Session 4: Hands-on Object Detection Lab

Transfer Learning for Building Detection from Sentinel Imagery

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Lab Overview

Duration: 2.5 hours **Type:** Hands-on Coding Lab **Platform:** Google Colab with GPU

You will:

- Load and configure pre-trained object detectors
- Prepare Sentinel-2 imagery and COCO annotations
- Fine-tune detector on Metro Manila building dataset
- Evaluate with mAP, Precision, Recall metrics
- Visualize detections and export results for GIS

Prerequisites:

- Session 3 (object detection theory)
- Google Colab account
- GPU runtime enabled
- Basic Python/TensorFlow knowledge

Resources:

- Notebook: `Day3_Session4_Object_Detection_STUDENT.ipynb`
- Demo dataset: Metro Manila urban patches

Case Study: Metro Manila

Philippine Urban Monitoring Context

Location: Metro Manila - National Capital Region (NCR) **Focus Areas:** Quezon City and Pasig River corridor **Challenge:** Rapid informal settlement growth and urban sprawl

Why This Matters

Metro Manila's rapid urbanization creates challenges for:

- **Disaster Risk Reduction** - Identifying vulnerable settlements in flood zones
- **Urban Planning** - Monitoring informal settlements and infrastructure
- **Population Estimation** - Building counts for demographic analysis
- **Resource Allocation** - Targeting social services and infrastructure

Data and Objectives

Data Source: Sentinel-2 Multispectral Imagery

- **Spatial Resolution:** 10m RGB bands (B4, B3, B2)
- **Temporal Coverage:** 5-day revisit for change detection
- **Additional Bands:** NIR (B8) for enhanced detection
- **Study Area:** Urban patches from Quezon City

Lab Goal:

Automate building detection using transfer learning to enable rapid, scalable urban monitoring

The Challenge

Manual Approach Problems

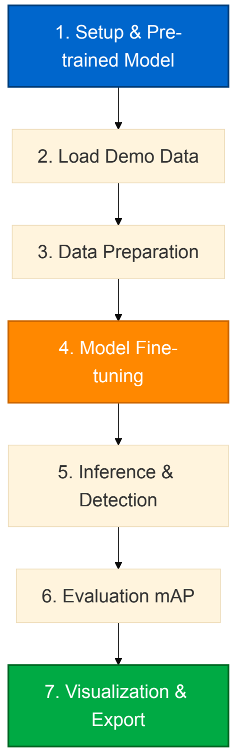
- Time-consuming digitization
- Inconsistent interpretation
- Cannot scale to city-wide mapping
- Difficult to update regularly
- Subjective delineation

Deep Learning Solution

- **Automated identification** from satellite imagery
- **Rapid mapping** of large areas in hours
- **Change detection** over time
- **Scalable monitoring** for metropolitan regions
- **Quantitative analysis** of urban patterns

Lab Workflow

Transfer Learning Workflow



7 Key Steps:

1. Setup & load pre-trained model
2. Load demo building dataset
3. Prepare data and annotations
4. Fine-tune detector (10-30 epochs)
5. Run inference on test images
6. Evaluate with mAP metrics
7. Visualize and export results

Part 1: Transfer Learning Concepts

What is Transfer Learning?

Definition: Adapt a model pre-trained on a large dataset to your specific task with minimal additional training data

Analogy: Like a doctor specializing in cardiology after completing general medical training - the foundational knowledge transfers, requiring less time to specialize

Transfer Learning for Object Detection

Pre-trained Model Knows

- What makes objects distinct from background
- How to propose bounding boxes
- How to classify regions
- General visual features (edges, textures, shapes)

Trained on: COCO dataset (330K images, 80 classes)

We Adapt It For

- Detecting buildings in satellite imagery
- Understanding urban patterns
- Philippine-specific urban morphology
- Sentinel-2 spectral characteristics

Fine-tune with: 100-500 labeled satellite images

Why Transfer Learning for Philippine EO?

Challenge: Limited Labeled Data

- Annotation is expensive (bounding boxes take time)
- Philippine-specific datasets are scarce
- Small agencies can't afford large labeling efforts
- Traditional approach: Need 10,000+ annotated images

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Solution: Transfer Learning

- Start with pre-trained model (free, publicly available)
- Fine-tune with **100-500** labeled satellite images
- Achieve **75-85%** accuracy (operational quality)
- Training time: **30-60 minutes** (vs. days from scratch)

Model Options

Model	Speed	Accuracy	Best For
SSD MobileNet V2	Fast	Good	Real-time applications, resource-constrained
Faster R-CNN ResNet50	Slow	Excellent	Offline analysis, high accuracy priority
YOLO v5/v8	Moderate	Very Good	Balanced speed and accuracy

Recommendation for Lab

We'll use **SSD MobileNet V2** - fast training, good accuracy, works well with Sentinel-2 imagery

Part 2: Data Preparation

Exercise 1: Load Pre-trained Model (20 min)

Objective: Load a pre-trained object detector from TensorFlow Hub

```python
import tensorflow_hub as hub

# Load pre-trained SSD MobileNet
model_url = "https://tfhub.dev/tensorflow/ssd_mobilenet_v2/fpnlite_320x320/1"
detector = hub.load(model_url)

# Test on sample image
detections = detector(sample_image)
```

What You'll Learn:

- How to load pre-trained models from TF Hub
- Understanding model input/output format
- Visualizing default detections (COCO classes)

Exercise 2: Prepare Training Data (30 min)

Objective: Load and prepare satellite imagery with building annotations

Data Format:

Images:

- Sentinel-2 RGB patches
- Size: 320×320 or 512×512 pixels
- Format: PNG or GeoTIFF
- Normalized 0-1 range

Annotations:

- COCO JSON format
- Bounding boxes: [x, y, width, height]
- Category: building (id=1)
- Includes image metadata

COCO JSON Format Example

```json
{
  "images": [
    {"id": 1, "file_name": "metro_manila_001.png", "width": 512, "height": 512}
  ],
  "annotations": [
    {
      "id": 1,
      "image_id": 1,
      "category_id": 1,
      "bbox": [120, 150, 80, 60],
      "area": 4800,
      "iscrowd": 0
    }
  ],
  "categories": [
    {"id": 1, "name": "building", "supercategory": "structure"}
  ]
}
```

Data Preparation Tasks

Steps:

1. **Load demo dataset** - 100 pre-annotated urban patches
2. **Visual inspection** - View images with bounding boxes overlay
3. **Data split** - 70% train, 15% validation, 15% test
4. **Convert format** - Transform to model's expected input
5. **Data augmentation** (optional) - Rotation, flip, brightness

> **Demo Data Included**
>
> For this lab, we provide ready-to-use Metro Manila satellite patches with pre-annotated buildings. No lengthy data collection required!

Part 3: Fine-Tuning

Exercise 3: Fine-tune Model (40 min)

Objective: Adapt the pre-trained detector to recognize buildings in satellite imagery

Fine-tuning Strategy:

- **Freeze early layers** - Keep general feature extractors
- **Train detection head** - Adapt bounding box prediction
- **Small learning rate** - 0.0001 to 0.001 (avoid catastrophic forgetting)
- **Limited epochs** - 10-30 epochs typically sufficient
- **Early stopping** - Monitor validation loss

Fine-Tuning Code Structure

```
# Configure optimizer
optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)

# Training loop
for epoch in range(20):
    for batch_images, batch_boxes in train_dataset:
        with tf.GradientTape() as tape:
            # Forward pass
            predictions = model(batch_images, training=True)

            # Calculate loss (classification + localization)
            loss = detection_loss(predictions, batch_boxes)

        # Backpropagation
        gradients = tape.gradient(loss, model.trainable_variables)
        optimizer.apply_gradients(zip(gradients, model.trainable_variables))

    # Validation
```

What You'll Observe

Training Progress:

- Training loss decreases steadily over epochs
- Validation loss decreases then plateaus (convergence)
- Typical training time: **30-45 minutes** on Colab GPU
- Without GPU: 5-6 hours (GPU acceleration essential!)

Signs of Good Training:

- Train and validation loss both decrease
- Small gap between train and val loss
- Validation loss stabilizes (not increasing)

Part 4: Evaluation

Exercise 4: Evaluate with mAP (25 min)

Objective: Calculate mean Average Precision - the standard object detection metric

What is mAP?

Precision: Of detected buildings, how many are correct?

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: Of all actual buildings, how many did we detect?

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Understanding Average Precision

Average Precision (AP):

- Area under the precision-recall curve
- Summarizes precision at all recall levels
- Higher AP = better model performance

mAP (mean Average Precision):

- Mean AP across all classes
- For single-class (buildings): mAP = AP
- Standard metric for comparing detectors

IoU Threshold

Intersection over Union (IoU):

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Common Thresholds:

- **mAP@0.5** (VOC metric) - Detection correct if IoU ≥ 0.5
- **mAP@[0.5:0.95]** (COCO metric) - Average across IoU 0.5 to 0.95

> **For This Lab**
>
> We'll use **mAP@0.5** - more lenient, suitable for satellite imagery where exact boundaries are challenging

Evaluation Code

```python
# Evaluate on test set
from object_detection.utils import object_detection_evaluation

evaluator = object_detection_evaluation.ObjectDetectionEvaluator(
    categories=[{"id": 1, "name": "building"}]
)

for test_image, test_boxes in test_dataset:
    detections = model(test_image)
    evaluator.add_single_ground_truth_image_info(test_boxes)
    evaluator.add_single_detected_image_info(detections)

results = evaluator.evaluate()

print(f"mAP@0.5: {results['mAP_50']:.3f}")
print(f"Precision: {results['precision']:.3f}")
print(f"Recall: {results['recall']:.3f}")
```

Expected Performance

Phase	mAP@0.5	Interpretation
Before fine-tuning	0.10-0.20	Pre-trained on natural images, not adapted for buildings
After fine-tuning	0.70-0.85	Operational quality, suitable for urban monitoring
Production target	>0.80	High confidence for decision-making

Performance Depends On

- Quality and quantity of training data
- Annotation accuracy
- Model architecture chosen
- Fine-tuning hyperparameters

Part 5: Visualization

Exercise 5: Visualize Detections (20 min)

Objective: Visualize model predictions on Metro Manila satellite imagery

Tasks:

1. Run inference on test images
2. Draw bounding boxes with confidence scores
3. Compare before/after fine-tuning
4. Analyze false positives and false negatives

Visualization Code

```python
import matplotlib.pyplot as plt
import matplotlib.patches as patches

# Load test image
image = load_satellite_image("metro_manila_test_001.tif")
detections = model.predict(image)

# Create figure
fig, ax = plt.subplots(1, figsize=(12, 12))
ax.imshow(image)

# Draw bounding boxes
for det in detections:
    if det['score'] > 0.5:  # Confidence threshold
        x, y, w, h = det['bbox']
        rect = patches.Rectangle((x, y), w, h,
                                 linewidth=2, edgecolor='red',
                                 facecolor='none')
```

Analysis Tasks

Quantitative:

- Count detected buildings per image
- Compare against ground truth count
- Calculate detection rate (recall)
- Identify confidence score distribution

Qualitative:

- Inspect false positives (non-buildings detected)
- Inspect false negatives (buildings missed)
- Identify challenging cases:
  - Dense urban areas
  - Buildings with shadows
  - Partially occluded structures

Common Detection Patterns

Well-Detected

- Isolated buildings with clear boundaries
- Moderate-sized structures (20-100m^2)
- Good contrast with surroundings
- Minimal shadow occlusion

Challenging Cases

- **Dense informal settlements** - Buildings too close
- **Shadows** - From tall buildings or terrain
- **Vegetation cover** - Trees obscuring rooftops
- **Construction sites** - Temporary structures

Part 6: Applications & Deployment

Metro Manila Urban Monitoring Applications

1. Informal Settlement Mapping

Application: Identify unplanned settlements in flood-prone areas **Stakeholder:** NDRRMC, Local Government Units (LGUs) **Output:** Building density maps, population estimates

Workflow:

- Detect all buildings in area of interest
- Calculate building density (buildings per km^2)
- Overlay with flood hazard maps
- Prioritize vulnerable areas

2. Urban Growth Monitoring

Application: Track new construction over time **Method:** Compare detections from multi-temporal imagery **Output:** Change maps showing urban expansion hotspots

Process:

1. Detect buildings in 2020 imagery
2. Detect buildings in 2024 imagery
3. Identify new detections (2024 - 2020)
4. Quantify growth rate and patterns

3. Disaster Impact Assessment

Application: Post-typhoon damage assessment **Method:** Detect changes in building footprints **Output:** Damage severity maps for relief operations

Indicators:

- Missing buildings (collapsed structures)
- Changed building sizes (partial destruction)
- New debris areas
- Rapid assessment within 24-48 hours

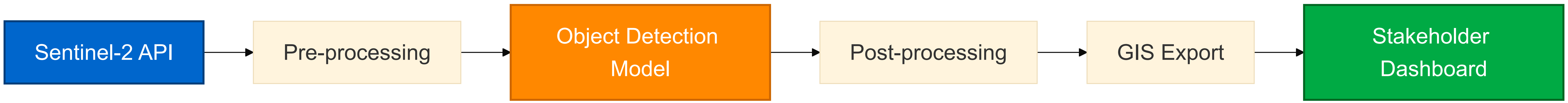
4. Infrastructure Planning

Application: Identify under-served areas **Stakeholder:** DPWH, MMDA **Output:** Priority areas for infrastructure development

Analysis:

- Map building density across city
- Identify low-density areas lacking services
- Correlate with existing infrastructure (roads, utilities)
- Plan targeted development projects

Operational Deployment Pipeline



Deployment Steps

1. Automated Data Acquisition

- Copernicus Open Access Hub API
- Google Earth Engine
- PhilSA Mirror Site

2. Pre-processing

- Cloud masking (QA bands)
- Atmospheric correction
- Geometric correction
- Tile into model input size (512×512)

Deployment Steps (Continued)

3. Inference

- Batch processing of tiles
- GPU acceleration for speed
- Confidence threshold filtering (>0.5)

4. Post-processing

- Non-Maximum Suppression (NMS) to remove duplicates
- Merge tile detections
- Convert pixel coordinates to geographic coordinates

5. GIS Export

- Export to GeoJSON or Shapefile
- Include attributes: confidence, area, centroid
- Integrate with QGIS/ArcGIS

Part 7: Production Considerations

Real Data Acquisition

For Production Deployment

1. Acquire Satellite Imagery:

- Google Earth Engine (free, cloud-based, massive archive)
- Copernicus Data Space Ecosystem (official Sentinel data)
- PhilSA Mirror Site (optimized for Philippines)

2. Create Annotations:

- **Manual tools:** RoboFlow, CVAT, Label Studio, LabelImg
- **Semi-automated:** Use model predictions + human review (active learning)
- **Crowdsourced:** Engage local communities for ground truth

Quality Control

3. Annotation Guidelines:

- Define clear building criteria (min size, structure types)
- Train annotators with examples
- Ensure consistent bounding box placement
- Review inter-annotator agreement (>90% target)

4. Validation:

- Field surveys where possible
- Cross-reference with OpenStreetMap
- Use high-resolution imagery for verification
- Iterative quality improvement

Model Improvement Strategies

To Increase Accuracy

- **More training samples** - 500-1000 recommended for production
- **Multi-temporal imagery** - Capture seasonal variations
- **Ensemble models** - Combine YOLO + SSD predictions
- **Post-processing** - Use existing building databases for validation
- **Multi-scale detection** - Train on various image resolutions

Handling Challenges

Challenge	Solution
Dense urban areas	Use higher resolution imagery (Pléiades, SPOT 6/7)
Cloud cover	Combine Sentinel-2 optical with Sentinel-1 SAR
Small buildings	Use models optimized for small objects (YOLO v8)
Shadow confusion	Include shadow-augmented training data
Computation cost	Use lighter models (MobileNet) or cloud GPUs

Time Plan & Troubleshooting

Lab Time Allocation

Activity	Duration	Notes
Introduction & Setup	15 min	GPU check, notebook familiarization
Load Pre-trained Model	20 min	TensorFlow Hub, test inference
Data Preparation	30 min	Load data, visualize, split
Fine-tuning	40 min	Training loop, monitor loss
Evaluation	25 min	Calculate mAP, interpret metrics
Visualization	20 min	Plot detections, analyze results
Export & Integration	10 min	GeoJSON export, GIS demo
Troubleshooting	10 min	Address common issues
Buffer	10 min	Q&A, extensions
Total	150 min	2.5 hours

Common Issues & Solutions

Issue 1: Out of Memory (OOM)

- **Symptom:** Training crashes with “ResourceExhausted” error
- **Solution:** Reduce batch size (try 4 or 8 instead of 16)
- **Solution:** Use smaller input images (320×320 instead of 512×512)
- **Solution:** Restart runtime and clear all outputs

Common Issues (Continued)

Issue 2: mAP Very Low (<0.30)

- **Cause:** Model not fine-tuned sufficiently
- **Solution:** Train for more epochs (30-50)
- **Solution:** Verify annotations are correct
- **Solution:** Increase learning rate slightly (try 0.001)
- **Solution:** Check for data loading bugs

Issue 3: Detects Everything as Buildings

- **Cause:** Confidence threshold too low
- **Solution:** Increase threshold from 0.3 to 0.5-0.7
- **Solution:** Add negative examples (non-building areas) to training
- **Solution:** Review training data for mislabeled samples

Common Issues (Final)

Issue 4: Training Very Slow

- **Check:** GPU is enabled (Runtime → Change runtime type → GPU)
- **Check:** Run `!nvidia-smi` to verify GPU allocation
- **Solution:** Use SSD MobileNet instead of Faster R-CNN
- **Solution:** Reduce training dataset size (use subset for debugging)
- **Solution:** Use smaller image size

Summary & Key Takeaways

What You’ve Accomplished

Key Achievements

✅ Loaded and understood pre-trained object detection models ✅ Prepared satellite imagery and COCO annotations ✅ Fine-tuned detector on urban building dataset ✅ Evaluated performance using mAP metrics ✅ Visualized detections on Metro Manila imagery ✅ Connected to real-world Philippine urban monitoring ✅ Understood deployment pipeline for operations

Comparison: Segmentation vs Detection

Aspect	Session 2 (Segmentation)	Session 4 (Detection)
Task	Pixel-wise classification	Object localization + classification
Output	Binary flood mask	Bounding boxes + labels
Metric	IoU, F1-score, Dice	mAP, Precision, Recall
Use Case	Flood extent mapping	Building counting, urban growth
Data	Sentinel-1 SAR	Sentinel-2 Optical
Granularity	Every pixel labeled	Objects with boxes

Both are complementary!

- Use **segmentation** for continuous phenomena (floods, vegetation, land cover)
- Use **object detection** for discrete objects (buildings, vehicles, ships)

Key Takeaways

1. **Transfer learning** dramatically reduces data and training time requirements
2. **Pre-trained models** provide strong baselines - no need to start from scratch
3. **mAP** is the standard metric for object detection evaluation
4. **Object detection** enables scalable urban monitoring for disaster preparedness
5. **Philippine applications** benefit from free Sentinel-2 data and open models
6. **Operational deployment** requires end-to-end pipeline thinking

Resources and Further Learning

Documentation

- **TensorFlow Object Detection API:** Official Tutorial
- **PyTorch Detection Tutorial:** PyTorch Docs
- **COCO mAP Explained:** Research Paper

Pre-trained Models

- **TensorFlow Hub:** https://tfhub.dev/ (search “object detection”)
- **PyTorch Hub:** https://pytorch.org/hub/ (search “detection”)
- **Ultralytics YOLO:** https://github.com/ultralytics/ultralytics

Philippine EO Resources

- **PhilSA SIYASAT:** Access Sentinel-2 data for Philippines
- **NAMRIA Geoportal:** Administrative boundaries for Metro Manila
- **OpenStreetMap Philippines:** Building footprints for validation
- **Copernicus Data Space:** Official Sentinel data access

Annotation Tools

- **RoboFlow:** https://roboflow.com (web-based, COCO export)
- **CVAT:** https://cvat.org (open-source, collaborative)
- **Label Studio:** https://labelstud.io (versatile labeling)

Next Steps

Apply This Workflow:

- Use your own area of interest in Philippines
- Collaborate with PhilSA/LGUs to acquire local annotations
- Integrate detections with GIS workflows
- Monitor urban changes using Sentinel-2 time series

Advanced Extensions:

- Multi-class detection (informal vs formal buildings)
- Change detection across time periods
- Integration with Sentinel-1 for cloud-free detection
- Anchor box optimization for Philippine building sizes

Optional Exercises (If Time Permits)

Advanced Exercise 1: Multi-class Detection

- Add “informal settlement” as second class
- Train model to distinguish formal vs informal buildings
- Analyze spatial distribution patterns

Advanced Exercise 2: Change Detection

- Load imagery from 2020 and 2024
- Compare building counts
- Quantify and map urban growth

Advanced Exercise 3: Anchor Box Optimization

- Analyze building size distribution in Metro Manila
- Customize anchor boxes for typical sizes
- Retrain with optimized anchors

Assessment Checklist

By the end of this lab, you should be able to:

- ☐ Explain transfer learning for object detection
- ☐ Load pre-trained model from TensorFlow/PyTorch Hub
- ☐ Prepare annotations in COCO JSON format
- ☐ Fine-tune detector on custom satellite imagery
- ☐ Calculate and interpret mAP metrics
- ☐ Visualize bounding box detections
- ☐ Apply object detection to Philippine urban monitoring
- ☐ Understand operational deployment pipeline

Conclusion

Object detection with transfer learning is a **powerful and practical** tool for Earth observation applications.

Key Benefits:

- **Low data requirements** (100-500 annotations vs 10,000+)
- **Fast training** (30-60 minutes vs days)
- **High accuracy** (70-85% mAP with fine-tuning)
- **Scalable** (city-wide mapping in hours)
- **Operational** (ready for Philippine agency deployment)

Final Message:

Even small teams with limited resources can build production-quality detectors for critical applications like disaster preparedness and urban planning!

Ready to Start?

Open the Notebook and

📓 `Day3_Session4_Objec`

Estimated completion: 2

Questions? Ask your ins

Thank You!

Questions?

- Email: skotsopoulos@neuralio.ai
- Office Hours: [schedule]

Session 4: Hands-on Object Detection Lab - CoPhil 4-Day Advanced Training on AI/ML for Earth Observation, funded by the European Union under the Global Gateway initiative.