7.1 Summary of Findings

In this study, I conducted a comprehensive comparative analysis of three versions of the YOLO object detection algorithm: YOLOv5, YOLOv7, and YOLOv8. My analysis involved evaluating these models on a dataset of 1550 images across various performance metrics, including precision, recall, F1 score, and mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds.

Table 7.1 : Overall Performance

Metric	YOLOv5	YOLOv7	YOLOv8
Precision	0.37	0.435	0.829
Recall	0.246	0.474	0.75
F1 Score	0.296	0.454	0.788
mAP@0.5	0.0803	0.432	0.8
mAP@0.5:0.95	0.0407	0.238	0.596

Precision: YOLOv8 demonstrates a substantial improvement in precision compared to YOLOv5 and YOLOv7, indicating its enhanced capability in correctly identifying true positives as shown in Table 7.1.

Recall: Table 7.2 displays, YOLOv8's higher recall reflects its proficiency in capturing a greater number of relevant instances, reducing the chances of missing important detections.

F1 Score: With the highest F1 score, YOLOv8 balances both precision and recall effectively, making it the most reliable model among the three.

mAP@0.5: The significant leap in mAP@0.5 for YOLOv8 underscores its superior accuracy in object detection tasks.

mAP@0.5:0.95: YOLOv8 excels in this more stringent metric, highlighting its consistent performance across varying IoU thresholds.

Class-Specific Performance

Our class-specific performance analysis further substantiates the advancements in YOLOv8 across a diverse set of categories.

Table 7.2 : Class-Specific Performance

Class	YOLOv5 mAP@0.5	YOLOv7 mAP@0.5	YOLOv8 mAP@0.5
Axe	0.0261	0.175	0.568
BillGates	0.113	0.576	0.992
Bottle	0.0124	0.144	0.379
ElonMusk	0.192	0.712	0.99
Hammer	0.00839	0.158	0.626
Handgun	0.0252	0.325	0.804
Knife	0.0191	0.296	0.674
LeonardoCaprio	0.167	0.523	0.992
MarilynMonroe	0.0424	0.826	0.993
WillSmith	0.198	0.588	0.98

Axe: YOLOv8 shows a marked improvement, increasing the mAP@0.5 from 0.0261 (YOLOv5) and 0.175 (YOLOv7) to 0.568 as shown in table 7.2

BillGates: Achieves near-perfect detection with an mAP@0.5 of 0.992.

Bottle: Table 7.2 shows Significant improvement in YOLOv8, with mAP@0.5 rising to 0.379.

ElonMusk: Near-perfect performance with an mAP@0.5 of 0.99 of YOLOv8 model.

Hammer: YOLOv8 demonstrates improved detection with an mAP@0.5 of 0.626.

Handgun: Substantial improvements in detection accuracy with YOLOv8.

Knife: Significant performance increase in YOLOv8.

LeonardoCaprio: High detection accuracy with an mAP@0.5 of 0.992.

MarilynMonroe: Near-perfect detection with an mAP@0.5 of 0.993.

WillSmith: High detection accuracy with an mAP@0.5 of 0.98.

Recall

Our recall analysis further highlights the advancements in YOLOv8.

Table 7.3 : Recall

Class	YOLOv5 Recall	YOLOv7 Recall	YOLOv8 Recall
Axe	0	0.0345	0.586
BillGates	0.469	0.831	1
Bottle	0.00559	0.145	0.257
ElonMusk	0.7	0.95	1
Hammer	0	0.269	0.538
Handgun	0.05	0.342	0.683
Knife	0	0.296	0.629
LeonardoCaprio	0.724	0.724	0.94
MarilynMonroe	0.0345	0.722	0.966
WillSmith	0.476	0.429	0.905

Axe: YOLOv8 shows remarkable improvements, achieving a recall of 0.586 as displayed in Table 7.3

BillGates: Table 7.3 shows Perfect recall in YOLOv8, indicating all instances were correctly identified.

Bottle: YOLOv8 improves recall significantly to 0.257 as displayed in Table 7.3.

ElonMusk: Perfect recall in YOLOv8, highlighting its reliability.

Hammer: Improved recall to 0.538 in YOLOv8.

Handgun: Significant improvements in recall with YOLOv8.

Knife: Enhanced recall to 0.629 in YOLOv8.

LeonardoCaprio: High recall of 0.94 in YOLOv8.

MarilynMonroe: Near-perfect recall of 0.966 in YOLOv8.

WillSmith: High recall of 0.905 in YOLOv8.

7.2 Contributions and Implications of the Study

Enhanced Object Detection

This study demonstrates how YOLOv8 significantly enhances object detection accuracy and speed. The improvements in precision and recall metrics indicate that YOLOv8 can reliably identify and classify objects with higher confidence and fewer errors. This enhancement is particularly crucial for real-time applications where quick and accurate detections are necessary.

Facial Recognition Advancements

Incorporating facial recognition within the YOLO framework presents a novel approach to early victim identification in forensic investigations. The high accuracy of YOLOv8 in detecting and recognizing specific individuals (e.g., celebrities) suggests its potential utility in forensic applications, where accurate identification can lead to quicker and more effective investigations.

Resource Efficiency

The study highlights how newer models like YOLOv8 manage to balance high performance and computational efficiency. This balance makes YOLOv8 suitable for deployment in resource-constrained environments, such as mobile devices and edge computing scenarios, where processing power and memory are limited.

Forensic Applications

The research underscores the potential of advanced YOLO models in forensic science. The high accuracy and reliability of YOLOv8 in identifying objects and individuals can significantly aid forensic experts in analyzing crime scenes, identifying suspects, and gathering evidence. This application is particularly relevant in scenarios requiring high accuracy and quick turnaround times.

7.3 Future Research Directions in YOLO

Exploring Lightweight Models

Future work could focus on developing lightweight versions of YOLOv8 that retain high accuracy while being more efficient for deployment on edge devices. This direction involves optimizing the model architecture and reducing its computational requirements without compromising detection performance.

Integration with Other Technologies

Combining YOLOv8 with other AI technologies, such as natural language processing and context-aware computing, can enhance its application in more complex forensic scenarios. For instance, integrating YOLOv8 with a contextual analysis framework could provide deeper insights into the detected objects and their surroundings, improving the overall forensic analysis process.

Extended Datasets

Applying the models to larger and more diverse datasets can further validate and refine their performance. Expanding the dataset to include more varied and challenging images will help ensure that the models generalize well across different scenarios and improve their robustness and reliability.

Real-time Applications

Investigating the application of YOLOv8 in real-time forensic analysis, including live video feeds, is crucial to assess its practical utility and performance under operational conditions. Real-time applications require the model to process and analyze video frames swiftly, making it essential to optimize YOLOv8 for such tasks.

7.4 Concluding Remarks

The comparative analysis of YOLOv5, YOLOv7, and YOLOv8 on a dataset of 1550 images demonstrates clear advancements with each version. YOLOv8 significantly outperforms its predecessors across all key metrics, including precision, recall, and average precision (mAP), showcasing its superior capability in object detection and classification tasks. The study's contributions highlight the practical implications for enhanced object detection and facial recognition, especially in forensic applications. Future research directions suggest exploring lightweight models, integration with other AI technologies, validation on larger datasets, and real-time applications to further advance the field.

In conclusion, YOLOv8 represents a significant step forward in the field of object detection, offering substantial improvements over earlier versions. Its enhanced performance metrics and potential applications in real-time and forensic scenarios underscore its importance and utility in advancing both academic research and practical implementations in various domains