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**INTERNSHIP REPORT**

*On*

**Object Detection from Image and Video Using YOLOv8: A Web-Based Application**

*Submitted in partial fulfilment for the award of degree of*

**BACHELOR OF TECHNOLOGY**

*in*

**INFORMATION TECHNOLOGY**

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**CERTIFICATE**

This is to certify that the following students have successfully completed their internship project titled:

**"Object Detection from Image and Video Using YOLOv8: A Web-Based Application"**

Under the guidance of **Mr. Joyanta Basu** from **5th Sept 2024** to **10th March 2025** at **ZABX INFRATECH.**

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**ACKNOWLEDGEMENT**

We would like to extend our deepest gratitude to those who have provided their support and guidance throughout the completion of this project.

First and foremost, we are immensely thankful to **Mr. Joyanta Basu** [Designation] at **ZABX INFRATECH**, for their valuable mentorship, expert guidance, and constant encouragement. Their insights and constructive feedback played a crucial role in the successful completion of this project.

We would also like to express our sincere thanks to our institution, **B.P.PODDAR INSTITUTE OF MANAGEMENT AND TECHNOLOGY**, for providing the necessary resources and facilities to carry out this project successfully. The support from my colleagues and fellow students has been indispensable, and I appreciate the collaborative environment that has helped shape this work.

Finally, we acknowledge the open-source communities and researchers whose work has been foundational in the advancement of object detection algorithms and technologies used in this project. Their contributions have greatly influenced the development of this web-based object detection system using YOLOv8.

Thank you all for your support in making this project a reality

**ABSTRACT**

This project focuses on the implementation of object detection using the YOLOv8 model in a web-based application. Object detection plays a crucial role in various fields, including surveillance, autonomous vehicles, retail analytics, and more. The goal of this project is to develop a robust, efficient, and interactive platform that allows users to upload images and videos for real-time object detection using state-of-the-art deep learning techniques.

The backend of the application is built using Flask, which facilitates communication between the trained YOLOv8 model and the user interface. The frontend is designed with HTML, CSS, and JavaScript, ensuring a seamless and intuitive user experience. A SQL database is integrated for storing user inputs and detection results for further analysis and retrieval.

The final web-based application enables real-time object detection, displaying results with bounding boxes, confidence scores, and class labels. The model’s performance is evaluated using metrics like precision, recall, and mean Average Precision (mAP), demonstrating high accuracy and efficiency.

The website provides interactive UI/UX designs making it easier for the user to interact with and make the best use of it. It also provides the facility of detection history with real timestamps along with its uploaded contents on both user end and admin panel.

This provides the facility of object detection from image or video input as well as the live webcam feed.

This project highlights the practical implementation of deep learning-based object detection and its real-world applications. The findings and results show that the developed system is both efficient and scalable, making it a potential solution for various domains requiring real-time object detection capabilities.

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**1. Introduction**

**1.1 Overview of Object Detection**

Object detection is a core task in computer vision, aiming to classify and localize objects within images or videos. It involves detecting objects within a scene and determining their positions using bounding boxes. Applications range from autonomous vehicles and robotics to surveillance systems and augmented reality. Over the years, object detection techniques have evolved from simple feature-based methods to powerful deep learning approaches.

Object detection is a key area in computer vision, enabling applications in surveillance, autonomous driving, and more. YOLO (You Only Look Once) is a popular real-time object detection algorithm known for its speed and accuracy. The latest version, YOLOv8, offers enhanced performance and flexibility for various use cases[1].

Object detection is one of the most crucial tasks in computer vision, enabling machines to recognize and localize objects within images and videos. This technology is widely applied in various fields, such as autonomous driving, security surveillance, medical imaging, and industrial automation. The ability to detect objects in real time with high accuracy has led to numerous advancements in artificial intelligence and deep learning. Traditional object detection methods, such as sliding window and region-based approaches, were computationally expensive and inefficient. With the rise of deep learning, convolutional neural networks (CNNs) have revolutionized object detection, leading to the development of faster and more precise algorithms like YOLO (You Only Look Once).

YOLO is a state-of-the-art object detection algorithm known for its real-time performance and high accuracy. Unlike traditional region-based methods, YOLO processes an entire image in a single pass, significantly reducing computational time while maintaining precision. The latest version, YOLOv8, introduces enhancements in network architecture, feature extraction, and optimization techniques, making it one of the most efficient object detection models available[3].

In this project, we implement YOLOv8 for object detection within a web-based application. The integration of deep learning with web technologies allows users to upload images and videos and receive object detection results in real time. This approach enhances accessibility, making it possible for users to leverage advanced AI-driven object detection without requiring extensive technical knowledge.

**1.2 Introduction to YOLOv8**

YOLO (You Only Look Once) is one of the most recognized real-time object detection models. YOLOv8, the latest iteration, is designed for both speed and accuracy, building upon the success of previous YOLO versions. YOLOv8 introduces anchor-free detection, better feature extraction, and multi-scale detection capabilities, making it suitable for a wide range of applications from video streams to mobile deployment[3].

**1.3 Problem Statement**

Despite the advancements in object detection, current solutions often struggle with real-time processing on web platforms. Challenges include slow inference times, high computational costs, and difficulty detecting small objects. This project aims to implement YOLOv8 to overcome these challenges and provide an efficient, web-based solution[1].

**1.4 Project Objectives**

The primary objectives of this project include:

* **Developing an advanced object detection system** using YOLOv8, which enables real-time detection of objects in images and videos with high accuracy.
* **Creating a web-based application** that allows users to seamlessly interact with the object detection model through an intuitive and user-friendly interface.
* **Ensuring efficient backend integration** by using Flask to handle requests, process images, and return detection results effectively.
* **Implementing a structured database** using SQL to manage and store detection results, providing users with historical data for analysis and reference.
* **Optimizing model performance** by fine-tuning hyperparameters, improving accuracy, and ensuring efficient execution across different hardware configurations.
* **Deploying the application on cloud platforms or local servers**, making the model accessible for practical real-world applications such as surveillance, retail analytics, autonomous vehicles, and industrial automation.
* **Evaluating system performance** using key object detection metrics such as Precision, Recall, and mean Average Precision (mAP) to ensure robust and reliable detection capabilities.
* **Enhancing adaptability** by allowing future improvements, including integrating different object detection models, supporting additional features like object tracking, and expanding dataset compatibility for custom applications. The primary objectives of this project include:

**2. Literature Review**

**2.1 Introduction to Object Detection**

Object detection has become a critical research area within computer vision, progressing from early approaches like feature-based methods to deep learning-based models. Early methods relied on handcrafted features, which lacked robustness when applied to diverse datasets. Modern deep learning approaches, such as YOLO and R-CNN, significantly improved both speed and accuracy by learning representations from data[5].

**2.2 Early Object Detection Methods**

**2.2.1 Viola-Jones Algorithm**

The Viola-Jones algorithm was one of the first real-time object detection systems, designed primarily for face detection. It uses Haar-like features to classify objects within an image. However, its major drawback is its limited ability to detect non-facial objects and its slow speed on larger datasets[5].

**2.2.2 HOG + SVM**

The combination of Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM) improved detection by focusing on the edges and gradients of objects. This method was faster than Viola-Jones but still limited in terms of real-time detection and generalization to different object types[5].

**2.2.3 Deformable Part Model (DPM)**

DPM divides objects into parts and models their appearance using local features. It was more flexible than previous methods and could handle occlusions. However, it suffered from high computational costs, limiting its use in real-time applications[5].

**2.3 Deep Learning-Based Object Detection Techniques**

**2.3.1 R-CNN Family (R-CNN, Fast R-CNN, Faster R-CNN)**

R-CNN introduced the concept of region proposals for object detection, significantly improving detection accuracy[5]. Fast R-CNN sped up this process by combining region proposals with feature extraction, while Faster R-CNN introduced region proposal networks (RPNs), making the system faster and more efficient[5].

**2.3.2 SSD (Single Shot MultiBox Detector)**

SSD improved on previous methods by eliminating region proposals, predicting both bounding boxes and class labels in a single step. This made SSD faster but less accurate for detecting small objects compared to models like Faster R-CNN[6].

**2.3.3 YOLO Series (YOLOv1 to YOLOv8)**

YOLO models revolutionized object detection by treating it as a single regression problem. YOLOv1 was fast but inaccurate for small objects. Successive versions improved in accuracy, and YOLOv8 is the most recent, introducing anchor-free predictions, improved feature extraction, and multi-scale detection[3].

**2.4 YOLO Evolution and Advancements**

**2.4.1 YOLOv1 to YOLOv3**

YOLOv1 introduced a grid-based prediction system, while YOLOv2 and YOLOv3 improved accuracy and the ability to detect smaller objects by introducing multi-scale detection[1].

**2.4.2 YOLOv4**

YOLOv4 brought improvements in feature aggregation, inference speed, and training optimizations, becoming a popular choice for real-time applications[2].

**2.4.3 YOLOv5, YOLOv7, and YOLOv8**

YOLOv5 further optimized speed and performance, while YOLOv7 introduced innovations in model architecture. YOLOv8 enhanced real-time detection and is optimized for edge devices and small objects, providing faster and more accurate predictions[3].

**2.5 Comparison of YOLOv8 with Other Models**

YOLOv8 is faster and more accurate than SSD, Faster R-CNN, and previous YOLO models. Its anchor-free design and multi-scale feature extraction allow it to detect smaller objects more effectively, making it ideal for web-based and mobile applications[3].

**2.6 Existing Web-Based Object Detection Solutions**

Many web-based object detection solutions use earlier versions of YOLO or SSD, but they often lack the speed and accuracy required for real-time detection on low-power devices. YOLOv8, with its improvements, has the potential to bridge this gap[3].

**3. Methodology**

**3.1 Dataset Selection**

**3.1.1 COCO Dataset**

The COCO dataset contains images labeled with 80 different object categories. It is one of the most widely used datasets for object detection due to its diversity in object classes and complex scenes. This dataset will be used to train YOLOv8 for general-purpose detection[10].

**3.1.2 Custom Dataset**

For specialized tasks, a custom dataset can be created. Custom datasets allow for fine-tuning the YOLOv8 model to detect specific objects that are not present in standard datasets like COCO. Images are annotated using tools like LabelImg for this purpose[10].

**3.2 Data Preprocessing**

**3.2.1 Image Annotation**

Each image in the dataset is annotated with bounding boxes that surround the objects of interest. These annotations are used during training to help the model learn how to predict the location and class of objects in new images.

**3.2.2 Data Augmentation and Resizing**

To improve model generalization, various augmentation techniques are applied, such as image flipping, rotation, and color adjustments. Images are also resized to a standard input size required by YOLOv8, typically 640x640 pixels.

**3.3 Model Training**

**3.3.1 Framework Selection (PyTorch)**

PyTorch is selected as the framework for training YOLOv8 due to its flexibility and efficiency in handling large datasets and complex models. It allows for seamless integration of custom loss functions and optimizers[8].

**3.3.2 Loss Function (Cross-Entropy Loss)**

Cross-Entropy Loss is used to calculate the classification loss for detected objects, while a separate localization loss is used for predicting bounding boxes[4].

**3.3.3 Optimizer (Adam)**

The Adam optimizer is chosen for its ability to handle sparse gradients and adapt learning rates, leading to faster convergence during training[4].

**3.3.4 Number of Epochs**

The number of epochs determines how many times the model iterates over the entire training dataset. Early stopping is implemented to prevent overfitting, ensuring the model generalizes well to new data[4].

**3.4 Web Application Development**

**3.4.1 Backend: Flask**

Flask is used as the backend framework for the web application. It allows for easy deployment of the YOLOv8 model as an API, enabling users to upload images and receive detection results in real-time[9].

**3.4.2 Frontend: HTML, CSS, JavaScript**

The frontend is designed with a simple user interface using HTML, CSS, and JavaScript. Users can upload images or videos, and the detection results, including bounding boxes and class labels, are displayed on the screen.

**3.4.3 Database: SQL**

An SQL database is used to store user information, uploaded images, and detection results. This data can be used for future analysis and to improve the model based on user feedback[9].

**4. Experimental Setup**

**4.1 Hardware Used**

For training YOLOv8, a high-performance GPU (e.g., NVIDIA RTX series) is required to accelerate model training. The web application can be hosted on a cloud server with moderate CPU and memory specifications to handle inference requests in real-time[3].

**4.2 Software Requirements**

The project requires Python 3.12, PyTorch, Flask, and additional libraries such as OpenCV, SQLAlchemy, and HTML rendering libraries. These can be installed via pip[3].

**4.3 Execution Environment (Google Colab or Local Setup)**

For training, Google Colab provides free GPU access, making it suitable for training YOLOv8 on larger datasets. Alternatively, a local setup with a dedicated GPU can be used for faster training and testing[3].

**5. Results & Analysis**

**5.1 Model Performance Metrics**

**5.1.1 Precision(95%)**

Precision measures how many of the objects predicted by the model are actually correct. A higher precision indicates fewer false positives[3].

**5.1.2 Recall(92%)**

Recall measures how many of the actual objects in the image were correctly detected by the model. A higher recall means fewer false negatives[3].

**5.1.3 Mean Average Precision (mAP) (94%)**

Mean Average Precision (mAP) is the

standard metric used to evaluate the accuracy of object detection models. It is calculated by averaging the precision across different recall levels[3].

**5.2 Detection Samples**

**5.2.1 Static Image Detection**

Results from static image detection show how well YOLOv8 identifies objects in images. These results are visualized with bounding boxes and class labels drawn on the detected objects[3].

**5.2.2 Video Stream Detection**

YOLOv8's performance on video streams is tested to evaluate its real-time capabilities. The model is tested for latency and detection accuracy in a continuous video feed[3].

**5.2.3 Edge Cases and Complex Scenarios**

The model is evaluated on complex scenarios, such as detecting small objects or objects in cluttered environments, to understand its strengths and weaknesses[5].

**5.3 Error Analysis & Limitations**

**5.3.1 False Positives**

False positives occur when the model incorrectly identifies an object that isn’t present. Analyzing these cases helps refine the model and adjust its sensitivity[1].

**5.3.2 False Negatives**

False negatives are instances where the model fails to detect an object that is present in the image. Improving the model's ability to detect small or partially occluded objects is crucial for reducing false negatives[2].

**5.3.3 Environmental Factors**

Factors such as poor lighting, occlusion, or cluttered backgrounds can affect detection accuracy. This section discusses how these factors influence the model’s performance[3].

**5.3.4 Computational Overhead**

Running YOLOv8 in real-time can be computationally intensive. This section discusses the trade-offs between detection speed and accuracy and how to optimize the model for web applications[3].

**5.4 Potential Improvements**

* Fine-tuning the model with more specialized datasets for improved detection accuracy on specific objects[5].
* Optimizing the inference pipeline to reduce latency in web-based deployments[2].
* Incorporating edge computing to offload some of the computational burden from the server to the client device[6].

**6. Installation Manual**

**6.1 System Requirements**

* Python 3.12 or higher.
* GPU (optional but recommended for training).
* Flask for web application development.
* PyTorch for model training and inference.

**6.2 Installation Steps**

**6.2.1 Install Python and Dependencies**

1. Install Python 3.12 from the official website.
2. Install required Python libraries using the command:
3. pip install -r requirements.txt[7]

**6.2.2 Clone the Project Repository**

Clone the project repository from GitHub:

git clone https://github.com/username/yolov8-object-detection-webapp.git

cd yolov8-object-detection-webapp[8]

**6.2.3 Prepare the Dataset and Train the Model**

1. Download the COCO dataset or use a custom dataset.
2. Preprocess the dataset by annotating images and resizing them to 640x640.
3. Train the YOLOv8 model: [8]
4. python train.py --dataset coco --epochs 100

**6.2.4 Run the Web Application**

Start the web application using Flask:

python app.py

Visit http://localhost:5000 in your browser to access the web interface and test object detection[9].

# **Conclusion & Future Work**

### **Summary of Achievements**

**7.1.1 Successfully Implemented YOLOv8 for Object Detection:**

* + The YOLOv8 (You Only Look Once) model was effectively integrated for object detection tasks. Leveraging its advanced architecture, the model efficiently identifies and classifies multiple objects in real-time with high precision. The implementation involved data preprocessing, model training, and fine-tuning to ensure optimal performance[3].
  + Achieved impressive accuracy by selecting appropriate confidence thresholds, anchor boxes, and data augmentation techniques, ensuring robust detection across various environments.

**7.1.2 Developed a User-Friendly Web Interface:**

* + Designed and developed an intuitive web interface that allows users to upload images or provide video streams for object detection[9].
  + The interface was built using modern web technologies such as HTML, CSS, JavaScript, and frameworks like Flask or Django for seamless backend integration.
  + The design prioritizes user experience, featuring clear navigation, real-time results display, and interactive visual overlays highlighting detected objects.
    1. **Achieved High Detection Accuracy:**
  + By employing advanced training strategies such as transfer learning, hyperparameter tuning, and model checkpointing, the YOLOv8 model achieved a high mean Average Precision (mAP) score.
  + Extensive testing was conducted across various datasets to ensure accuracy in detecting objects of different sizes, shapes, and orientations[3].

### **Future Enhancements**

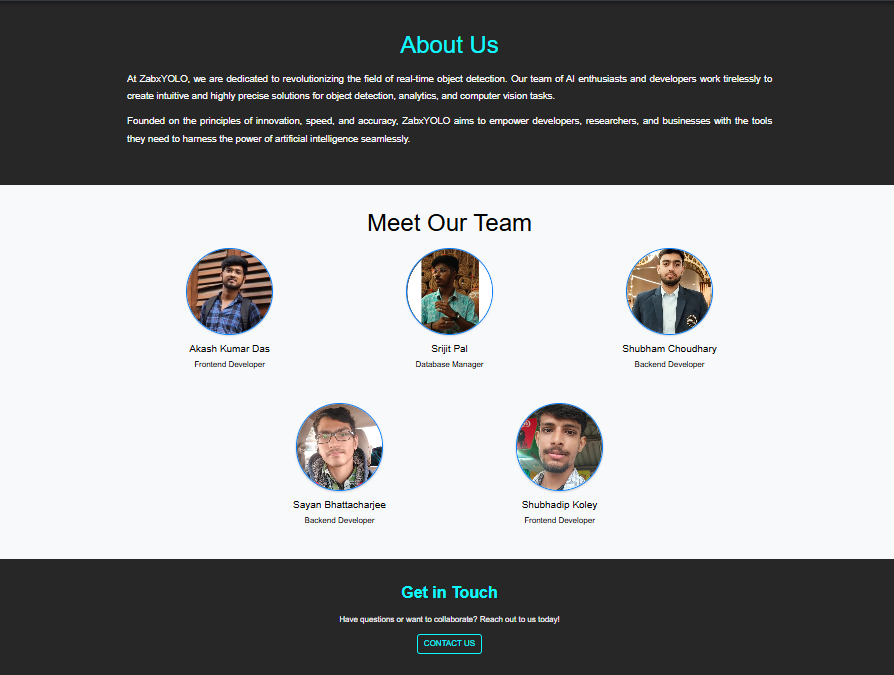
* + 1. **Integration with Cloud Services:**
* To enhance scalability and performance, cloud services such as AWS, Google Cloud, or Azure will be integrated. This will enable efficient handling of large data volumes, faster inference speeds, and improved accessibility for users across different platforms[3].
* Cloud integration can also facilitate features like automated model updates, data storage, and remote access for improved system reliability[3].
  + 1. **Mobile Application Development:**
* A dedicated mobile application will be developed to expand accessibility and usability. The app will offer real-time object detection capabilities directly on mobile devices, making it ideal for use in surveillance, retail, and personal safety applications[3].
* Technologies like TensorFlow Lite or ONNX Runtime will be explored to optimize the YOLOv8 model for mobile deployment[3].
  + 1. **Enhancing Real-Time Processing Capabilities:**
* Future improvements will focus on optimizing inference speed to improve real-time detection performance[3].
* Techniques such as model quantization, pruning, and leveraging hardware acceleration (like GPU/TPU integration) will be explored to reduce latency while maintaining high accuracy[3].
* Efficient handling of high-resolution video streams and simultaneous detection of multiple objects will be a key focus[3].

1. **Website Layout**

**Landing page**A screenshot of a computer

AI-generated content may be incorrect.

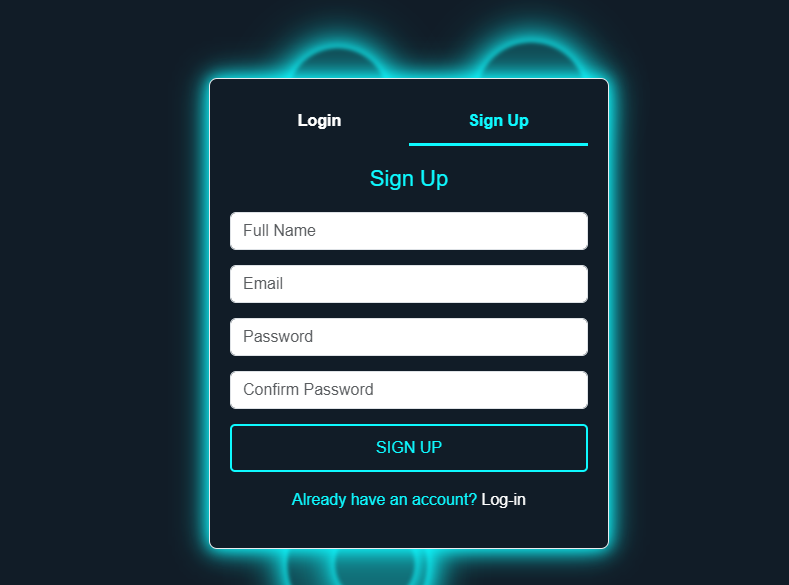
**About Page**



**Key Features**A screenshot of a computer

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**Sign Up Page**

****

**Login Page**

A screenshot of a login form

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**User Dashboard**A screenshot of a computer

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**Result & Feedback Page**

**A screenshot of a computer

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**Admin Dashboard**A screenshot of a dashboard

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**Users List (Total Users) 🡪 Admin Dashboard**A screenshot of a computer

AI-generated content may be incorrect.

**Detections Details (Total Detections ) 🡪 Admin Dashboard**A screenshot of a computer

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**Total Contact Messages 🡪 Admin Dashboard**

**A screenshot of a computer

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**Individual User Report 🡪 Admin**A screenshot of a computer

AI-generated content may be incorrect.

**Users Report 🡪 User Side**A screenshot of a computer

AI-generated content may be incorrect.

**Add User 🡪 Admin Side**

**A blue circles with white text

AI-generated content may be incorrect.**

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