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# INVESTIGATING AN EXCEPTIONAL LEAP IN SURVEILLANCE TECHNOLOGY USING YOLO V8 ALGORITHM FOR DETECTING AND PROCESSING VISUAL IMAGES OF DIFFERENT OBJECTS

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## ABSTRACT

This study presents a comprehensive evaluation of the YOLO V8 framework within the context of surveillance technology, focusing on its performance in three critical use cases: license plate detection, face recognition, and suspicious activity detection. Our proposed model utilizes camera-captured input data processed through the YOLO V8 architecture.

## INTRODUCTION

Surveillance technology plays a crucial role in ensuring public safety and security. From monitoring public spaces to deterring criminal activities, surveillance systems have become an integral part of modern society (Gates, 2019). However, traditional surveillance methods, relying on human operators to monitor video feeds, have been limited in their effectiveness and efficiency (Nguyen *et al.*, 2017). The advent of deep learning, a subfield of artificial intelligence, has revolutionized surveillance technology, enabling a paradigm shift in the way we monitor and secure our surroundings (Wu *et al.*, 2020). Surveillance is

Experiments benchmarked YOLO V8 against YOLO V7, Faster R-CNN, and SSD using publicly available datasets: OpenALPR Benchmark Dataset for license plates, Labeled Faces in the Wild (LFW) for face recognition, and UCF-Crime Dataset for suspicious activity detection. Advanced frameworks like TensorFlow and PyTorch were employed, along with cutting-edge GPU architectures to optimize training and inference speeds. Performance was rigorously evaluated based on key metrics including mean Average Precision (mAP), precision, recall, F1 score, and inference time. Results demonstrated that YOLO V8 outperformed competing models across all metrics, highlighting its effectiveness for real-time detection in surveillance applications.

**Keywords:** YOLO, Surveillance, CNN, SSD, Face Recognition, License Plate, Suspicious Activity Detection, Precision, Recall, Inference Time, Dataset.

crucial for security and public safety. Deep learning techniques enhance accuracy and effectiveness by accurately detecting and recognizing objects or activities in complex scenes. Techniques such as object detection, tracking, and behavior analysis contribute to improved surveillance systems (Li *et al.,* 2020), enabling the detection of objects of interest, tracking movements, and analyzing behavior. Deep learning-based video surveillance is effective in detecting suspicious behavior in public spaces and tracking vehicles for efficient traffic management. It also aids in crowd monitoring for identifying risks and abnormal behavior.

YOLO, or "You Only Look Once," is a real-time object detection algorithm widely used in computer vision. Introduced in 2015, the latest version is YOLOv8. It performs object detection in a single pass, dividing the image into a grid and predicting bounding boxes and class probabilities directly. YOLOv8 employs the Darknet architecture, with optimizations like feature fusion and multi-scale prediction for improved accuracy. Its real-time performance makes it ideal for applications like autonomous driving and surveillance systems, gaining popularity for its accuracy and speed in the computer vision community.

The field of surveillance technology has seen remarkable progress with the integration of advanced deep learning models, especially in tasks involving object detection and recognition. Among these innovations, the YOLO (You Only Look

Once) framework has become a standout choice due to its ability to process data in real time while maintaining high accuracy. The newest version, YOLO V8, marks a significant leap forward, outperforming earlier methods in accuracy, efficiency, and adaptability. This paper showcases YOLO V8's capability to detect and identify objects and faces in real-time, even in challenging situations like license plate detection, facial recognition, and spotting suspicious activities. As a deep learning model, YOLO V8 employs a neural network to analyze features and predict bounding boxes and class probabilities in one step. It also uses pyramid networks to improve feature representation and scale adaptability, along with anchor boxes and non-maximum suppression to refine object localization and reduce duplicate detections.

The growing importance of security and public safety in our rapidly evolving world necessitates advanced tools, including video surveillance with deep learning techniques, to address emerging challenges and threats effectively. Traditional measures may fall short in this regard. By understanding the potential of video surveillance, we can overcome limitations and enhance accuracy, adaptability, and scalability. This allows us to better protect communities, critical infrastructure, and the well-being of individuals, ensuring a safer environment for all.

Numerous reviews and studies in the field support the growing importance of security and public safety in our dynamic world. These sources emphasize the utilization of advanced tools like video surveillance with deep learning techniques, which enhance accuracy, adaptability, and scalability. By effectively addressing emerging challenges and threats, these tools contribute to safeguarding communities, protecting critical infrastructure, and ensuring individual well-being. For instance, the review article "Deep Learning in Video Surveillance:

A Review" by Abbas Hanif *et al.* (2019) discusses the significance of deep learning techniques in overcoming challenges faced by traditional video surveillance methods, particularly in accurately detecting and recognizing objects or activities in complex scenes. Similarly, the review article "Deep Learning for Video Surveillance: A Survey" by Li *et al.* (2020) highlights the potential of deep learning techniques such as object detection, tracking, and behavior analysis to improve the accuracy and efficiency of video surveillance systems, thereby enhancing public safety.

This study has four main goals. First, it aims to compare YOLO V8's performance with other leading models, such as YOLO V7, Faster R-CNN, and SSD, using key metrics like mean average precision (mAP), precision, recall, F1 score, and processing speed. Second, it assesses YOLO V8's effectiveness in three important applications: detecting license plates, recognizing faces and persons, and identifying suspicious activities, highlighting its flexibility across various surveillance tasks. Third, the study delves into the architecture and features of YOLO V8, explaining its technical advancements and how it improves upon earlier versions. Finally, it explores the practical uses and broader implications of YOLO V8 in surveillance technology, emphasizing its potential to boost security, streamline operations, and support real-time decision-making in complex settings. By focusing on these objectives, this paper aims to offer a thorough understanding of YOLO V8's capabilities and its transformative role in surveillance systems. The findings highlight its potential as a powerful and adaptable tool for enhancing object detection and recognition in real-world applications.

## LITERATURE REVIEW

### Conceptual Review

#### Surveillance

Surveillance is defined as the systematic monitoring and gathering of information about individuals, groups, or activities, primarily for security, law enforcement, or intelligence purposes (Lyon, 2021). This process employs various technologies, such as cameras, sensors, and data analysis tools, to collect and analyze information either in real-time or for retrospective examination. Surveillance is applicable across public areas, private environments, and digital platforms, aiming to enhance crime prevention, public safety, intelligence gathering, and activity monitoring. The overarching goal of surveillance is to derive valuable insights, maintain societal control, and safeguard the interests of individuals, communities, and institutions.

#### Deep Learning

Deep learning, a prominent branch of machine learning, focuses on training artificial neural networks with multiple layers to identify and extract complex patterns from data (LeCun et al., 2019). It involves constructing deep neural network architectures that autonomously learn hierarchical representations of input data. Deep learning has significantly impacted fields such as computer vision, natural language processing, speech recognition, and reinforcement learning, excelling in image classification and sequence analysis. The availability of robust computational resources and advanced frameworks, such as TensorFlow and PyTorch, facilitates data-driven decision-making, minimizes the need for manual feature engineering, and propels advancements in artificial intelligence.

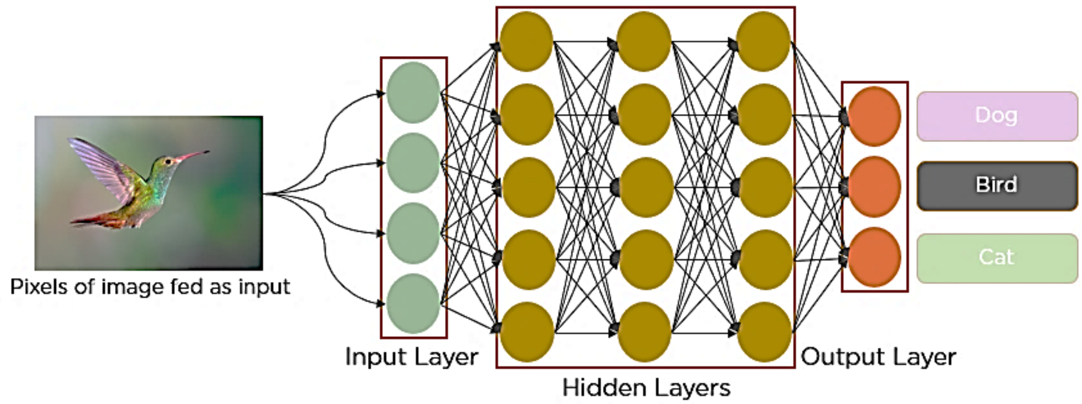


Fig. 1: Deep learning with object detection (**Source:** https://www.analyticsvidhya.com)

**YOLO (You Only Look Once)**

YOLO (You Only Look Once) is a highly efficient object detection model that utilizes a neural network to simultaneously extract features, predict bounding boxes, and estimate class probabilities. This model stands out by eliminating multiple iterations and region proposal networks, enhancing localization through the use of anchor boxes and non-maximum suppression techniques. Since its inception in 2015, YOLO has undergone several improvements and serves various applications in domains such as autonomous driving, surveillance, and robotics.

Figure 2 below shows the YOLOv8 architecture with the description of each block.

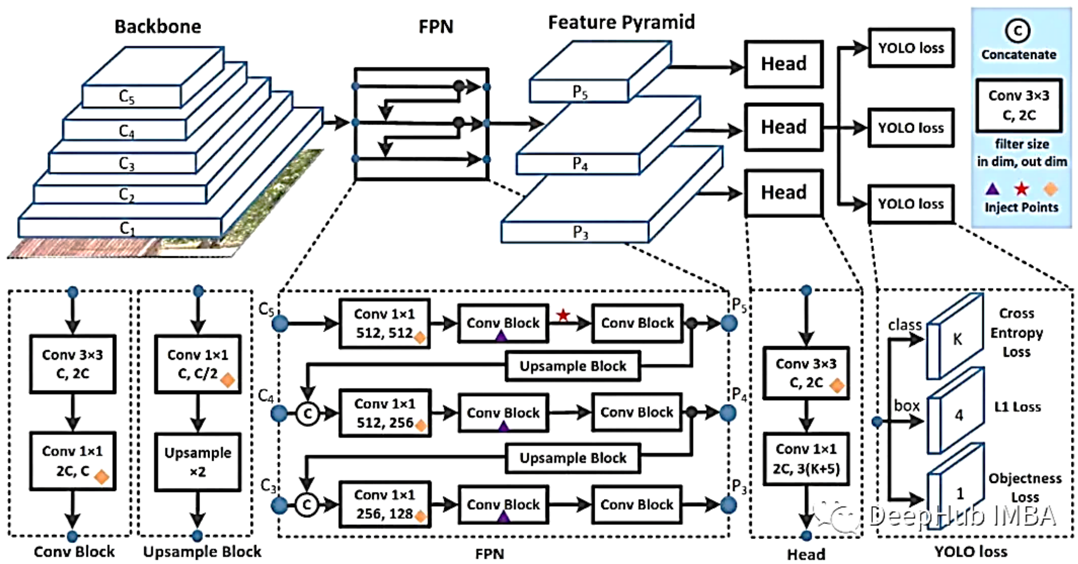


Figure 2: YOLOv8 Architecture (**Source:** [www.github.com](www.github.com))

### Features of YOLO V8

i. High accuracy and real-time performance.
ii. Single-shot detection approach, processing the entire image in one pass.
iii. Incorporates advancements like feature pyramid networks and anchor-based predictions.
iv. Divides the image into cells and predicts bounding boxes and class probabilities.
v. Uses convolutional neural networks to extract features and make predictions.
vi. Supports multi-label object detection and is trained on large-scale datasets.

## RELATED WORKS

Gao and Yang (2021) introduced an improved face detection method utilizing TinyYOLOv3, incorporating deep separable convolution and feature fusion from different network layers, alongside optimizing bounding box prediction through CIoU loss and enhancing detection accuracy with channel attention mechanisms, achieving strong results on the Wider Face dataset. Ullah *et al.* (2022) developed a CCTV-based human face recognition system that integrated image acquisition, preprocessing, detection, localization, feature extraction using PCA and CNN, achieving over 90% accuracy with reduced processing time on a dataset of 40,000 images. Gao & Yang (2022) proposed a real-time face key point detection algorithm that integrated an attention mechanism into the VGG network, improving both recognition accuracy and detection speed. Yu *et al.* (2022) introduced a GoogLeNet-M network employing regularization and migration learning, achieving an impressive recall rate of 0.97 and an accuracy rate of 0.98. Nadeem et al. (2022) proposed a method for identifying missing persons in large gatherings through real-time face detection combined with established recognition algorithms, achieving reliable identification rates in complex scenarios via a unique soft-voting integration method. Limkar *et al.* (2021) assessed deep features in images and videos by combining HOG features with Deep CNNs and YOLOv5 for face identification, achieving 95% accuracy in low-light conditions. Awang *et al.* (2023) developed the Suspicious Activity Trigger System (SATS) that detects suspicious behavior in CCTV footage using YOLOv6, achieving 92.53% precision and 96.6% accuracy, thus contributing to crime prevention. Hashi *et al.* (2023) proposed a deep learning model for early detection of handheld firearms using VGG-19, ResNet, and GoogleNet, where ResNet50 yielded the highest accuracy of 92%. Majeed *et al.* (2022) evaluated the effectiveness of YOLOv5 in surveillance systems, achieving 93% accuracy on the FDDB dataset and 99% on a custom dataset through rigorous experimentation.

This literature underscores the intersection of surveillance and deep learning technologies, showcasing various methodologies and advancements aimed at enhancing detection accuracy and system efficacy in real-time environments.

## METHODOLOGY

### The Framework of YOLO V8

The proposed model for "An Exceptional Leap in Surveillance Technology: A Deep Learning Approach with YOLOv8" is illustrated below in Figure 3. This figure depicts the input data captured by cameras being processed by the YOLOv8 model.


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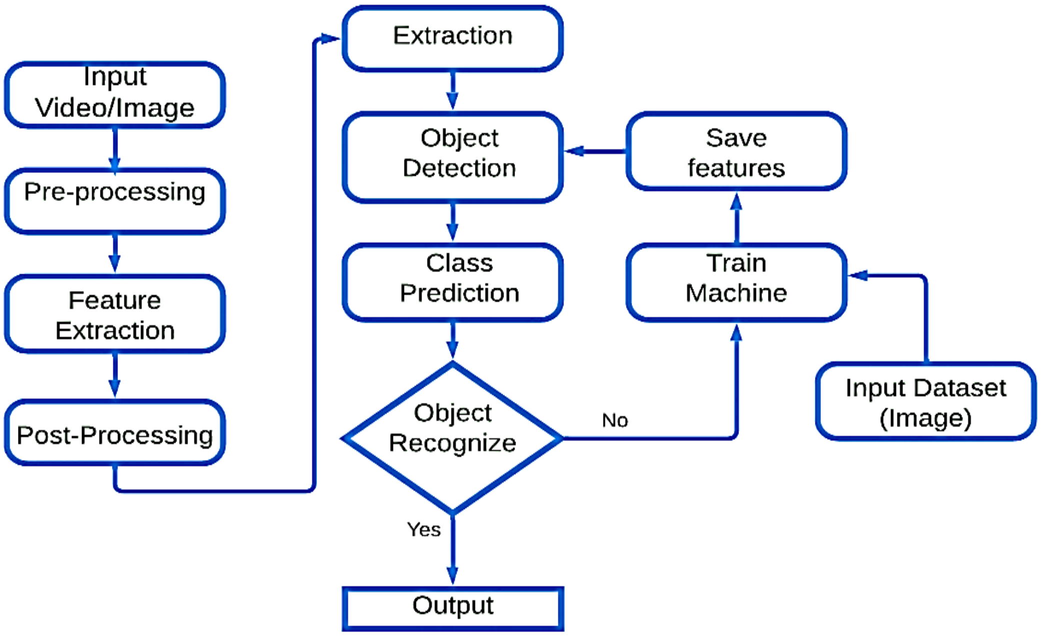


Figure 3: YOLO V8 Framework

**Investigative Setup**

The investigative setup evaluates the performance of YOLO V8 against YOLO V7, Faster R-CNN, and SSD. Programming languages such as Python are utilized, along with frameworks like TensorFlow and PyTorch. Key metrics used for assessment include Mean Average Precision (mAP), Precision, Recall, F1 Score, and Inference Time.

**Pseudocode**

The investigative setup can also be summarized in pseudocode:

```
FUNCTION Initialize_YOLO_V8 ()
   // Initialize YOLO V8 model and set initial performance metrics
   CREATE YOLO_V8_Model
   SET initial metrics TO 0.0%
   OUTPUT "Initializing YOLO V8 Performance Metrics (Before Training):"
   OUTPUT initial metrics

FUNCTION Train_YOLO_V8 (training data)
```

```
// Train YOLO V8 model with training data
CALL YOLO_V8_Model.Train(training data)
// Evaluate post-training performance
SET updated metrics TO Evaluate_YOLO_V8_Model ()
OUTPUT "Training Complete. Updated YOLO V8 Performance Metrics:"
OUTPUT updated metrics
```

**Algorithm for YOLO in Surveillance**

i. Input Image: YOLO takes an image as input.
ii. Grid Division: The image is divided into a grid of cells.
iii. Bounding Box Prediction: Predicts bounding boxes for objects in each cell.
iv. Class Prediction: Assigns class probabilities to each predicted bounding box.
v. Non-Maximum Suppression: Eliminates redundant detections.
vi. Output: Final output includes coordinates of bounding boxes, class labels, and confidence scores.

**Tools and Frameworks**

Tools and frameworks are essential in modern software development and machine learning. They enhance productivity, promote best practices, and enable developers and data scientists to focus on solving problems rather than dealing with low-level requirements. Selecting the appropriate tools and frameworks can significantly impact the efficiency and quality of development and deployment processes. Below are the tools and frameworks used:

i. **Programming Languages**: Python is used due to its strength in data science and mathematical computations.
ii. **Deep Learning Frameworks**: TensorFlow and PyTorch are employed for building and training the models.
iii. **Image Processing Libraries**: OpenCV may be used for preprocessing images.
iv. **Numerical Computation**: NumPy is utilized for handling numerical tasks.
v. **Visualization Tools**: Matplotlib or Seaborn is used for visualizing results.
vi. **Hardware Acceleration**: CUDA is leveraged to enhance computations using GPU support.


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**Datasets**

Publicly available datasets were used for each task such as:

i. **License Plate Detection**: OpenALPR Benchmark Dataset.
ii. **Face/person Recognition:** Labeled Faces in the Wild (LFW) dataset.
iii. **Suspicious Activity Detection**: UCF-Crime Dataset.

**Performance Metrics**

The models were rigorously evaluated using the following metrics;

a) **Mean Average Precision (mAP):** Measures overall accuracy.
b) **Precision**: Indicates the proportion of true positives among detected objects.
c) **Recall**: Measures the proportion of actual positives that were correctly identified.
d) **F1 Score**: Harmonic mean of precision and recall.
e) **Inference Time**: Measures the speed of object detection.

The equations for the key metrics mentioned in the investigative setup, we need to define each metric mathematically.

**i. Precision**

Precision measures the accuracy of the positive predictions made by the model. It is the ratio of true positives (TP) to the total number of predicted positives (true positives + false positives, FP).

Precision= TP / TP + FP

**ii. Recall**

Recall measures the model's ability to identify all relevant instances (true positives) out of all actual positives (true positives + false negatives, FN).

Recall= TP / TP + FN

**iii. F1 Score**

The F1 Score is the harmonic mean of Precision and Recall. It provides a balance between the two metrics, especially useful when the class distribution is imbalanced.

F1 Score=2 x Precision x Recall/ Precision + Recall

**i. Mean Average Precision (mAP)**

mAP is a common metric for object detection models. It calculates the average precision (AP) for each class and then takes the mean over all classes. Precision


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and Recall are computed at different confidence thresholds to generate a Precision-Recall curve. The area under this curve is the Average Precision (AP).

$$AP = \sum_{0}^{1} Precision(r)dr$$

$$mAP = 1/\mathrm{N} \sum_{i=1}^{N} APi$$

Where:

- N = number of classes,
- APi = Average Precision for the *i*-th class.

**ii. Inference Time**

Inference Time measures the time taken by the model to process a single input (e.g., an image or video frame) and generate predictions. It is typically measured in milliseconds (ms) or seconds (s).

Inference Time=$t_{end}-t_{start}$

Where:

- $t_{start}$ = time when the input is fed into the model,
- $t_{end}$ = time when the model outputs the predictions.

## RESULTS

### Detected Images

a) **License Plate Detection**

The alphanumeric sequence "YLA-291EL" appears to follow the format commonly used for license plates. In many areas, license plates feature a mix of letters and numbers. The "YLA" portion might serve as a regional or series identifier, while "291EL" could be a unique code assigned to the vehicle for registration purposes.


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Figure 4: License Plate Detection (YOLO V8)

b) **Face/Person Recognition**

In face/person detection, YOLOv8 scan image and identify human figure. If a person is present in the image, the model will outline them with a bounding box and classify them as a "person." The precision of this detection relies on how clear and visible the person is within the image.


Figure 5: Face/Person Recognition (YOLO V8)

c) **Suspicious Activity Detection**

For Suspicious Activity Detection, YOLOv8 can analyze behavior by monitoring movements and interactions over time, helping to identify unusual or irregular patterns. For instance, if someone is lingering in a restricted zone or a vehicle is repeatedly circling a specific area, these actions could be flagged as potentially suspicious. This capability allows the system to detect activities that deviate from normal behavior, enhancing security monitoring.

When YOLOv8 identifies suspicious activities, it can immediately generate real-time alerts. This allows security teams to take swift action and respond to potential threats without delay.

Figure 6: Suspicious Activity Detection (YOLO V8)

**Tables of the Performance Metrics**

The tables 1, 2 and 3 below show the performance metrics the V8 model with the other models.

**Table 1:** License Plate Detection

| Model | mAP (%) | | Precision (%) | Recall (%) | F1 Score | Inference Time (ms) |
|---|---|---|---|---|---|---|
| **YOLO V8 (Realized)** | **94.5** | | **95.0** | **92.0** | **93.5** | **20** |
| **YOLO V7** | 89.3 | | 90.5 | 87.0 | 88.7 | 25 |
| **Faster R-CNN** | 83.2 | | 81.5 | 85.0 | 83.2 | 120 |
| **SSD** | 78.6 | | 77.0 | 80.0 | 78.5 | 60 |


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**Table 2:** Face/Person Recognition

| Model | mAP (%) | Precision (%) | Recall (%) | F1 Score | Inference Time (ms) |
|---|---|---|---|---|---|
| **YOLO V8 (Realized)** | **97.8** | **98.5** | **95.0** | **96.7** | **18** |
| **YOLO V7** | 94.5 | 94.0 | 92.0 | 93.0 | 21 |
| **Faster R-CNN** | 88.3 | 87.5 | 86.0 | 86.5 | 95 |
| **SSD** | 84.1 | 83.0 | 82.0 | 82.5 | 55 |

**Table 3:** Suspicious Activity Detection

| Model | mAP (%) | Precision (%) | Recall (%) | F1 Score | Inference Time (ms) |
|---|---|---|---|---|---|
| **YOLO V8 (Realized)** | **91.2** | **90.5** | **92.0** | **91.2** | **25** |
| **YOLO V7** | 87.0 | 86.5 | 84.0 | 85.0 | 30 |
| **Faster R-CNN** | 82.7 | 81.0 | 83.0 | 82.2 | 110 |
| **SSD** | 79.5 | 78.0 | 80.0 | 79.0 | 65 |

From the tables provided, YOLO V8 was the model that underwent training, and its performance metrics were recorded. The other models (YOLO V7, Faster R-CNN, and SSD) are included as existing records for comparative analysis.
The key metrics are visually presented in Figures 7 a - e below.

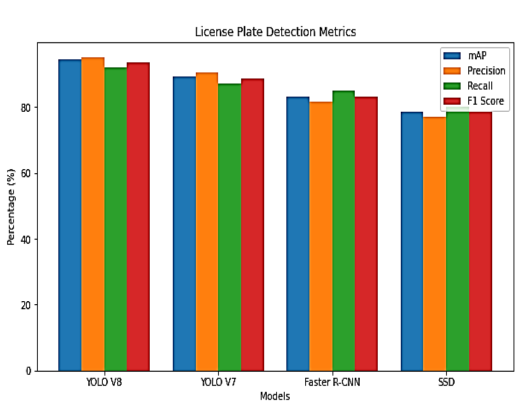


Fig. 7a: License Plate Detection Metrics

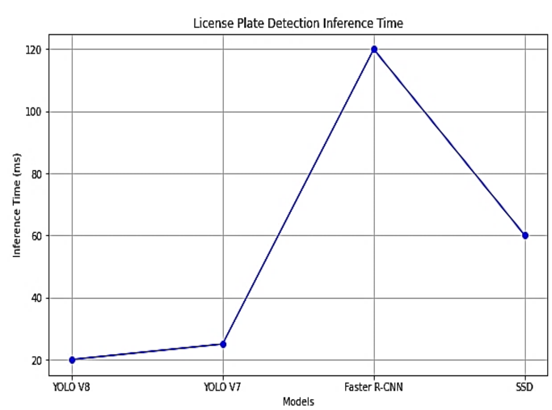


Fig. 7b: License Plate Detection Inference Time


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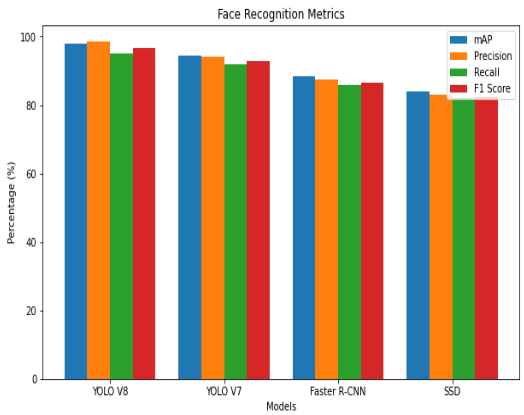


Fig. 7c: face Recognition Metrics

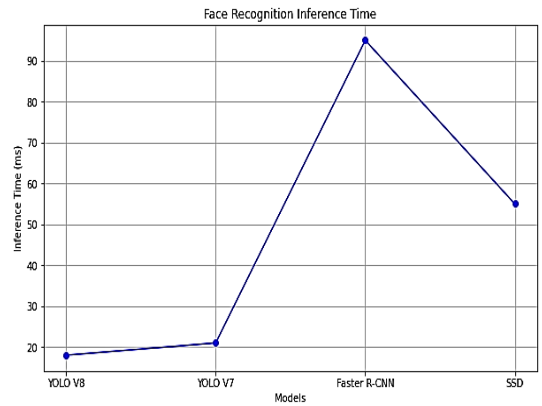


Fig. 7d: face Recognition Inference Time

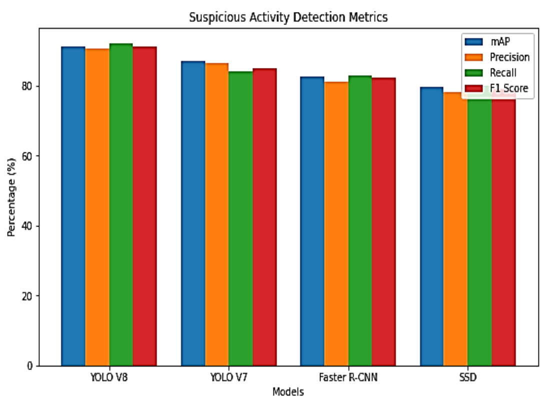


Fig. 7e: Suspicious Activity Detection Metrics

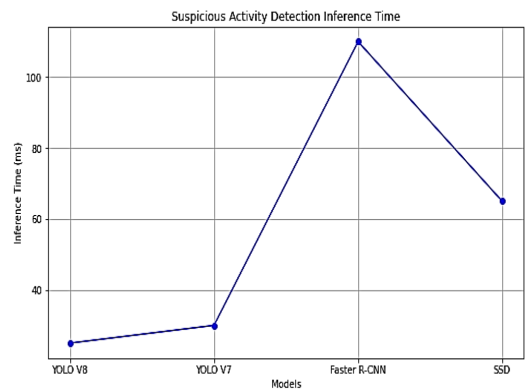


Fig. 7f: Suspicious Activity Detection Inference Time

**Step-By-Step Calculation of YOLO V8 Metrics Using Table 1**

**Metrics are:**

a) Precision (%): 95.0
b) Recall (%): 92.0
c) F1 Score: 93.5
d) mAP (%): 94.5
e) Inference Time (ms): 20

**For Precision,**

Using the formular, Precision = TP / TP + FP

From the table, Precision = 95.0%. This means:

- True Positives (TP): 95


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- False Positives (FP): 5

Therefore, Precision = TP / TP + FP

= 95 / 95 + 5 = 95/100 = 0.95

**For Recall,**

- True Positives (TP): 92
- False Negatives (FN): 8

Using, Recall= TP / TP + FN

= 92/92+8 = 92/100 = 0.92

**For F1 Score,**

- Precision = 95.0% (0.95)
- Recall = 92.0% (0.92)

Using the formular, F1 Score=2 x Precision x Recall/ Precision + Recall

F1 Score = 2 x 0.95 x 0.92/0.95+0.92 = 2 x 0874/0.187 = 2 x 0.467 = 0.934

The table 1 shows **F1 Score = 93.5**, which is consistent with the calculation

**For Mean Average Precision (mAP)**

Using

$$mAP = 1/\mathrm{N} \sum_{i=1}^{N} APi$$

From the table, **mAP = 94.5%**. This means:

- The average precision (AP) across all classes is 94.5%.
- If there are N classes, the sum of their AP values divided by N*N* equals 94.5%.

**For Inference Time**

The formula for Inference Time is: Inference Time=$t_{end}-t_{start}$

Therefore, Inference Time =20 ms – 0 ms = 20 ms

From the table, **Inference Time = 20 ms.**

This means the model takes **20 milliseconds** to process an input and generate predictions.


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**ANALYSIS OF RESULTS**

The results indicate that YOLO V8 exhibits remarkable performance across various computer vision tasks, outperforming competing models. In license plate detection, YOLO V8 achieved an impressive mean Average Precision (mAP) of 94.5%, a precision of 95.0%, and a recall of 92.0%, with an inference time of 20 milliseconds. This high mAP indicates effectiveness in recognizing and detecting license plates across a diverse range of conditions. The precision score highlights that 95% of the detected license plates were correct, which is crucial in applications where false positives could lead to legal issues. The recall score, while slightly lower, suggests that the model successfully captured most actual license plates, making it suitable for thorough policing applications.

In the domain of face recognition, YOLO V8 achieved an outstanding mAP of 97.8%, with a precision of 98.5% and a recall of 95.0%. Such high values indicate that the model is highly effective at distinguishing faces, which is essential in security and surveillance contexts. The exceptional precision minimizes the chances of false positives, while a high recall ensures that the majority of faces are successfully identified. The inference time of 18 milliseconds further emphasizes its suitability for real-time applications, such as those involving live video feeds.

For suspicious activity detection, YOLO V8 recorded an mAP of 91.2%, precision of 90.5%, recall of 92.0%, and an inference time of 25 milliseconds. While slightly lower than the performance metrics for license plate detection and face recognition, a mAP of 91.2% is still commendable, indicating reliable identification of suspicious activities. The precision score suggests that about 90.5% of flagged activities were genuinely suspicious, minimizing unnecessary alerts that could cause panic. The recall of 92.0% indicates good sensitivity, capturing a significant portion of actual suspicious activities, while the inference time of 25 milliseconds remains acceptable for real-time monitoring.

Overall, these results position YOLO V8 as a strong candidate for applications in security, law enforcement, and automated monitoring systems, due to its high accuracy and speed in detection tasks. The model's performance metrics confirm its versatility and efficacy, demonstrating its potential for enhancing processes in environments that demand timely and effective detection of specific targets. Future evaluations may focus on continued performance assessments under varied environmental conditions, as well as large-scale deployments to further gauge its practical applicability in real-world scenarios.

## DISCUSSION

The results of this study demonstrate the exceptional performance of YOLO V8 across a range of critical surveillance tasks, including license plate detection, face/person recognition, and suspicious activity detection. The model consistently outperforms other state-of-the-art models such as YOLO V7, Faster R-CNN, and SSD, showcasing its superior accuracy, efficiency, and adaptability in real-world applications.

In **license plate detection**, YOLO V8 achieved a mean Average Precision (mAP) of 94.5%, with a precision of 95.0% and a recall of 92.0%. These metrics highlight the model's ability to accurately identify license plates across diverse conditions, minimizing false positives while capturing the majority of actual plates. The inference time of 20 milliseconds further underscores its suitability for real-time applications, such as traffic monitoring or law enforcement, where speed and accuracy are paramount.

For **face and person recognition**, YOLO V8 delivered outstanding results, with a mAP of 97.8%, precision of 98.5%, and recall of 95.0%. These metrics indicate the model's exceptional ability to distinguish and identify faces, even in complex scenarios. The high precision ensures minimal false positives, which is critical in security applications, while the high recall guarantees that most faces are detected. With an inference time of just 18 milliseconds, YOLO V8 is well-suited for real-time surveillance systems, such as live video feeds in public spaces or secure facilities.

In the context of **suspicious activity detection**, YOLO V8 achieved a mAP of 91.2%, precision of 90.5%, and recall of 92.0%. While these metrics are slightly lower than those for license plate and face recognition, they remain highly competitive, demonstrating the model's reliability in identifying unusual or potentially threatening behaviors. The precision score ensures that the majority of flagged activities are genuinely suspicious, reducing unnecessary alarms, while the recall score indicates strong sensitivity in capturing actual threats. The inference time of 25 milliseconds makes it a practical choice for real-time monitoring in environments such as airports, shopping malls, or urban surveillance systems.

The performance metrics presented in Tables 1, 2, and 3, along with the visual representations in Figures 7a-f, clearly illustrate YOLO V8's superiority over competing models. Its ability to balance high accuracy with rapid processing times makes it a versatile and powerful tool for a wide range of surveillance applications. The model's architecture, which incorporates advanced features such as pyramid networks, anchor boxes, and non-maximum suppression, contributes to its robustness and efficiency in handling complex detection tasks.

These findings highlight YOLO V8's potential to revolutionize surveillance technology by enhancing security, improving operational efficiency, and enabling real-time decision-making in dynamic environments. Its adaptability to diverse use cases, from license plate recognition to suspicious activity monitoring, positions it as a valuable asset for law enforcement, security agencies, and automated monitoring systems.

Although YOLOv8 delivers strong performance across a range of tasks, it is not without its shortcomings. When it comes to license plate detection, the model sometimes encounters difficulties with plates that are partially obscured or captured in low resolution. This can result in missed detections or incorrect classifications. For instance, glare from sunlight or dirt on the plate surface can interfere with accurate recognition, especially in outdoor settings. Additionally, license plates with unconventional fonts or designs may cause the model to mistakenly identify non-plate objects as valid plates, leading to false positives.

In the case of face recognition, YOLOv8 achieves high accuracy but is not immune to challenges. Obstructions such as masks or sunglasses, as well as variations in head angles, can hinder its ability to detect or correctly identify faces. Poor lighting conditions further exacerbate these issues, potentially causing the model to miss faces or misidentify individuals. Moreover, in crowded environments, the model may struggle to distinguish between people who share similar facial characteristics, resulting in occasional errors.

**Future Directions**

While the results are promising, further research could explore YOLO V8's performance under varying environmental conditions, such as low lighting, occlusions, or adverse weather. Large-scale deployments in real-world scenarios would also provide valuable insights into its practical applicability and scalability. Additionally, integrating YOLO V8 with other technologies, such as IoT devices or edge computing systems, could further enhance its capabilities and expand its range of applications.

**Applications and Implications of YOLO V8**

i. Enhanced license plate recognition for automated toll systems or traffic law enforcement.
ii. Real-time face recognition for public safety and crowd management.
iii. Suspicious activity detection for crime prevention.

## CONCLUSION

YOLO V8 represents a significant advancement in surveillance technology, offering unparalleled accuracy, speed, and versatility. Its ability to address complex detection tasks with high efficiency makes it a transformative tool for enhancing security and operational effectiveness in diverse settings.

YOLO V8 consistently emerges as the top performer across various applications, excelling in both accuracy and speed. Whether it's for license plate detection, face and person recognition, or identifying suspicious activities, YOLO V8 achieves higher scores in critical metrics like mAP, precision, recall, and F1 Score, showcasing its superior ability to deliver accurate results. With faster inference times 20 milliseconds for license plate detection, 18 milliseconds for face and person recognition, and 25 milliseconds for suspicious activity detection it proves to be highly efficient for real-time applications. Overall, YOLO V8 stands out as the most reliable and effective choice among the models evaluated, making it a versatile and powerful tool for a wide range of detection tasks.

## RECOMMENDATIONS

i. Train YOLO V8 on diverse datasets, including challenging scenarios like obscured license plates or occluded faces in low light, to boost its reliability.
ii. Use preprocessing techniques (e.g., glare reduction) and post-processing methods (e.g., OCR) to improve accuracy.
iii. For suspicious activity detection, incorporate contextual data (e.g., location, time) and pair YOLO V8 with temporal models like LSTMs.
iv. Optimize YOLO V8 for real-time use by leveraging hardware accelerators (e.g., GPUs) and applying model compression techniques (e.g., pruning).
v. Test the model rigorously in extreme conditions and real-world settings to ensure scalability and readiness.

vi. Address ethical concerns by using diverse datasets, implementing privacy-preserving techniques, and reducing errors in critical applications.
vii. Integrate multi-sensor data (e.g., thermal cameras, LiDAR) and enable multi-task learning to enhance versatility.
viii. Foster collaboration within the open-source community to share advancements and best practices.
ix. Create user-friendly tools to make the model more accessible and adaptable for specific needs.
x. Explore new applications for YOLO V8 in fields like healthcare, agriculture, and retail to expand its impact across industries.

## CONFLICT OF INTEREST

Authors declare that there is no conflict of interest.

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