to match the number of custom classes.
    - Moves the model to the configured device (CPU/GPU).
- **Freezing/Unfreezing:** Supports selective freezing of backbone or transformer layers for staged training.

4.3 Transfer Learning Rationale

- **Why Transfer Learning?**
    - Leverages pre-trained visual and spatial representations.
    - Reduces data requirements and accelerates convergence.
- **Image Diff vs. Feature Diff:**
    - Image diffs are preferred for this task, as they directly encode scene changes, which is critical for moved object detection.

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5. Training Pipeline

5.1 Training Arguments and Hyperparameters

- **Configurable Parameters:**

    - Batch size (raw and simulated via gradient accumulation)
    - Number of epochs
    - Learning rate and scheduler type
    - Device (CPU/GPU)

  - Logging and checkpoint intervals

- **Example Configuration:**

```
batch_size = 2  # Tesla T4 GPU
gradient_accumulation_steps = 16  # Simulated batch size = 32
learning_rate = 1e-4
lr_scheduler_type = "cosine_with_restarts"
num_epochs = 80
```

5.2 Trainer Setup

- **Framework:** HuggingFace `Trainer`
- **Custom Data Collator:** Handles batching of variable-sized images and targets.
- **Evaluation:** Runs after every N steps/epochs; supports custom metrics.
- **Callbacks:** TensorBoard logging, model checkpointing, and early stopping.

5.3 Training Strategies

- **Staged Training:**
  1. **Stage 1:** Freeze encoder/decoder; train only classification head (20 epochs, LR=1e-4).
  2. **Stage 2:** Unfreeze all layers; reduce LR to 5e-5 (20 epochs).
  3. **Stage 3:** Further reduce LR to 1e-5; train all layers (80 epochs).
- **Gradient Accumulation:** Used to simulate larger batch sizes for stable training on limited GPU memory.
- **Learning Rate Scheduling:** Cosine annealing with restarts every 5 cycles to escape local minima and encourage exploration.

5.4 Logging and Monitoring

- **TensorBoard:** Tracks training/validation loss, learning rate, and custom metrics.
- **Model Checkpoints:** Best model saved based on validation loss.
- **Evaluation Frequency:** Every 20 iterations for close monitoring.

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6. Evaluation and Results

6.1 Quantitative Metrics

- **Primary Metric:** Validation loss (cross-entropy + bounding box loss).
- **Additional Metrics:** Precision, recall, F1-score as a function of IoU and score thresholds.
- **Results:**
  - **Stage 1:** Train loss ≈ 2.1, Eval loss ≈ 2.38
  - **Stage 2:** Train loss ≈ 1.56, Eval loss ≈ 1.62
  - **Stage 3:** Train loss ≈ 0.44, Eval loss ≈ 0.6 (minor overfitting)
- **Interpretation:** Progressive reduction in loss and improved precision after staged unfreezing and LR reduction.

6.2 Qualitative Analysis

- **Visualization:** Bounding boxes and class labels overlaid on image diffs.
- **Success Example:** Accurate detection of moved objects.
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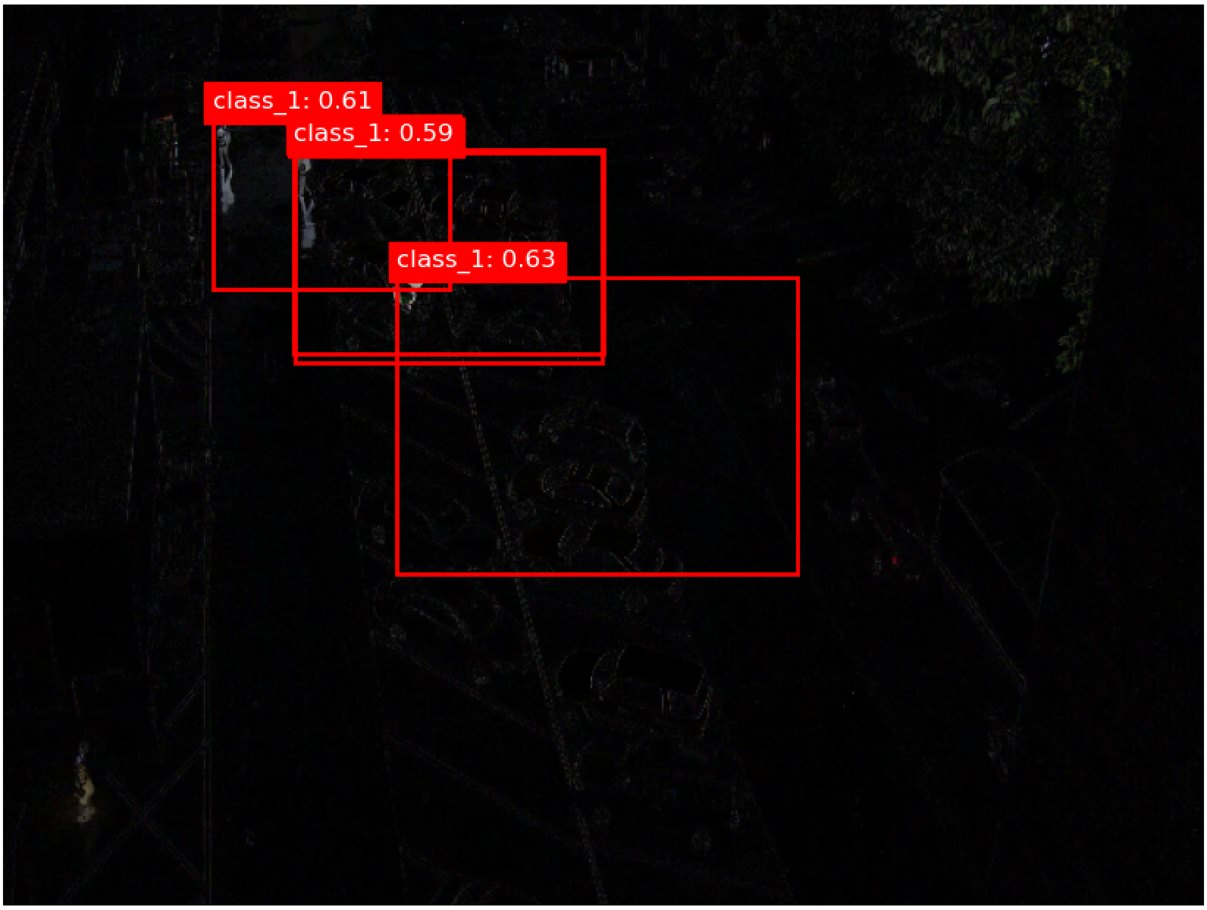
- **Failure Example:** Camera movement introduces excessive diff, leading to false positives.
  - 

- Only 2 objects should have been predicted.

6.3 Failure Modes and Limitations

- **Camera Movement:** Large scene changes degrade diff quality and model performance.
- **Data Scarcity:** Limited training data restricts achievable precision and recall.
- **Mitigation:** Increasing score threshold improves precision but may reduce recall.

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7. Assumptions and Workarounds

- All annotation files are present and correctly formatted.
- Image and annotation directories are specified in the config.
- Image processor and model loader are compatible with the dataset.
- For rapid iteration, a subset of data may be used during development.

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8. Pipeline Summary

1. **Initialize:** Set up output and logging directories.
2. **Load Processor:** Prepare image processor for preprocessing.
3. **Prepare Dataset:** Discover annotation files, split into train/val, instantiate dataset objects.
4. **Load Model:** Load and configure DETR model.
5. **Set Training Args:** Define hyperparameters and logging.
6. **Setup Trainer:** Use HuggingFace Trainer for training and evaluation.
7. **Monitor:** Log metrics and save best model.
8. **In-depth Evaluation:** Compute precision, recall, F1 as a function of IoU and score thresholds; perform qualitative analysis.

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9. Future Improvements

- **Data Augmentation:** Incorporate geometric and photometric augmentations to improve generalization.
- **Hyperparameter Optimization:** Integrate automated search (e.g., Optuna, Ray Tune).
- **Advanced Evaluation:** Add mAP (mean Average Precision) and per-class metrics.
- **Robustness:** Explore feature-diff approaches and camera motion compensation.

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10. References

- DETR: End-to-End Object Detection with Transformers
- HuggingFace Transformers Documentation
- COCO Dataset Format