

Enhancing Automotive Safety Through Advanced Object Behaviour Tracking for Intelligent Traffic and Transport System

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Abstract— In the ever-evolving landscape of vehicle motion analysis, the imperative for enhanced road safety has underscored the importance of tracking object behavior, with a particular focus on vehicles. This paper proposes an innovative approach specifically designed for tracking vehicle behavior, emphasizing collision risk analysis. Central to this approach is the development of a powerful model for meticulous vehicle detection and classification, using real-world video feeds. By leveraging the YOLO algorithm, our method achieves real-time object detection, which is crucial for effective traffic monitoring. We extend our work beyond simple detection to include trajectory tracking, wherein we analyze the complexities of vehicle movement to identify patterns of traffic behavior and potential congestion hotspots. To refine our system further, we have integrated the DeepSORT algorithm, which applies the Kalman Filter and Hungarian algorithm to achieve enhanced multi-object tracking. This allows for seamless tracking through occlusions and at intersections. Our system is adept at identifying potential collision risks by employing advanced risk analysis techniques that assess severity and predict possible incidents. This paves the way for robust preventative measures and underscores our commitment to improving road safety, reducing accidents, saving lives, and enhancing traffic flow. As urban environments grow, such technological advancements are poised to make a significant impact on traffic management and safety standards. We have validated our system's performance using comprehensive datasets, showcasing marked improvements in detection accuracy, precision, and tracking capabilities under various conditions. The development and successful validation of our system not only confirm the viability of our approach but also lay the foundation for future developments in object-tracking technology for autonomous systems.

Keywords— *Object Detection, Trajectory Tracking, DeepSORT, Collision Risk Analysis, Deep Learning, Intelligent Traffic and Transport System*

I. INTRODUCTION

In pursuit of Enhanced road safety, this research investigates the intersection of transportation engineering and advanced computational analytics to revolutionize Intelligent Transportation Systems (ITS). Through this paper, we introduce an innovative ITS framework utilizing a single-camera system, bolstered by the synergistic application of image processing, machine learning, and deep learning techniques. Our goal is to adeptly address the sophisticated challenges of object tracking, particularly under conditions of occlusion, scale variation, and complex motion patterns. Central to this research is the development of a highly precise

and resilient object-tracking system that promises to significantly advance road safety while seamlessly integrating with existing infrastructure.

The key contributions of the paper include:

- (a) The creation of enhanced image processing and tracking algorithms that proficiently handle occlusions and scale variations by integrating machine learning and deep learning to adapt to the dynamic nature of real-world traffic.
- (b) The formulation of a predictive model for the real-time assessment of collision risks by analyzing object distances, behaviors, velocities, and trajectories, aimed at enabling proactive safety measures.
- (c) The design of a system is crafted to fit smoothly within the framework of current traffic management systems, thereby optimizing traffic flow and reducing incidents on the road.

Utilizing the COCO dataset complemented by a wide array of video feeds, our approach is designed to underpin extensive model training and validation. This rigorous process is pivotal in establishing a robust analysis of object behavior, which is essential for the precision and effectiveness of our intelligent tracking system. The performance of comprehensive field testing using surveillance cameras on the highways of Milton Keynes, England, United Kingdom, was critical to authenticate the system's effectiveness under a variety of traffic and infrastructural conditions.

These advancements are poised to significantly benefit to both manual and autonomous systems and intelligent robotics by enhancing road safety and elevating traffic management standards, thereby fostering safer and more efficient applications.

II. RELATED WORKS

The advancement of Intelligent Transportation Systems (ITS) has been closely tied to developments in computer vision, image processing, machine learning, and deep learning. These technologies are essential in tracking object behavior, a critical element for enhancing traffic management systems. This review discusses significant contributions to the field, focusing on the challenges encountered, methodologies applied, and the practical applications of these advancements. Research in object tracking through single camera sensors has demonstrated the effectiveness of combining background subtraction with Gaussian models, despite challenges related to changes in lighting and speed estimation inaccuracies [1].

Innovations in multi-object tracking have included dual learning processes, indicating a shift toward more adaptable models capable of managing complex interactions [2]. Studies have also focused on the use of machine vision in traffic management to optimize traffic flow on highways and enhance public transportation systems. These have employed traffic sign recognition and deployed advanced object detection models, pointing toward a trend in demand-responsive and multimodal traffic systems [3], [4].

Rapid object detection and tracking have been achieved through pixel difference operations and the application of efficient tracking algorithms, reflecting a broader movement from traditional methods to real-time, efficient ITS applications [5].

A significant contribution in the form of a three-layered approach to traffic management and speed regulation within electric vehicle systems has incorporated Data Analytics, Machine Learning, Deep Learning, and IoT, indicating a significant step forward in vehicular safety and traffic flow optimization [6].

The role of deep learning in object tracking and collision risk analysis has been highlighted by studies employing convolutional neural networks and tracking algorithms, emphasizing the potential of these technologies to transform ITS with improved predictive accuracy and response mechanisms [7].

The assessment of these technologies has utilized common metrics such as accuracy, precision, and recall, crucial for measuring the performance of object tracking methods and influencing the evolution of ITS applications.

Despite these technological leaps, adapting to the unpredictability of real-world environments and integrating various data sources remains a challenge. Future research is directed toward enhancing real-time processing capabilities and improving energy efficiency.

In the smart city domain, innovative models for autonomous vehicle navigation and cloud-based traffic management systems have been proposed. These models feature secure cloud databases that facilitate real-time vehicle-to-traffic signal communication, greatly reducing the incidence of traffic accidents [8].

This literature review encapsulates the progress within Intelligent Transportation Systems (ITS), illuminated by the integration of advanced computational techniques for object behavior tracking. The foundational work has paved the way for ongoing enhancements in traffic management systems. Yet, considering the challenges of environmental adaptability, data integration, and system efficiency, continuous innovation is crucial to ensure the safety and efficiency of transportation networks. Building on this, our research proposes a novel framework that not only leverages the unique strengths of each sensor modality but also introduces advanced deep learning techniques to enhance the accuracy and robustness of object detection and localization tasks. These endeavors aim to bridge the gap identified in existing literature, offering a comprehensive solution that can significantly advance both manual and autonomous transportation systems, promote safer and more efficient applications, and contribute to the elevation of traffic management standards in various infrastructural conditions.

III. METHODOLOGY

This research introduces an innovative approach to traffic management through the development of an advanced architecture, centering on real-time collision risk analysis and multi-object tracking. The efficacy of the system is demonstrated through its sophisticated processing stages, from video input to collision risk analysis, ensuring robustness across various traffic scenarios and infrastructural conditions.

A. Integrated Traffic Management Architecture

At the core of our methodology is a cohesive architecture for real-time traffic management, focusing on a collision risk analysis module. The proposed system's architecture is illustrated in Figure 1. It is constructed as an end-to-end solution, commencing with video input and culminating in a comprehensive collision risk analysis. Each stage within the system is interconnected and sequential, allowing for real-time processing and analysis of traffic data.

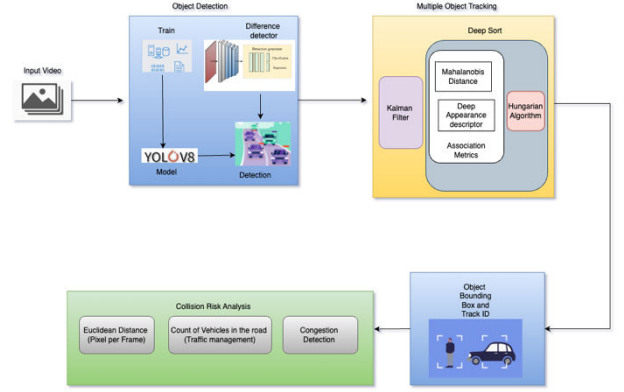


Figure 1: The High-level Architecture

B. Acquisition and Synchronization of Traffic Data

The COCO dataset, augmented by a robust collection of video sources, is employed to create a comprehensive dataset, crucial for the accuracy of the object detection model. The preprocessing workflow is streamlined using Roboflow's platform, to prepare the data meticulously for training, validation, and testing [9].

C. Training and Optimization of the Detection Model

The YOLOv8l model is optimized to balance accuracy and processing speed, demonstrating the use of mAP as a quantifier of performance across different model sizes and computational speeds.

D. Feature Extraction and Network Architecture

Our approach incorporates the YOLOv8 model for its advanced architectural features, enhancing feature extraction capabilities crucial for accurate object detection and classification.

E. Implementation Using the Ultralytics Framework

The robust and user-friendly Ultralytics YOLOv8 framework is adopted for model training and evaluation. This includes the systematic training approach, bounding box prediction decoding, and the computation of training and validation losses.

F. Object Detection and Classification Process

We outline a step-by-step process of object detection using the YOLO model, including model loading, image preprocessing, inference, and application of non-maximum suppression to refine detection outputs [10].

G. Trajectory Analysis and Collision Risk Assessment

The application of the Deep SORT algorithm for trajectory analysis is discussed in detail, including the initialization of object tracks and the data association mechanics using the Hungarian Algorithm [11]. This involves prediction and update steps of the Kalman Filter, with visualization techniques for object tracking. We incorporated a two-step Kalman Filter process forms the basis of our tracking system, handling prediction and update stages [12].

To predict the next state of the system based on the previous state and the system model which is expressed as

$$\text{Predicted covariance} : P_k|_{k-1} = M_k P_{k-1} |_{k-1} M_k^T + Q_k \quad (1)$$

The predicted state here refers to the estimation of the future state of a system based on the current known state and a model of how the system evolves. The predicted covariance in the Kalman filter refers to the estimation of the uncertainty associated with the predicted state of the system while measuring the confidence in its prediction of the next state. Integrating the predicted state with actual measurements refines the state estimate. The 'Kalman Gain' guides the adjustment extent based on new data, followed by updating the state's covariance to refine our estimate's certainty [13].

$$\text{Kalman gain} : K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \quad (2)$$

$$\text{Update covariance} : P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (3)$$

H. Predictive Collision Risk Analysis

The analytical process for assessing collision risks is delved into, employing Euclidean distances to monitor the movement of detected objects and calculate potential collision points [14]. This predictive analysis is vital for assessing the model's real-time effectiveness [15].

$$\text{distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (4)$$

I. Dynamic Traffic Management

Finally, the system's dynamic traffic management capabilities are detailed [16]. This includes vehicle counting, congestion detection, and real-time traffic condition monitoring, with approaches for managing vehicle counts and detecting congestion flow, enabling responsive traffic control measures [17].

This methodical approach ensures the development of a robust framework for precise detection and localization of objects, enhancing the safety and efficiency of transportation networks.

IV. RESULTS

A. Quantitative Evaluation of Model Precision and Recall During Training

The model's precision and recall were quantitatively evaluated through the precision-recall curve as shown in Figure 2. At a high confidence level of 0.995, the model

achieved a perfect precision score of 1.00, signifying that all predicted instances of the class were accurate with no false positives. Conversely, the recall metric indicated the model correctly identified 76% of the true instances across classes, showcasing robust detection capabilities with room for improvement in capturing the complete set of relevant objects.

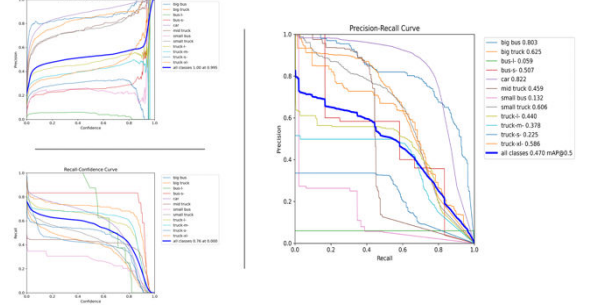


Figure 2: Precision-Recall Curve (Model Training)

The F1-Confidence curve in Figure 3, further delineated the model's performance, striking a balance between precision and recall with an F1 score of 0.48 at a confidence threshold of 0.395. This score reflects the model's accuracy holistically, considering both the precision of the detection and the recall of the true instances. Collectively, these curves underscore the model's proficiency in object detection within the training dataset, with a mean Average Precision (mAP) of 0.470 at an IoU threshold of 0.5. Such a level of mAP is indicative of the model's satisfactory detection performance, particularly considering the complexity and variability inherent in the dataset utilized for this study.

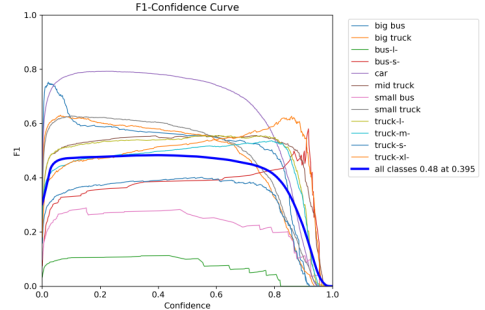


Figure 3: F1-Confidence Curve (Model Training)

B. Quantitative Evaluation of Model Precision and Recall During Validation

The validation phase involved a quantitative evaluation of the model's precision and recall, analyzed through the precision-recall curve shown in Figure 4. At a notably high confidence threshold of 0.986, the model accomplished a perfect precision score of 1.00, indicating that all predicted instances were precise, with zero false positives recorded. This reflects the model's accuracy in object detection at high confidence levels. In terms of recall, the model demonstrated the capacity to correctly identify 19% of the actual objects of interest across all classes when considering all detections made, irrespective of the confidence level.

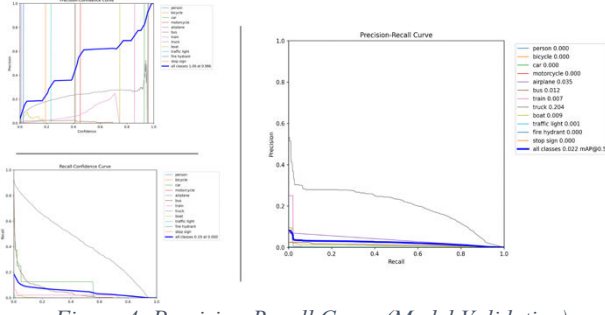


Figure 4: Precision-Recall Curve (Model Validation)

This suggests that while the model is highly precise, there is a scope for improvement in its ability to detect all relevant objects within the images. Further insights into the model's performance were provided by the F1-Confidence curve in Figure 5. At a confidence threshold of 0.387, the model achieved an F1 score of 0.48, revealing the model's moderate success in balancing precision and recall.

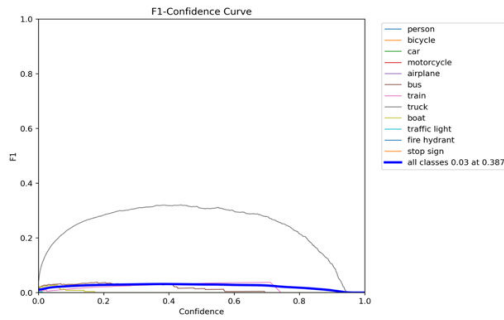


Figure 5: F1-Confidence Curve (Model Validation)

The aggregate performance of the model across all object classes is summarized with a mean Average Precision (mAP) of 0.22, considering an Intersection over Union (IoU) threshold of 50%. Although this mAP may appear modest, it is indicative of the model's overall satisfactory object detection capabilities. This is particularly noteworthy given the challenges associated with the complexity and variability of the dataset used during validation. The collective results from the precision-recall and F1-Confidence curves emphasize the model's competence in object detection, providing a nuanced view of its strengths and areas for improvement.

C. Showcasing the set of Training batches of the COCO Dataset

The data batches utilized in the model training process, rather than single sample updates, advance the model's weights. Starting from the initial sequence implies a comprehensive and uninterrupted training process. Uniformity in sample presentation across batches reflects the stability of the data handling throughout the training.



Figure 6: Set of Training Batches

D. Showcasing the set of Validation batches of the COCO Dataset

The images appearing below in Figure 7, present the model's predictions on the validation set. They are compared to the ground truth labels truths to compute the validation metrics.

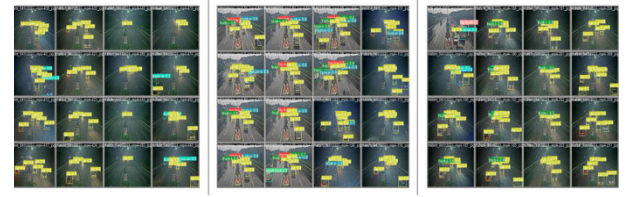


Figure 7: Set of Validation Batches

E. Object Detection and Trajectory Tracking Outcomes

Object detection and trajectory tracking shown in Figure 8, illustrate the model's ability to detect and track objects accurately across frames.



Figure 8: Object Detection and Trajectory Tracking

The consistent IDs and movement trajectories evidenced the effective application of DeepSORT for real-time tracking.

F. Prediction of the Future Path Movement

An initial observation from the sequence highlights the filter's efficacy; the directional arrows corresponding to each detected object align with their subsequent actual movements, underscoring the predictive accuracy in earlier frames depicted in Figure 9. Further scrutiny of the images reveals an adaptive quality in the predictive model. Notably, in the third frame, an object's shift in trajectory is promptly accounted for, with the Kalman Filter recalibrating its prediction to reflect this change in direction. This adaptability is illustrated when the object in the bottom-right corner alters

its path, and the corresponding arrow adjusts in anticipation of the new trajectory. The subsequent frame consolidates the filter's predictive capability, with arrows uniformly indicating forward movement, suggesting a continuous trajectory for all objects. This uniformity in prediction, however, is tempered by the real-world unpredictability of object movement, which can entail abrupt directional changes [18].



Figure 9: Prediction of the Future Trajectory

G. Collision Risk Analysis

The collision risk assessment shown in Figure 10, utilised Euclidean distance measurements between objects to identify potential risks, with real-time analysis conducted on highway scenarios to validate the system's predictive abilities.



Figure 10: Collision Risk Analysis

H. Real-Time Collision Risk Analysis on Highway Roads

In a real-time collision risk analysis conducted on the Milton Keynes highway, as shown in Figure 11, a video feed was processed into 7,259 frames to identify potential collision scenarios, with a processing time of 0.5ms pre-process, 13.1ms inference, and 1.8ms post-process per image at a resolution of (1, 3, 640, 640). The analysis categorized six key scenarios: a single vehicle potentially deviating from its path, a vehicle changing lanes without maintaining a safe distance, multiple vehicles in close proximity on a motorway, vehicles approaching an intersection with potential intersecting paths, an emergency lane change by a vehicle due to an obstruction, and vehicles navigating a roundabout with possible incorrect yielding. This comprehensive categorisation assists in pinpointing high-risk moments that could lead to collisions, thereby facilitating the development of enhanced predictive collision avoidance systems to improve road safety [19].



Figure 11: Real-Time Collision Risk Analysis

I. Prediction of Future Risk Analysis

Forecasting collision risks on the Milton Keynes highway involves predicting vehicular paths for safety as shown in Figure 12. A single vehicle's trajectory indicates future risks, while lane changes require alerts for safe execution. Trajectories on a motorway anticipate potential sudden stops to avoid rear-end collisions. At intersections, predicted paths highlight crossing dangers. Emergency lane changes are monitored for risky manoeuvres, and in roundabouts, predicted paths aid in safe vehicle merging. This predictive analysis is vital for proactive collision avoidance [20].



Figure 12: Prediction of Future Risk Analysis

J. Traffic Management Applications

Strategic planning in traffic management was explored through vehicle counting and congestion detection shown in Figures 13 and 14, demonstrating how the system could effectively monitor and manage traffic flow. An exhaustive examination of the model's performance across various real-world scenarios is carried out highlighting its strengths and identifying areas for further refinement. The insights gleaned from this analysis pave the way for subsequent discussions on the implications and potential enhancements of the developed system.

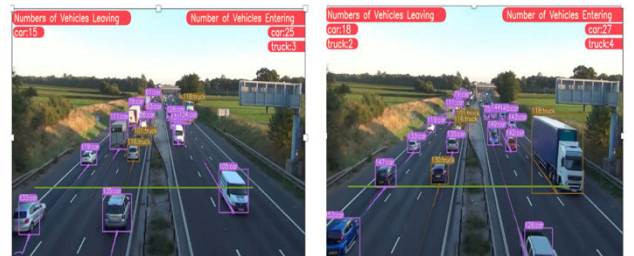


Figure 13: Count of Vehicles

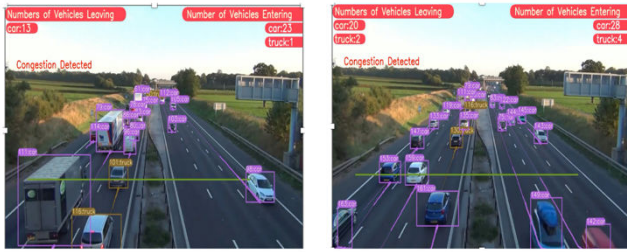


Figure 14: Congestion Detection

V. DISCUSSION

The figures in results describe the outcomes of an Intelligent Transportation System (ITS) project. It details the achievement of set objectives, system performance, collision risk evaluation, traffic management integration, robustness in various conditions, handling of data challenges, and predictions for future vehicle trajectories. Notable highlights include effective object detection, handling of tracking challenges, commendable processing speed, precision in trajectory tracking, potential for traffic management, and system robustness under diverse conditions. The document also notes areas for improvement, such as benchmarking, computational overhead, and scalability. This concise summary encompasses the key findings and considerations from the ITS research outcomes.

VI. CONCLUSION

The research demonstrates the effectiveness of an object detection model in traffic management, enhancing road safety and efficiency. Validation confirms its precision and practical utility. Achievements in safety and efficiency showcase the system's value and its contribution towards smart city and advanced transport infrastructure development. Future research will focus on improving training methods, integrating multi-sensor data, employing advanced spatial detection, leveraging vehicle-to-everything (V2X) communication, and incorporating continuous learning to adapt to changing traffic patterns. This marks a step forward in the evolution of intelligent transportation systems.

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