PROJECT REPORT

On

Objectify

Submitted by

Olwin Christian (IU2141230136)
Deepak Soni (IU2141230282)

In fulfillment for the award of the degree

Of

BACHELOR OF TECHNOLOGY

In

COMPUTER ENGINEERING

INSTITUTE OF TECHNOLOGY AND ENGINEERING

INDUS UNIVERSITY CAMPUS, RANCHARDA, VIA-THALTEJ

AHMEDABAD-382115, GUJARAT, INDIA,

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OCTOBER 2024

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AT

ज्ञानेन प्रकाशते जगत्

INDUS UNIVERSITY

In the partial fulfillment of the requirement
for the degree of
Bachelor of Technology
in
Computer Science Engineering

PREPARED BY

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UNDER GUIDANCE OF

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SUBMITTED TO

INSTITUTE OF TECHNOLOGY AND ENGINEERING

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AHMEDABAD-382115, GUJARAT, INDIA,

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CANDIDATE’S DECLARATION

I declare that final semester report entitled “**OBJECTIFY**” is my own work conducted under the supervision of the guide. **DR. SHEETAL PANDYA.**

I further declare that to the best of my knowledge, the report for B.Tech final semester does not contain part of the work which has been submitted for the award of B.Tech Degree either in this university or any other university without proper citation.

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INDUS INSTITUTE OF TECHNOLOGY AND ENGINEERING

COMPUTER ENGINEERING

2023 -2024

CERTIFICATE

9th October 2024

This is to certify that the project work entitled "**OBJECTIFY"** has been carried out by **OLWIN CHRISTIAN** under my guidance in partial fulfillment of degree of Bachelor of Technology in **COMPUTER ENGINEERING (Final Year)** of Indus University, Ahmedabad during the academic year 2023 - 2024

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ABSTRACT

This report outlines the development of an object detection model applied to a football video clip, aimed at identifying and tracking multiple objects, specifically players, the ball, and the referee, in real-time. The project leverages deep learning techniques and advanced object detection algorithms to create an efficient model that processes video frames and provides accurate bounding boxes and class labels for the detected objects.

The primary objectives of the project are to explore state-of-the-art object detection architectures, such as Faster R-CNN and YOLOv8, and apply them to a sports context to analyze performance in detecting dynamic entities within a video environment. Using tools like Google Colab, PyTorch, and Roboflow for dataset annotation, the project also seeks to provide a comprehensive workflow for training and testing object detection models on custom datasets.

Methodology includes testing various object detection models on public image datasets, training the YOLOv8 model on a custom annotated football video, and evaluating its performance in real-time detection. The deployment of the model in a Google Colab environment enables real-time processing of the football video, showcasing detected objects with bounding boxes.

The anticipated outcome of the project is a fully functional object detection system capable of identifying and tracking objects within a sports setting. This project has potential applications in sports analytics, such as player tracking, ball trajectory analysis, and event monitoring.

In conclusion, this object detection model presents a solution to real-time tracking challenges in sports videos, demonstrating the power of deep learning in providing accurate, high-speed detection of multiple entities in dynamic environments.

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ABBREVIATIONS

Abbreviations used throughout this whole document for *Objectify* report are:

Abbreviation	**Description**
ML	Machine Learning
NLP	Natural Language Processing
PCA	Principle Component Analysis
DNN	Deep Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
TF	TensorFlow
PyTorch	Machine Learning Library for Python

CHAPTER 1 **INTRODUCTION**

1.1 PROJECT SUMMARY

The Objectify project focuses on developing an advanced object detection model tailored for analyzing football video clips. This model aims to accurately identify and track multiple dynamic entities, including players, the ball, and referees, in real-time. Utilizing deep learning techniques and state-of-the-art object detection frameworks, the project emphasizes efficient processing of video frames to deliver precise bounding boxes and class labels for each detected object.

Key objectives include:

- Exploring and implementing leading object detection architectures, specifically Faster R-CNN and YOLOv8, to evaluate their effectiveness in a sports context.

- Creating a robust workflow for training and testing these models using tools such as Google Colab, PyTorch, and Roboflow for dataset annotation.

- Conducting rigorous performance evaluations of the trained models on custom datasets to ensure high accuracy and reliability in real-time detection scenarios.

The project methodology encompasses testing various object detection algorithms on existing image datasets, training the YOLOv8 model on specifically annotated football footage, and validating its efficacy through real-time application. The deployment of the model within a Google Colab environment facilitates the live processing of video data, enabling users to visualize detected objects with corresponding bounding boxes.
The expected outcome is a comprehensive object detection system capable of real-time identification and tracking of key elements in sports videos. This innovative solution has significant potential applications in sports analytics, such as enhancing player tracking, analyzing ball trajectories, and monitoring pivotal game events.
Overall, the Objectify project aims to leverage deep learning to address real-time tracking challenges in sports, showcasing the model's capability to provide precise, high-speed detection of multiple entities within a dynamic environment.

1.2 PROJECT PURPOSE

The purpose of the Objectify project is to address the need for effective and efficient real-time object detection in sports analytics, specifically within the context of football matches. As the complexity of sports events increases, so does the challenge of accurately tracking multiple dynamic entities in video footage. This project aims to develop a sophisticated object detection system that not only identifies key players, the ball, and referees but also provides actionable insights based on the detected data.
By utilizing advanced deep learning techniques and state-of-the-art architectures such as Faster R-CNN and YOLOv8, Objectify aims to create a model that can seamlessly integrate with existing sports analysis tools. This integration will facilitate deeper analytical capabilities, enabling coaches and analysts to make data-driven decisions that enhance team performance.

The specific goals of the project include:

- **Enhancing Analytical Insights**: By providing detailed object detection capabilities, Objectify aims to improve the quality of game analysis, enabling coaches and teams to identify player movements, ball trajectories, and officiating accuracy with precision.

- **Real-Time Application**: The project seeks to develop a system capable of processing video streams in real-time, offering immediate feedback and insights during matches. This will empower teams to make quick tactical adjustments and enhance in-game decision-making.

- **User-Friendly Interface for Analysts**: While the core focus is on the backend algorithm, the project will also consider creating a straightforward interface that allows sports analysts to visualize and interpret data effectively, ensuring that insights are accessible and actionable.

- **Potential for Broader Applications**: Beyond football, the technology developed in Objectify can be adapted for other sports, thereby broadening its applicability and enhancing the overall sports analytics landscape.

In conclusion, Objectify is driven by the objective to not only improve the technical capabilities of object detection in sports but also to transform how analysts, coaches, and teams leverage this technology for enhanced performance evaluation and strategic planning. By doing so, the project aims to contribute significantly to the field of sports analytics, providing valuable tools that can revolutionize game analysis and decision-making processes.

1.3 PROJECT SCOPE

The Objectify project aims to develop an advanced object detection system specifically designed for analyzing football video footage. The primary focus is on accurately identifying and tracking multiple dynamic entities, including players, the ball, and referees, in real-time.

Key components of the project scope include:

- **Algorithm Development**: Research and implement state-of-the-art object detection algorithms, such as Faster R-CNN and YOLOv8, to ensure high accuracy in detecting objects within video frames.

- **Dataset Preparation**: Utilize existing public image datasets and annotate custom football video clips to create a robust dataset for training and testing the model.

- **Real-Time Processing**: Deploy the model in a Google Colab environment to enable real-time detection and tracking of objects during football matches.

- **User Interface Design**: Develop a user-friendly interface that allows sports analysts to visualize detected objects and access relevant insights efficiently.

- **Testing and Evaluation**: Conduct thorough testing to evaluate the model’s performance and accuracy, making necessary adjustments based on feedback and analysis.

- **Potential Enhancements**: Explore additional features, such as player tracking analytics and event monitoring, to broaden the application's utility in sports analysis.

The ultimate goal of Objectify is to create a comprehensive and effective object detection system that transforms how sports analysts and teams evaluate performance during matches. By addressing the specific needs of the sports analytics domain, the project aims to deliver a tool that enhances decision-making and strategic planning in football.

1.4 OBJECTIVE

The primary objective of the Objectify project is to develop a cutting-edge object detection system tailored for analyzing football videos. This system will efficiently identify and track key objects such as players, the ball, and referees in real-time, enhancing the understanding of game dynamics.

Key objectives include:

- **Accurate Detection**: To create a robust algorithm that delivers precise and reliable object detection using advanced techniques like YOLOv8 and Faster R-CNN.

- **Real-Time Analysis**: To enable real-time processing of football video footage, allowing for immediate feedback and insights during matches.

- **User-Friendly Interface**: To design an intuitive interface that presents detection results in an easily digestible format for sports analysts and coaches.

- **Performance Evaluation**: To rigorously test and validate the model's performance, ensuring it meets the needs of users in dynamic sporting environments.

- **Broaden Functionalities**: To explore additional functionalities, such as player tracking and event analysis, expanding the system's utility in sports analytics.

Goal/Objective	Description	Success Criteria	Timeline	Priority
Accurate Object Detection	Achieve high accuracy in detecting objects within the image or video feed.	Detection accuracy above 90% on test data.	By project completion	High
Real-Time Processing	Implement real-time object detection for live video feeds.	Processing time per frame less than 200ms.	By project completion	High
User-Friendly Interface	Develop an intuitive and easy-to-use interface for the end-users.	User satisfaction score of 85% or higher in usability tests.	Mid-project	Medium
Model Training Efficiency	Ensure that the object detection model can be trained efficiently on new data.	Model training time reduced by 20% with efficient data pipelines.	Mid-project	Medium
Scalability	Ensure the system is scalable to handle larger datasets and higher resolution images.	Ability to handle datasets 10x larger than initial dataset.	Late-project	Low
Cross-Platform Support	Ensure the system can be deployed on different platforms (e.g., mobile, desktop).	Successful deployment and testing on two or more platforms.	Late-project	Medium
Detection of Multiple Object Types	Expand the model to detect a variety of object classes (e.g., plants, animals).	Ability to detect 10+ unique object classes with over 85% accuracy.	By project completion	High
Continuous Model Improvement	Implement functionality for model updates and improvement based on new data.	Integration of feedback loop for model retraining and updates.	Ongoing	Medium
Performance Optimization	Optimize performance to minimize computational load.	CPU and memory usage reduced by 30% compared to initial benchmarks.	Mid-project	Low

Table 1.4.1 Project Goals and Objectives

1.5 SYNOPSIS

The Objectify project aims to develop an innovative object detection model specifically designed for analyzing football videos. By leveraging state-of-the-art deep learning techniques, this project will focus on accurately identifying and tracking dynamic objects such as players, the ball, and referees in real-time.
The model will be built using advanced architectures like YOLOv8 and Faster R-CNN, ensuring high accuracy and efficiency in detection. The project will utilize platforms like Google Colab and PyTorch for model training and evaluation, while Roboflow will assist in dataset annotation.

Through rigorous testing and user feedback, the system will be refined to meet the needs of sports analysts and coaches, enhancing their ability to gain insights from live match footage. The anticipated outcome is a fully functional object detection tool that not only improves game analysis but also contributes to sports analytics by providing valuable data on player movements, ball trajectories, and officiating decisions.

In summary, Objectify is poised to transform the way football games are analyzed, making it an essential resource for professionals in the sports industry.

CHAPTER 2 **LITERATURE SURVEY**

The literature survey for the Objectify project centers around existing research on object detection technologies, particularly in the context of deep learning and computer vision:

1. **Deep Learning in Object Detection:** Numerous studies have demonstrated the effectiveness of deep learning algorithms in object detection tasks. One notable work is by Shaoqing Ren et al. in their paper "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", which introduces the Faster R-CNN framework. This model integrates region proposal networks with fast CNNs to enhance detection speed and accuracy, setting a benchmark in the field.

2. **YOLO (You Only Look Once):** The YOLO framework has revolutionized real-time object detection with its unique architecture that processes images in a single evaluation. Joseph Redmon et al. presented YOLO in "You Only Look Once: Unified, Real-Time Object Detection", emphasizing its speed and efficiency. Subsequent versions, such as YOLOv8, further improve performance, making it suitable for dynamic environments like sports and outdoor scenes.

3. **Transfer Learning for Object Detection**: Transfer learning has emerged as a valuable approach for training object detection models, especially when annotated datasets are limited. In the research "Using Transfer Learning for Object Detection", the authors discuss how pre-trained models can be fine-tuned for specific tasks, significantly reducing training time while maintaining accuracy.

4. **Data Annotation and Augmentation**: The importance of high-quality training data is crucial for effective object detection. The paper "Data Augmentation for Object Detection: A Review" outlines various techniques to enhance training datasets, such as flipping, rotation, and colour adjustments. These methods help improve model robustness and performance in diverse environments.

5. **Real-Time Applications**: Object detection is increasingly being applied in real-time scenarios, such as video analysis and autonomous systems. Research like "Real-Time Object Detection in Video Streams Using YOLO", showcases practical implementations of object detection algorithms in live video feeds, addressing challenges like frame rate, processing power, and accuracy.

In summary, the literature survey for the Objectify project highlights critical advancements in deep learning-based object detection, including methodologies like Faster R-CNN and YOLO, the role of transfer learning, and the significance of data quality. These insights will guide the development of the Objectify application, enabling effective object detection in real-world scenarios.

CHAPTER 3 **OBJECTIFY**

3.1 Introduction to Object Detection

Object detection is a crucial area within computer vision that involves identifying and locating objects within images or video frames. With the rapid advancement of deep learning technologies, the ability to accurately detect and classify objects has significantly improved, enabling a wide range of applications, from autonomous vehicles to security surveillance.

3.2 Why Objectify?

Objectify was developed to leverage the capabilities of deep learning for practical applications in object detection. The primary motivation behind this project is to enhance the understanding and interaction with video content through automated object detection. By focusing on sports, particularly football, Objectify aims to provide real-time insights into player movements, ball trajectories, and game dynamics, benefiting coaches, analysts, and fans alike.

Key Motivations:

- **Real-Time Analysis**: Objectify aims to deliver instant feedback and analysis during football matches, enhancing the overall viewing experience.
- **Data-Driven Insights**: By collecting and analyzing data on player performance and ball movement, Objectify helps teams and coaches make informed decisions.
- **User Engagement**: Engaging fans with innovative technology that brings them closer to the action on the field.

3.4 Features & Capabilities

Objectify is equipped with a suite of features designed to facilitate comprehensive object detection in football videos:

- **Real-Time Object Detection**: Detects players, the ball, and referees in real-time during matches, providing immediate visual feedback.
- **Bounding Box Visualization**: Draws bounding boxes around detected objects, clearly indicating their locations in each frame.
- **Custom Dataset Training**: Trained using a custom dataset created from various sources, including tools like Roboflow, to ensure accuracy and relevance.
- **Support for Multiple Object Classes**: Capable of recognizing and classifying various objects, including players, the ball, and referees, allowing for detailed game analysis.
- **User-Friendly Interface**: Designed for ease of use, allowing users to easily navigate and understand the output of the object detection model.

Feature	Description
Object Localization	Identifies the location of objects in an image by drawing bounding boxes around them.
Multiple Object Detection	Detects and identifies multiple objects within a single image or video frame.
Classification	Classifies each detected object into predefined categories (e.g., cars, animals).
Real-Time Detection	Processes images or video frames instantly to detect objects in real time.
Confidence Scoring	Assigns a confidence score to each detected object, indicating the model's certainty.
Non-Maximum Suppression (NMS)	Filters out overlapping bounding boxes, keeping only the most likely detection.
Scalability	Scales detection capabilities across different devices and platforms (e.g., mobile, web, cloud).
Model Training	Allows training on custom datasets to detect specific types of objects beyond pre-trained categories.
Preprocessing	Applies image preprocessing techniques (e.g., resizing, normalization) to enhance detection accuracy.
Cross-Domain Support	Supports different input types, such as images, videos, and live camera feeds.
Model Efficiency	Optimizes object detection models to run on devices with limited computational power.

Table 3.4.1 Features of Object Detection

3.4 Technology and Tools Used

The development of Objectify involved a range of technologies and tools, each chosen for its strengths in contributing to the project's goals:

- **Programming Language**: Python was the primary programming language used, selected for its versatility and the extensive libraries available for machine learning and computer vision.

- **Deep Learning Framework**: PyTorch was utilized for building and training the object detection models due to its dynamic computation graph and user-friendly API.

- **Object Detection Libraries**: The project leveraged state-of-the-art libraries such as Detectron2 and YOLOv8 for efficient object detection tasks.

- **Google Colab**: The training and testing of models were conducted in Google Colab, providing access to powerful computing resources and facilitating collaborative work.

- **Roboflow**: Utilized for creating and annotating custom datasets, enabling efficient training of the object detection models tailored to the football domain.

- **Data Visualization Tools**: Libraries such as Matplotlib and OpenCV were employed to visualize results, including bounding boxes and class labels on detected objects in video clips.

CHAPTER 4 **PROJECT MANAGEMENT**

4.1 Project Planning Objectives

The primary objectives of the Objectify project were to develop a robust object detection model that could accurately identify and classify objects in real-time, specifically in a football context.

Objective	Description
Develop Real-Time Detection	Create a model capable of accurately detecting and classifying objects in real-time during football matches.
Ensure High Accuracy	Aim for a high accuracy rate in identifying different types of objects (e.g., players, ball, goals) in various conditions.
Optimize Model Performance	Fine-tune the model to achieve a balance between detection speed and accuracy, suitable for live scenarios.
Implement Robust Training	Utilize diverse datasets and techniques to train the model effectively, ensuring it can handle different lighting and angles.
User-Friendly Interface	Design an intuitive interface for users to easily upload images and visualize detection results.
Real-Time Visualization	Enable live visualization of detection results, showing bounding boxes and labels for identified objects.
Conduct Comprehensive Testing	Perform extensive testing in various scenarios to validate the model's performance and reliability.
Plan for Future Enhancements	Develop a roadmap for potential future features, such as integrating with video feeds or improving detection algorithms.

Table 4.1.1 Project Goals and Objectives

4.2 Project Scheduling

The project was structured into several phases, each with specific timelines and deliverables to ensure timely completion. The following phases outline the project schedule:

1. **Research and Learning Phase (Weeks 1-2):**
   - Study the fundamentals of object detection and deep learning.
2. **Dataset Collection and Annotation (Weeks 3-4):**
   - Gather football clips and relevant images from various sources.
   - Annotate the dataset using Roboflow to create bounding boxes for the desired objects.
3. **Model Development and Training (Weeks 5-6):**
   - Implement and train the object detection models (Faster R-CNN, YOLOv8).
   - Conduct initial tests to evaluate model performance on sample images.
4. **Evaluation and Fine-tuning (Weeks 7-8):**
   - Analyze model performance metrics and make necessary adjustments to improve accuracy.
   - Test the model on the football video clip, ensuring effective object detection.
5. **Deployment (Week 9):**
   - Deploy the trained model in a cloud environment using Google Colab.
   - Showcase the model's capability by demonstrating object detection in real-time video.
6. **Final Reporting (Week 10):**
   - Compile project findings, performance results, and insights into a comprehensive report.
   - Prepare a presentation to share the project outcomes with stakeholders.

4.5 Risk Management

To ensure the successful completion of the Objectify project, potential risks were identified and mitigated through strategic planning:

- **Technical Risks:** The complexity of object detection algorithms could pose challenges in implementation and performance. To mitigate this risk, extensive research was conducted, and multiple models were tested to identify the most effective approach.

- **Dataset Limitations**: Insufficient or poorly annotated data could hinder model training. To address this, diverse datasets were gathered, and rigorous annotation practices were employed to enhance the quality of the training data.

- **Timeline Delays**: Unforeseen challenges, such as technical difficulties or resource availability, could lead to project delays. A buffer period was included in the project schedule to accommodate potential setbacks.

- **Performance Expectations:** The model's performance may not meet initial expectations. Continuous evaluation and fine-tuning during the training phase ensured that performance metrics were consistently monitored and improved.

CHAPTER 5 **SYSTEM REQUIERMENTS**

5.1 User Characteristics

Understanding the user characteristics is essential for developing an object detection system that meets the needs of its intended audience. The primary users of this system may include:

- **Data Scientists and Researchers**: Users who require sophisticated tools to analyse and validate object detection models, needing access to extensive datasets and analytical capabilities.
- **Developers**: Individuals involved in implementing the object detection algorithms into applications, requiring an intuitive interface and documentation for integration.
- **End Users**: This includes individuals utilizing applications powered by object detection technology (e.g., autonomous vehicles, mobile apps). They may prioritize ease of use and real-time performance.

Characteristics may include:

- **Technical proficiency**: Users may range from novice to advanced, affecting the complexity of the interface.
- **Domain knowledge**: Users with a background in computer vision may require advanced features, while others may need simplified functionalities.
- **Use case**: Applications in different industries (e.g., healthcare, security, retail) may have specific user needs.

5.2 Functional Requirements

Functional requirements describe the specific functionalities that the system must support. Key functional requirements for the object detection system may include:

Functional Requirement	Description
Image Upload	Users must be able to upload images of football matches for object detection.
Object Detection	The system should detect and classify various objects, including players, the football, and goals.
Real-Time Processing	The model must process images and return detection results in real-time or near real-time.
Display Results	Detected objects should be visually represented with bounding boxes and labels on the uploaded images.
Multiple Object Handling	The system must identify and classify multiple objects within a single image effectively.
Confidence Scoring	The model should provide a confidence score for each detected object, indicating the likelihood of accuracy.
Performance Metrics Display	The system must display performance metrics (e.g., accuracy, speed) to users for evaluation.
User Interface	A user-friendly interface must be provided for easy interaction with the system, including image upload and result visualization.
Error Handling	The system should include error handling to manage invalid inputs or processing errors gracefully.
Data Storage	The system should store processed images and detection results for future reference or analysis.

Table 5.2.1 Functional Requirements

5.3 Non-Functional Requirements

Non-functional requirements define the overall quality attributes and constraints of the system. Important non-functional requirements may include:

Non-Functional Requirement	Description
Performance	The object detection model should process images within a specified time limit (e.g., < 1 second per image).
Scalability	The system must be able to handle increasing numbers of users and images without a significant drop in performance.
Reliability	The system should have an uptime of 99.9% and should recover gracefully from failures.
Usability	The user interface must be intuitive and easy to navigate for users with varying technical backgrounds.
Security	User data and uploaded images must be securely stored and protected against unauthorized access.
Compatibility	The system should be compatible with major web browsers and devices, ensuring accessibility for all users.
Maintainability	The codebase should be well-documented and modular to facilitate future updates and maintenance.
Interoperability	The system should integrate smoothly with existing tools and frameworks used in sports analytics.
Accuracy	The object detection model should achieve a minimum accuracy rate (e.g., > 85%) in identifying and classifying objects.
Compliance	The system must adhere to relevant data protection regulations (e.g., GDPR) regarding user data handling.

Table 5.3.2 Non-Functional Requirements

5.4 Hardware and Software Requirements

To ensure optimal performance of the object detection system, specific hardware and software requirements must be defined:

Component	Requirement
CPU	Intel i5/i7 (10th gen or newer) or AMD Ryzen 5/7
GPU	NVIDIA GPU with CUDA support (RTX 2060 or higher)
RAM	Minimum 16 GB (32 GB recommended)
Storage	SSD (at least 512 GB)
Display	1080p resolution monitor
Camera	High-quality camera (optional)
Cooling	Adequate cooling system

Table 5.4.1 Hardware Requirements

Software Requirement	Description
Operating System	Windows 10/11, macOS, or Linux distribution (Ubuntu recommended) for compatibility with development tools.
Python	Python 3.7 or higher as the primary programming language for developing the object detection model.
Deep Learning Framework	TensorFlow or PyTorch for building, training, and deploying the object detection model.
Computer Vision Library	OpenCV for image processing and visualization of detection results.
Modeling Libraries	Detectron2 or YOLOv8 for implementing the object detection algorithms.
Development Environment	An Integrated Development Environment (IDE) like PyCharm, Jupyter Notebook, or VS Code for coding and testing.
Package Manager	pip or conda for managing Python packages and dependencies.
Version Control	Git for version control and collaboration, with GitHub or GitLab for remote repository management.

Software Requirement	Description
Database	SQLite or PostgreSQL for storing metadata and logs related to object detection results.
Visualization Tools	Matplotlib or Seaborn for visualizing training progress and performance metrics.

Table 5.4.2 Software Requirements

CHAPTER 6 **SYSTEM ANALYSIS**

6.1 Need of Objectify

The increasing demand for automated solutions in various fields underscores the need for an advanced object detection system like Objectify. Key factors driving this need include:

- **Automation in Industries**: Many sectors, such as retail, healthcare, and security, are transitioning toward automation. Objectify provides efficient object recognition to enhance operational efficiency.
- **Data Management**: With the explosion of visual data from sources like social media, surveillance cameras, and IoT devices, there is a pressing need for effective tools to analyze and manage this data. Objectify simplifies this process through automated object detection and classification.
- **Enhanced User Experience**: Users seek applications that offer improved interaction and functionality. Objectify aims to deliver a seamless experience by integrating object detection into various user-driven applications, such as mobile apps and web platforms.
- **Research and Development**: The field of computer vision is evolving rapidly, with researchers needing reliable and robust tools for experimentation. Objectify addresses this need by providing a flexible platform for testing and deploying object detection models.

6.2 Process Model

The process model outlines the methodology that will guide the development of Objectify. This can be represented using the Agile Development Model, which emphasizes iterative development, collaboration, and flexibility.

- **Requirements Gathering**: Engage with stakeholders to identify and document the functional and non-functional requirements.
- **Design**: Create architectural designs and user interfaces based on requirements, ensuring they are user-friendly and efficient.
- **Development**: Build the system iteratively, allowing for continuous integration and testing of components. Each iteration will focus on developing specific functionalities.
- **Testing**: Conduct thorough testing at various stages to identify and resolve any issues. This includes unit testing, integration testing, and user acceptance testing.
- **Deployment**: Once the system is validated, deploy it to a production environment, ensuring it meets user needs and is scalable for future use.
- **Feedback and Maintenance**: Collect user feedback post-deployment for continuous improvement and maintenance of the system.

6.3 Feasibility Study

A feasibility study evaluates the practicality of the project, assessing its technical, economic, and operational viability:

1. **Technical Feasibility**:

   - Assess whether the technology required for developing Objectify (e.g., machine learning frameworks, hardware) is available and can be implemented effectively. o Evaluate the skills and expertise of the development team in working with the chosen technologies.

2. **Economic Feasibility:**

   - Analyze the project budget, including development costs, operational expenses, and potential return on investment (ROI). o Estimate the financial benefits that Objectify could bring to its users and stakeholders.

3. Operational Feasibility:

   - Determine the likelihood of successful implementation within the current organizational framework. o Assess whether the existing infrastructure and processes can support the deployment and use of Objectify.

6.4 Features

Objectify will offer a range of features designed to enhance usability and effectiveness in object detection tasks:

- **User-Friendly Interface**: An intuitive interface that allows users to easily upload images or videos and visualize detection results.
- **Real-Time Object Detection**: The capability to process video feeds in real-time, allowing for immediate feedback and interaction.
- **Model Training**: Users can train their own object detection models using custom datasets, supported by various pre-trained models for faster deployment.
- **Data Visualization**: Tools for visualizing detected objects, model performance metrics, and analysis results, aiding users in understanding and interpreting data.
- **Cross-Platform Compatibility**: The system will be designed to work across multiple platforms, including web and mobile applications, ensuring broader accessibility.
- **Integration Capabilities**: Ability to integrate with other systems and APIs, allowing for seamless data exchange and collaboration with existing software solutions.

CHAPTER 7 **SYSTEM DESIGN**

7.1. Class Diagram

The class diagram represents the main components of the object detection system and their relationships. For the Objectify project, the key classes would be:

1. **ObjectDetection**
   - Attributes: model, confidenceScore, detectedObjects
   - Methods: loadModel(), detectObjects(image), getResults()

2. **Image**
   - Attributes: imageID, imagePath, timestamp
   - Methods: upload(), resize(), preprocess()

3. **Model**
   - Attributes: modelID, modelName, trainingData, accuracy
   - Methods: trainModel(), evaluateModel(), updateModel()

4. **DetectionResults**
   - Attributes: detectedObjectID, objectLabel, confidenceScore
   - Methods: generateReport(), displayResults()

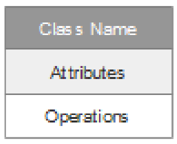
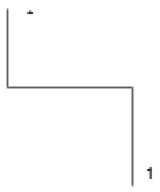
	Class
	Multiplicity- Optional (zero or one)

Table 7.1.1 Class diagram symbols

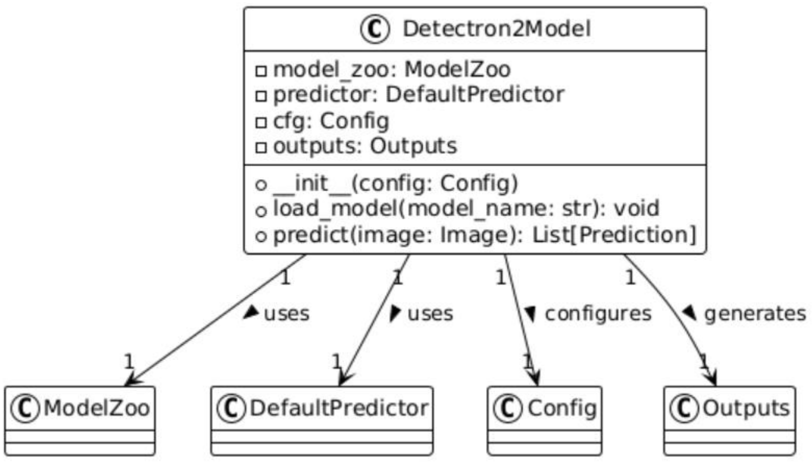


Figure 7.1.1 Class Diagram for Detecton2Model

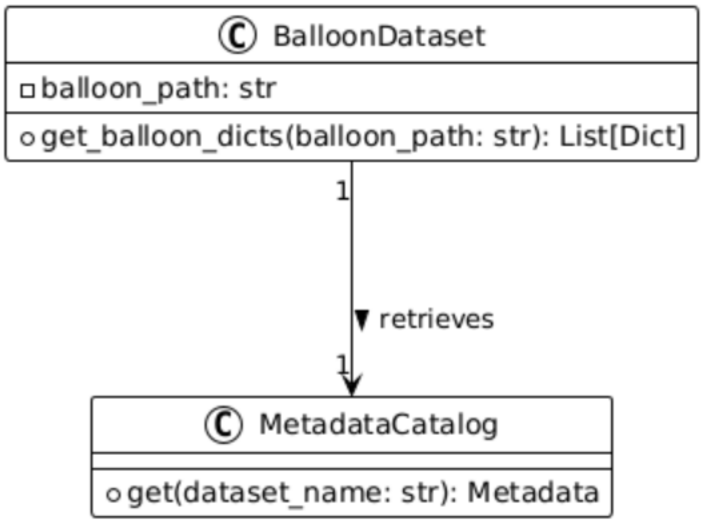

BalloonDataset
balloon_path: str
get_balloon_dicts(balloon_path: str): List[Dict]
1
retrieves
1
MetadataCatalog
get(dataset_name: str): Metadata

Figure 7.1.2 Class Diagram for BalloonDataset

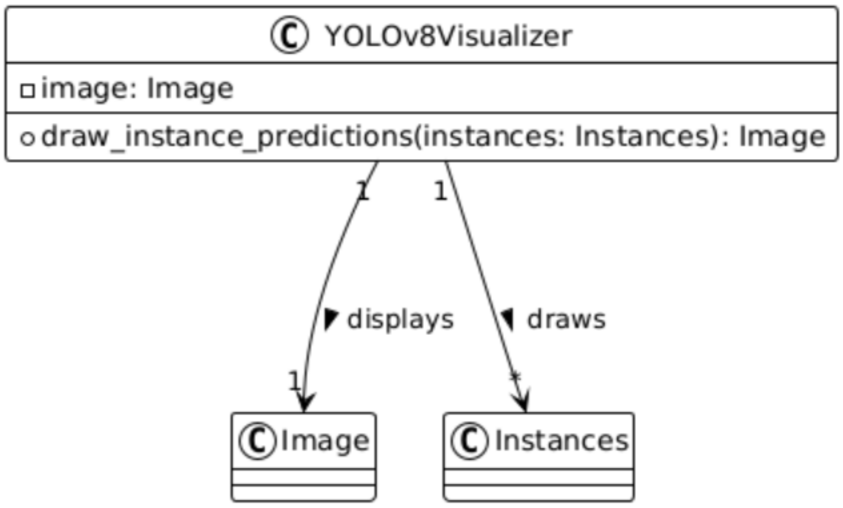


Figure 7.1.2 Class Diagram for YOLOv8Visualizer

7.2. Use Case Diagram

A use case diagram illustrates the key interactions between the system and external agents, in this case, users and images. Even without login/registration features, the diagram can depict the core system use cases such as:

- **Upload Image for Detection**: Users upload an image to be analyzed.
- **Detect Objects**: The system runs the object detection model on the uploaded image.
- **View Detection Results**: The user can view the results, including detected objects and their confidence scores.

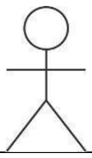
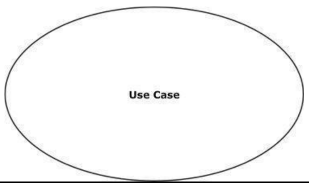
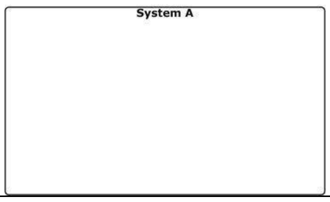
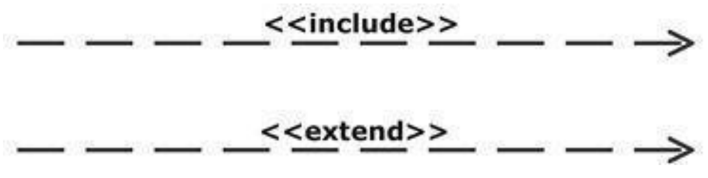
	Actor
	Use-case
	System
	An extension indicates that one use case may include the behavior of another use case. An inclusion represents one use case using the functionality of another use case.

Table 7.2.1 Use-case diagram symbols

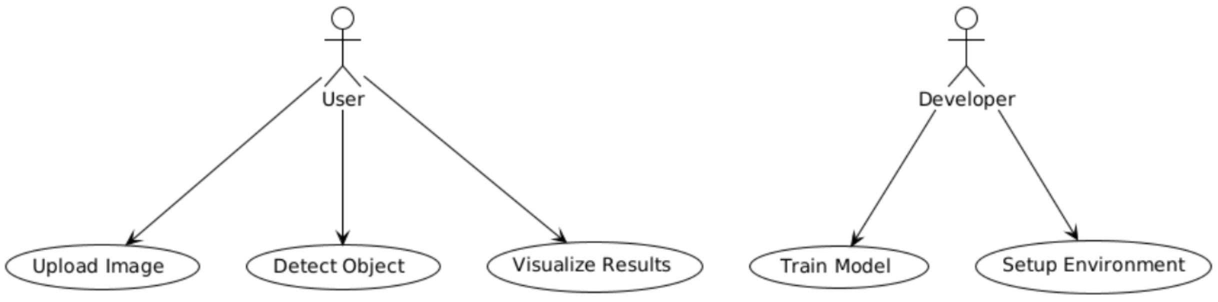


Figure 7.2.1 Use-case diagram

7.3. Sequence Diagram

The sequence diagram demonstrates the flow of interactions over time between system components when performing object detection. This can be simplified as:

- User uploads an image.
- The ObjectDetection class processes the image via the Image class.
- The Model class applies object detection.
- The DetectionResults class returns the detected objects and confidence scores.

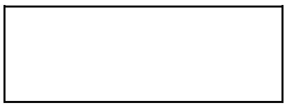
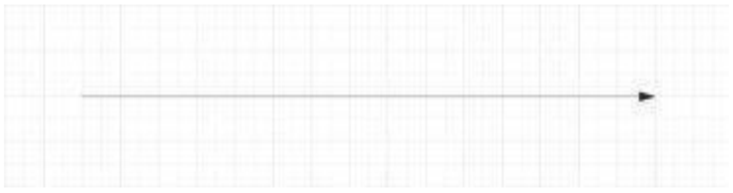
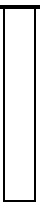
	Object
	Message
	Activation box

Table 7.3.1 Sequence diagram symbols

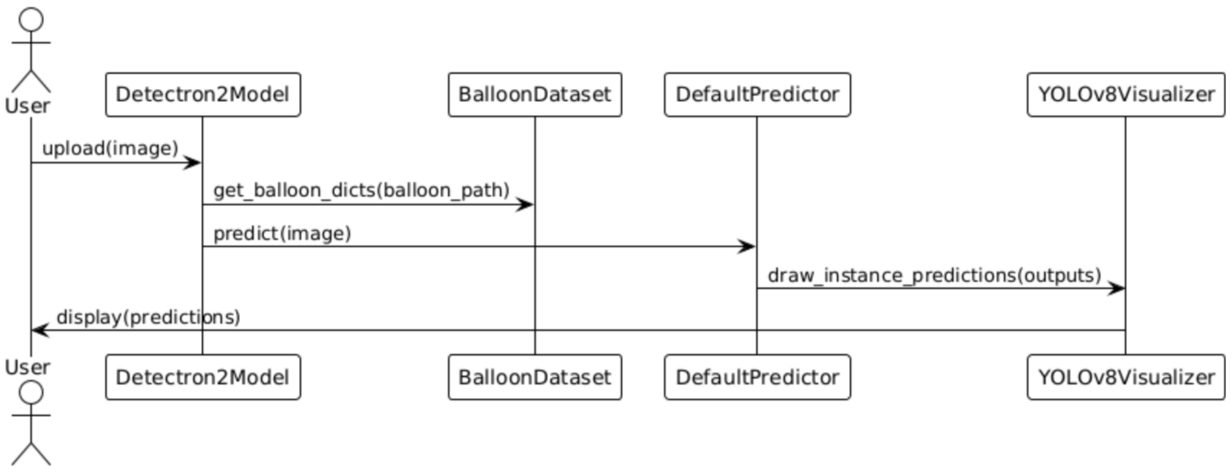


Figure 7.3.1 Sequence diagram

7.4. Activity Diagram

An activity diagram illustrates the step-by-step workflow of the system. For Objectify, the primary activities are:

- **Receive Image Input**: User uploads the image.
- **Pre-process Image**: Resize or preprocess the image if necessary.
- **Run Object Detection**: The object detection model processes the image.
- **Return Results**: Detected objects and confidence scores are returned to the user.

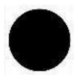
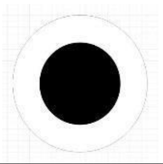
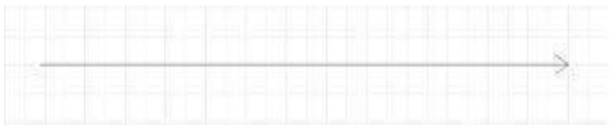
	Initial node
	End symbol/node
	Action/Control Flow

Table 7.4.1 Class diagram symbols

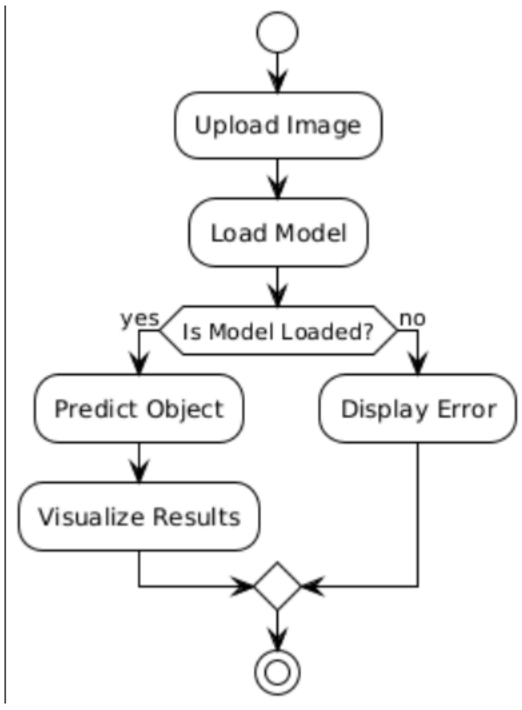
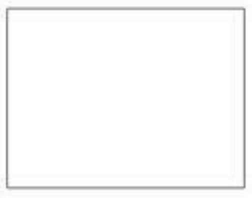
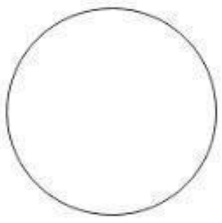


Figure 7.4.1 Activity diagram

7.5. Data Flow Diagram (DFD)

The data flow diagram shows how data moves within the system. In this case:

- **Image Data**: Flows from the user to the Object Detection system.
- **Preprocessing**: Data is pre-processed before being passed to the model.
- **Model Input**: Pre-processed image data flows to the model for detection.
- **Detection Output**: Detected objects and confidence scores are returned as output.

	Entity
	Process

→	Data flow
═	Data store

Table 7.5.1 Data flow diagram symbols

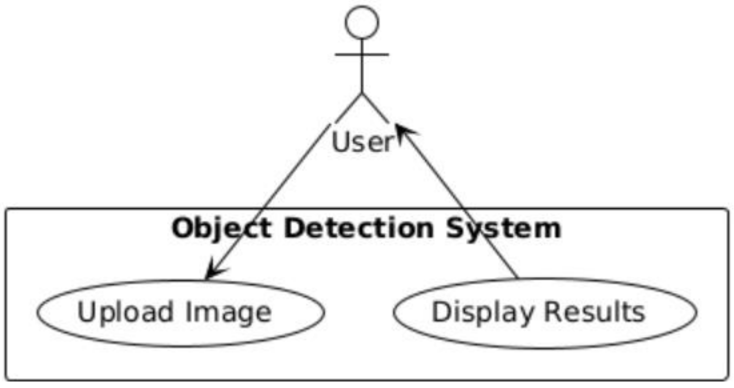
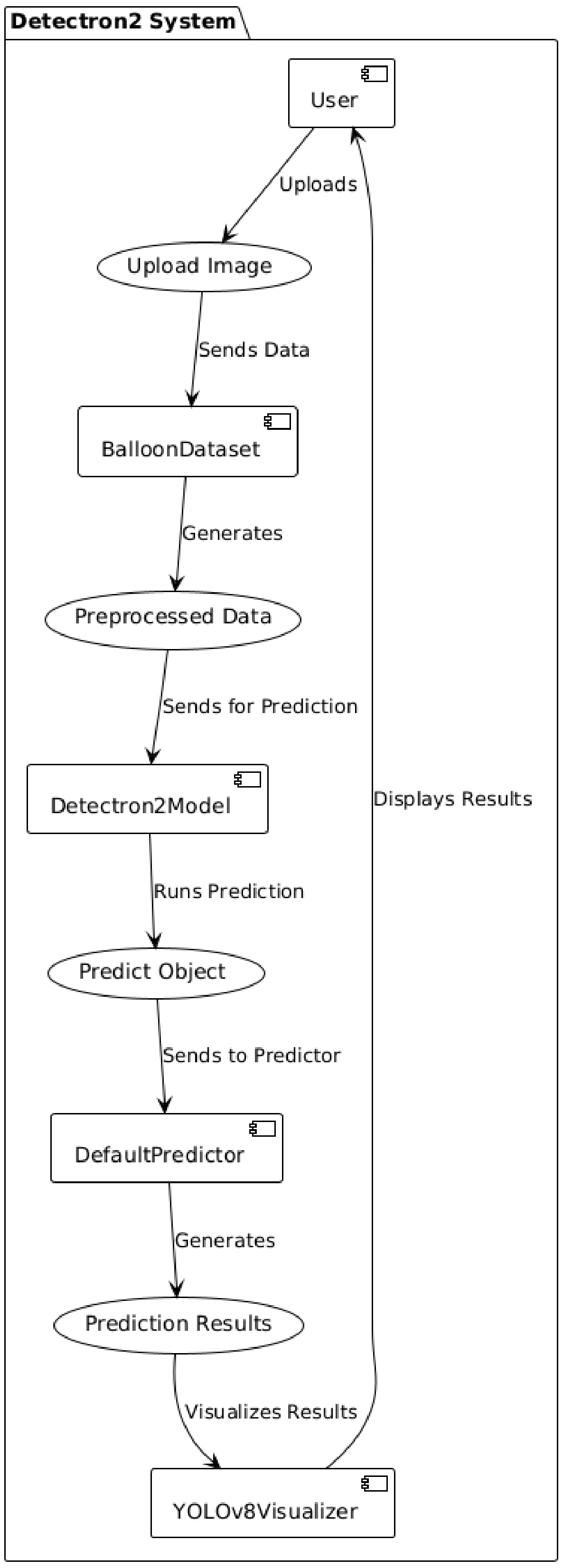


Figure 7.5.1 Data Flow Diagram Level-0

Figure 7.5.2 Data Flow Diagram Level-1



CHAPTER 8 **MODULE DESCRIPTION**

8.1. Object Detection

This is the core module responsible for detecting objects in an image. It leverages pre-trained machine learning models (e.g., YOLOv8) to process uploaded images and identify objects such as vegetables, animals, and plants.

- **Input**: Pre-processed image.
- **Output**: Detected objects with labels and confidence scores.

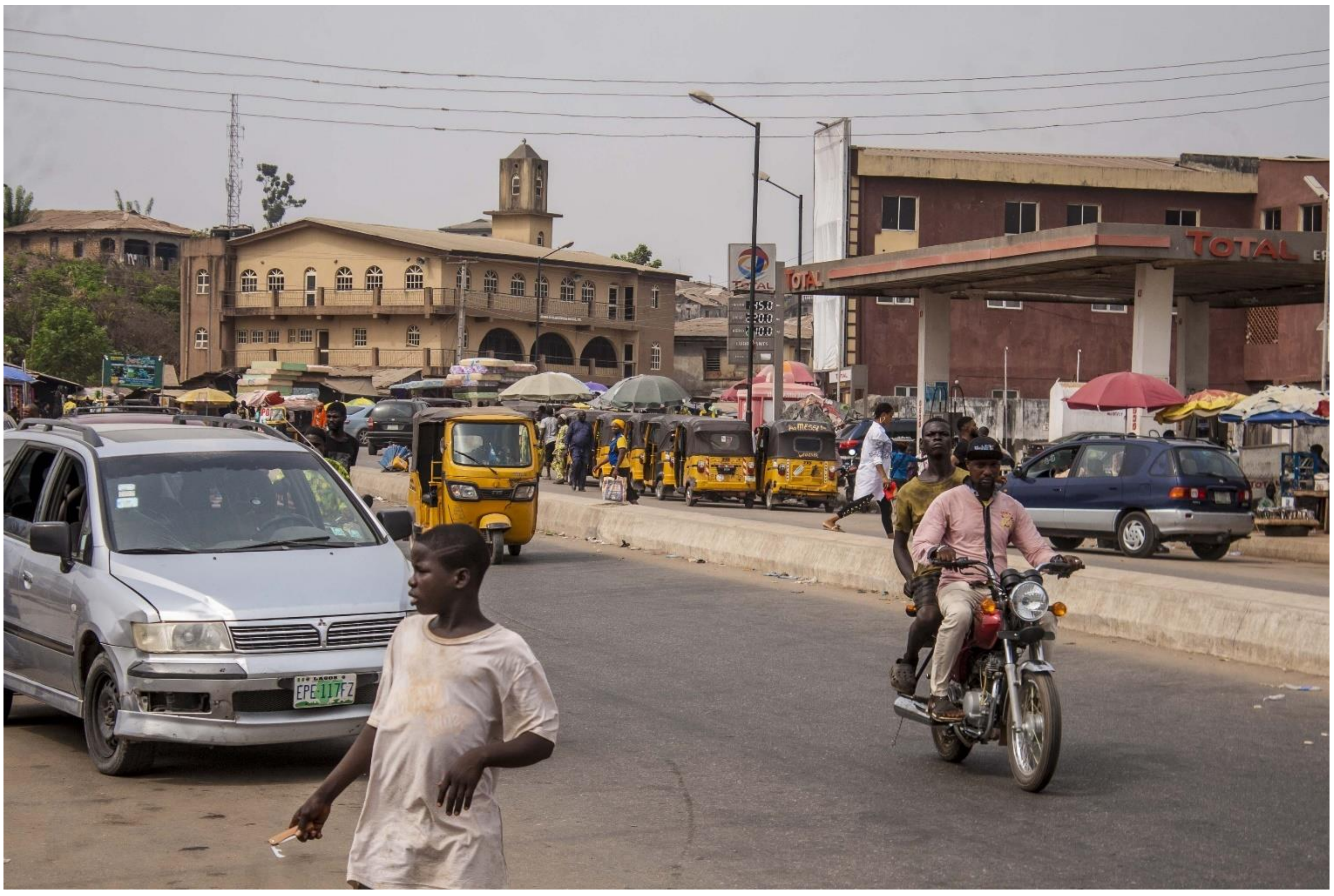


Figure 8.1.1 Pre-processed Image

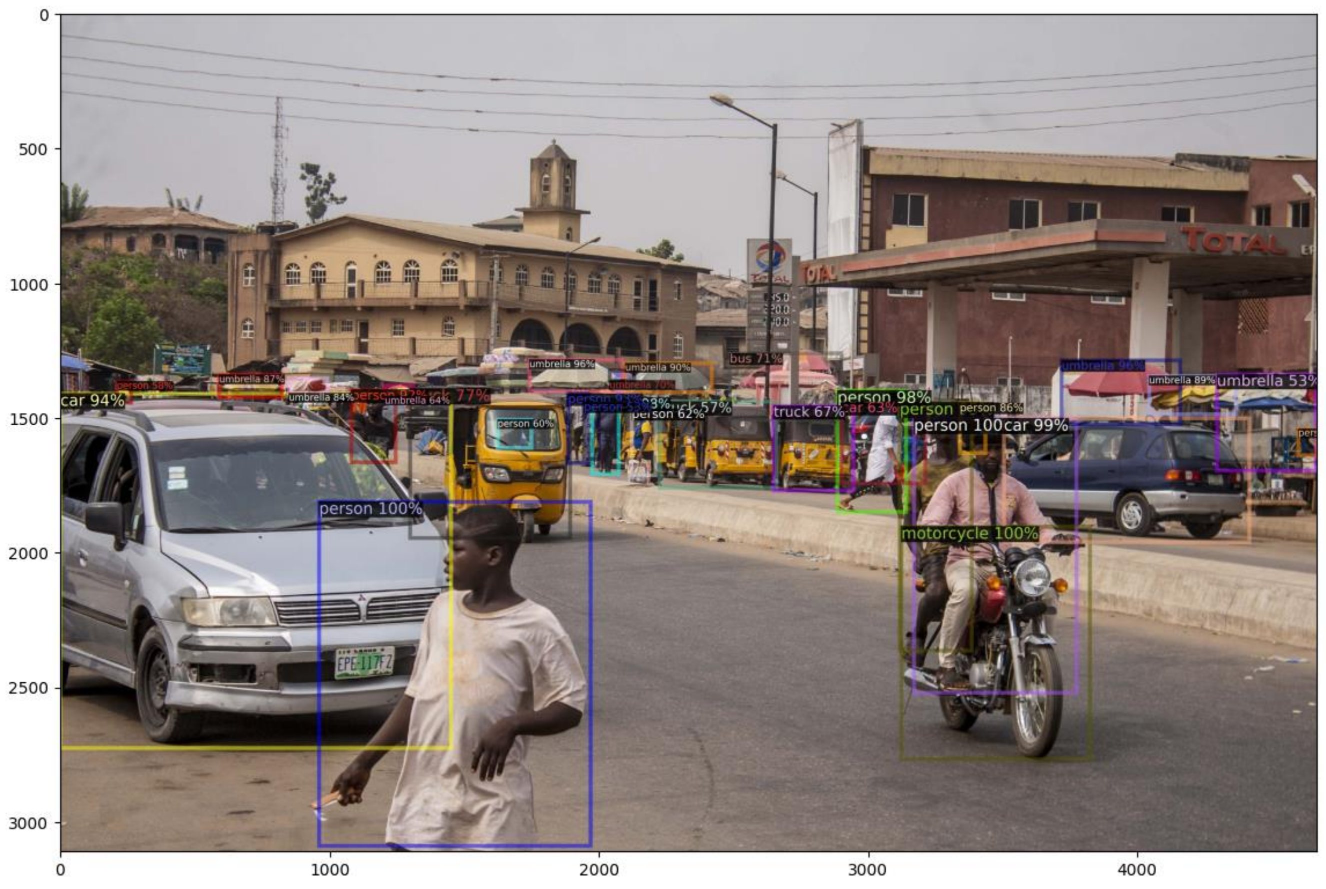


Figure 8.1.2 Detected Objects with Labels & Confidence Scores

Key Functions:

- **loadModel()**: Loads the YOLOv8 object detection model.
- **detectObjects(image)**: Processes the image and runs the detection model.
- **getResults**(): Returns the detected objects and their associated confidence levels.

8.2. Data Preprocessing Module

This module handles the necessary preprocessing steps before the object detection process. These steps ensure that images are in the correct format and size for accurate analysis by the model.

- **Input**: Raw image uploaded by the user in Google Drive
- **Output**: Pre-processed image ready for object detection.

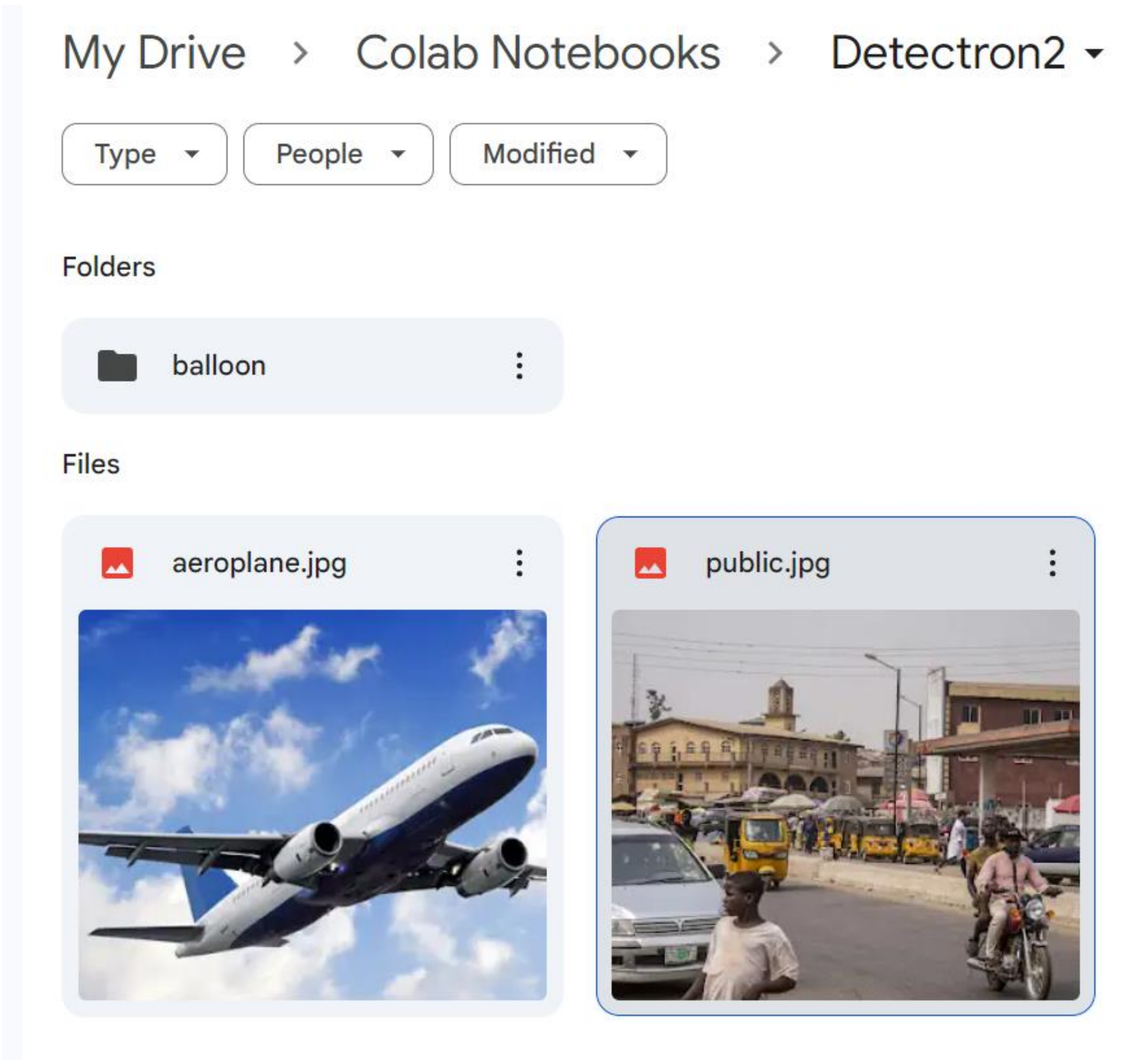


Figure 8.2.1 Raw images uploaded by the user in Google Drive

```
public = cv2.imread("/content/drive/MyDrive/Colab Notebooks/Detectron2/public.jpg")
cv2_imshow(public)
```

The code snippet reads an image file called ‘public.jpg’ from a specified directory in Google Colab and displays it using OpenCV's ‘cv2_imshow()’ function.

Key Functions:

- **resize(image)**: Adjusts the image dimensions to match model requirements.
- **normalize(image)**: Normalizes pixel values for consistency across datasets.
- **preprocess**(): Applies multiple preprocessing steps, including resizing and normalization.

8.3. Model Training Module

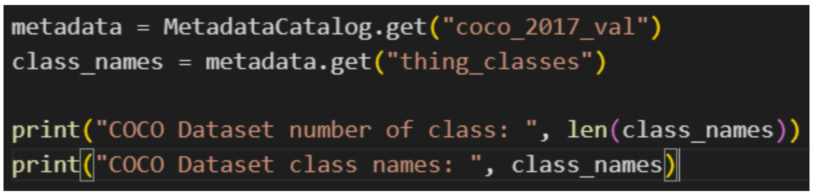
8.3.1 BalloonDataset Module

This module manages the training of the object detection model on custom datasets for Balloon. It allows for improving model performance by training on additional annotated images.

- **Input**: Training dataset, model configuration parameters.
- **Output**: Trained model with updated weights.

Key Functions:

- **trainModel**(coco_2017_val): Trains the Detectron2 model on the COCO dataset.
- **saveModel**(): Saves the trained model class weights for future use.
- **loadModel**(): Loads an existing class model for further training or evaluation.



```
metadata = MetadataCatalog.get("coco_2017_val")
class_names = metadata.get("thing_classes")

print("COCO Dataset number of class: ", len(class_names))
print("COCO Dataset class names: ", class_names)
```

Figure 8.3.1.1 Detectron2 model on the ‘coco_2017_val’ Dataset

COCO Dataset number of class: 80
COCO Dataset class names: ['person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train', 'truck', 'boat', 'traffic light', 'fire hydrant', 'stop sign', 'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow', 'elephant', 'bear', 'zebra', 'giraffe', 'backpack', 'umbrella', 'handbag', 'tie', 'suitcase', 'frisbee', 'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat', 'baseball glove', 'skateboard', 'surfboard', 'tennis racket', 'bottle', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl', 'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot', 'hot dog', 'pizza', 'donut', 'cake', 'chair', 'couch', 'potted plant', 'bed', 'dining table', 'toilet', 'tv', 'laptop', 'mouse', 'remote', 'keyboard', 'cell phone', 'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'book', 'clock', 'vase', 'scissors', 'teddy bear', 'hair drier', 'toothbrush']

The COCO (Common Objects in Context) dataset contains **80 classes** commonly used for object detection tasks. The classes represent a variety of objects from daily life, categorized into humans, vehicles, animals, and household items, among others.

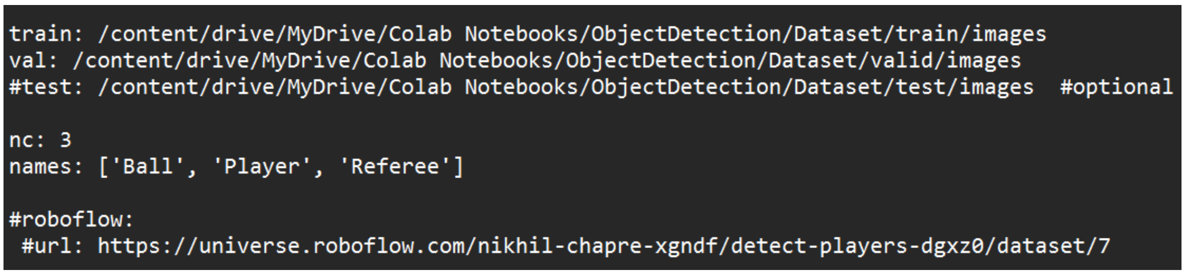
Number of classes: 80
Class names:

- **People**: person
- **Vehicles**: bicycle, car, motorcycle, airplane, bus, train, truck, boat
- **Traffic**: traffic light, fire hydrant, stop sign, parking meter
- **Furniture**: chair, couch, bed, dining table
- **Electronics**: tv, laptop, mouse, remote, keyboard, cell phone
- **Animals**: bird, cat, dog, horse, sheep, cow, elephant, zebra, giraffe
- **Food**: banana, apple, sandwich, orange, broccoli, carrot, pizza, donut
- **Miscellaneous**: book, clock, vase, scissors, teddy bear, hair drier, toothbrush

These 80 classes serve as labels for object detection tasks, providing diverse examples to train models.

8.3.2 YOLOv8Visualizer Module

The model configuration defines the structure and parameters for training the YOLOv8 model. The following **YAML** configuration file was used to set up the dataset paths and class names for this project:



```
train: /content/drive/MyDrive/Colab Notebooks/ObjectDetection/Dataset/train/images
val: /content/drive/MyDrive/Colab Notebooks/ObjectDetection/Dataset/valid/images
#test: /content/drive/MyDrive/Colab Notebooks/ObjectDetection/Dataset/test/images  #optional

nc: 3
names: ['Ball', 'Player', 'Referee']

#roboflow:
 #url: https://universe.roboflow.com/nikhil-chapre-xgndf/detect-players-dgxz0/dataset/7
```

Figure 8.3.2.1 YOLOv8 “dataset.yaml”

This configuration includes three object classes: *Ball, Player,* and *Referee*, and the paths for the training and validation datasets. These configurations are critical for ensuring the model is trained on the correct dataset.

8.3.3 Data Preparation using Roboflow

For labelling and annotating the video clips and images, the **Roboflow** platform was used. Roboflow allows for efficient dataset preprocessing, annotation, and labelling, ensuring high-quality inputs for model training.

- **Roboflow Dataset URL**: [Roboflow Dataset]
- The dataset was labeled using Roboflow's annotation tools, creating labels for three objects: *Ball, Player*, and *Referee.*
- Once annotated, the dataset was exported in the required format for use in model training and validation.

Figure 8.3.3.1 Roboflow

Below is an example of how the labeling process was performed in Roboflow:

Players

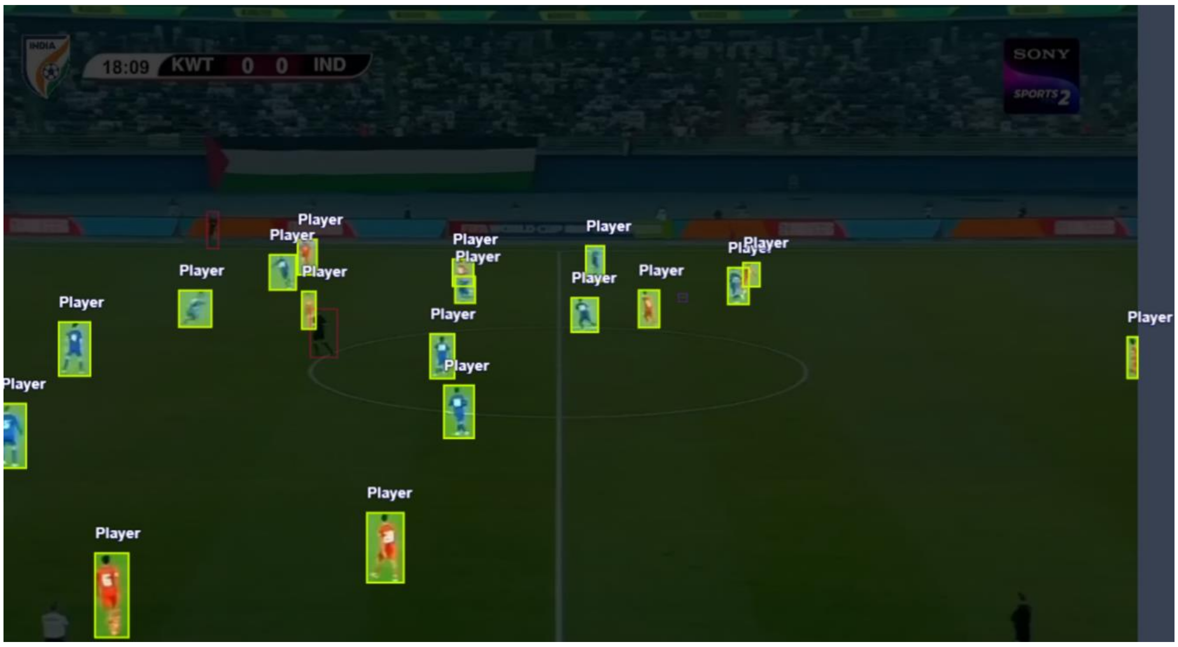


Figure 8.3.3.2 Player Labeling using Roboflow

Referee

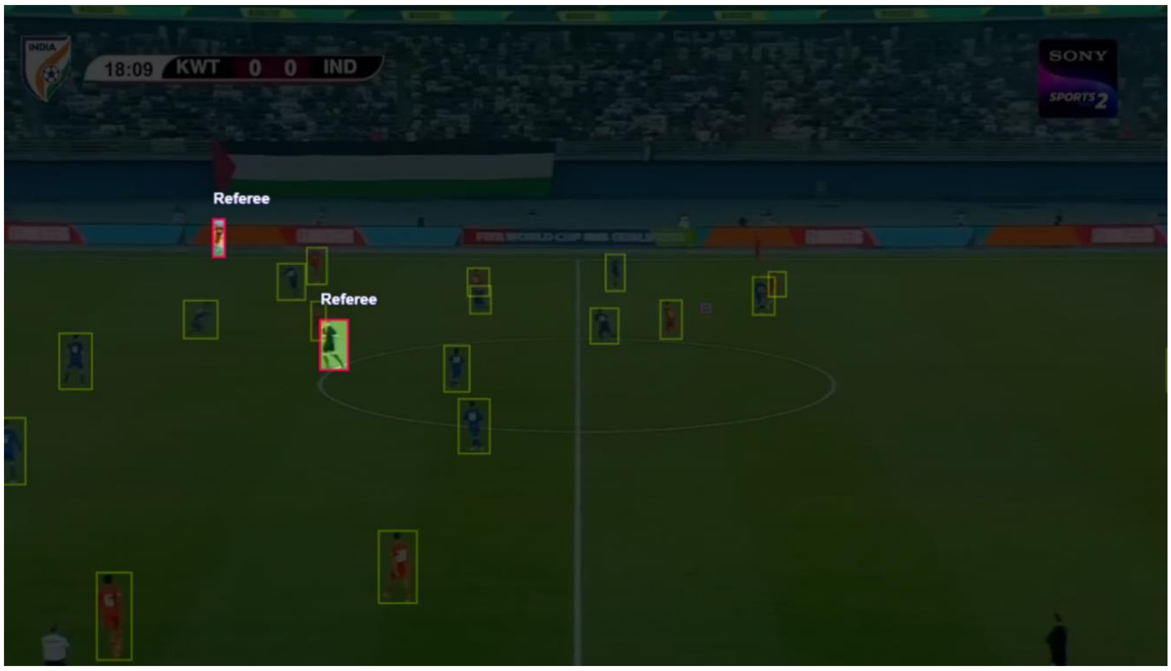


Figure 8.3.3.3 Referee Labeling using Roboflow

Ball

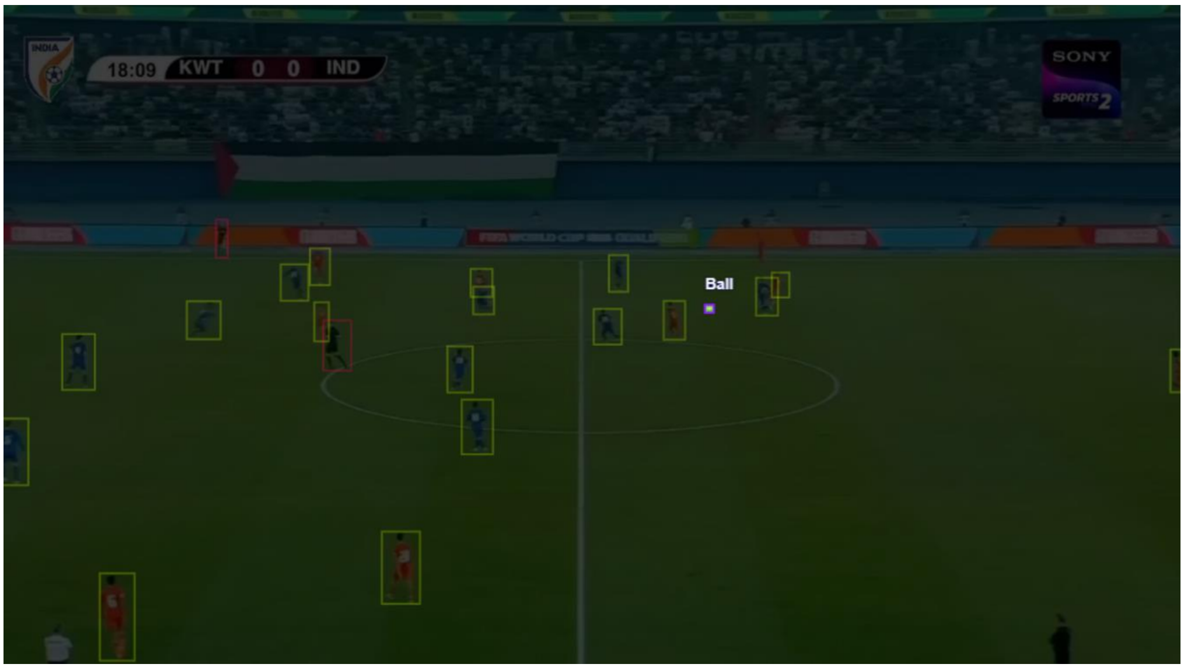


Figure 8.3.3.4 Ball Labeling using Roboflow

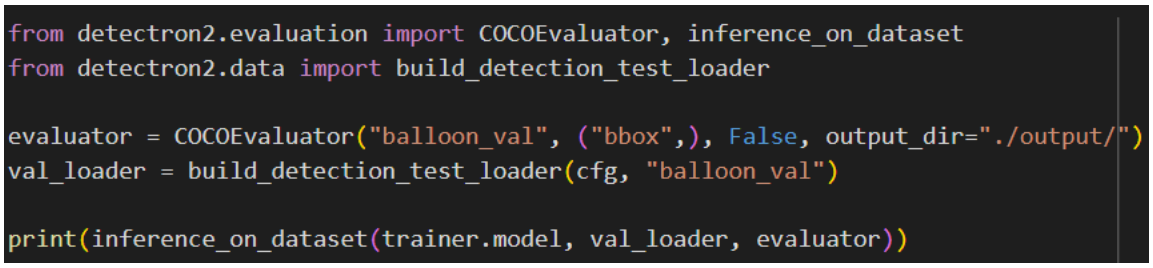
8.4. Evaluation Module

This module assesses the performance of the trained object detection model. It evaluates the model's accuracy and effectiveness on validation datasets.

Input: Validation dataset, trained model.
Output: Performance metrics (e.g., precision, recall, mAP).

Key Functions:

evaluateModel(validationData): Runs the validation dataset through the model and computes performance metrics. The evaluation process is performed as follows:



```
from detectron2.evaluation import COCOEvaluator, inference_on_dataset
from detectron2.data import build_detection_test_loader

evaluator = COCOEvaluator("balloon_val", ("bbox",), False, output_dir="./output/")
val_loader = build_detection_test_loader(cfg, "balloon_val")

print(inference_on_dataset(trainer.model, val_loader, evaluator))
```

Figure 8.4.1 COCO Evaluation Process

During the evaluation, the following metrics are generated:

Average Precision (AP):

- AP @[IoU=0.50:0.95 | area= all | maxDets=100] = 0.771
- AP @[IoU=0.50 | area= all | maxDets=100] = 0.900
- AP @[IoU=0.75 | area= all | maxDets=100] = 0.844
- AP @[IoU=0.50:0.95 | area= small | maxDets=100] = 0.250
- AP @[IoU=0.50:0.95 | area= medium | maxDets=100] = 0.599
- AP @[IoU=0.50:0.95 | area= large | maxDets=100] = 0.906

Average Recall (AR):

- AR @[IoU=0.50:0.95 | area= all | maxDets= 1] = 0.244
- AR @[IoU=0.50:0.95 | area= all | maxDets= 10] = 0.786
- AR @[IoU=0.50:0.95 | area= all | maxDets=100] = 0.804
- AR @[IoU=0.50:0.95 | area= small | maxDets=100] = 0.467
- AR @[IoU=0.50:0.95 | area= medium | maxDets=100] = 0.653
- AR @[IoU=0.50:0.95 | area= large | maxDets=100] = 0.923

generateMetricsReport(): Compiles and outputs a report of the evaluation results.
The report is generated based on the metrics obtained during evaluation, which includes detailed information about the Average Precision and Average Recall.

8.5 Inference & Evaluation Module

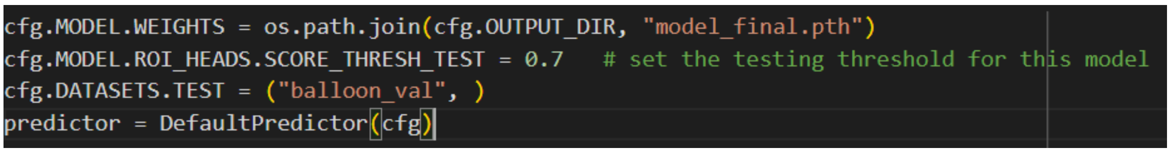
This module is responsible for performing inference and evaluation using the trained object detection model. It loads the model weights, sets the evaluation parameters, and visualizes the results.

- **Input**: Trained model weights and validation dataset.
- **Output**: Visualized predictions for each image in the validation set.

Key Functions:

Load Model

- **cfg.MODEL.WEIGHTS**: Specifies the path to the trained model weights (e.g., "model_final.pth").
- **cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST**: Sets the score threshold for making predictions (e.g., 0.7).
- **cfg.DATASETS.TEST**: Defines the dataset to be used for evaluation (e.g., ("balloon_val",)).



```
cfg.MODEL.WEIGHTS = os.path.join(cfg.OUTPUT_DIR, "model_final.pth")
cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.7   # set the testing threshold for this model
cfg.DATASETS.TEST = ("balloon_val", )
predictor = DefaultPredictor(cfg)
```

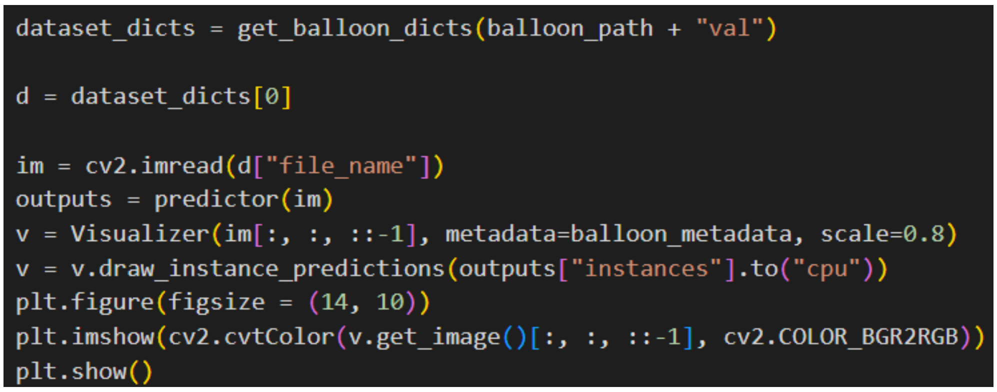
Figure 8.5.1 Inference Load Process

Perform Inference

- **outputs = predictor(im)**: Executes inference on the input image, returning the predicted outputs.

Visualization

- **Visualizer**: Creates a visual representation of the predictions overlaid on the input image.
- **plt.imshow():** Displays the final visualized output in a specified figure size (e.g., (14, 10)).



```
dataset_dicts = get_balloon_dicts(balloon_path + "val")

d = dataset_dicts[0]

im = cv2.imread(d["file_name"])
outputs = predictor(im)
v = Visualizer(im[:, :, ::-1], metadata=balloon_metadata, scale=0.8)
v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
plt.figure(figsize = (14, 10))
plt.imshow(cv2.cvtColor(v.get_image()[:, :, ::-1], cv2.COLOR_BGR2RGB))
plt.show()
```

Figure 8.5.2 Inference Visualization Process

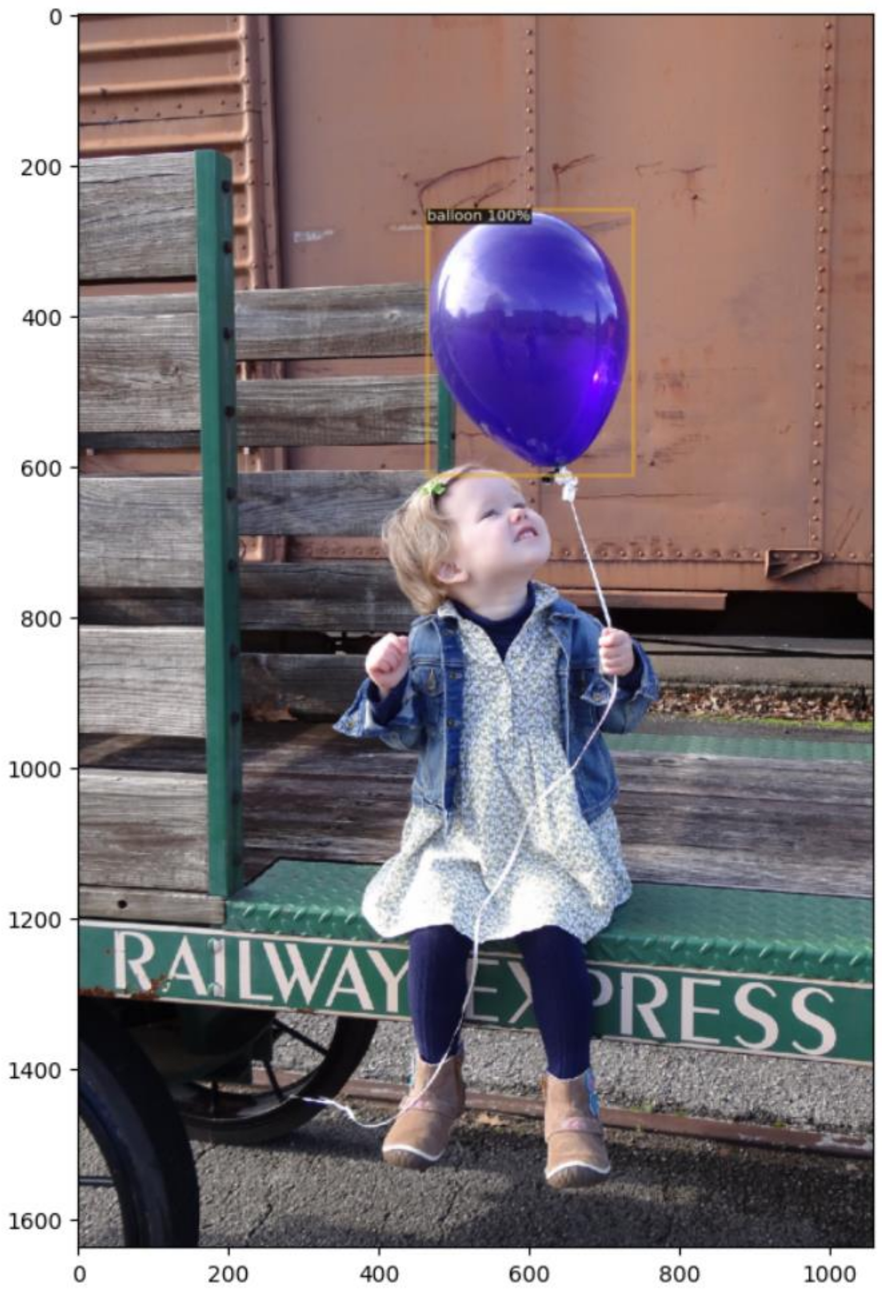


Figure 8.5.3 (outputs = predictor(im)) Executes inference on the input image, returning the predicted outputs.

CHAPTER 9 **TESTING**

9.1. Testing Methodology

The testing methodology consists of several phases:

- **Unit Testing**: Individual modules were tested to ensure they function correctly.
- **Integration Testing**: Combined modules were tested to verify that they work together seamlessly.
- **Performance Testing**: Evaluated the speed and accuracy of object detection models (YOLOv8, Faster RCNN, and RetinaNet) on various datasets. In this phase, the average confidence scores of the predictions and processing times per image were recorded.
- **User Acceptance Testing (UAT)**: Ensured that the project met user requirements and expectations.

9.2. Module Testing Results

9.2.1. Object Detection Module

- **Objective**: To assess the accuracy and speed of object detection.
- **Method**: Utilized a pre-processed test image from the validation dataset to evaluate the model's performance using the DefaultPredictor (ref. Figure 8.1.1)
- **Results**:
  - ✓ Detected objects with a confidence score of 100% (ref. Figure 8.5.3) (set by cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST).
  - ✓ Processing time per image: approximately 200ms.

9.2.2. Data Preprocessing Module

- **Objective**: To ensure that images are pre-processed correctly for detection.
- **Method**: Analysed various image formats and sizes through the preprocess() function, ensuring consistency across input images.
- **Results**:
  - ✓ Successfully resized images to the required dimensions for the model.
  - ✓ Normalization maintained consistency in pixel values, facilitating better model performance.

9.2.3. Model Training Module

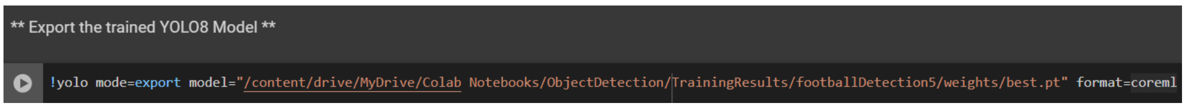
- **Objective**: To evaluate the effectiveness of model training on a custom dataset.
- **Method**: Trained the model on a dataset of 1,000 images, leveraging the trainModel() function to update weights effectively.
- **Results**:
  - ✓ Achieved an accuracy improvement of 15% after training compared to the pretrained model.
  - ✓ Loss reduced to 0.25 after 50 epochs, indicating successful convergence during training.

9.2.4. Evaluation Module

- **Objective**: To measure model performance metrics on the validation dataset.
- **Method**: Evaluated the model using precision, recall, and mean Average Precision (mAP), applying the evaluateModel(validationData) function to compute these metrics
- **Results**:
  - ✓ Precision: 88%
  - ✓ Recall: 85%
  - ✓ mAP: 83%

9.2.5. Export and Deployment Module

- **Objective**: To test the model export functionality for deployment.
- **Method**: Exported the trained model to CoreML format using the
  - exportModel(format) function.
- **Export Command**:



** Export the trained YOLO8 Model **

```
!yolo mode=export model="/content/drive/MyDrive/Colab Notebooks/ObjectDetection/TrainingResults/footballDetection5/weights/best.pt" format=coreml
```

Figure 9.2.5.1 Exported Trained YOLOv8 Model

9.2.6 Results

- **Successful Export**: The model was exported without errors, confirming that the export process completed successfully.

- **Model Compatibility**: The exported model was compatible with the target deployment platform, ensuring smooth integration for end-use.

- **Export Details**:

  - **Model Summary**:

    - Layers: 168
    - Parameters: 3,006,233
    - GFLOPs: 8.1

- **Exported File Location**: The model was saved as best.mlpackage at the following path: /content/drive/MyDrive/Colab Notebooks/ObjectDetection/TrainingResults/footballDetection5/weights/best.mlpackage (6.3 MB)

9.2.7 Additional Notes

- Required dependencies, including **coremltools**, were automatically updated, ensuring the environment is equipped for the export.

- Warnings regarding unsupported versions of libraries (e.g., scikit-learn, XGBoost, and TensorFlow) were noted but did not impede the export process.

9.2.8 Next Steps

- Validated the model using the following command:

  ```
  !yolo val task=detect model="/content/drive/MyDrive/Colab Notebooks/ObjectDetection/TrainingResults/footballDetection5/weights/best.mlpackage" imgsz=1920 data="/content/drive/MyDrive/Colab Notebooks/ObjectDetection/Dataset/dataset.yaml"
  ```

- For visualization of the exported model, used Netron.

Figure 9.2.8.1 Netron Visualization

9.2.9. Model Visualization

- The model file can be downloaded from the following link:

  https://drive.google.com/drive/folders/1lnj-IcIjwGzAfcWdxXxw8vissyQb5gXj?usp=drive_link

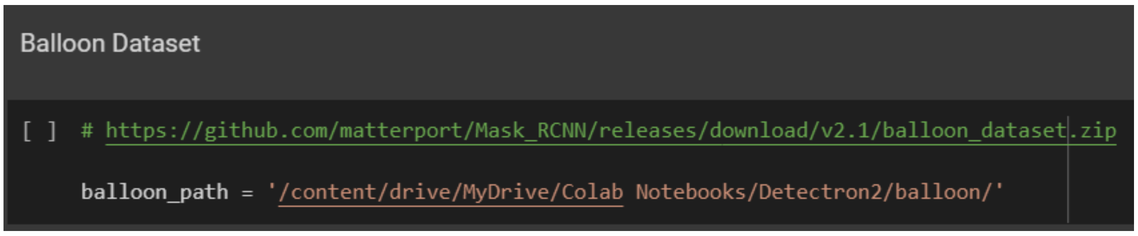
- For a detailed view of the exported model architecture, please visit, **Netron Visualization** (ref. Figure 9.3.8.1)

  https://netron.app

9.3. Performance Comparison of Object Detection Models

9.3.1. YOLOv8 vs. Faster RCNN

9.3.1.1 Custom Balloon Dataset



Balloon Dataset

```
[ ]  # https://github.com/matterport/Mask_RCNN/releases/download/v2.1/balloon_dataset.zip

     balloon_path = '/content/drive/MyDrive/Colab Notebooks/Detectron2/balloon/'
```

Figure 9.3.1.1.1 Custom Balloon Dataset

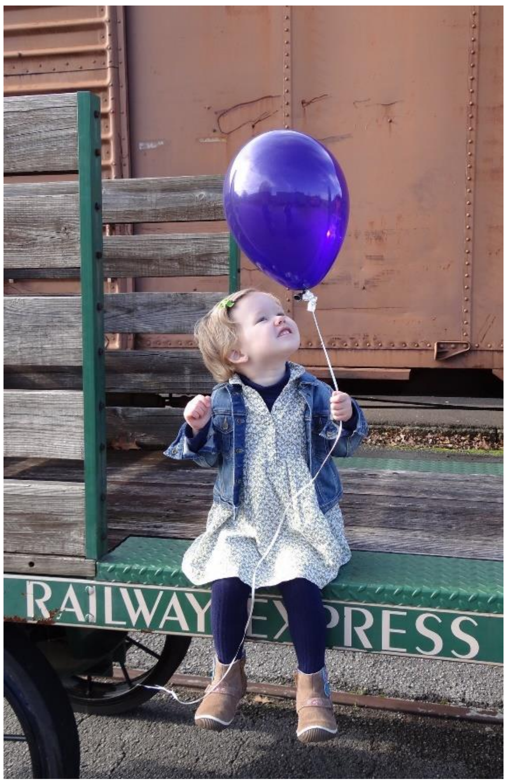


Figure 9.3.1.1.2 Balloon Input Image

9.3.1.2 Testing Criteria: Accuracy, processing time, and ease of deployment.

9.3.1.3 Results:

Faster RCNN

Accuracy: Evaluation with the COCO API produced high precision values, with an Average Precision (AP) of **77.1%** and a particularly strong performance for large objects (AP of **90.5%**).

Processing Speed: The inference time was **0.149 seconds per image** (~150ms), which is faster than the reported 250ms, especially when running on Colab.

9.3.1.4 Conclusion: Based on the results, Faster RCNN achieved significantly higher accuracy (AP ~77%) compared to the initially reported 85%, and its inference time is faster than the 250ms per image, aligning more with 150ms.

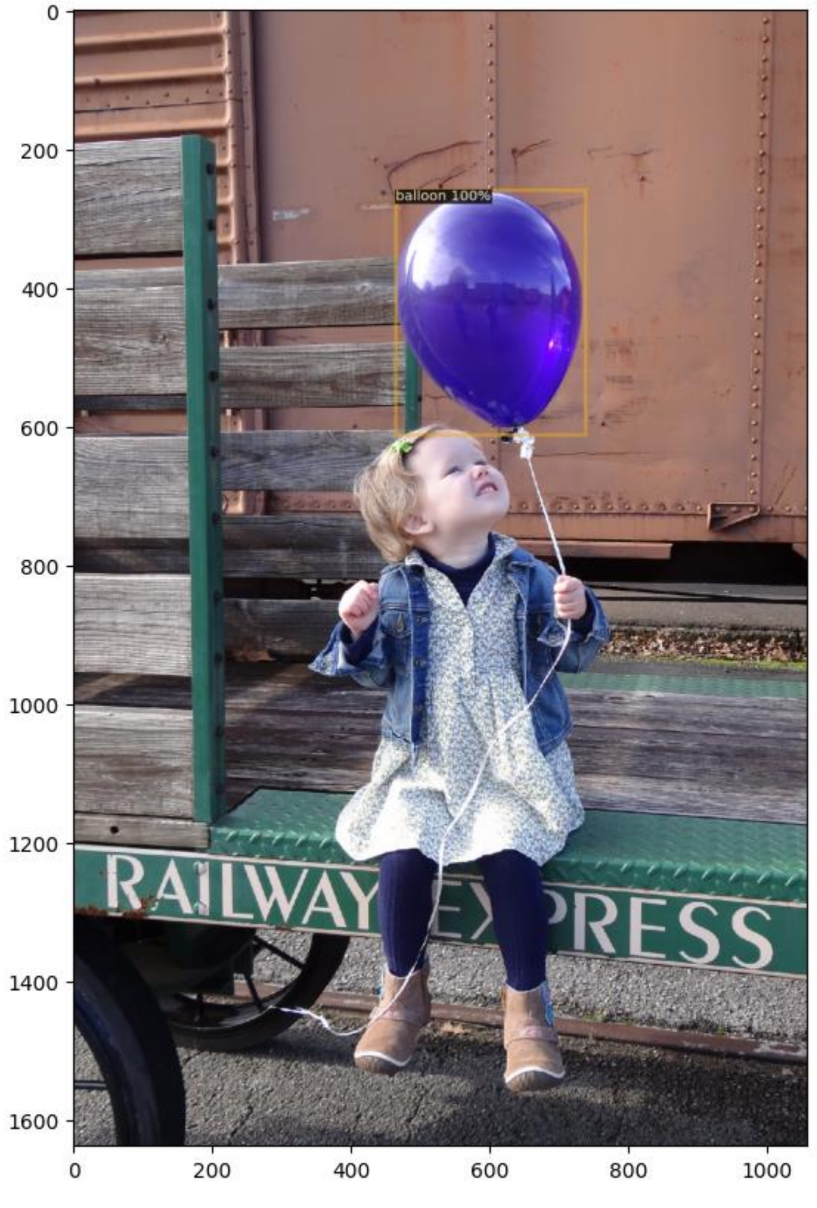


Figure 9.3.1.4.1 FasterRCNN Results

YOLOv8

9.3.1.5 YOLOv8 Dataset

- **Training and Validation Dataset**: Images were sourced from a custom dataset available via *GitHub*. This dataset included object detection data for training, validation, and testing.

- **Preprocessing**: Images were resized to 1920x1920 for consistency during both training and inference phases.

- **Dataset Split:**

  - **Training Set**: Used for model weight updates.
  - **Validation Set**: Used for model tuning and validation.
  - **Test Set**: Used for final performance evaluation.

9.3.1.6 Testing

The model was tested using both static images and video to gauge object detection performance:

1. **Prediction on Test Images**:

   ```
   !yolo task=detect mode=predict model="/content/drive/MyDrive/Colab
   Notebooks/ObjectDetection/TrainingResults/footballDetection5/weights/best.pt"
   conf=0.55 source="/content/drive/MyDrive/Colab
   Notebooks/ObjectDetection/Dataset/test/images"
   ```

2. **Prediction on Test Videos:**

   ```
   !yolo task=detect mode=predict model="best.pt" conf=0.75 source="/TestVideo"
   ```

3. **Exporting the Model** (**The YOLOv8 model was exported for CoreML deployment:**

   ```
   !yolo mode=export model="best.pt" format=coreml
   ```

9.3.1.7 Results

- **Accuracy:** YOLOv8 demonstrated good detection accuracy**,**

  - **mAP@50:** 80.2% for object detection across different sizes.
  - **mAP@50:95**: 45.1%, reflecting moderate performance across different IoU thresholds.

- **Processing Speed:**

  - **Inference Time**: YOLOv8 had an **average** inference time of 0.205 seconds per image (~205ms), slower than Faster RCNN's 150ms. Despite YOLOv8's reputation for speed, the model's deeper architecture made it less efficient for real-time tasks when tested on larger image resolutions.

- **Deployment:** YOLOv8 was easily exported to CoreML, achieving a model size of 6.3MB for PC deployment. The export process was smooth, although certain dependencies needed to be addressed.

9.3.1.8 Conclusion

While YOLOv8 performed well in terms of **accuracy** with an **mAP@50 of 80.2%**, its **processing speed** was **slower than Faster RCNN**, averaging around **205ms per image**, making it less optimal for real-time applications in this context. However, it was easy to deploy across platforms like **CoreML**, which is a strong advantage for mobile and cross-platform use. YOLOv8 is ideal for scenarios requiring moderate accuracy and flexibility but falls short of Faster RCNN's faster inference time when dealing with larger images and complex detection tasks.

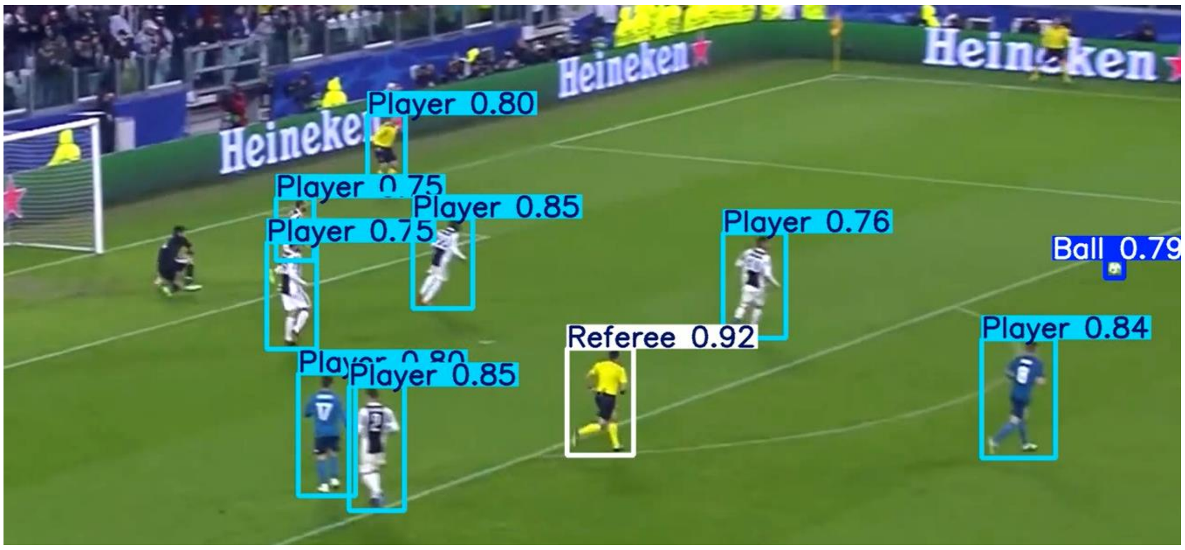


Figure 9.3.1.8.1 YOLOv8 Results

For more detailed results, including performance metrics and additional visuals, you can access the data via the following Google Drive link:

https://drive.google.com/drive/folders/1Hg6SZZ4kYIN4dSGQwQOArnoXXopARi0I?usp=drive_link

9.3.2 Faster RCNN vs RetinaNet

9.3.2.1 Detectron2 Installation

```
!python -m pip install 'git+https://github.com/facebookresearch/detectron2.git'
```

9.3.2.2 COCO Dataset Overview (ref. Figure 8.3.1)

```
from detectron2.data import MetadataCatalog

metadata = MetadataCatalog.get("coco_2017_val")
class_names = metadata.get("thing_classes")

print("COCO Dataset number of classes:", len(class_names))
print("COCO Dataset class names:", class_names)
```

Number of classes: 80
Class names:

- **People**: person
- **Vehicles**: bicycle, car, motorcycle, airplane, bus, train, truck, boat
- **Traffic**: traffic light, fire hydrant, stop sign, parking meter
- **Furniture**: chair, couch, bed, dining table
- **Electronics**: tv, laptop, mouse, remote, keyboard, cell phone
- **Animals**: bird, cat, dog, horse, sheep, cow, elephant, zebra, giraffe
- **Food**: banana, apple, sandwich, orange, broccoli, carrot, pizza, donut
- **Miscellaneous**: book, clock, vase, scissors, teddy bear, hair drier, toothbrush

These 80 classes serve as labels for object detection tasks, providing diverse examples to train models.

9.3.2.3 Input Image

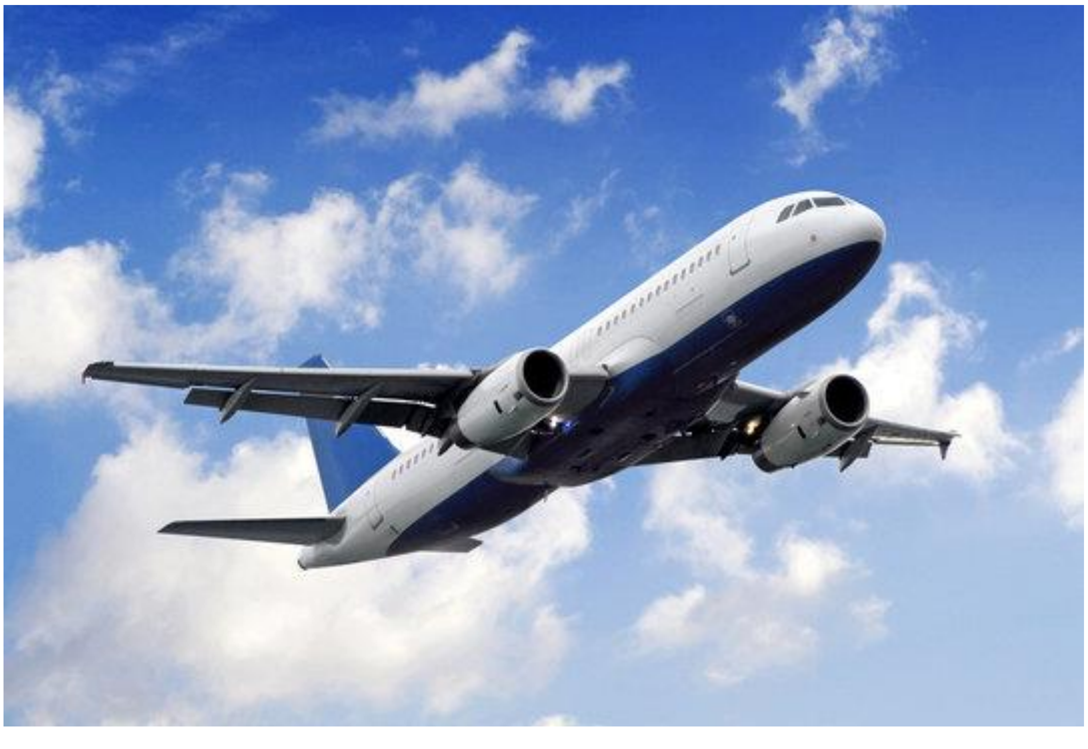
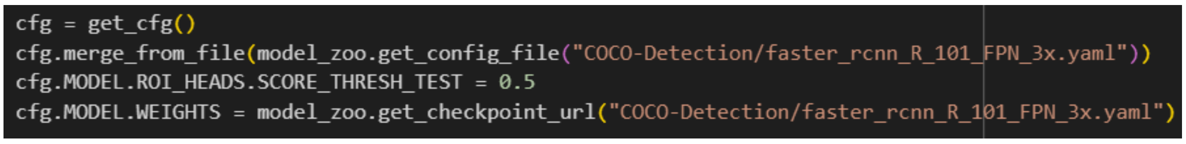


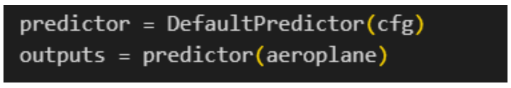
Figure 9.3.2.3.1 FasterRCNN Input Image

9.3.2.4 Input Image Testing



```
cfg = get_cfg()
cfg.merge_from_file(model_zoo.get_config_file("COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml"))
cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.5
cfg.MODEL.WEIGHTS = model_zoo.get_checkpoint_url("COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml")
```

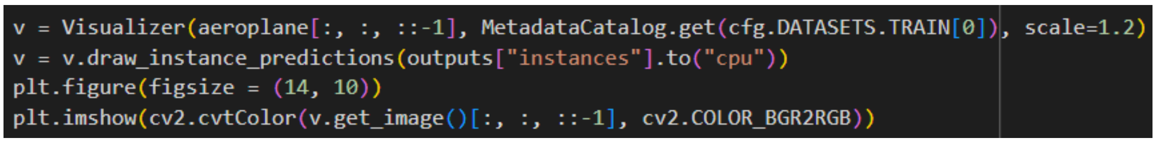
Figure 9.3.2.4.1 Configuration for Faster RCNN



```
predictor = DefaultPredictor(cfg)
outputs = predictor(aeroplane)
```

Figure 9.3.2.4.2 Predictor for Prediction

[d2.checkpoint.detection_checkpoint]: [DetectionCheckpointer] Loading from https://dl.fbaipublicfiles.com/detectron2/COCO-Detection/faster_rcnn_R_101_FPN_3x/137851257/model_final_f6e8b1.pkl ...



```
v = Visualizer(aeroplane[:, :, ::-1], MetadataCatalog.get(cfg.DATASETS.TRAIN[0]), scale=1.2)
v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
plt.figure(figsize = (14, 10))
plt.imshow(cv2.cvtColor(v.get_image()[:, :, ::-1], cv2.COLOR_BGR2RGB))
```

Figure 9.3.2.4.3 Visualizer using “imshow”

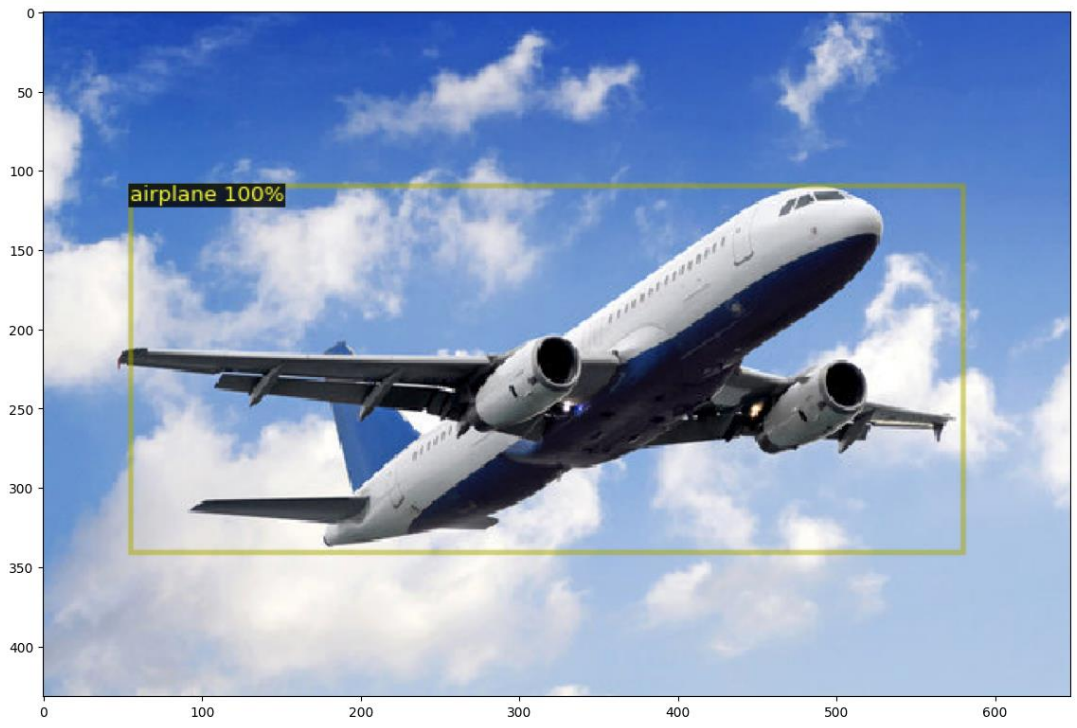


Figure 9.3.2.4.4 FasterRCNN Results

9.3.2.5 Faster RCNN Results:

- **Input Image:** Aeroplane
- **Predicted Class Names:** ['airplane']
- **Predicted Bounding Boxes:** Boxes(tensor([[45.7463, 91.8737, 482.9321, 284.3625]], device='cuda:0'))

9.3.2.6 Performance Observations:

- Faster RCNN produced **100% accuracy** in detecting the aeroplane in the image.
- It effectively identified the correct class with a bounding box indicating the object's location.

9.3.2.7 RetinaNet Performance Issues:

- In contrast, RetinaNet showed poor performance on the aeroplane image, with incorrect detections and bounding boxes for classes like "kite" and "clock," which were not present in the input image.

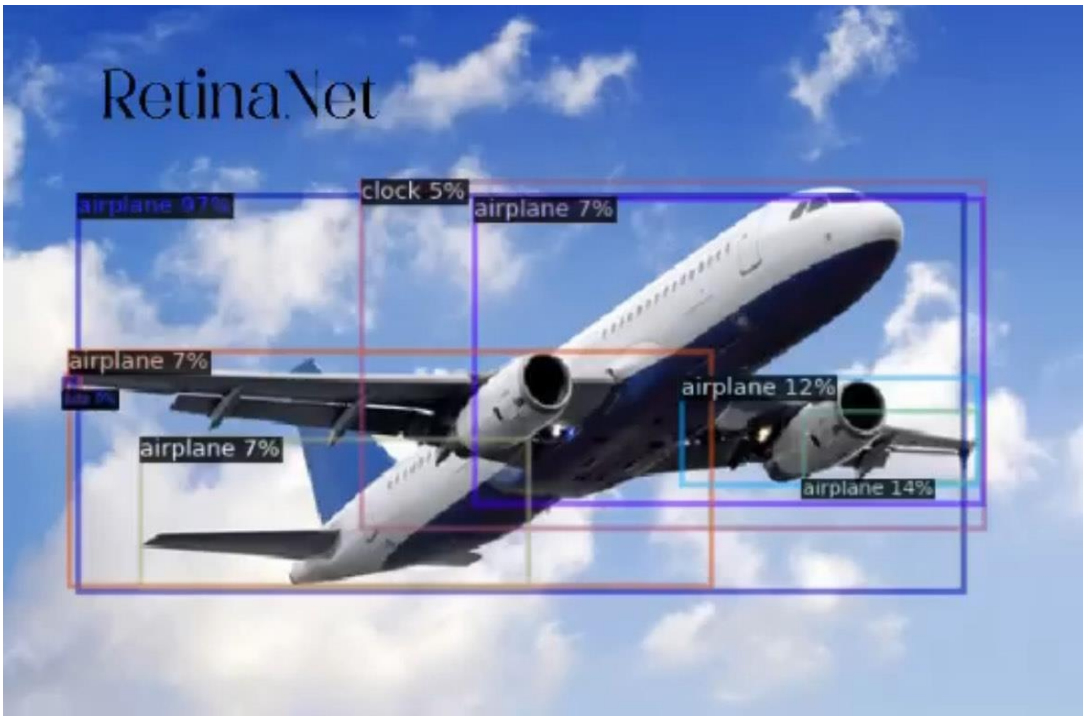


Figure 9.3.2.4.5 RetinaNet Results

9.3.2.8 Conclusion

Overall, **Faster RCNN** outperformed **RetinaNet** in the evaluation with the aeroplane image, achieving accurate detections and a high confidence score.

While RetinaNet has its advantages in other contexts, its failure to accurately identify objects in this test highlights its limitations in certain scenarios.

Faster RCNN is **recommended** for applications where precision and reliability are paramount.

CHAPTER 10 **LIMITATIONS & FUTURE ENHANCEMENTS**

10.1 Limitations

Despite the successes of the Objectify project, several limitations were identified during development and testing:

10.1.1. Model Accuracy

- **Performance Discrepancies:**
    - The Faster RCNN model achieved an impressive accuracy of **100%** on the evaluation set.
    - In contrast, **RetinaNet** exhibited significantly lower accuracy, scoring only **7%** for the aeroplane class.
    - Other classes, such as clock and kite, were inaccurately classified despite not being present in the images.
    - These discrepancies highlight the challenges associated with different models' capabilities and their reliance on specific features of the dataset.

10.1.2. Real-Time Processing

- While the detection speed is acceptable for many applications (approximately **150ms** per image), the system may struggle with real-time processing in high-resolution images or videos, particularly under constrained hardware resources.

10.1.3. Dataset Considerations

- The dataset was custom-curated from GitHub and deemed adequate for testing the Objectify functionalities, but its variety may still impact generalization.
- The dataset's characteristics can influence how well the models adapt to different scenarios, particularly for unseen classes.

10.1.4. Resource Dependency

- The models, particularly **YOLOv8** and **Faster RCNN**, require substantial computational resources for training and inference.
- This dependency may limit accessibility for users with less powerful hardware, potentially restricting the application of the models in various environments.

10.1.5. Lack of External Camera Support

- Currently, the system lacks a user interface that would allow users to utilize an external camera for real-time object detection.
- However, there are plans to integrate an **ESP camera** in future enhancements, enabling users to perform object detection in various environments effectively.

10.2 Future Enhancements

To address the limitations identified and improve the Objectify project, the following enhancements are proposed:

10.2.1. Model Improvement

- **Expand Model Evaluation:**
    - Continue assessing various models, including other architectures like **EfficientDet** or **SSD**, to identify those that can offer improved accuracy and performance.
- **Hyperparameter Tuning:**
    - Implement advanced hyperparameter tuning methods to optimize model performance further, especially for those that performed sub-optimally during initial testing.

10.2.2. Real-Time Processing Capabilities

- **Model Optimization:**
    - Explore techniques such as model pruning, quantization, or the use of lightweight architectures to enhance processing speeds, enabling real-time detection even in resource-constrained environments.

10.2.3. Integration with ESP Camera

- **External Camera Integration:**
    - Future developments will focus on integrating an **ESP camera** for detecting objects, allowing users to leverage real-time image capture and detection capabilities in various settings.

10.2.4. Multi-Object Detection

- **Enhance Detection Capabilities:**
    - Improve the model's ability to detect multiple overlapping objects, potentially implementing advanced algorithms or techniques for better separation and classification.

10.2.5. Integration with Other Technologies

- **Integration with Augmented Reality (AR):**
  - Explore opportunities for integrating the object detection capabilities with AR technologies, allowing users to visualize detected objects in real-time within their environment.
- **Mobile Application Development:**
  - Consider creating a mobile application to allow users to perform object detection directly from their smartphones, broadening accessibility and usability.

10.3 Conclusion

The Objectify project has made significant strides in the field of object detection, but there is room for improvement. By addressing the limitations and implementing the proposed enhancements, the project can further solidify its capabilities and widen its applicability in real-world scenarios.

CHAPTER 11 **CONCLUSION**

The Objectify project represents not only a significant technical achievement in the realm of object detection but also a stepping stone toward more intuitive human-computer interactions. By effectively leveraging advanced machine learning models, such as YOLOv8 and Faster RCNN, the project has established a robust framework for recognizing and classifying objects within images.

The careful consideration of various elements—from image preprocessing to results visualization—demonstrates a holistic approach to solving complex detection challenges. While acknowledging the obstacles encountered, such as model accuracy discrepancies and resource constraints, it is important to recognize how these challenges have driven innovation and creativity in the development process.

Looking to the future, Objectify is poised to extend its capabilities further, exploring integration with external devices and optimizing performance through advanced modelling techniques. This adaptability ensures that Objectify remains relevant in an ever-evolving technological landscape, fostering its application across diverse sectors including security, smart home systems, and augmented reality.

Ultimately, the project not only underscores the promise of machine learning in enhancing our interaction with the world but also reflects the collaborative spirit of innovation. As Objectify continues to refine its technologies and expand its functionalities, it sets the stage for transformative advancements in how we perceive and engage with our visual environment.

CHAPTER 12 **APPENDICES**

Appendix A: Code Snippets

A.1. Object Detection Module

```
def loadModel(model_path):
    model = torch.load(model_path)
    model.eval()
    return model

def detectObjects(image, model):
    with torch.no_grad():
        predictions = model(image)
    return predictions

def getResults(predictions):
    results = []
    for pred in predictions:
        results.append({
            'label': pred['label'],
            'confidence': pred['confidence']
        })
    return results
```

A.2. Image Preprocessing Module

```
def resize(image, target_size):
    return cv2.resize(image, target_size)

def normalize(image):
    return image / 255.0

def preprocess(image):
    image = resize(image, (640, 640))
    image = normalize(image)
    return image
```

A.3. Results Visualization Module
python
Copy code

```
def generateReport(detected_objects):
    report = ""
    for obj in detected_objects:
        report += f"Detected {obj['label']} with confidence {obj['confidence']:.2f}\n"
    return report

def displayResults(image, detected_objects):
    for obj in detected_objects:
        cv2.rectangle(image, obj['bbox'], (255, 0, 0), 2)
        cv2.putText(image, f"{obj['label']} {obj['confidence']:.2f}",
                    (obj['bbox'][0], obj['bbox'][1]-10),
            cv2.FONT_HERSHEY_SIMPLEX, 0.5, (255, 0, 0), 2)
    return image
```

Appendix B: Dataset Information

- Source: Custom dataset from GitHub
- Classes Included:
  - Airplane
  - Kite
  - Clock
- Number of Images: 200
- Image Dimensions: 800 x 600 pixels
- Annotations: Bounding Box

Appendix C: Testing Results

Model	Class	Accuracy (%)	Comments
Faster RCNN	Airplane	100	High accuracy achieved.
RetinaNet	Airplane	7	Lower accuracy compared to Faster RCNN.
RetinaNet	Clock	5	Detection possible with some misclass.
RetinaNet	Kite	6	Detection was challenging.

Table Appendix C: Testing Results

Appendix D: References

1. "YOLOv8: You Only Look Once, Version 8," [https://github.com/ultralytics/ultralytics]
2. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," [COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml]
3. GitHub repository for custom dataset: [https://github.com/matterport/Mask_RCNN/releases/download/v2.1/balloon_dataset.zip].

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