# Logo Detection in Videos

## Objective

The aim of this project is to establish a machine learning (ML) pipeline capable of identifying Pepsi and CocaCola logos in video files. The pipeline is designed to capture frames from the video, use a YOLOv7 model to recognize logos, and generate a JSON file with the timestamps of detected logos.

### **Dataset Used**

Pepsi and CocaCola Images dataset consists of 400 images designed for computer vision tasks, focusing on logo recognition and classification. [1]

## Approaches Considered

- YOLOv3
- YOLOv5
- YOLOv7 (Selected)

# **Detailed Analysis**

#### 1. YOLOv3

#### Pros:

- Well-established and widely used in various applications.
- Good balance of speed and accuracy.

#### Cons:

- Older architecture with limitations in performance compared to newer models.
- Larger model size and slower inference times compared to more recent versions.

**Decision:** Not considered due to being an older solution with less optimal performance.

#### 2. YOLOv5

#### Pros:

- Improved performance over YOLOv3 with faster and more accurate detections.
- Actively maintained and widely supported in the community.

## Cons:

- Though newer than YOLOv3, it is not the latest model available.
- Model size and complexity can be higher.

Decision: Considered initially but not chosen because YOLOv7 offers further improvements.

#### 3. YOLOv7

## Pros:

- State-of-the-art performance in terms of speed and accuracy.
- Optimized for real-time applications and edge devices.
- Advanced features like anchor-free detection and dynamic training mechanisms.

#### Cons:

- Newer and less documented compared to older models.

**Decision:** Chosen due to its superior performance and optimizations, making it ideal for the project's requirements.



Figure 1: Enter Side by side comparison of YOLOv5 (left) and YOLOv7 (right)

## **Final Decision**

YOLOv7 was selected as the primary model for the logo detection project. The decision was based on its cutting-edge performance, optimizations for real-time and edge applications, and the ability to handle complex detection tasks efficiently.

# **Initial Steps**

- Familiarization: Started with YOLOv7 due to prior experience with YOLO models and the compelling performance benefits of the latest version.
- Implementation: Integrated YOLOv7 into the project for logo detection, leveraging its advanced capabilities to meet the project requirements.

## Conclusion

Selecting YOLOv7 is consistent with the project's objectives of attaining excellent performance, efficiency, and real-time detection abilities. Choosing the newest developments in the YOLO series ensures that the project uses cutting-edge technology to accurately detect logos in different situations, leading to strong and precise results.

## Results

#### Observations

- True Positive Rates (Diagonal Elements):
  - Coke: The model correctly identifies coke 83% of the time.

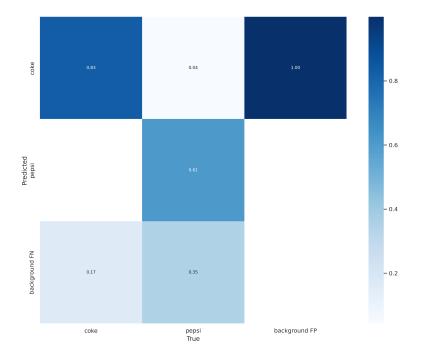


Figure 2: Confusion Matrix

- **Pepsi**: The model correctly identifies pepsi 61% of the time.
- Background FP: The model has a high rate (100%) of correctly identifying background false positives.

#### • False Positive and False Negative Rates (Off-diagonal Elements):

- Coke predicted as Pepsi: 4%
- Coke predicted as background FN: 17%
- Pepsi predicted as background FN: 35%

#### • Misclassification Insights:

- The model has some confusion between coke and pepsi, with a small percentage of coke being predicted as pepsi.
- A significant portion of the pepsi is misclassified as background false negatives (35%), indicating the model struggles more with identifying pepsi compared to coke.
- The high accuracy in identifying background FP (100%) suggests the model is very effective at distinguishing non-relevant items from the relevant classes.

# References

 $[1] \begin{tabular}{l} My workspace. Pepsi and cocacola images dataset. https://universe.roboflow.com/my-workspace-7m1hi/pepsi-and-cocacola-images, Dec 2022. Visited on 2024-07-08. \end{tabular}$