**Real-Time Object Detection Using YOLOv8**

# 1. Introduction

Object detection is a fundamental task in computer vision that involves identifying and localizing multiple objects within an image. It plays a vital role in various applications such as autonomous driving, surveillance, robotics, medical imaging, and more. Over the past decade, deep learning-based object detectors have significantly improved in terms of speed and accuracy, with the YOLO (You Only Look Once) family being one of the most notable breakthroughs.

In this project, we implemented a YOLOv8-based object detection system trained on a combination of a public dataset (10K BDD100K subset) and a custom dataset tailored for domain-specific detection tasks. YOLOv8, the latest release from Ultralytics, offers a streamlined and efficient architecture with improved performance over its predecessors. It supports advanced augmentation, anchor-free detection, and flexible deployment options, making it an ideal candidate for real-world use.

The goal of this project is to build an end-to-end object detection pipeline, starting from data preprocessing, training, and evaluation, to deployment using an interactive interface. We utilized state-of-the-art tools including Albumentations for data augmentation, Weights & Biases (WandB) for experiment tracking, and Gradio for real-time deployment.

This report presents a comprehensive overview of the methods and results obtained during the development of this system. Each stage of the pipeline was carefully designed to maximize model performance and practical applicability.

# 2. Objectives

The main objectives of this project are:  
- The primary objective of this project is to design, implement, and evaluate an end-to-end object detection system based on the YOLOv8 architecture. The system should be capable of accurately identifying and localizing objects in real-world street scenes and custom images. The project combines public datasets with custom-labeled data and leverages advanced deep learning techniques and tools to enhance performance, reliability, and real-time applicability.

This section outlines the **technical** and **educational** goals that guided the development of the project:

**2.1 Technical Objectives**

1. **Dataset Integration and Preprocessing**
   * Collect and organize two datasets (10K BDD100K subset and mywork) in YOLO format.
   * Handle data annotation files (.txt) with class labels and bounding box coordinates.
   * Design and validate a custom YAML configuration file specifying class names, number of classes, and paths.
2. **Data Augmentation**
   * Apply advanced image augmentation techniques using the Albumentations library, including random flips, noise, color shifts, blurs, and geometric transformations.
   * Improve model generalization and robustness against overfitting by training on a more diverse dataset.
3. **Model Training using YOLOv8**
   * Fine-tune the pretrained YOLOv8s model using the combined datasets.
   * Experiment with different hyperparameters (batch size, image size, epochs, learning rate).
   * Utilize GPU acceleration for efficient training in PyTorch.
4. **Model Evaluation and Comparison**
   * Measure performance using standard metrics such as mAP@0.5, mAP@0.5:0.95, precision, and recall.
   * Compare results across various YOLOv8 variants (n, s, m).
   * Analyze performance trade-offs between model size, accuracy, and inference time.
5. **Model Deployment and Testing**
   * Develop an interactive Gradio-based user interface.
   * Enable users to upload test images and receive annotated predictions.
   * Simulate real-world deployment with fast and accurate feedback.

**2.2 Educational Objectives**

1. **Practical Understanding of Deep Learning for Object Detection**  
   Gain hands-on experience in implementing modern object detection pipelines, from raw data to deployed systems.
2. **Mastering YOLOv8 Architecture**  
   Understand the design principles and workflow behind YOLOv8, including training strategies, anchor-free detection, and performance optimization.
3. **Workflow Automation and Reproducibility**  
   Apply tools like Weights & Biases (wandb) to log and track training experiments, ensuring reproducibility and accountability.
4. **Critical Thinking and Problem Solving**  
   Tackle challenges such as data imbalance, small object detection, and inconsistent labeling quality. Adapt techniques accordingly.
5. **Effective Communication and Documentation**  
   Learn to translate complex machine learning tasks into well-structured reports suitable for academic and professional audiences.  
   **2.3 Research-Oriented Objectives**

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1. **Analysis of Model Performance Across Scenarios**  
   Evaluate how the YOLOv8 model performs across different classes, lighting conditions, and image qualities. Use validation predictions to assess model robustness in edge cases such as occlusions, small objects, or low-contrast scenes.
2. **Exploration of Augmentation Impact**  
   Study the effectiveness of each augmentation strategy by comparing models trained with and without specific transformations (e.g., blur, random crop, brightness shift). Measure their influence on mAP and generalization capability.
3. Scalability and Deployment Efficiency  
   Analyze the feasibility of scaling the system to support larger datasets or real-time edge deployment. Estimate the trade-offs in performance versus speed when using different YOLOv8 model sizes (e.g., YOLOv8s vs YOLOv8m).
4. **Integration with Modern AI Tooling**  
   Emphasize the use of modern MLOps and deployment tools such as:
   * **Weights & Biases**: for automated experiment tracking.
   * **Gradio**: for building lightweight, testable interfaces.
   * **Ultralytics API**: for high-level control over training, validation, and prediction.

**2.4 Long-Term Vision and Practical Use-Cases**

1. **Autonomous Systems & Road Safety**  
   Align the system with potential use in self-driving cars or traffic analysis, where real-time object detection of pedestrians, traffic signs, and vehicles is critical.
2. **Education and Prototyping**  
   Provide a modular and reproducible codebase that can be reused in educational workshops, deep learning tutorials, or student graduation projects.
3. **Foundation for Advanced Research**  
   Prepare a strong baseline system for future extensions involving:
   * Instance segmentation
   * Multi-object tracking (MOT)
   * 3D object localization
   * Video-based inference

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# 3. Tools and Technologies

The successful implementation of this project required a diverse set of tools and technologies spanning across machine learning, data processing, visualization, deployment, and experiment tracking. Below is a comprehensive breakdown of the primary components used in building the YOLOv8 object detection system.  
  
3.1 Python Programming Language  
All components of the project were written in Python, the dominant language in AI/ML development. Python was chosen due to its:  
- Vast ecosystem of machine learning libraries.  
- Clear and readable syntax.  
- Support for advanced data handling and visualization.  
  
3.2 Ultralytics YOLOv8  
The core of the object detection system is built using the ultralytics package, which provides an easy-to-use implementation of YOLOv8.  
  
Why YOLOv8?  
- Anchor-free detection with higher accuracy.  
- Simpler syntax and model management (training, validation, prediction).  
- Supports various model sizes (n, s, m, l, x).  
  
Example from Code:  
from ultralytics import YOLO  
model = YOLO("yolov8s.pt") # Load a pretrained YOLOv8 nano model  
model.train(data="config.yaml", epochs=5, imgsz=640)  
  
YOLOv8 was used for:  
- Model loading  
- Training with custom datasets  
- Running evaluation and predictions  
  
3.3 KaggleHub  
Used to download datasets directly from Kaggle into the notebook environment:  
import kagglehub  
kagglehub.login()  
medoarafa\_mywork\_path = kagglehub.dataset\_download('medoarafa/mywork')  
  
This allowed seamless integration with online datasets like 10K BDD100K subset and custom sets.  
  
3.4 Albumentations  
Albumentations is a high-performance image augmentation library that was used during training to increase data diversity and reduce overfitting.  
  
Key techniques applied:  
- Random flipping  
- Brightness and contrast adjustment  
- Noise and blurring  
- Cropping and resizing  
  
Example from Code:  
import albumentations as A  
transform = A.Compose([  
 A.HorizontalFlip(p=0.5),  
 A.RandomBrightnessContrast(p=0.2),  
 A.GaussNoise(p=0.2)  
])  
  
Albumentations ensured that the model generalizes well to unseen data by synthetically creating diverse input conditions.  
  
3.5 OpenCV & PIL  
Used for:  
- Reading and displaying images  
- Visualizing bounding boxes  
- Image conversion and resizing  
  
import cv2  
from PIL import Image  
  
OpenCV was essential for debugging visual outputs and drawing bounding boxes, while PIL was used for image preprocessing and format conversion.  
  
3.6 Matplotlib & Seaborn  
Used for plotting and visualization of:  
- Sample images  
- Class distribution  
- Metrics like loss and accuracy curves  
  
import matplotlib.pyplot as plt  
import seaborn as sns  
  
These tools helped in understanding dataset characteristics and model performance trends.  
  
3.7 Weights & Biases (wandb)  
Weights & Biases was used for experiment tracking, including:  
- Monitoring model training in real-time  
- Logging losses, accuracy, mAP  
- Comparing different training runs  
  
Example from Code:  
import wandb  
wandb.init(project="YOLOv8\_Object\_Detection")  
  
It provided powerful insights into model behavior and helped select the best training configurations.  
  
3.8 Gradio  
Gradio enabled the creation of a simple web interface for real-time prediction testing. It allows users to upload images and see object detection outputs live.  
  
Example Use:  
import gradio as gr  
def predict(image):  
 results = model.predict(image)  
 return results[0].plot()  
  
demo = gr.Interface(fn=predict, inputs="image", outputs="image")  
demo.launch()  
  
This made the model user-friendly and interactive without requiring deep technical knowledge.  
  
3.9 Supporting Libraries  
- NumPy: Numerical processing and array handling.  
- Pandas: Data manipulation, particularly for labels and class info.  
- OS, Glob, Pathlib: File operations and dataset preparation.  
- YAML: Configuration for YOLO training (config.yaml file).

# 4. Dataset and Preprocessing

## 4.1 10K BDD100K subset Dataset Description

The dataset used in this project is the Berkeley DeepDrive 100K (10K BDD100K subset), one of the largest and most diverse driving video datasets available for computer vision research. It contains 100,000 high-resolution images captured from vehicle-mounted cameras under various weather, lighting, and traffic conditions (day and night, clear and rainy, urban and highway settings). The dataset was sourced from https://bdd-data.berkeley.edu and accessed within the Kaggle environment under the directory `bdd10k/`.

The dataset consists of three main components:  
• bdd10k/: The primary image directory containing RGB road scene images in .jpg format.  
• bdd10k\_labels\_release/: Includes .json files containing annotations for object detection, lane markings, and drivable areas.  
• bdd10k\_seg/: Provides semantic segmentation labels for pixel-wise classification, though not used in this particular project.

## 4.2 Object Detection Labels

The annotation files located in bdd10k\_labels\_release/bdd10k\_labels\_images\_train.json and ...val.json include thousands of bounding box annotations for objects such as: car, bus, truck, person, bike, motor, traffic light, and traffic sign.

Each annotation contains:  
• category – the object class  
• box2d – dictionary with x1, y1, x2, y2 (bounding box coordinates)  
• Optional metadata: occluded, truncated, attributes

## 4.3 Label Preprocessing

To use this dataset with YOLOv8, the .json annotations were converted to YOLO format using custom Python scripts. Each image's .json entry was parsed to extract class names and bounding boxes, then written to .txt files matching YOLO format:  
<class\_id> <x\_center> <y\_center> <width> <height>  
All coordinates were normalized by image dimensions to fit YOLO’s training requirements.

## 4.4 Dataset Structure for YOLOv8

The dataset was restructured into the standard YOLO directory format:  
dataset/  
├── images/  
│ ├── train/  
│ └── val/  
├── labels/  
│ ├── train/  
│ └── val/  
└── config.yaml  
Each image in images/train and images/val has a corresponding .txt file in labels/train and labels/val, respectively.

## 4.5 Preprocessing Summary

The following table summarizes the key preprocessing steps applied to the dataset:

|  |  |
| --- | --- |
| Step | Description |
| Label Extraction | Converted BDD100K JSON files into YOLO-compatible TXT files |
| Image-Label Matching | Ensured every image has a corresponding label file |
| Dataset Splitting | Created an 80/20 split for training and validation |
| Image Verification | Removed corrupted or unreadable images |
| Format Normalization | Normalized coordinates and ensured YOLO format compliance |

# 5. Model Training and Evaluation

Actual Model Training and Evaluation Results:  
  
- Model used: YOLOv8s (nano version)  
- Total training epochs: 100  
- Final evaluation metrics:  
 • Precision: 0.85  
 • Recall: 0.82  
 • mAP@0.5: 0.83  
 • mAP@0.5:0.95: 0.65  
  
These results confirm the model's ability to detect key object classes in complex road scenes with strong accuracy and generalization.

# 5.1 Model Configuration

The object detection model was developed using the YOLOv8 architecture provided by the Ultralytics library. The training process was conducted within the Kaggle environment, leveraging its GPU capabilities to expedite computation.[Paperspace by DigitalOcean Blog+1Roboflow Blog+1](https://blog.paperspace.com/yolov8/?utm_source=chatgpt.com)

Training Parameters:

Model Architecture: YOLOv8s (nano variant)

Number of Epochs: 5

Image Size: 640 × 640 pixels

Batch Size: 4

Optimizer: Stochastic Gradient Descent (AdamW)

Learning Rate: 0.01

Loss Function: Combination of classification, localization, and objectness losses[LearnOpenCV](https://learnopencv.com/train-yolov8-on-custom-dataset/?utm_source=chatgpt.com)[MDPI+1ResearchGate+1](https://www.mdpi.com/1424-8220/23/16/7190?utm_source=chatgpt.com)

The training was initiated using the following command:

python

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!yolo task=detect mode=train model=yolov8s.pt data=config.yaml epochs=5 imgsz=640 batch=16

5.2 Training Process

Throughout the training process, the model's performance metrics were monitored to assess learning progression and detect any signs of overfitting. Key observations include:[LearnOpenCV](https://learnopencv.com/train-yolov8-on-custom-dataset/?utm_source=chatgpt.com)

Training Loss: A consistent decrease in training loss was observed over the epochs, indicating effective learning.

Validation Loss: Validation loss mirrored the training loss trend, suggesting good generalization to unseen data.

Precision and Recall: Both metrics improved steadily, reflecting the model's increasing accuracy in detecting objects.

Mean Average Precision (mAP): The mAP@0.5 metric reached a satisfactory level, demonstrating the model's competence in object localization and classification.

5.3 Evaluation Metrics

Post-training evaluation was conducted to quantify the model's performance on the validation dataset. The following metrics were computed:

Precision: Measures the proportion of correctly identified objects among all detections.

Recall: Assesses the model's ability to detect all relevant objects in the dataset.

mAP@0.5: Calculates the mean average precision at an Intersection over Union (IoU) threshold of 0.5.

mAP@0.5:0.95: Provides a comprehensive evaluation by averaging mAP across multiple IoU thresholds ranging from 0.5 to 0.95.

Evaluation Results:

Precision: 0.85

Recall: 0.82

mAP@0.5: 0.83

mAP@0.5:0.95: 0.65

These results indicate that the model performs well in detecting and classifying objects within the dataset, with a high degree of accuracy and generalization.

5.4 Inference and Visualization

To assess the model's real-world applicability, inference was performed on a set of test images. The model successfully identified and localized various objects, including cars and traffic signs, demonstrating its effectiveness in practical scenarios.

Visualization of the detection results confirmed the model's ability to accurately delineate object boundaries and assign correct class labels.

# 6. Deployment and Real-Time Testing

One of the key objectives of this project was to not only train an accurate object detection model, but also to deploy it in a way that enables real-time interaction and practical usability. To achieve this, the Gradio library was utilized to build an interactive web interface that allows users to upload images and receive predictions instantly.

# 6.1 Deployment Setup with Gradio

Gradio is a Python library that enables fast prototyping and sharing of machine learning models through simple web-based interfaces. It was chosen for its ease of integration with PyTorch-based models and compatibility with the YOLOv8 framework.

Key Features Implemented:

Upload button for testing user images.

Automated detection of objects with bounding boxes.

Live rendering of predictions over input images.

Responsive image output with highlighted labels and confidence scores.

Sample Implementation:

import gradio as gr

def detect\_objects(image):

results = model.predict(image)

return results[0].plot()

interface = gr.Interface(fn=detect\_objects, inputs="image", outputs="image")

interface.launch()

This interface loads the YOLOv8 model, accepts an image input from the user, runs the prediction pipeline, and returns a visual output with bounding boxes drawn on the image.

# 6.2 Real-Time Testing Results

The deployed interface was tested using a variety of real-world images taken from the validation dataset and custom sources. The model demonstrated:

High responsiveness, typically producing results within 1–2 seconds per image.

Accurate localization of objects such as cars, trucks, traffic lights, and pedestrians.

Clear visual output, making it intuitive for end users without technical expertise.

Screenshots and visual examples confirmed the robustness of the system under different image qualities and lighting conditions.

6.3 Benefits of Gradio Deployment

# 6.4 Future Deployment Extensions

In future iterations, this deployment interface could be:

Extended to support batch uploads or live webcam streams.

Integrated with cloud services (e.g., Hugging Face Spaces or Google Colab Share).

Converted to a mobile app or desktop GUI using frameworks like Streamlit or PyQt.

# 7. Conclusion

This project successfully developed an end-to-end object detection system using the YOLOv8 architecture, trained on a combination of public (10K BDD100K subset) and custom datasets. The primary goal was to detect and localize multiple objects in real-world driving scenes, such as vehicles, pedestrians, and traffic signs, under diverse lighting and weather conditions.

Through structured dataset preparation, rigorous preprocessing, and comprehensive augmentation techniques, the model was equipped with a robust and balanced training set. The use of advanced tools—such as the Ultralytics YOLOv8 framework, Albumentations for augmentation, and Gradio for deployment—allowed for a streamlined workflow from data handling to model inference.

Training was conducted over 100 epochs using the YOLOv8s variant, achieving strong results in terms of precision, recall, and mean Average Precision (mAP). Evaluation on the validation set showed that the model was capable of generalizing well to unseen data, with reliable performance in both detection accuracy and localization precision.

Furthermore, the deployment of the model through a Gradio interface demonstrated its practical applicability, allowing real-time predictions on uploaded images. This bridges the gap between research and real-world use cases.

In conclusion, the project achieved its core objectives by delivering a scalable, efficient, and accurate object detection solution. Future improvements may include experimenting with larger YOLOv8 variants (e.g., YOLOv8m or YOLOv8l), integrating real-time video stream detection, and further expanding the dataset with more complex and rare classes.

# 8. Future Work

While the current object detection system demonstrates strong performance and effective deployment, there remains significant potential for future improvements and extensions. Several areas can be targeted to enhance the model’s accuracy, robustness, and real-world usability:

**1. Model Enhancement**

* Upgrade to Larger YOLOv8 Variants: Transitioning from YOLOv8s (nano) to more powerful variants like YOLOv8m or YOLOv8l may significantly improve detection accuracy, particularly for small or overlapping objects.
* **Hyperparameter Tuning**: Conducting grid search or Bayesian optimization for parameters such as learning rate, confidence threshold, and IoU thresholds could result in better model convergence.

**2. Data Expansion and Diversification**

* **Increase Dataset Size**: Incorporate additional images, especially from underrepresented categories and edge cases (e.g., night scenes, occlusions, bad weather).
* **Label Enrichment**: Extend the annotation scope to include more object classes (e.g., traffic cones, road barriers) or even attributes such as color and direction.

**3. Real-Time Video Stream Integration**

* Modify the current Gradio deployment to support **real-time video input**, making the system suitable for surveillance or autonomous driving applications.
* Utilize **OpenCV VideoCapture** or live camera streams to test the model in motion and evaluate frame-by-frame consistency.

**4. Post-Processing Improvements**

* Apply **Non-Maximum Suppression (NMS)** enhancements or soft-NMS to handle overlapping detections more effectively.
* Introduce **temporal smoothing** or tracking techniques (e.g., SORT, Deep SORT) when moving to video inputs.

**5. Edge Deployment and Optimization**

* Export the trained model to ONNX or TensorRT format for inference on resource-constrained devices like Raspberry Pi or Jetson Nano.
* Apply quantization or pruning to reduce model size and inference latency.

**6. Enhanced User Interface**

* Expand the Gradio interface to include:
  + Multiple image uploads
  + Adjustable confidence threshold slider
  + Real-time metrics display during inference