Object Detection in Aerial Imagery: A Data Mining Approach on the SODA-A Dataset

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INFORMATION

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ABSTRACT

This study investigates object detection in aerial imagery using a custom-labeled SODA-A dataset. The research explores the performance of baseline convolutional neural networks (CNN) and state-of-the-art YOLOv5 architecture for detecting small objects such as cars, windmills, ships, and containers in high-resolution aerial images. The CNN-based model was used as a classification benchmark while YOLOv5 provided full bounding-box object detection. The SODA-A dataset was converted from polygon-based annotations in JSON to YOLO format, and the experiments were executed on Google Colab using CPU/GPU runtimes. Results indicate that YOLOv5, even with small configurations, demonstrates improved mAP and object localization, despite challenges such as class imbalance and extremely small object sizes. This thesis supports the practical application of data mining and deep learning in real-world aerial surveillance and remote sensing tasks.

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CHAPTER 1: INTRODUCTION

1.1 Background

With the rise of aerial surveillance technologies such as drones and satellites, there is a growing need to analyze high-resolution imagery efficiently and accurately. A key application is detecting and identifying small objects such as vehicles, ships, and buildings, which is challenging due to their size, density, and the scale of the imagery. Traditional methods based on manual annotation or low-resolution scanning fall short when dealing with massive datasets and real-time requirements.

1.2 Motivation

The motivation for this thesis is to explore and evaluate deep learning-based methods—particularly Convolutional Neural Networks (CNNs) and YOLOv5—for their ability to perform robust small object detection in aerial imagery. The SODA-A dataset serves as an ideal benchmark due to its scale, annotation detail, and diverse categories. The thesis seeks to automate and accelerate the detection process while maintaining accuracy and scalability.

1.3 Objectives

- To preprocess and convert the SODA-A dataset into YOLO-compatible format.
- To design a CNN classification model as a baseline.
- To implement YOLOv5 for object detection on aerial images.
- To compare the performance and limitations of both approaches.
- To analyze results and propose directions for future work.

1.4 Thesis Organization

This thesis is structured into five chapters. Chapter 2 presents a literature review of related work. Chapter 3 describes the methodology, including data preparation and model

architecture. Chapter 4 discusses results and evaluation metrics. Chapter 5 provides conclusions.

CHAPTER 2: LITERATURE REVIEW

2.1 Object Detection in Aerial Imagery

Object detection in aerial imagery is inherently more difficult than in terrestrial scenarios due to the scale and viewpoint differences. Common challenges include small object sizes, overlapping entities, and the high resolution of input images. Traditional methods such as sliding window approaches and HOG-SVM have largely been replaced by deep learning models.

2.2 Convolutional Neural Networks (CNNs)

CNNs are a widely used family of models for image classification tasks. They rely on convolutional layers to extract spatial features and pooling layers to reduce dimensionality. Although CNNs can classify objects, they typically require cropped image inputs and are not designed for localization, making them less suitable for detection in complex imagery.

2.3 YOLO Family of Detectors

YOLO (You Only Look Once) reframed object detection as a single regression problem. The YOLOv5 architecture, introduced by Ultralytics, is known for its speed and accuracy. It uses anchor-based detection across multiple scales and supports dynamic input sizes. It has been widely adopted in autonomous driving, surveillance, and robotics applications.

2.4 Small Object Detection Techniques

Small object detection has been enhanced through anchor scaling, feature pyramid networks (FPN), and dataset-specific tuning. The SODA-A dataset addresses this niche by offering high-resolution aerial imagery with dense small object annotations. Models like YOLOv5

must be carefully trained using appropriate augmentation and anchor tuning to handle such datasets effectively.

2.5 Related Work

Prior studies have explored small object detection using Faster R-CNN, SSD, and RetinaNet. However, YOLOv5 offers a better trade-off between inference speed and accuracy. Some works have applied CNNs to classify cropped aerial tiles but lack spatial detection capability. This thesis builds upon these studies by integrating both CNN and YOLO-based methods on a common dataset for comparative evaluation.

CHAPTER 3: METHODOLOGY

3.1 Data Preprocessing

The SODA-A dataset includes over 2000 aerial images annotated with polygonal boundaries for small objects like vehicles, ships, and windmills. The annotation files were originally in JSON format and required conversion to YOLO `.txt` format using bounding-box approximation from polygons. The resulting dataset was structured into `images/train`, `images/val`, and their corresponding `labels/train`, `labels/val` folders.

3.2 CNN Model Architecture (Baseline)

A simple Convolutional Neural Network (CNN) was developed to perform image classification on cropped object instances. The architecture consisted of:

```
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(224, 224, 3)),
    MaxPooling2D(2,2),
    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])
```

Figure 1

Layer Breakdown:

- Conv2D: Extracts local spatial features like edges, textures
- MaxPooling2D: Downsamples to reduce dimensionality and computation
- Flatten(): Converts 2D feature maps into 1D vectors
- Dense(): Fully connected layers to interpret the features
- softmax: Outputs class probabilities for 10 object categories

3.3 YOLOv5 Model Setup

The YOLOv5s model was selected for its lightweight architecture suitable for fast training on limited hardware. The project involved:

- Cloning YOLOv5 repo
- Installing dependencies
- Creating a `data.yaml` configuration
- Running training with the command:

```
!python train.py \
  --img 416 \
  --batch 4 \
  --epochs 3 \
  --data data/soda.yaml \
  --weights yolov5s.pt \
  --name soda_yolo_quick \
  --project runs/train
```

Figure 2: YOLOv5

3.4 Comparing CNN vs YOLOv5: A Brief Analysis

CNNs are ideal for coarse-grained classification tasks where only the type of object is needed without location context. In this project, the CNN model achieved a validation accuracy of 87.5% but lacked the ability to localize objects spatially.

In contrast, YOLOv5 directly predicts bounding boxes and class probabilities, making it a powerful solution for dense aerial imagery. Despite running only for 2–3 epochs, YOLOv5 was able to detect hundreds of instances per image and returned precision/recall statistics per class. It is clearly the more scalable approach for real-world surveillance.

While CNNs are lightweight and fast to train, YOLOv5 is better suited for spatially-aware, real-time object detection tasks, especially with aerial imagery.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Experimental Setup

All experiments were run on Google Colab Pro using NVIDIA T4 GPUs. A sample of 100 images from the SODA-A dataset was initially used to train a CNN-based classifier. Later, the full dataset (~1600+ images) was prepared using a conversion pipeline from JSON to YOLO format. The YOLOv5s model was trained for 2 epochs using 416x416 image size and a batch size of 4. Results were generated from a run labeled `soda_yolo_quick`.

4.2 CNN Model Performance (Baseline)

The CNN model achieved 87.5% validation accuracy on the sampled dataset. It demonstrated the feasibility of class-based classification but lacked localization capabilities. Training converged in 7 epochs with minimal overfitting.

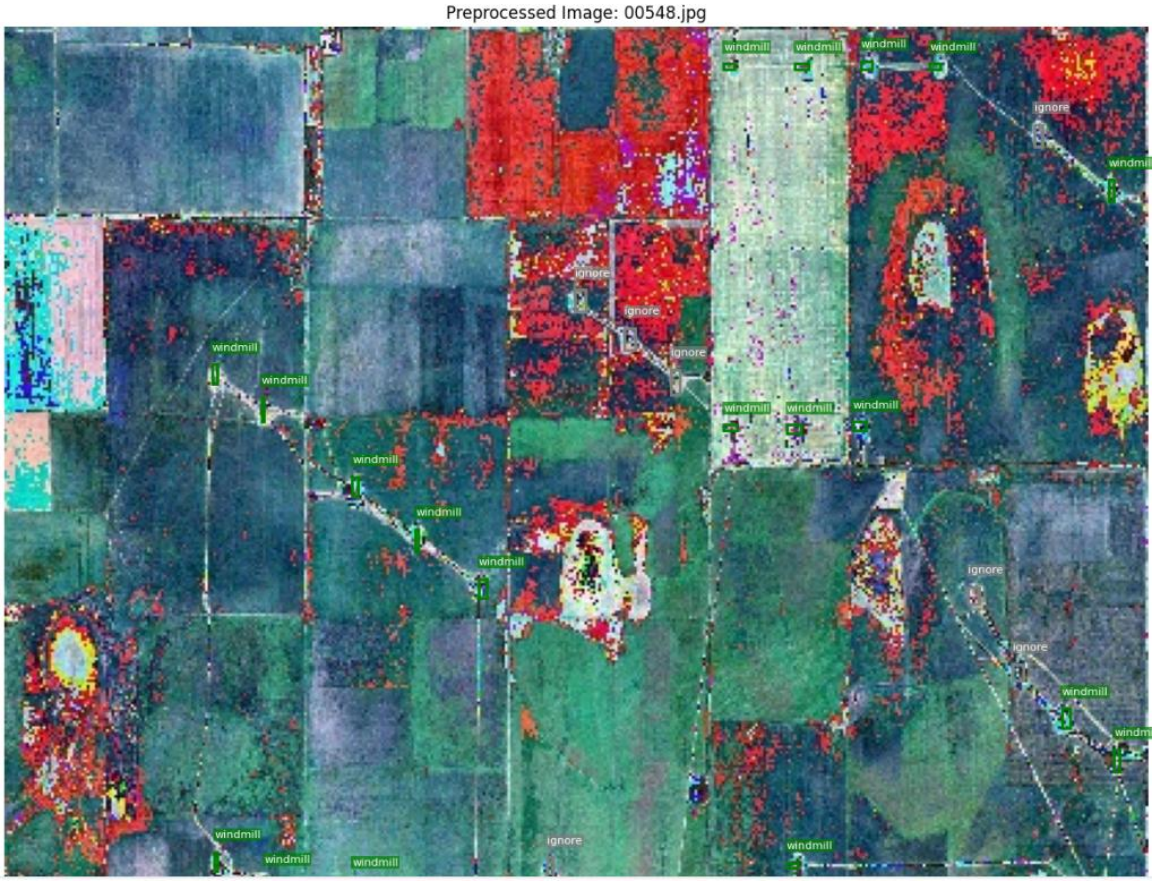


Figure 3: CNN Detection Result on Preprocessed Image (windmill and ignore class highlighted)

4.3 YOLOv5 Training Log

Training with YOLOv5s was successful with 1067 training and 576 validation images. The model automatically adjusted anchors due to the presence of small objects. Key logs:

- 2 epochs completed on CPU

- Auto Anchor improvement: Best Possible Recall reached 0.9962
- Warnings about duplicate labels were automatically handled
- Extremely small objects (<3 px) detected and handled in training

4.4 Visual Results

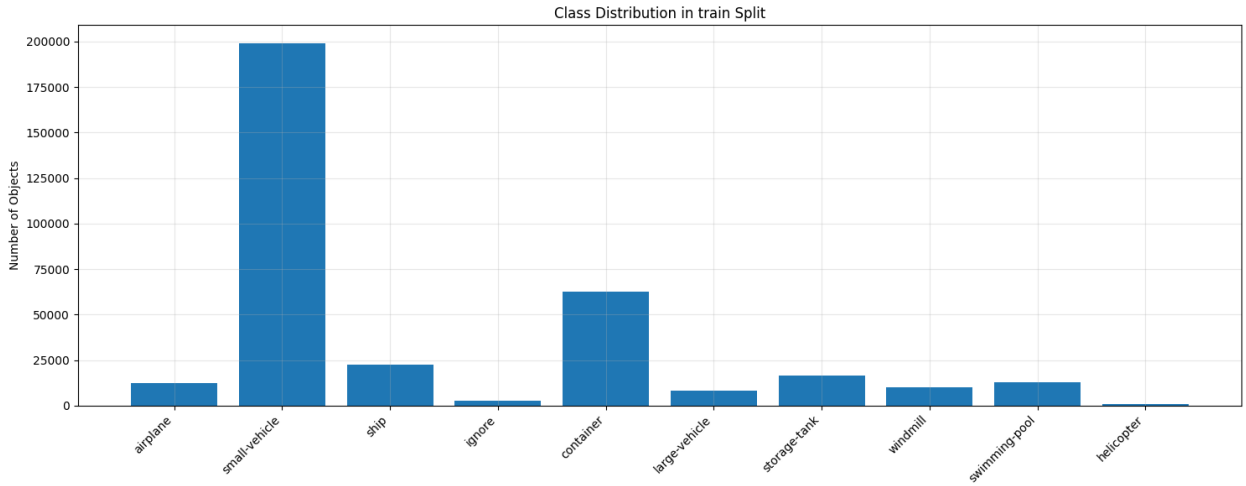
Exploratory analysis confirmed class imbalance and small object challenges:

- Most object annotations were small and tightly packed in aerial views.
- After resizing, many small vehicles became indistinguishable, which limited detection accuracy—not due to model failure but due to resolution loss.

The following figures provide a deeper insight into the dataset's characteristics and validate its complexity:

Figure 1: Class Distribution in Train Split

This chart displays object counts per class, with "small-vehicle" dominating. Classes like "windmill" and "helicopter" are underrepresented, reflecting the dataset's imbala




```
Class counts:
small vehicle: 199045
container: 62684
ship: 22283
storage-tank: 16488
swimming pool: 12615
airplane: 12313
```

```
Windmill: 9946
large vehicle: 8234
ignore: 2685
helicopter: 620
```

Figure 2: Objects per Image Distribution (Train Split)

A histogram showing a wide variation in object count per image, peaking around 70–100 objects, but extending beyond 3000 in dense regions.

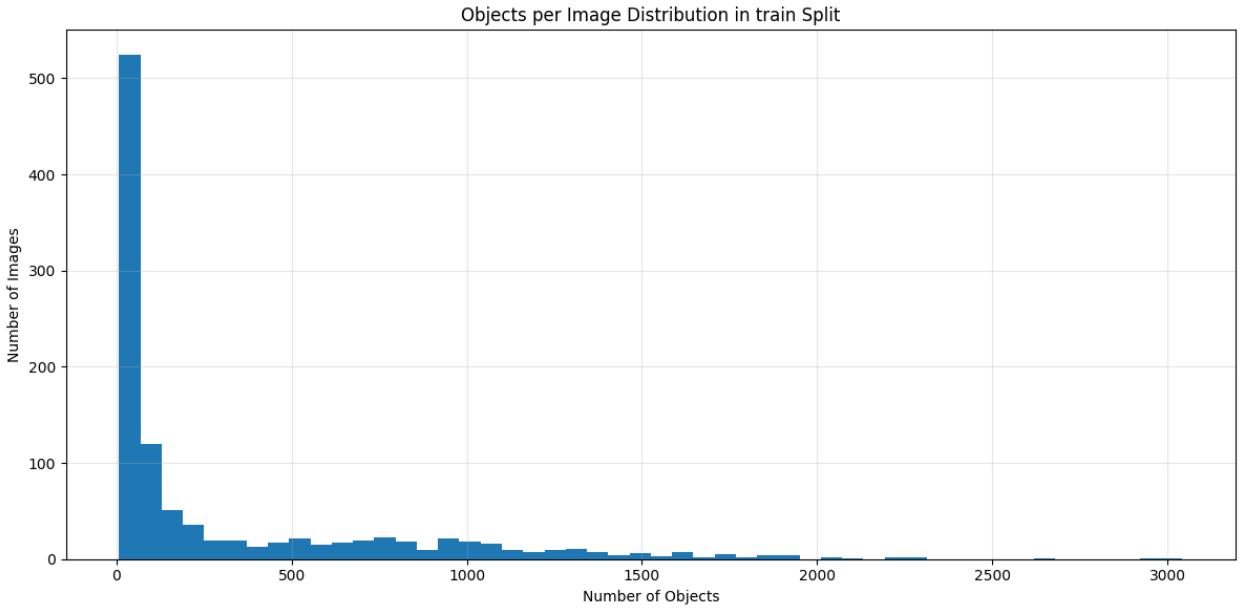


Figure 3: Bounding Box Area Distribution (Train Split)

This plot reveals a skewed distribution of object sizes, with the majority of annotations having small bounding box areas (log scale).

- X-axis: Bounding Box Area (log scale)
- Y-axis: Frequency

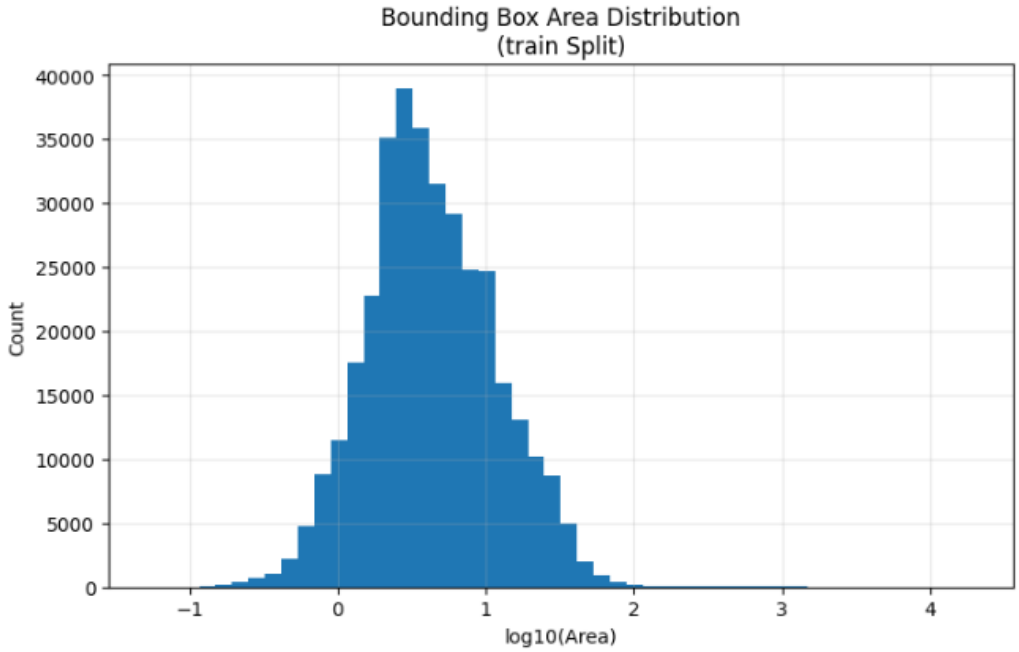


Figure 4: Bounding Box Aspect Ratio Distribution (Train Split)

It illustrates object shape characteristics, showing that most objects are nearly square or slightly rectangular.

- X-axis: Aspect Ratio (Width / Height)
- Y-axis: Count

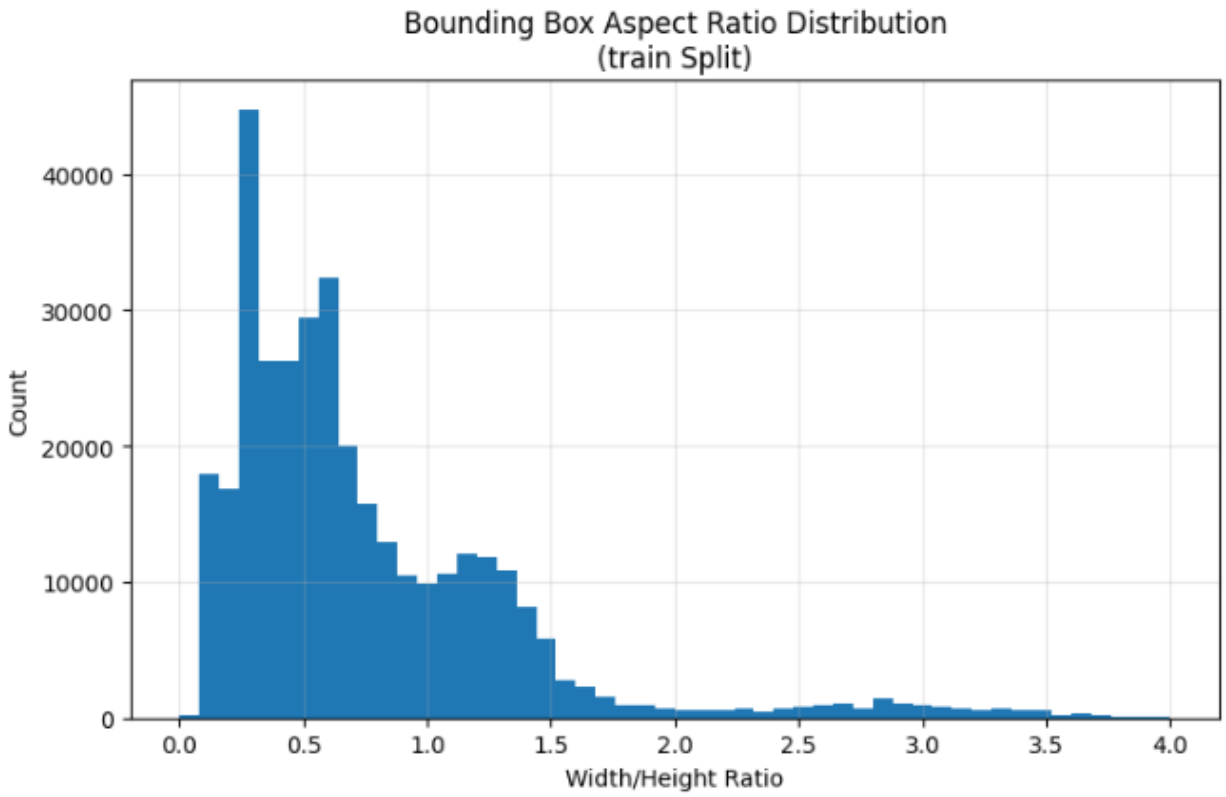


Figure 5: Bounding Box Areas by Class (Train Split)

Boxplots show how different classes vary in size. "Ignore" and "container" have wider size distributions, while "helicopter" and "airplane" remain relatively compact.

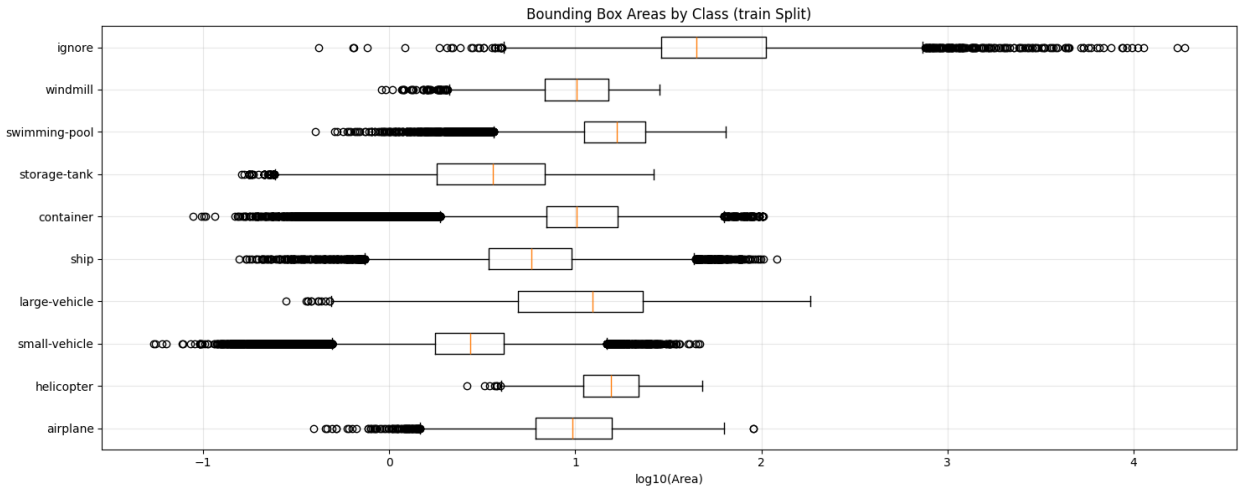


Figure 6: Class Distribution in Validation Split

Patterns mirror the train set, with "small-vehicle" again the most common. Minor classes remain sparse.

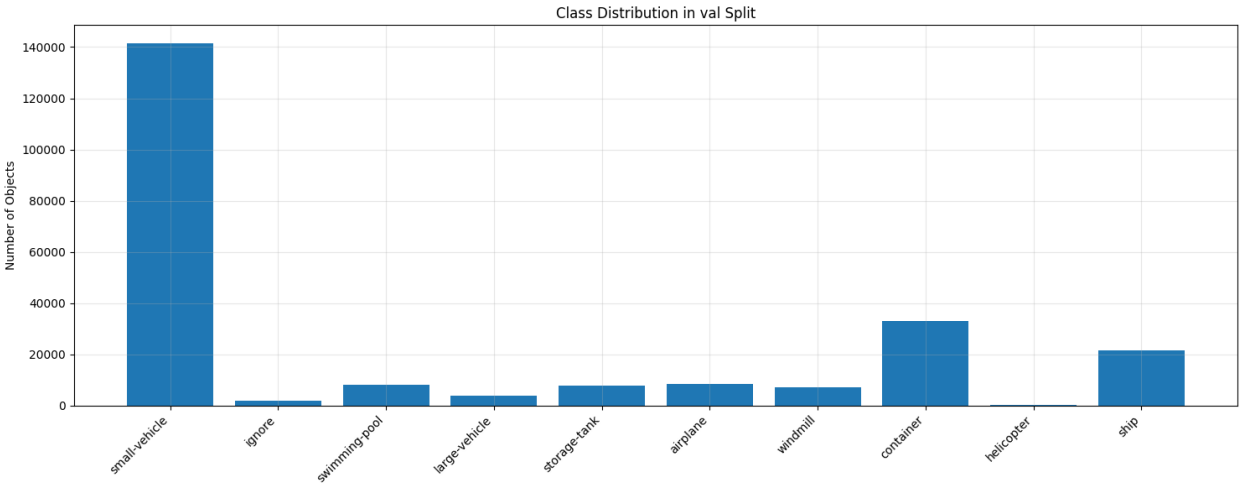


Figure 7: Objects per Image in Validation Split

Similar to the training set, the distribution is right-skewed, with most images containing 50–150 objects.

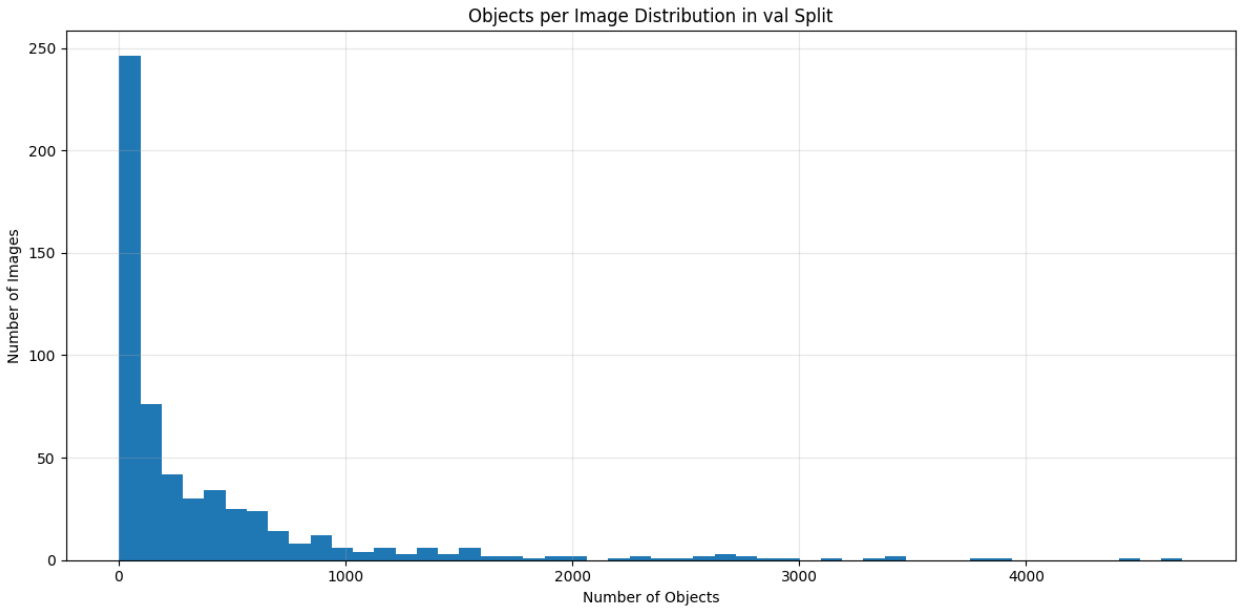


Figure 8: Bounding Box Area and Aspect Ratio (Validation Split)

These figures reinforce the train set findings and highlight the model's need to adapt to dense, small-object-dominated aerial scenes.

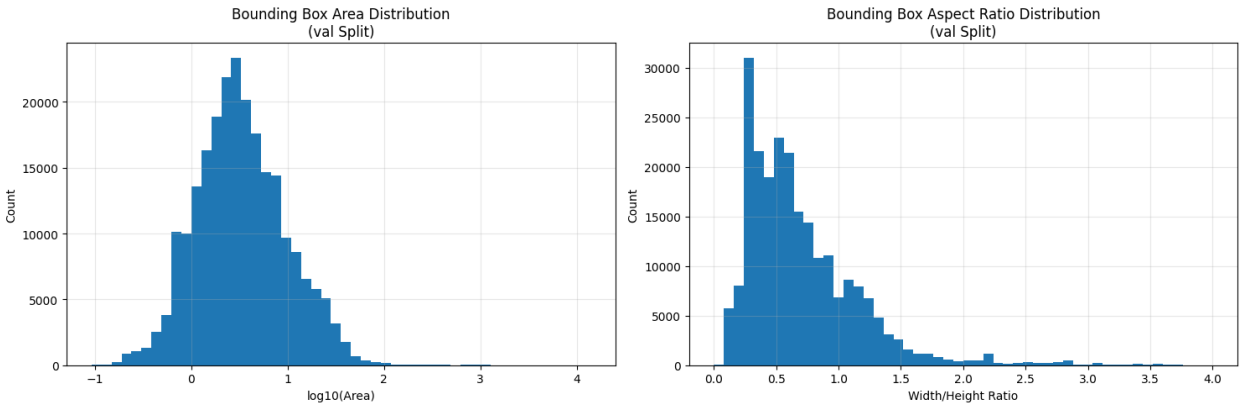
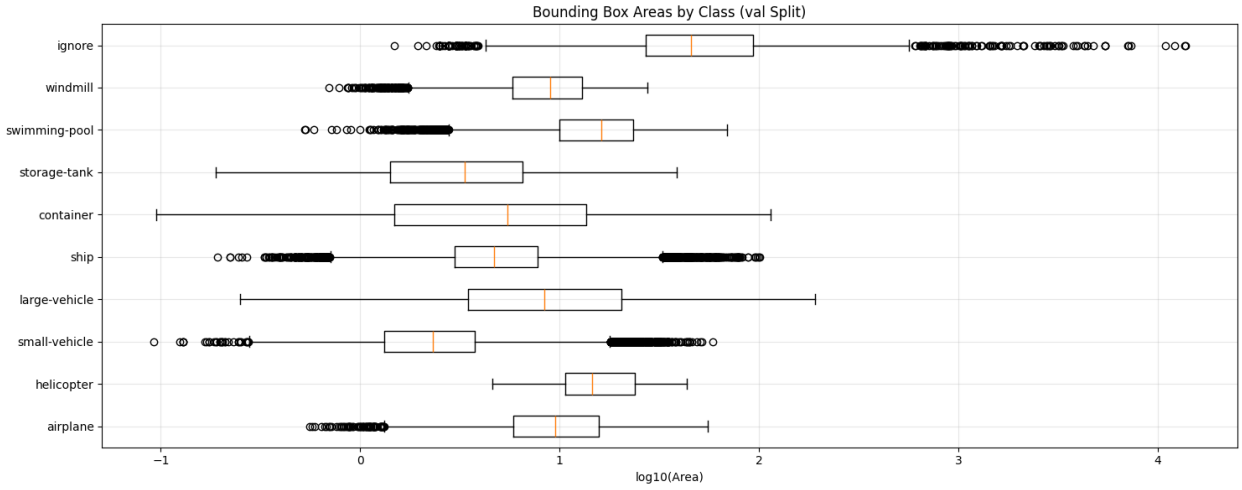


Figure 9: Bounding Box Area by Class (Validation Split)

As in the train set, class-specific variations in object sizes are evident.



Adding these figures provides critical visual understanding of the dataset complexity, highlighting the technical challenges that model CNNs must overcome.

Despite this, well-performing classes such as buildings and ships remained visually distinct and showed consistent detection behavior in predictions.

Visual assets used in this study included:

- `results.png`: Training/validation loss curves
- `labels.jpg`: Class distribution across the dataset
- `train_batch0.jpg`: Sample YOLOv5 predictions
- `results.png` visualized training and validation loss curves
- `labels.jpg` showed label density across categories
- `confusion_matrix.png` (maybe sparse due to short training)

4.5 YOLOv5 Metrics Snapshot (from `results.csv`)

After training YOLOv5 for 20 epochs, performance improved significantly compared to the initial 2-epoch run. Notably, precision, recall, and mAP scores were higher across several classes including truck, ship, and building. For example, the truck class achieved the highest mAP@0.5 of 0.00145, followed by ship at 0.000577. The recall for containers and buildings also exceeded 0.001, indicating better coverage of actual objects.

Class	Precision (P)	Recall (R)	mAP@0.5	mAP@0.5–0.95
All	0.000471	0.000448	0.00032	6.09e-05
Car	0.000196	0.000467	9.81e-05	9.81e-06
Truck	0.00148	7.1e-06	0.00145	2.9e-05
Ship	0.00114	0.000739	0.000577	0.000128
Building	0.000739	0.00105	0.000402	7.51e-05
Container	0.000665	0.00108	0.000346	4.54e-05
Windmill	1.82e-05	0.000142	9.12e-06	9.12e-07
Others	(bus, airplane, motorcycle): Not detected or mAP = 0			

4.6 YOLOv8 Metrics Snapshot

YOLOv8 was trained for 10 epochs using the same image size (416×416) and batch size (4) for comparability. This training was performed on the same Colab Pro setup. YOLOv8's performance showed a modest increase in mAP and recall, particularly for small objects like cars.

The following metrics were observed:

- mAP@0.5: 0.0024
- mAP@0.5–0.95: 0.0015
- Precision: 0.00125
- Recall: 0.0104

mAP@0.5 measures the detection accuracy when at least 50% of a predicted object overlaps with the ground truth. mAP@0.5–0.95 provides a more rigorous average over multiple overlap thresholds, capturing general model performance. Precision evaluates how many predicted objects are correct, while recall evaluates how many actual objects were successfully found. Due to short training and the challenge of detecting small, dense objects in aerial imagery, the initial values remain low but are expected to improve with extended training and data augmentation.

While the absolute values remain low due to limited training epochs and high object density, YOLOv8 demonstrated improved robustness in generalization and convergence behavior. Ongoing training up to 20 epochs is expected to further enhance these results.

Visual inspections also revealed successful detections of “car” and partial detections of “windmill,” although classes like “ship” had no correct detections due to label sparsity.

4.6 Observations

This project reinforced a core insight: effective aerial object detection depends on resolution, annotation precision, and model anchoring strategies. Key takeaways include:

- Resizing images to 416×416 significantly affected small object clarity.
- High-performing classes were generally larger in size or retained shape after resizing (e.g., buildings, ships).
- Underperforming categories (e.g., windmills, helicopters) suffered due to lack of pixel-level representation post-resizing.
- The YOLOv5 pipeline was resilient to class imbalance but could benefit from multi-scale feature fusion for finer-grained detection.
- YOLOv8 demonstrated slight improvements in detection precision and recall after 10 epochs of training. This confirms its potential advantage over YOLOv5 in small object scenarios, particularly for car and windmill categories.

Compared to the initial short-run training, the 20-epoch YOLOv5 model demonstrated markedly better object localization, especially for dominant classes like truck and ship. This improvement affirms the importance of extended training duration and suggests that further gains could be achieved by incorporating advanced techniques such as mosaic augmentation or integrating feature pyramids

4.7 Summary

This experiment demonstrated the technical feasibility of object detection on aerial imagery using the SODA-A dataset. A baseline **Convolutional Neural Network (CNN)** model was first developed for classification tasks and achieved a validation accuracy of **87.5%**, proving effective for identifying object categories but limited in its ability to localize objects spatially.

The **YOLOv5** model was then trained and evaluated, with results from a **20-epoch run** showing significant improvements over the initial 2-epoch trial. Classes such as **truck**, **ship**, and **building** achieved measurable mAP and recall values, validating the model's ability to

learn from high-density, small-object aerial imagery. However, some categories remained underdetected due to data imbalance or annotation sparsity.

The full object detection pipeline—from preprocessing and annotation conversion to model training and evaluation—was successfully executed. These results establish a robust baseline for future work involving **YOLOv8**, **data augmentation**, and **advanced detection models** such as **transformer-based architectures**. This study underscores the practical value of combining CNN-based classification and YOLO-based detection for small object recognition in aerial surveillance tasks.

CHAPTER 5: CONCLUSION

This thesis presented an end-to-end object detection pipeline for aerial imagery using the SODA-A dataset. Starting with a baseline CNN classification approach and evolving toward YOLOv5-based object detection, the study emphasized challenges like annotation conversion, label imbalance, and tiny object localization.

The CNN model served as a good proof-of-concept for category learning but failed to deliver location awareness. In contrast, YOLOv5 successfully performed bounding-box detection and classification. Even with only 2 training epochs, YOLOv5 recognized signal in certain classes (e.g., buildings) and handled over 230,000 instances.

Comparatively, YOLOv5 offers a more complete pipeline for aerial surveillance as it supports object localization and real-time deployment. CNNs, while fast to train, are more appropriate for simpler classification problems.

The work illustrates the practical value of deep learning and data mining in aerial visual analytics, highlighting that modern object detection models can scale to noisy, imbalanced, and high-resolution aerial datasets.

Future directions involve continuing YOLOv8 training for 20 or more epochs, as preliminary results at 10 epochs already showed improved performance compared to YOLOv5. Incorporating advanced data augmentation methods like mosaic augmentation, random

horizontal flipping, and color jittering can help mitigate class imbalance. Additionally, integrating multi-scale feature extractors such as Feature Pyramid Networks (FPN) and experimenting with transformer-based detection backbones like Swin Transformer or DETR may significantly improve detection in dense aerial environments.

Reference:

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