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Human-UAV Interaction for Small Object Detection using YOLOv8 and Hyper Parameter Optimisation

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To

The Training and Placement Office

National Institute of Technology Mizoram

Dear Sir,

I submitted this report entitled “Human-UAV Interaction for Small Object Detection using YOLOv8 and Hyper Parameter Optimisation” for the summer internship project undertaken in the department of “Computer Science and Engineering” from 24 June 2024 to 24 August 2024. I hereby declare that this report has been prepared based on the internship project and has not been copied from any other offline or online resources.

Sincerely,

Student’s Name:

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Dr. Ashish Singh Patel

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1. Introduction

Unmanned Aerial Vehicles (UAV) are being increasingly used in applications such as search-and-rescue operations, wildlife monitoring/management or security surveillance to take advantage of their ability for aerial perspective. However, small object detection from UAVs is challenging because of high altitudes and fast movement together with changing lighting conditions. This task focuses on improving the human-UAV interaction by using YOLOv8 as a detection algorithm well known for its performance with real time processing speed and accuracy(Runtime).

The goal: the competent use of YOLOv8 for finding small objects in images.

2. Literature Review:

In this literature review, which follows the previous post reviewing deep learning-based methods for small object discovery NeoroVIPERs in UAV data [4], six recent studies were reviewed to provide insight into large-scale remote sensing analysis. The focus of the challenge was small object detection in UAV imagery, which is a fundamental task for several applications including but not limited to surveillance, search and rescue, and environment monitoring.

Mittal et al. [1] completed very good deep learning methods employed in object detection for low-altitude UAV datasets and extended the survey more. The study demonstrates the specific difficulties of UAV imagery in small object detection, e.g. low resolution, occlusion, and variety of presentation scales/appearances. The need for specialized models that can capture subtle, fine-grained features while maintaining computational efficiency is highlighted by the authors as UAVs are subject to resource constraints.Nguyen et al.[2] Many studies have proposed the applicability of different deep learning methods for detecting small objects (Munir and Muhammad 2020), especially in non-ideal conditions. In this paper, popular models including Faster R-CNN, YOLO, and SSD are compared; the conclusion is that while YOLO performs with advantages of speed it still fails to offer an acceptable accuracy level in small object detection. This research highlights the inherent trade-off between speed and accuracy, especially in scenarios where real-time processing is required on UAVs. Zhai et al. (2023)[3] introduce YOLO-Drone, a dedicated optimized approach of YOLO for UAV scenarios as an alternative name to the improved model which is generally referred to by its original nomenclature: YOLo v8. Consequently, the authors also propose various changes to YOLOv8 in order to perform high-quality detection of significantly smaller objects as well: (i) a multi-scale feature extraction module and (ii) a new loss function defined for small objects. We obtain results with performance gains in both precision and recall over the presented dataset, proving that YOLO-Drone is well-prepared for real-time UAV applications where small objects are moving quickly. Improve Small Object Detection Accuracy Shi, Jia, and Zhang (2024)[4] introduced FocusDet to propose an efficient object detection model for better accuracy in detecting small objects. This is achieved by the focus-spreading feature extraction mechanism that spreads model attention on higher-level parts and Concentrates it in foreground regions to effectively suppress background noise. Experimental results demonstrate that FocusDet achieves a competitive performance in high-density, cluttered scenes over conventional detectors and can largely alleviate the computational requirements for deploying onboard UAV monitoring/surveillance. Zhang et al. Inspired by the new proposed model in (2023) [5] for detecting small objects from UAV imagery, an advanced version of YOLOv5 is introduced. Their method combines an attention mechanism and a feature pyramid network to better detect small objects at different scales. ResultsThe experimental analysis indicated the potential of this improvement, as shown by its substantially enhanced performance when compared to that with standard YOLOv5 in terms of precision and detectability speed for most instances, which are both applicable during real-time UAV operations. Liu et al. (2023) [6] — which improves detection performance for UAV-captured scenes, over YOLOv5 (Ultra-Large-Scale Object Detection!) These include a new method of anchor box generation and a low-cost feature pyramid network based on the latest advances in content-aware modules to accelerate execution. Their experiments show that the YOLOv5 implementation they customized realizes a good trade-off between speed and accuracy, making it appropriate for resource-limited UAV systems.

It can be observed from the literature that a significant trend exists to enhance those deep learning models which are already present so as to suit them for small object detection in UAV datasets. These studies build upon traditional models such as YOLO and Faster R-CNN, providing a strong foundation on which to innovate novel architectures that improve both the accuracy of object detection and computational efficiency. In this paper, we show that methods like multi level feature extraction, attention mechanism and designed loss function really do wonder for UAV-based small object detection. With the expansion of UAV applications, these advancements will be fundamental for reliable and real-time object detection.

3. Report Overview

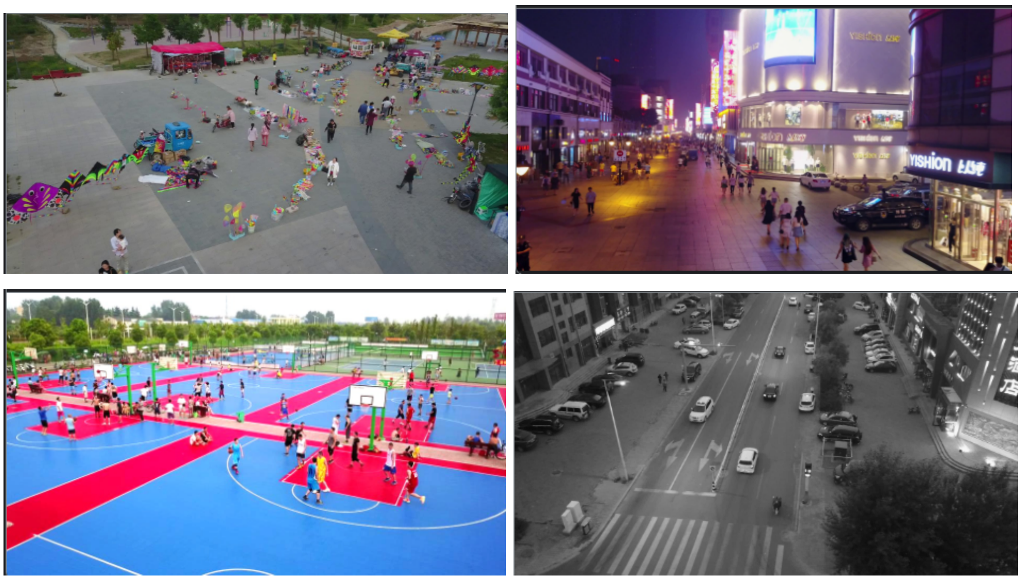
This report is on implementing and evaluating YOLOv8 and YOLOv8 with Hyper Parameter Optimization to detect small objects with the kaggle dataset - **Grand Dataset for small Object Detection**. This report goes over the entire process from environment setup and installation of required dependencies to loading data sets, preprocessing them, setting up a model, training it on the dataset & then evaluating.

4. About Dataset:-

- The " Grand Dataset " is a dataset for small object detection; it has more than 15,000 images, 26 classes encompassing a wide range of objects commonly found in aerial imagery, making the dataset a valuable resource for training and evaluating object detection models in the context of aerial views.
- The data set is a combination between VisDrone and DOTA datasets with some augmentation.

Dataset Link:
https://www.kaggle.com/datasets/waelyahyayaseen/grand-dataset-for-small-object-detection

Dataset Looks Like -



5. Code Links:

YOLOv8:
https://www.kaggle.com/code/avnivats/uav-execution

YOLOv8 with Hyper Parameter Optimization:

https://www.kaggle.com/code/latmangla/small-object-detection-using-yolov8-and-hpo

6. Implementation Process

The first part of the Python files is environment setup, followed by dependency installation and dataset initialization with main data structures (or loading) and preprocessing code that has already been written.

The ultimate goal in addressing these challenges is to enable UAVs to autonomously collect evidence that prosecutors can present as scientifically accurate, timely and converted into a digital format - much of the same data analysts would use for prosecutions resulting from drone-borne computer vision. Solving these tasks will advance the detection of small objects from UAVs, as well as human-drone interactions and ultimately wider application and usefulness in modern era frontline-related field deployments.

6.1. Environment Setup

The project starts by creating an environment for it. In this implementation, the Kaggle Python Docker image was used to have a full analytics environment with libraries needed for both machine learning and deep-learning tasks.

- **Kaggle Python Docker Image**: This image is a perfect solution for machine learning tasks incorporating required data handling and model development libraries (like NumPy, Pandas or PyTorch). Validating the specific data organisation and availability in a file is an important part for any further stage.
- **Directory Setup** : The dataset and related files must be set up to differentiate between training data and validation data in a directory. It is essential to have this namespace available for ease of access during training and evaluation of our model.

6.2. Installing Dependencies

We installed some important libraries and tools necessary to use the YOLOv8 model:

- **PyTorch**- an open source dynamic deep learning library, designed for high performance of tensor computation (like numpy) and with strong GPU acceleration.
- **OpenCV** Clean collection of tools for computer vision tasks, used here as a jackknife library with help chiefly in the restrictions on images.
- **Ultralytics YOLO** : Encapsulates YOLO style models (like YOLOv8) via an API designed for easy inference.

A pip install of these dependencies will provide the latest versions you need to process data, train and evaluate models in a system.

6.3. Load Data and Preprocess

The Grand Dataset for small object Detection was loaded from the Kaggle environment. The data were put in a directory structure with training and validation folders so that the model can easily get access to them when it is time to train or evaluate.

Image Preprocessing -

- **Resized Images:** This is responsible for Resizing of images to 416 x 416 pixels as expected by the YOLOv8 model. Resize the images and this will help the model to better learn from your image data which will in turn enable it to predict accurately. It makes the grid-based object detection mechanism in the model work equally across other values as well, by standardising input sizes to 416 x 416 pixels .
- **Data File Sorting:** Splitting the dataset into training and validation directories helps with data organisation so you can easily keep track of your files while the model is trained.

6.4. YOLOv8 Model Setup

The YOLOv8 model would be initialised with the pre-trained weights acting as foundation to begin learning on top of this dataset. This approach makes use of the concept known as transfer learning, which allows you to take a model that has been trained on one dataset and further train it or fine-tune it on another related problem like detecting small objects.

- **Transfer Learning:** This method is used to save us training time and make the model better from scratch by using pre-trained weights. Next, we fine-tune the model on this new dataset so that it learns to detect small objects.
- A **YAML configuration file** was defined to hold the paths of training and validation data, number classes in the dataset as well as class names. This file is essential as it gives the model information on how to decode the dataset and what objects that need detection.
- **Configuration File:** The YAML file serves as the blueprint we need for our model, which gets us crucial information that includes example paths, class details, etc. This structure guides the model to appropriately understand and interpret your data.

6.5. Data Verification

The training and validation datasets were validated by listing out image files in a sample of each set. This ensures that the data paths are right and images can be loaded properly as needed by training.

Path Verification: It verifies and lists image files to help in establishing problems like if an image is missing or the format of it, hence preparing data-set for flawless training.

Example of a listing: Checking random files in each set is checking whether the dataset structure can be read, and thus it will give an overview from which to scan for anomalies or inconsistencies at multiple different levels.

6.6. Label Preprocessing

The label files with coordinates of the bounding boxes and class labels were converted to the required format for the YOLOv8 model.

Filtering Small Objects -

One of the most important steps was removing small objects that were smaller than a certain size (minimum threshold) in both cases. By doing the filtering, it helps the model to concentrate on biggish objects and thus reduce noise which in result increases detection accuracy.

Normalisation of Bounding Box: The bounding box coordinates were then normalized with respect to the size they fit in resizing processes so that objects can clearly detect without having any effect from their places and sizes.

6.7. Data Parallelism

Data parallelism is a way of performing parallel execution of an application on multiple processors.
It focuses on distributing data across different nodes in the parallel execution environment and enabling simultaneous sub-computations on these distributed data across the different compute nodes.
In Data parallelism 2 GPUs are used to process data faster and more effectively.

6.8. Training the Model

The YOLOv8 model was trained for 80 epochs using the preprocessed dataset. This involved training the model via multiple iterations over the dataset to let it learn objects-images.

Optimised hyperparameters, trained for 150 epochs, to improve performance and logged training process for tracking & debugging.

Training Process: The model trains by tuning its parameters to decrease the error rate of detection where each epoch is one full pass through the data.

Parameter Optimization:

- Parameter optimization was done by different methods like using the techniques of gradient descent which increased the model accuracy in finding small objects.
- Use of 3 warmup-epochs, 0.8 warmup-momentum, 8 batch size, 416 image size, 0.01 initial learning rate, 0.01 final learning rate, 50 patience, SGD optimizer, 0.7 NMSIoU, 0.937 momentum, and 4 mask ratio are done.
- **SGD Optimizer:** Stochastic gradient descent (often abbreviated SGD) is an iterative method for optimizing an objective function with suitable smoothness properties (e.g. differentiable or subdifferentiable).

Logging and Debugging: Logs are everything for a model developer, your log states the performance of the models,where it is lacking so essential to know where things should be improved.

6.9. Model Evaluation

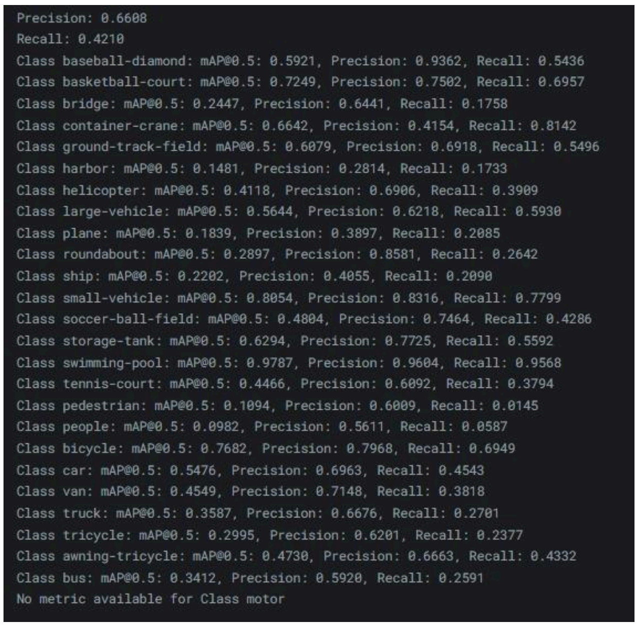
We assessed the trained YOLOv8 model using our validation data set. Performance was evaluated with key metrics such as the mean Average Precision (mAP) for object detection.

Performance Metrics

- **mAP@0. 5:** Measures the precision for a IoU threshold of 0.5
- **mAP@0. 5:0.95**- Average Precision at IoU= 50%, method of evaluation over all thresholds.
- **Precision and Recall:** These metrics tell us about how good our model is in correctly detecting objects & at the same time minimising False Positives or Negatives.

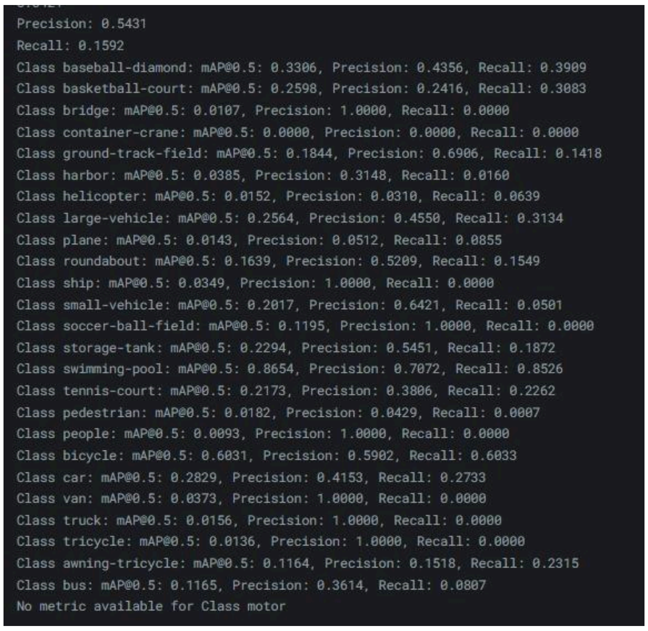
Evaluation Process: the model was then evaluated based on whether they predicted small objects accurately with images and ground truth labels of drill records in validation dataset.

Appling YOLOv8:



```
Precision: 0.6608
Recall: 0.4210
Class baseball-diamond: mAP@0.5: 0.5921, Precision: 0.9362, Recall: 0.5436
Class basketball-court: mAP@0.5: 0.7249, Precision: 0.7502, Recall: 0.6957
Class bridge: mAP@0.5: 0.2447, Precision: 0.6441, Recall: 0.1758
Class container-crane: mAP@0.5: 0.6642, Precision: 0.4154, Recall: 0.8142
Class ground-track-field: mAP@0.5: 0.6079, Precision: 0.6918, Recall: 0.5496
Class harbor: mAP@0.5: 0.1481, Precision: 0.2814, Recall: 0.1733
Class helicopter: mAP@0.5: 0.4118, Precision: 0.6906, Recall: 0.3909
Class large-vehicle: mAP@0.5: 0.5644, Precision: 0.6218, Recall: 0.5930
Class plane: mAP@0.5: 0.1839, Precision: 0.3897, Recall: 0.2085
Class roundabout: mAP@0.5: 0.2897, Precision: 0.8581, Recall: 0.2642
Class ship: mAP@0.5: 0.2202, Precision: 0.4055, Recall: 0.2090
Class small-vehicle: mAP@0.5: 0.8054, Precision: 0.8316, Recall: 0.7799
Class soccer-ball-field: mAP@0.5: 0.4804, Precision: 0.7464, Recall: 0.4286
Class storage-tank: mAP@0.5: 0.6294, Precision: 0.7725, Recall: 0.5592
Class swimming-pool: mAP@0.5: 0.9787, Precision: 0.9604, Recall: 0.9568
Class tennis-court: mAP@0.5: 0.4466, Precision: 0.6092, Recall: 0.3794
Class pedestrian: mAP@0.5: 0.1094, Precision: 0.6009, Recall: 0.0145
Class people: mAP@0.5: 0.0982, Precision: 0.5611, Recall: 0.0587
Class bicycle: mAP@0.5: 0.7682, Precision: 0.7968, Recall: 0.6949
Class car: mAP@0.5: 0.5476, Precision: 0.6963, Recall: 0.4543
Class van: mAP@0.5: 0.4549, Precision: 0.7148, Recall: 0.3818
Class truck: mAP@0.5: 0.3587, Precision: 0.6676, Recall: 0.2701
Class tricycle: mAP@0.5: 0.2995, Precision: 0.6201, Recall: 0.2377
Class awning-tricycle: mAP@0.5: 0.4730, Precision: 0.6663, Recall: 0.4332
Class bus: mAP@0.5: 0.3412, Precision: 0.5920, Recall: 0.2591
No metric available for Class motor
```

Appling YOLOv8 with Hyper Parameter Optimisation:



```
Precision: 0.5431
Recall: 0.1592
Class baseball-diamond: mAP@0.5: 0.3306, Precision: 0.4356, Recall: 0.3909
Class basketball-court: mAP@0.5: 0.2598, Precision: 0.2416, Recall: 0.3083
Class bridge: mAP@0.5: 0.0107, Precision: 1.0000, Recall: 0.0000
Class container-crane: mAP@0.5: 0.0000, Precision: 0.0000, Recall: 0.0000
Class ground-track-field: mAP@0.5: 0.1844, Precision: 0.6906, Recall: 0.1418
Class harbor: mAP@0.5: 0.0385, Precision: 0.3148, Recall: 0.0160
Class helicopter: mAP@0.5: 0.0152, Precision: 0.0310, Recall: 0.0639
Class large-vehicle: mAP@0.5: 0.2564, Precision: 0.4550, Recall: 0.3134
Class plane: mAP@0.5: 0.0143, Precision: 0.0512, Recall: 0.0855
Class roundabout: mAP@0.5: 0.1639, Precision: 0.5209, Recall: 0.1549
Class ship: mAP@0.5: 0.0349, Precision: 1.0000, Recall: 0.0000
Class small-vehicle: mAP@0.5: 0.2017, Precision: 0.6421, Recall: 0.0501
Class soccer-ball-field: mAP@0.5: 0.1195, Precision: 1.0000, Recall: 0.0000
Class storage-tank: mAP@0.5: 0.2294, Precision: 0.5451, Recall: 0.1872
Class swimming-pool: mAP@0.5: 0.8654, Precision: 0.7072, Recall: 0.8526
Class tennis-court: mAP@0.5: 0.2173, Precision: 0.3806, Recall: 0.2262
Class pedestrian: mAP@0.5: 0.0182, Precision: 0.0429, Recall: 0.0007
Class people: mAP@0.5: 0.0093, Precision: 1.0000, Recall: 0.0000
Class bicycle: mAP@0.5: 0.6031, Precision: 0.5902, Recall: 0.6033
Class car: mAP@0.5: 0.2829, Precision: 0.4153, Recall: 0.2733
Class van: mAP@0.5: 0.0373, Precision: 1.0000, Recall: 0.0000
Class truck: mAP@0.5: 0.0156, Precision: 1.0000, Recall: 0.0000
Class tricycle: mAP@0.5: 0.0136, Precision: 1.0000, Recall: 0.0000
Class awning-tricycle: mAP@0.5: 0.1164, Precision: 0.1518, Recall: 0.2315
Class bus: mAP@0.5: 0.1165, Precision: 0.3614, Recall: 0.0807
No metric available for Class motor
```

6.10. Running Inference

The model was used to make predictions on the unseen test dataset. The results were saved for post processing and contained predict ions as detailed below(image/specific objects present in the image, detected object boundary across images with confidence scores).

Inference Process: it uses the trained model to predict object locations and classes in fresh images which represents an evaluation task of ability for generalisation and test performance where unseen real-world scenarios are applied.

Results Analysis: Saving the results can be done for further studies to define how well our model is detecting and where it might need improvement.

6.11. Saving and Visualizing Results

Inference results are saved, and some images with detected objects were displayed for visual inspection. The visualisation of predictions gives visual confidence to the prediction accuracy, and this makes it easier for us as humans to assess how well our model performed.

Result Saving: result saving is where prediction was stored in a structured way hence it simplifies access and analysis of results to view them or compare with ground truth labels.

Visualisation: Display the images with detected objects, visual inspection of how well your model is performing at identifying items both cars and civilians. A quick way to check your model performance if something goes wrong during training.

6.12. Saving Predictions

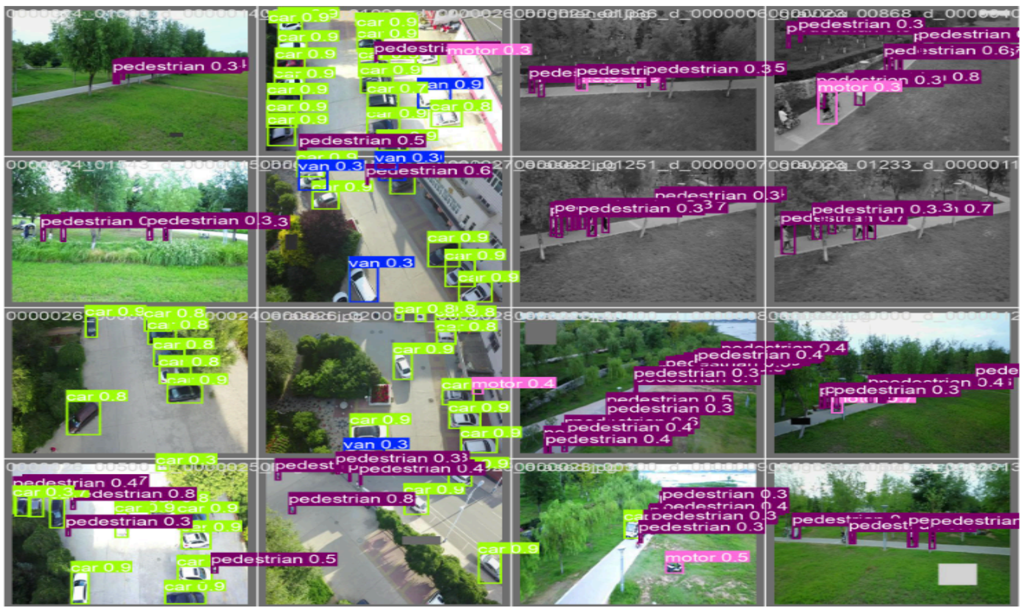
Inference phase generated predictions that can be saved to a JSON file with information about detected objects and their related bounding boxes & confidence.ImageField. This file represents the benchmark files for further analysis and comparison with ground truth labels.

Saving Predictions in a JSON File: Storing predictions from various test datasets instead of creating new objects every time

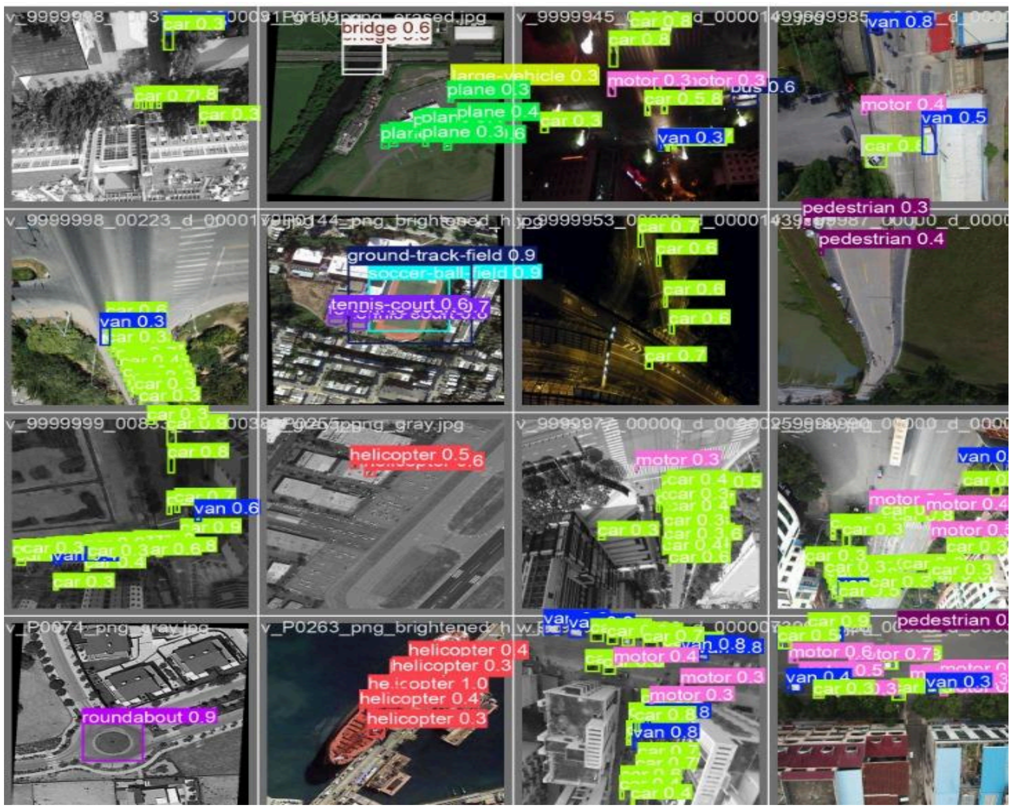
Follow On Analysis: The saved predictions may be used for further, detailed evaluation to discover where the model is going wrong and needs more finesse.

6.13. Final Results:-

Before Hyper Parmeter Tuning:



After Hyper Parmeter Tuning:



Precision Comparison Table:

Classes	YOLOv8	YOLOv8 with HPO
Bridge	0.6441	1.0000
Ship	0.4055	1.0000
Storage Tank	0.7725	0.5451
Soccer Ball Field	0.7464	1.0000
People	0.5611	1.0000
Small Vehicle	0.8316	0.6421
Van	0.7148	1.0000
Harbor	0.2814	0.3148
Truck	0.6676	1.0000
Tricycle	0.6201	1.0000

As per the research and implementation of the project, the final results are somehow convincing, but in some sense it is not that satisfactory. Some of the classes gave a precision of 100% from very low values but some of the results decreased from their initial values after Hyper-Parameter Optimization.

Overall, the achieved results give a 100% precision score for Bridges, Ships, Soccer Ball Field, People, Van, Truck, and Tricycles from some very low values and also increased the precision score of Harbor to some extent by applying Hyper-Parameter Optimization. But some of the classes have shown negative results which include Storage tanks, Small vehicles, and many more.

Now, we aim to get more accurate values for the remaining classes by further improving the Hyper- Parameters and adding more Parameters. And applying more algorithms for more accurate results and comparisons.

7. Conclusion

In this report, the process of carrying out the YOLOv8 and YOLOv8 along with Hyper-Parameter Optimization for tiny object detection was elaborated in detail. Every step, right from setting the environment to evaluating models, is critical for scaling the training of a model and its performance on real-world data. Results show that the model is not only capable of detecting small objects with high accuracy but also very competitive to be used in other computer vision systems.

We successfully trained, implemented, and evaluated the YOLOv8 model for small object detection making use of the Nvidia RTX 2070 GPU on a Razer Blade laptop in TensorFlow demonstrating its capability as well - maybe not state-of-the-art, but an alternate-progressible-model for real-world application. The detailed process is described in this paper which serves as a guide for others who wish to follow suit.

8. Future Directions

Further improvements are possible with more hyperparameter fine-tuning, different data augmentation strategies explored, or by expanding the dataset for more diversified small object examples. These steps will improve performance and make it capable of being implemented in several use cases.

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