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Object Detection and Annotation in Videos Using Deep Learning

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Abstract -This project develops an advanced video processing system capable of detecting and annotating objects in video footage. By leveraging deep learning-based object detection models, the system identifies, tracks, and labels objects across video frames, ensuring accurate analysis over time. The implementation uses Flask as a web framework, OpenCV for video handling, and the YOLO model for efficient object detection. Users can upload videos, specify target objects, and receive annotated outputs with bounding boxes and confidence levels. The system supports real-time processing, enabling automated monitoring applications such as surveillance, traffic analysis, and security enforcement. A Firebase backend facilitates cloud storage and retrieval of processed videos and detection results. Optimized frame sampling ensures efficient computation, reducing processing time without compromising accuracy. The application enhances decision-making by providing structured data insights extracted from video content. Additional features include detection result saving, cloud synchronization, and historical data access for further analysis. The system's flexible architecture allows future enhancements, including integration with live camera feeds and expanded detection capabilities.

Key Words:Video Processing, Object Detection, Annotation, Computer Vision, Automated Monitoring, Surveillance, Deep Learning.

1. INTRODUCTION

In the modern era of artificial intelligence and computer vision, object detection and tracking have become essential tools across various industries. This project presents a **Flask-based video processing system** that utilizes **YOLOv8 (You Only Look Once)** for real-time object detection in uploaded and streamed videos. The system allows users to upload video files, specify detection parameters, and analyze frames efficiently using deep learning-based models.

The core functionality of this project includes:

- Uploading and processing video files for object detection.
- Identifying specific objects in videos using **YOLOv8**.
- Drawing bounding boxes around detected objects and generating result reports.
- Streaming video analysis and saving detection logs for future reference.
- Storing and retrieving processed data using **Firebase** for cloud-based accessibility.

This project leverages **Flask** as the backend framework, integrates **OpenCV** for image processing, and implements **multi-threaded operations** for efficient video analysis. The results are stored in structured formats, ensuring usability in various applications such as security surveillance, traffic monitoring, and automated inspection systems.

Through this report, we will explore the system architecture, implementation details, and performance evaluation, providing insights into the potential use cases and future enhancements of the project.

2. LITERATURE REVIEW

[1] **Sangeeta Yadav, Preeti Gulia, Nasib Singh Gill, Ishaani Priyadarshini, Rohit Sharma, Kusum Yadav, Ahmed Alkhayyat, "Video Object Detection from Compressed Formats for Modern Lightweight Consumer Electronics". IEEE Transactions on Consumer Electronics, Vol. 70, No. 1, (February 2024)**

The detection tasks are carried out from compressed video formats instead of raw video as it makes the process simple and fast. This comprises an already-designed video compression network, which has been extended to incorporate object detection capabilities primarily using YOLOv5. Although it is beneficial for processing individual video files, it becomes detrimental when processing video streams. [1]

[2] **Gouri Amol Vaidhya, "Object Detection in Video Streaming using Machine Learning and CNN Techniques". Journal of Advanced Zoology (JAZ INDIA), Vol. 45, S-4, (2024)**

To develop system that requires less training and no human intervention for object detection in live video streaming. The system works in three stages of processing. They are Image Classification, Object Localization and Object Detection. This system makes use of different Algorithms based on the requirement such as CNN and YOLOv3 for detection of objects in images. [2]

[3] **Omar Imran, Shikharesh Majumdar, Sreeraman Rajan, "Enhancing the Performance of Deep Learning Model based Object Detection using Parallel Processing". Companion of the 15th ACM/SPEC International Conference on Performance Engineering (ICPE '24) (May 2024)**

This paper focuses on leveraging parallel processing techniques for enhancing the performance of object detection. Apache Spark is used to efficiently distribute workloads and data across cores of the Processor to cut down the processing time. The application of parallel processing on Object Detection may be beneficial, but there will be difficulties when annotating the objects. [3]

[4] **M. Monika, Udutha Rajender, A. Tamizhselvi, Aniruddha S Rumale, "Real-Time Object Detection in Videos using Deep Learning models". ICTACT Journal on Image and Video Processing, Vol. 14, No. 2 (November 2023)**

This research endeavors to enhance the efficiency of video object detection, offering a timely and accurate approach to address contemporary demands. The system involves a two-step process: Object Feature Extraction using a CNN and Object Detection using the YOLOv8. Even though the usage of CNN and YOLOv8 provides harmonious balance between speed and detection quality, there will be need for high-end systems due to its large amount of computation required. [4]

3. EXISTING SYSTEM

Traditional object detection models like R-CNN, Fast R-CNN, Faster R-CNN, and SSD face challenges in real-time video processing due to high storage needs, selective search dependency, intensive computation, and reduced accuracy for small or overlapping objects.

Recent advancements address these issues with alternative approaches. Yadav et al. (2024) proposed object detection from compressed video formats using YOLOv5, improving speed but struggling with video streams. Vaidhya (2024) introduced a training-free system using CNN and YOLOv3 for live video detection, requiring optimized processing for dynamic feeds. Imran et al. (2024) leveraged Apache Spark for parallel processing, enhancing speed but facing annotation challenges. Monika et al. (2023) combined CNN and YOLOv8 for real-time detection, achieving a balance between accuracy and speed but demanding high-end hardware. [1, 2, 3, 4]

Despite improvements, challenges like computational costs, real-time inefficiencies, and scalability persist, highlighting the need for a more optimized and efficient object detection system. [1, 2, 3, 4]

4. PROPOSED SYSTEM

The proposed system is a Flask-based web application for video object detection using the YOLOv8 model. Users can upload videos, extract frames, and detect objects with optional bounding boxes. The system also supports live streaming detection and saves detection results for further analysis.

The architecture consists of a user-friendly frontend for video uploads, object selection, and detection settings. The Flask-based backend handles video processing, detection requests, and result storage. OpenCV is used for video frame extraction and manipulation.

When a video is uploaded, it is saved in a designated folder, verified, and processed based on the specified frame interval. YOLO identifies objects in each frame and assigns confidence scores. If enabled, bounding boxes are overlaid on detected objects, and an annotated video is generated. The processed video and results are available for download or review.

Session-based management stores user preferences and file paths, while temporary file clearing optimizes storage. A secure secret key ensures safe session handling. For live detection, video streams are processed in real time, maintaining a structured record of detected objects with timestamps. Results can be saved in JSON format for further analysis.

Firebase integration enables cloud storage for detected videos and JSON reports. Users can upload, retrieve, and download stored results easily. The system employs multi-threading and optimized YOLO inference for efficient processing.

Designed for scalability, the system supports additional object detection models and extended cloud storage. It provides a robust and efficient solution for video-based object detection with both batch and live processing capabilities.

Advantages:

• **Efficient Object Detection:** The system utilizes the YOLOv8 model for fast and accurate object detection in videos, ensuring reliable results. [5, 9, 11, 12]
• **Batch and Live Processing:** Supports both video file-based detection and real-time object detection in live streams, catering to diverse use cases. [2, 4, 11]
• **Optimized Video Processing:** Extracts frames at specified intervals to balance detection accuracy and processing efficiency, reducing computational overhead. [1, 3, 14]
• **Customizable Detection Settings:** Users can select specific objects to detect and choose whether to overlay bounding boxes for better visualization. [6, 7]
• **Structured Result Storage:** Detection results, including timestamps and object details, are saved in JSON format for easy retrieval and further analysis. [10, 13]
• **Cloud Integration:** Firebase support enables seamless uploading, retrieval, and sharing of processed videos and detection reports, enhancing accessibility. [10]
• **Session-Based Management:** Stores user preferences and uploaded file paths securely, improving user experience and workflow continuity. [8, 13]
• **Secure and Scalable:** Incorporates session security, temporary file management, and multi-threading for optimized performance and safe data handling. [3, 18, 20]

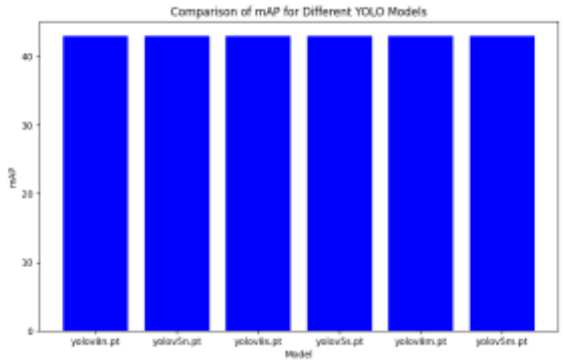

Fig 4.1 Comparison of mAP for variations of YOLOv5 and YOLOv8 models

For our project, we selected multiple versions of the YOLO (You Only Look Once) model to assess their performance. Upon reviewing the available versions, we identified YOLOv5 and YOLOv8 as the most recent and lightweight models within the YOLO family.

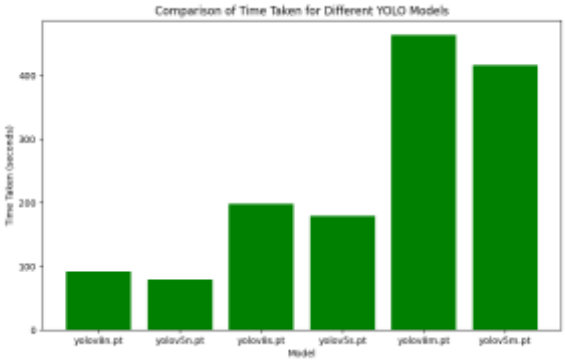

Fig 4.2 Comparison of Processing Duration for variations of YOLOv5 and YOLOv8 models

To evaluate their effectiveness, we compared different variations of YOLOv5 and YOLOv8 based on key performance metrics, including Precision, Recall, mean Average Precision (mAP), and processing time. Through this analysis, we observed that the Nano variations of both YOLOv5 and YOLOv8 offer quick processing times while maintaining a comparable level of accuracy.

After a thorough comparison, we ultimately chose YOLOv8 Nano over YOLOv5 Nano due to its slight performance advantage, making it the optimal choice for our application.

5. SYSTEM OVERVIEW

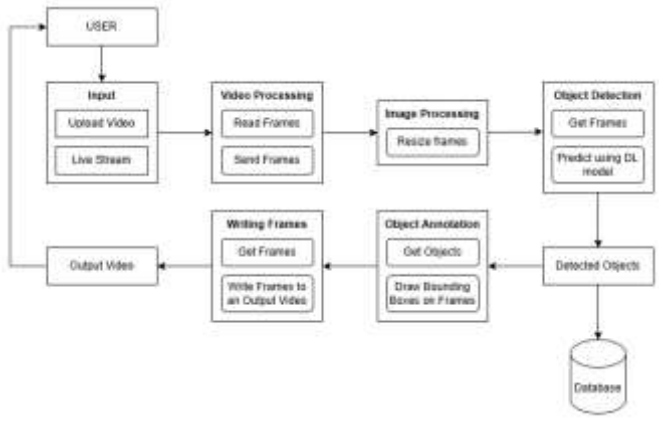

Fig 5.1 Architecture of the System

The system follows a modular **client-server architecture**, where the **frontend** provides a user-friendly interface for uploading videos, selecting objects for

detection, and configuring frame intervals. The **backend**, built with Flask, handles video uploads, processes detection requests, and stores results. The **YOLOv8 Nano model** is used for object detection, with **OpenCV** managing video frame extraction and annotation. Detection results are structured and stored in JSON format, with an option to overlay bounding boxes on detected objects. The system supports **batch video processing and real-time live detection**, dynamically updating logs. Additionally, **Firebase integration** enables cloud storage for processed videos and reports. Optimized using **multi-threading**, the architecture ensures efficient, scalable, and secure performance.

6. SYSTEM IMPLEMENTATION

Fig 6.1 Index Page

6.1 Live Stream

The "Live Stream" functionality allows users to stream real-time video feeds directly from their webcam, with automatic object detection happening in the background. As the webcam captures live video, the system continuously analyzes the footage for any objects of interest. Detected objects are highlighted with bounding boxes, and their confidence levels are displayed in real-time on the screen. This feature is particularly useful for monitoring environments in real time, as it does not require pre-recorded footage. Users can immediately see which objects are being detected as they are captured by the webcam, offering an interactive and responsive way to monitor their surroundings with object detection capabilities.

6.2 Records Retrieval

Fig 6.2.1 Records Retrieval Page

The "Records" feature enables users to access and review previously stored detection data. This functionality allows users to search for specific events by specifying a range of dates and times, along with particular objects they are interested in. Once the search parameters are set, the system filters and displays the relevant detections, providing users with detailed insights into when and where specific objects were detected in past recordings. This feature is highly valuable for retrospective analysis, allowing users to track and analyze the occurrence of objects over time. It can be used for a variety of purposes, such as security monitoring or event tracking, providing users with a powerful tool for reviewing historical detection data.

6.3 Upload Video

The "Upload Video" feature provides users with the ability to upload a video file from their local device to the web application. Once the video has been successfully uploaded, the system processes the video to detect and identify objects in the video frames, based on the user's preferences. Users can specify which particular objects they want to detect or leave it open for general detection. Additionally, the option is provided to display bounding boxes around the detected objects, offering a clear visual representation of the detection process. After the processing is completed, the user is provided with a downloadable version of the processed video, which includes the detected objects and any additional annotations, such as bounding boxes, depending on the settings chosen.

7. ALGORITHMIC STRATEGIES

7.1 YOLO (You Only Look Once)

YOLO is a state-of-the-art, real-time object detection system that identifies and classifies objects in

images or video streams. Unlike traditional object detection methods that scan the image multiple times using sliding windows or region proposals, YOLO is designed to detect objects in a single pass through the network, hence the name "You Only Look Once".

The model works by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell. YOLO simultaneously detects and classifies multiple objects in an image, making it highly efficient for real-time object detection tasks. It has gained significant attention due to its speed, accuracy, and ability to detect objects in live video streams, which makes it suitable for applications in various fields such as autonomous vehicles, surveillance, robotics, and more. [5, 9, 11, 12, 15]

7.2 History

YOLO was first introduced by **Joseph Redmon** and his collaborators in a paper titled "**You Only Look Once: Unified, Real-Time Object Detection**" in 2016. The concept behind YOLO was a significant departure from previous object detection algorithms like R-CNN and Fast R-CNN, which used region proposals and sliding windows to scan images in multiple steps. YOLO, on the other hand, combined the tasks of object localization and classification into a single neural network. [5, 16, 17]

The YOLO architecture was revolutionary because it provided a way to perform both tasks in real time, making it more efficient for time-sensitive applications. [5, 18, 20]

From YOLOv1 to YOLOv8, the model has evolved significantly, becoming faster, more accurate, and more efficient, while continuing to serve as a benchmark for object detection research and development. [5, 9, 11, 12]

7.3 Working

Grid Division

YOLO divides an input image into a grid of cells. Each cell is responsible for detecting objects whose center falls within the cell. [5, 9, 11]

Bounding Boxes and Class Predictions:

For each grid cell, YOLO predicts multiple bounding boxes with associated confidence scores (indicating how likely the box contains an object). Each bounding box is predicted by a set of parameters (x, y, width, height) along with a class label that identifies what object the box represents (e.g., car, person, dog). [6, 12, 13]

Single Pass Detection

Unlike earlier methods that required multiple passes over an image to detect various object features, YOLO only processes the image once. This single pass allows for much faster detection and makes YOLO highly suitable for real-time applications. [5, 15, 19]

Non-Maximum Suppression (NMS)

YOLO uses NMS to eliminate duplicate detections, keeping the most confident bounding boxes while discarding overlapping boxes that are likely to be redundant. [7, 8, 9]

7.4 Ideal Models and their variation

The **YOLOv5 Nano** and **YOLOv8 Nano** are both lightweight versions of the YOLO (You Only Look Once) object detection models, designed to balance speed and accuracy, but they differ in several key aspects. Below is a comparison between the two:

Architecture and Design

YOLOv5, a more established version in the YOLO series, introduced different model sizes, including Nano, to cater to use cases requiring faster processing times and lower computational resources. YOLOv5 Nano is specifically optimized for tasks where computational efficiency and speed are more critical than absolute accuracy.

YOLOv8, a more recent release in the YOLO series, introduces several improvements over YOLOv5 in terms of architecture, training, and inference speed. The Nano version of YOLOv8 is further optimized for speed and efficiency, with enhancements in its network architecture, resulting in faster processing times with minimal accuracy trade-off.

Performance (Accuracy and Speed)

YOLOv5 Nano provides good accuracy while ensuring a fast processing time. However, it may not always be as precise or efficient as the newer YOLOv8 versions, especially in more complex detection tasks.

YOLOv8 Nano improves upon YOLOv5 Nano by providing better accuracy with similar or even faster processing times. This is due to several architectural improvements and optimizations in YOLOv8, which allows it to achieve higher performance in detecting objects, even with smaller and faster models like the Nano.

Model Optimizations

YOLOv5 has a robust history and has undergone several iterations, but its optimizations are based on previous research and models. It is effective for many real-time object detection applications with an emphasis on lower-end hardware usage.

YOLOv8 introduces several state-of-the-art optimizations, including better training strategies and more efficient model layers. YOLOv8 Nano, as a result, offers better model efficiency, optimized inference speed, and improved detection capabilities, especially on devices with limited resources.

Deployment and Use Cases

YOLOv5 Nano is often used in real-time applications that require quick processing, such as video surveillance or autonomous vehicles, where detection speed is prioritized, and computational resources are constrained.

YOLOv8 Nano can be used in similar real-time applications, but it offers enhanced deployment opportunities, especially on edge devices. It is designed to run efficiently even on systems with very limited hardware capabilities, making it suitable for IoT devices, mobile applications, and resource-constrained environments.

Compatibility and Support

Being part of the YOLOv5 family, it benefits from a larger community, more pre-trained models, and extended support, making it easier for developers to integrate and deploy in various applications.

Although YOLOv8 is a newer release, it benefits from improvements in the core framework, offering enhanced compatibility with modern deployment environments. It also has a growing community and more advanced support for deploying cutting-edge applications.

Overall Comparison

While both YOLOv5 Nano and YOLOv8 Nano are lightweight and optimized for speed, YOLOv8 Nano generally provides a slight edge in terms of accuracy and processing speed. YOLOv8's newer architecture and advanced optimizations allow it to outperform YOLOv5 Nano in most cases, especially when higher detection accuracy with faster performance is required.

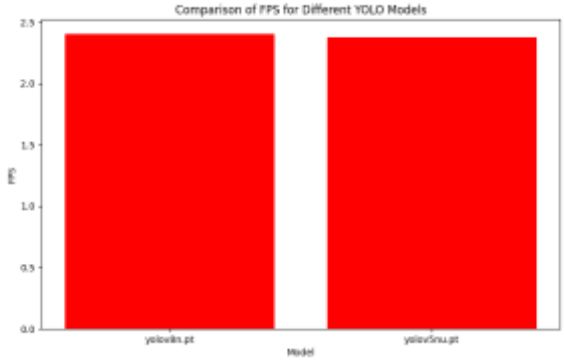

Fig 7.4.1 Comparison of FPS for YOLOv8n.pt vs YOLOv5nu.pt

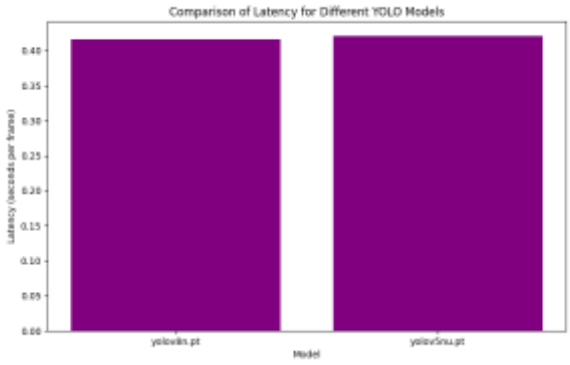

Fig 7.4.1 Comparison of Latency for YOLOv8n.pt vs YOLOv5nu.pt

Therefore, YOLOv8 Nano is typically favored for applications where both speed and accuracy are essential, making it the preferred choice for the project at hand.

7.5 Evaluation Metrics

The performance of YOLO models is evaluated based on four key metrics: **Mean Average Precision** (mAP), **Frames Per Second** (FPS), **Latency**, and **Time Taken**. Each of these metrics provides insights into the effectiveness and efficiency of the models when processing video data. These metrics are essential in

determining how well the models perform in real-world applications like video analysis.

Mean Average Precision (mAP)

Mean Average Precision (mAP) is a metric commonly used in object detection tasks to measure the accuracy of models. It evaluates how well the model detects and localizes objects, taking into account both precision and recall.

Formula:

$$mAP = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

Where:

- N is the number of object classes.
- AP is the Average Precision for class.

Frames Per Second (FPS)

FPS measures how many frames the model can process per second. A higher FPS indicates that the model can process video frames faster, which is important for real-time applications.

Formula:

$$FPS = \frac{\text{Total Frames Processed}}{\text{Time Taken (in seconds)}}$$

Latency (Time Per Frame)

Latency refers to the time it takes for the model to process a single frame. Lower latency means that the model responds faster to each frame, which is critical for time-sensitive applications like live video processing.

Formula:

$$\text{Latency} = \frac{\text{Time Taken}}{\text{Frames Processed}}$$

Time Taken

The total time taken to process the entire video is a critical metric for evaluating the efficiency of the model. This value tells us how long the model took to process all the frames in the video.

Formula:

$$\text{Time Taken} = \text{End Time} - \text{Start Time}$$

8. MAIN FEATURES

8.1 Real-time Object Detection

The system enables continuous monitoring of live video feeds, identifying and classifying objects in real time. This functionality is crucial in various domains, such as security, automation, and smart surveillance, where immediate detection of objects can trigger automated alerts. [4, 6, 9, 11, 13]

8.2 Industrial Automation

Robotic arms in automated factories utilize object detection to accurately pick, sort, and place items, enhancing efficiency and precision in manufacturing processes. Additionally, object detection can be employed in warehouse automation for package sorting and real-time inventory tracking, ensuring streamlined logistics and optimized storage management. [7, 12, 14, 18]

8.3 Wildlife and Agricultural Monitoring

Drones equipped with object detection can track the movement of wild animals in forests, aiding conservation efforts by monitoring wildlife populations and preventing illegal activities like poaching. Farmers can utilize object detection for intrusion detection, identifying pests, and tracking livestock across large farmlands, improving security and management. Additionally, object detection can be integrated with AI-based crop monitoring systems to analyze plant health, detect diseases early, and optimize agricultural productivity. [12, 17, 19]

9. RESULTS & DISCUSSIONS

9.1 Video Processing and Object Detection

Upon receiving a video input, the system applies the YOLO (You Only Look Once) model to each frame of the video, detecting objects at specific intervals.

Fig 9.1.1 Video Processing and Object Detection

For each detection, the following steps are performed:

Detection: The YOLO model identifies objects within the frame and classifies them.

Timestamp and Confidence: Each detected object is assigned a timestamp and confidence score. The timestamp is the exact time at which the object appears in the video, and the confidence score indicates the certainty with which the model detected the object.

Bounding Boxes (Optional): The system optionally includes bounding boxes around detected objects in the processed video. The boxes are drawn with the object's class name and the associated confidence score.

9.2 Real-time Object Detection (Streaming)

In addition to processing uploaded video files, the system also supports real-time object detection using a webcam stream.

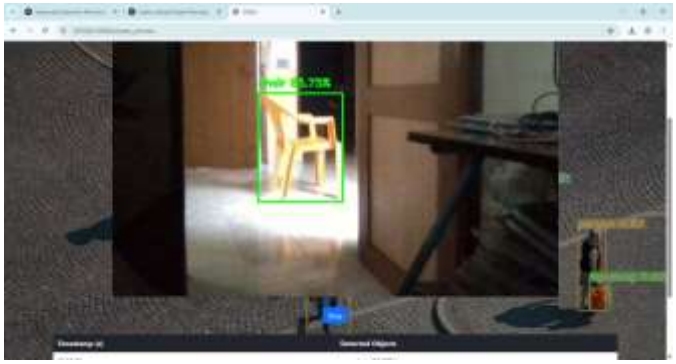

Fig 9.2.1 Real-time Object Detection (Streaming)

For each frame captured from the webcam, the following steps are repeated:

- Objects are detected and classified by the YOLO model.

- A timestamp is assigned to each detection.

- The detection results are shown in real-time with bounding boxes around detected objects.

- The system tracks the object's appearance, and if the same object is detected multiple times, the system calculates an average confidence score over the duration of the object's presence in the video.

9.3 Data Collection and Result Analysis

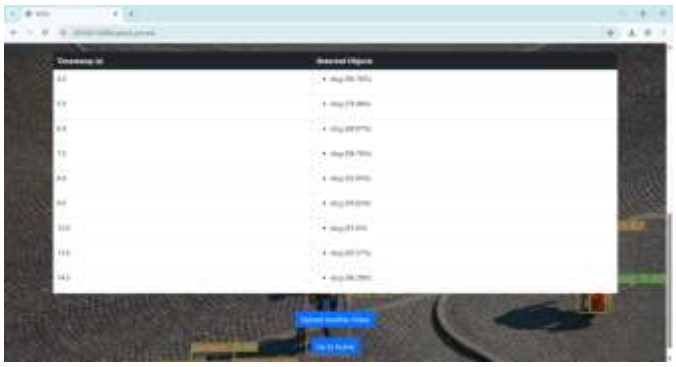

Fig 9.3.1 Data Collection

Video Results: After processing the uploaded video or streaming session, the system logs all detections, along with their respective timestamps and confidence scores. The user can review the detection results in a structured format.

Fig 9.3.2 Results Analysis

Detection Logs: Detection results are stored locally and can be accessed, viewed, or downloaded for further analysis. These results can also be uploaded to cloud storage (e.g., Firebase) for persistent storage and sharing.

9.4 User Interaction and Result Customization

Fig 9.4.1 User Interaction and Result Customization

The system allows users to customize their experience by choosing:

Specific Objects for Detection: Users can enter a specific object to search for (e.g., "car", "person") and the system will prioritize detecting only that object.

Frame Interval for Detection: The system lets users select how frequently they want to detect objects, allowing for more efficient processing if fewer detections are needed.

Bounding Box Display: Users can choose whether to show bounding boxes around the detected objects in the processed video.

10. CONCLUSION

The implemented Flask-based object detection system efficiently processes both uploaded and live-streamed video feeds using the YOLOv8 model. The application allows users to upload videos, specify detection parameters, and analyze objects with or without bounding boxes. The results are saved, displayed, and uploaded to Firebase for storage and retrieval. Additionally, real-time object detection is performed using a webcam stream, storing detection results dynamically for later analysis. The integration of OpenCV and YOLO ensures accurate object recognition, making this system useful for surveillance, automation, and intelligent video analytics applications.

11. FUTURE ENHANCEMENTS

- Train custom object detection models for specific industry use cases.
- Integrate with email, SMS, or push notification services. Trigger automated responses based on detected events (e.g., sounding an alarm for unauthorized access).
- Use machine learning to analyze trends and patterns in detected objects.
- Support multiple simultaneous video feeds. Implement distributed processing for handling large-scale surveillance networks.
- Extend compatibility to TensorFlow Object Detection API, Faster R-CNN, or SSD. Allow users to switch between models based on performance and accuracy needs.

AI-powered Summaries can be implemented to generate automated text-based insights from detected objects, making the results more actionable and user-friendly.

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