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Camera-based advanced driver assistance with integrated YOLOv4 for real-time detection

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ABSTRACT

Testing object detection in adverse weather conditions poses significant challenges. This paper presents a framework for a camera-based advanced driver assistance system (ADAS) using the YOLOv4 model, supported by an electronic control unit (ECU). The ADAS-based ECU identifies object classes from real-time video, with detection efficiency validated against the YOLOv4 model. Performance is analysed using three testing methods: projection, video injection, and real vehicle testing. Each method is evaluated for accuracy in object detection, synchronization rate, correlated outcomes, and computational complexity. Results show that the projection method achieves highest accuracy with minimal frame deviation (1-2 frames) and up to 90% correlated outcomes, at approximately 30% computational complexity. The video injection method shows moderate accuracy and complexity, with frame deviation of 3-4 frames and 75% correlated outcomes. The real vehicle testing method, though demanding higher computational resources and showing a lower synchronization rate ($>$ 5 frames deviation), provides critical insights under realistic weather conditions despite higher misclassification rates. The study highlights the importance of choosing appropriate method based on testing conditions and objectives, balancing computational efficiency, synchronization accuracy, and robustness in various weather scenarios. This research significantly advances autonomous vehicle technology, particularly in enhancing ADAS object detection capabilities in diverse environmental conditions.

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1. INTRODUCTION

In the rapidly evolving landscape of automotive technology, advanced driver assistance systems (ADAS) [1] have emerged as pivotal components in enhancing road safety and driving efficiency. Central to the effectiveness of ADAS is the capability for real-time object detection, a task that demands high accuracy and reliability under diverse and often challenging environmental conditions [2]–[5]. Recent developments in artificial intelligence (AI) are bringing the concept of self-driving automobiles closer to reality, with the potential to revolutionize transportation by enabling vehicles to drive themselves without human intervention [6]. The society of automotive engineers (SAE) defines six levels of driving automation, ranging from level 0 (no driving automation) to level 5 (full automation), reflecting the progressive sophistication of autonomous driving capabilities [7], [8]. Consumers worldwide are eagerly anticipating the introduction of driverless cars, which promise to navigate complex environments, classify objects, and adhere to traffic laws autonomously [9]–[11]. A notable milestone in this field is the Mercedes-Benz drive pilot, the first autonomous driving system to receive complete certification at level 3, marking significant progress towards fully autonomous vehicles.

Self-driving cars utilize an array of sensors, including radar, video cameras, light detection and ranging (LIDAR), and ultrasonic sensors, to gather comprehensive data about their surroundings [12], [13]. These sensors enable the vehicle to construct and continuously update a detailed map of its immediate environment. Radar monitors the positions of nearby vehicles, video cameras identify pedestrians, vehicles, and traffic signals, LIDAR measures distances and detects road features, and ultrasonic sensors detect obstacles at close range [14]. The integration of these sensor technologies with advanced computer vision systems is crucial for the performance of ADAS, as these systems must process real-time data to make instantaneous decisions [15]. The demand for ADAS is expected to surge with advancements in computer vision and deep learning (DL). Modern automobiles increasingly rely on camera-based environmental sensors to identify, classify, and localize objects accurately. Consequently, rigorous testing and validation of camera-based ADAS functions are essential to ensure their reliability and effectiveness under various conditions [16], [17]. Current ADAS testing methodologies include vehicle-level field trials and hardware-in-the-loop (HIL) testing [18], [19]. Vehicle testing on proving tracks validates ADAS functions but faces limitations regarding safety and environmental conditions, resulting in reduced test coverage [20]–[22]. Conversely, HIL validation offers a more comprehensive approach [23]. In HIL testing, various scenarios are created using simulation software. These simulated scenarios are then fed to the ADAS camera via a monitor to evaluate the system's performance [24], [25]. This method allows for thorough validation of ADAS functions under a wide range of environmental conditions and safety-critical scenarios, ensuring the system can handle real-world situations effectively.

This research delves into the integration and validation of a camera-based ADAS using the advanced YOLOv4 model [26], [27], a DL algorithm celebrated for its efficiency and accuracy in object detection. The main goal is to assess YOLOv4's performance within an ADAS framework, particularly focusing on its ability to detect and classify objects in real-time [28]. Given the complex, variable conditions encountered in real world driving such as adverse weather, this study aims to address the critical need for a robust and reliable object detection system. Through a structured approach incorporating various testing and validation scenarios such as monitor based scenario projection, camera based real-time scenario capture, and live drive testing—this research presents an in depth analysis of the ADAS system's effectiveness [29]. It examines the trade offs between computational efficiency and detection accuracy, offering valuable insights that can drive further advancements in ADAS technology. These findings contribute to the growing field of autonomous driving, highlighting the importance of accurate, high performance object detection as a foundational element on the path to fully autonomous driving solutions.

2. METHODOLOGY

This section describes a framework developed for testing and validating real-time object detection using a camera based ADAS. It is clearly illustrated in the Figure 1. The electronic control unit (ECU) is integrated with a well-trained DL network. The framework consists of four important units: in-front vehicle infotainment (including a video camera and ADAS cameras), a central gateway, a pre-trained YOLOv4 with the proposed video frame feeding (VFF) algorithm [30], and an ADAS-ECU based object detection model. The overview of the proposed framework is as follows: both the video camera and ADAS camera are mounted on the vehicle's windshield to continuously monitor the front road environment. Once the vehicle starts, both cameras are activated and instantaneously capture the road environment. This data is then forwarded to the pre-trained YOLOv4 and the ADAS-ECU separately with the help of the central gateway unit. The CarMaker (CM) tool creates real-world scenarios and feeds video to the proposed VFF algorithm, which processes the video frames and generates the object list to be applied to the object detection model. Similarly, the ADAS ECU provides vehicle dynamic information for the videos received from the ADAS camera, which is fed through ethernet. The partner ECU then starts to identify objects, and the output list is provided in CAN format. The object detection model processes this and provides an output as a list of detected objects. The developed framework cross-checks the outcomes received from the ADAS camera as CAN messages and from the VFF algorithm in real-time. It compares the object list from the proposed VFF algorithm and the CAN data against the simulation timestamp to ensure that there is no false positive or false negative identification of objects.

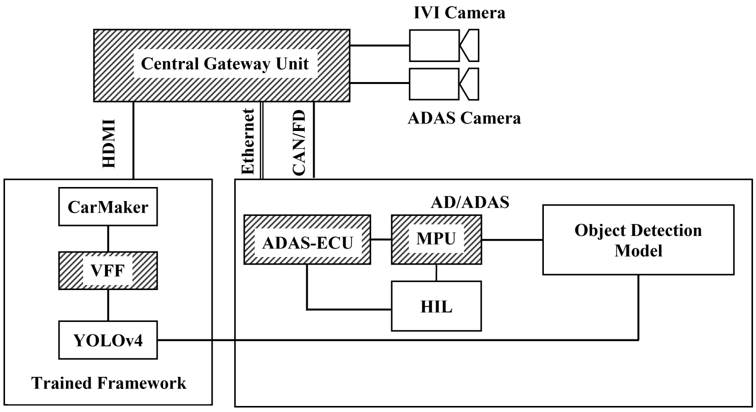

Figure 1. The real-time object detection testing and validation framework

2.1. In-front vehicle infotainment

The ADAS camera ECU is primarily responsible for processing visual data in real-time, which is crucial for detecting and warning about potential hazards such as pedestrians, other vehicles, and road signs. Its ability to swiftly handle large volumes of data from cameras is vital for effective decision-making and action in dynamic driving environments. It is mostly used for automating driving tasks such as parking assistance, lane keeping, and adaptive cruise control, all of which significantly reduce driver workload and enhance driving comfort and experience. Additionally, it adapts to various environmental conditions, including low light and adverse weather, to ensure consistent performance under different external factors. The video camera, having similar properties to the ADAS camera (such as field of view and frames per second), captures the road environment and feeds it to the pretrained YOLOv4 integrated with the proposed VFF algorithm.

2.2. Central gateway

It facilitates the flow of data between different components, in this case, the cameras (video and ADAS cameras), the pre-trained YOLOv4 with VFF algorithm, and the ADAS-ECU. Simply, it refers as a central hub or intermediary in the system. The high bandwidth of HDMI supports the transfer of uncompressed video data, which is crucial for maintaining the quality and fidelity of the visual information necessary for accurate object detection. Other hand, the processed data can be transmitted to the ADAS-ECU via an Ethernet connection. This ensures a reliable and fast transfer of crucial object detection information, which the ADAS-ECU can then use to make realtime decisions for driver assistance functionalities.

2.3. Pre-trained YOLOv4 with VFF algorithm

The main goal is to accurately detect traffic signboards object based on the German traffic sign recognition Benchmark (GTSRB) [31], [32] dataset which is pre-trained in YOLOv4 with additive support of proposed VFF algorithm that can be capable of performing detection and classification under various environmental conditions. In this process, real-time video frames are fed into the pre-trained YOLOv4 model, enhanced by the VFF algorithm, to identify specific traffic signboards from a selected set. It simplifies the process of object detection in a simulated environment. Its main objectives are i) setting up the camera model in CM, ii) generating video frames that represent the simulated environment, iii) pre-processing these video frames before they are input into the object detection model, and iv) comparing the detected objects from the model with the data from CM to ensure accuracy. The model's performance is measured by its ability to recognize these signboards consistently and accurately across different scenarios like day, foggy day, cloudy, dusk, foggy night, and night. The effectiveness of the pre-trained YOLOv4 model, coupled with the VFF algorithm, is further demonstrated through occlusion testing, where the model successfully identifies traffic signboards even when partially obscured, such as by trees, with maximum accuracy in percentage. The primary outcome of this process is the generation of a reliable and accurate object list (in this case, traffic signboards) under varying environmental conditions and occlusions, ensuring robust performance of the object detection system.

2.4. ADAS-ECU based object detection model

The operation of the ADAS-ECU, which is interconnected with both microprocessor unit (MPU) and HIL, and then connected to an object detection model, can be described simply as follows: The ADAS-ECU serves as the central processing unit in this setup. It receives input from the MPU, which handles the initial processing of data, such as signals from various sensors and cameras. This processed data is then sent to the HIL system, where real-time simulations are conducted to emulate driving conditions and scenarios. These simulations are crucial for testing and validating the performance of the ADAS-ECU under different conditions. The output from the HIL, which represents processed and simulated sensor data, is then fed into the object detection model. This model, possibly based on proposed VFF algorithms, analyzes the data to detect and classify objects in the vehicle's vicinity, contributing to various ADAS functionalities such as collision avoidance, lane keeping, or adaptive cruise control. This interconnected system ensures that the ADAS-ECU operates effectively, accurately processing real and simulated data for enhanced vehicle safety and driver assistance.

3. RESULTS AND DISCUSSION

This section explores the evaluation results of the developed framework used for object detection analysis carried out in a real-time outdoor environment. Its performance is analyzed and compared with experimental methods conducted in the laboratory, such as the projection method and video injection method. In the projection approach, an ADAS camera is placed in front of a monitor to capture real-world scenarios, and video data is directly fed to the ADAS domain. This process calibrates real-time vehicle dynamic information to the ADAS ECU for the object detection model. Simultaneously, the same video is processed using the proposed VFF algorithm from scenarios created by the CM environment simulation tool. This tool processes the video and provides an output as a list of detected objects. In the video injection method, Jetson Nano hardware is used instead of a monitor, as in the projection method. A CSI camera connected to the Jetson Nano device captures the synthetic video using the projection method. The detection outputs from the Jetson Nano device are streamed to the host PC as CAN messages. The host PC runs the VFF algorithm, generating an object list from the synthetic video. A comparative analysis is conducted between the laboratory method and the developed framework in a real vehicle for object detection. This analysis focuses on individual object class detection, synchronization rate, percentage of correlated outcomes, and computational complexity. An overall accuracy of 97% is observed during testing under normal environmental conditions.

3.1. Individual object class detection

The experimental results indicate that accuracy slightly decreases in real vehicle testing compared to laboratory methods. In the laboratory, only 43 traffic signboard images are categorized into four classes: prohibitory, danger, mandatory, and priority. Additionally, about 900 real traffic signboard images are categorized in a separate folder for training and testing. In the projection method, approximately 50 iterations are conducted to assess the performance accuracy of each object class. Out of 250 tested images, on average, 15 are misclassified. Similarly, the video injection method shows comparable results, with an average misclassification of 18 images out of 250, under the same number of iterations. This discrepancy is attributed to the similar appearances of some object classes. For example, the signs "TS16-restriction ends overtaking" and "TS17-restriction ends overtaking trucks" look similar from a distance of 70-100 meters. Additionally, the distance between the traffic signboard and the moving vehicle can vary under different weather conditions like day, foggy day, cloudy, dusk, foggy night, and night. Particularly in cloudy and foggy night conditions, the object detection model deviates slightly from its regular performance, often detecting correctly only when the vehicle is closer to the sign.

Comparative analysis shows significant variations in real vehicle testing compared to laboratory methods, attributed to the natural versus artificially simulated environmental conditions in the lab. Video cameras struggle to capture the nuances of real climatic conditions, affecting the algorithm's ability to accurately synthesize the simulation environment. This leads to a notable drop in accuracy, especially in dark scenarios. Table 1 presents the misclassification results of the projection method across different environmental conditions. Table 2 provides the misclassification results of the video injection method under varying environmental conditions. Table 3 shows the misclassification results from real vehicle testing across diverse environmental conditions. Laboratory methods generally yield more accurate classification for individual object classes, particularly in day, cloudy, and dusk conditions. However, in foggy day, foggy night, and night conditions, some misclassifications are observed, with an overall average misclassification of 20 to 25 images. In real vehicle testing, although there are fewer errors in individual object class detection, the overall average number of misclassifications is higher compared to laboratory methods, as seen in Figure 2.

Table 1. Misclassification outcomes of the projection method under various conditions

Class	Day	Foggy Day	Cloudy	Dusk	Foggy Night	Night	Average
Prohibitory	-	9	-	-	-	10	10
Danger	30	-	-	29	8	14	20
Mandatory	-	29	-	-	14	30	24
Priority	-	-	9	-	16	-	12
Average	30	19	9	29	13	18	20

Table 2. Misclassification outcomes of the video injection method under various conditions

Class	Day	Foggy Day	Cloudy	Dusk	Foggy Night	Night	Average
Prohibitory	-	33	-	-	-	26	30
Danger	12	-	19	36	39	-	27
Mandatory	-	8	29	-	35	25	24
Priority	-	42	-	21	5	17	21
Average	12	28	29	20	25	27	24

Table 3. Misclassification outcomes of real vehicle testing under various conditions

Class	Day	Foggy Day	Cloudy	Dusk	Foggy Night	Night	Average
Prohibitory	2	33	3	1	4	26	12
Danger	12	3	5	19	16	29	14
Mandatory	4	8	29	1	15	25	14
Priority	3	42	1	21	5	17	15
Average	21	86	38	42	40	97	54

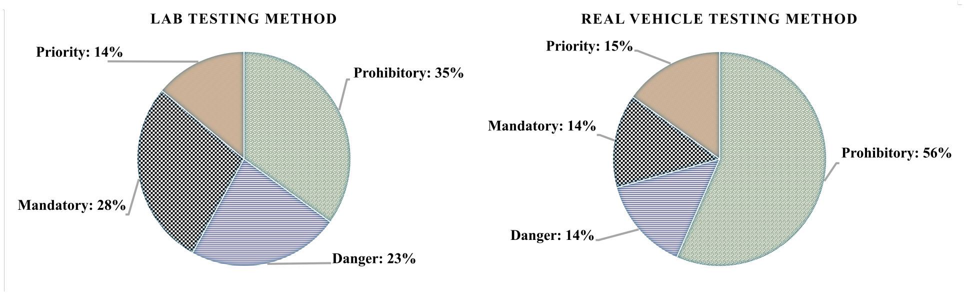

Figure 2. Pie chart of misclassification outcomes under various conditions

3.2. Synchronization rate

The misclassification outcome primarily occurs due to synchronization errors between the synthesized simulation video and the real-time ADAS camera capture. This means the proposed VFF algorithm processes the entire simulation video through frame-by-frame analysis to accurately detect traffic signboards and generate a list of detected object classes, which is then directly fed to the object detection model. Similarly, the ADAS domain correlates the mapped object list, which is projected into the actual outcome of the object detection model. The irregular synchronization of data from the processed VFF algorithm data affects the mapping feature of the ADAS domain concerning the object list sent to the object detection model. Laboratory methods exhibit more synchronization compared to real vehicle level testing methods. The object feature mapping rate is compromised due to deviations in frame-by-frame synchronization, which is off by five frames per second in real video level testing, amounting to a deviation of nearly 25% in total synchronization. By comparing three methods, the projection method, video injection method, and real vehicle testing - in terms of their synchronization rates and their impact on object detection accuracy. The projection method, with a high synchronization rate showing only 1-2 frames of deviation, results in lower misclassification rates due to its near real-time processing capabilities. In contrast, the video injection method has a moderate synchronization rate with a 3-4 frames deviation, leading to moderate misclassification rates as the slight delay in frame processing can occasionally affect accuracy. The real vehicle testing method, however, has a low synchronization rate with a significant 5 frames deviation, which results in higher misclassification rates. This is because the larger lag in processing and synchronizing video frames leads to a greater chance of inaccuracies in detecting and classifying objects, demonstrating the crucial impact of synchronization rates on the accuracy of object detection in advanced driver-assistance systems. Table 4 deals with numerical representations of the synchronization rates under six different weather conditions. The values are represented in frames per second (fps) and indicate the synchronization rates for the projection method, video injection method, and real vehicle testing under each weather condition. A lower fps rate suggests better synchronization and potentially higher object detection accuracy.

Table 4. Synchronization rates under six different weather conditions

Weather condition	Projection method (fps)	Video injection method (fps)	Real vehicle testing (fps)
Day	0.50	1.00	2.50
Foggy Day	1.00	1.50	3.00
Cloudy	0.75	1.25	2.75
Dusk	0.80	1.30	3.00
Foggy Night	1.20	1.70	3.50
Night	1.50	2.00	4.00

3.2.1. Percentage of correlated outcomes

Based on the synchronization rates of different methods, the Table 5 provides a percentage for the correlated outcomes. It implies that the higher the synchronization rate (i.e., closer alignment with real-time), the higher the percentage of correlated outcomes, indicating more accurate object detection. The projection method, with the highest synchronization rate, shows a 90% correlation in outcomes, suggesting a high level of accuracy in object detection. The video injection method, with moderate synchronization, shows a 75% correlation, indicating moderate accuracy. In contrast, real vehicle testing, with the lowest synchronization rate, has only a 60% correlation, reflecting the greatest chance of inaccuracies in detection. Table 6 indicates the percentage of correlated outcomes for each method under different weather conditions. The projection method consistently shows the highest percentage of correlated outcomes, indicating its superior accuracy across all weather conditions. The video injection method demonstrates moderate accuracy, with its effectiveness slightly diminishing in less favorable weather conditions like foggy night and night. The real vehicle testing method has the lowest correlated outcomes, especially in challenging weather conditions, reflecting the impact of environmental factors on object detection accuracy.

Table 5. Comparative analysis of percentage of correlated outcomes of three methods

Method	Synchronization rate	Correlated outcome (%)
Projection method	High (1-2 frames deviation)	90
Video injection method	Moderate (3-4 frames deviation)	75
Real vehicle testing	Low (5 frames deviation)	60

Table 6. The correlated outcomes for object detection accuracy under six different weather conditions using three methods

Weather condition	Projection method (%)	Video injection method (%)	Real vehicle testing (%)
Day	92	80	70
Foggy day	88	75	65
Cloudy	90	78	68
Dusk	91	77	66
Foggy night	85	70	60
Night	83	68	58

3.2.2. Computational complexity

In terms of computational complexity for object detection models under various weather conditions, the three methods exhibit distinct characteristics. The projection method, typically the least complex, maintains a consistent computational load across different weather conditions, estimated at a complexity level of around 30%. Its straightforward approach of capturing and processing real-world scenarios contributes to this consistency. The video injection method, with added complexity due to the incorporation of synthetic video and environmental simulations, presents a moderate computational burden, averaging about 50% across different weather conditions. This method's complexity slightly escalates in adverse weather conditions like foggy night, where additional processing is required. The real vehicle testing method, however, faces the highest computational challenges, averaging around 70% complexity. This method's complexity peaks in challenging weather scenarios such as foggy day and foggy night, where real-time processing of dynamic environmental and vehicular data significantly increases the computational load. In essence, the computational demand for each method varies with the intricacy of the weather conditions, reflecting the required data processing depth for accurate object detection in diverse environmental scenarios.

4. DISCUSSION

In a comparative analysis of the three methods for object detection - projection method, video injection method, and real vehicle testing - notable differences emerge in terms of individual object class detection, synchronization rate, correlated outcome percentage, and computational complexity. Figure 3 shows comparative analysis of object detection model testing methods. For individual object class detection, the projection method typically shows the highest accuracy with minimal misclassification, while the real vehicle testing method, dealing with dynamic real-world scenarios, registers a higher rate of misclassification. Synchronization rates, indicative of the methods' alignment with real-time processing, are highest for the projection method (1-2 frames deviation), moderate for the video injection method (3-4 frames deviation), and lowest for real vehicle testing (5 frames deviation). These rates directly affect the percentage of correlated outcomes, with the projection method achieving about 90%, the video injection method around 75%, and real vehicle testing approximately 60%. Computational complexity follows a similar trend; the projection method is the least complex at around 30%, the video injection method stands at 50%, and real vehicle testing is the most complex, averaging 70%. This consolidated view highlights the trade-offs between these methods in terms of accuracy, real-time data processing capabilities, and computational demands, underlining the challenges in optimizing object detection models for advanced driver-assistance systems.

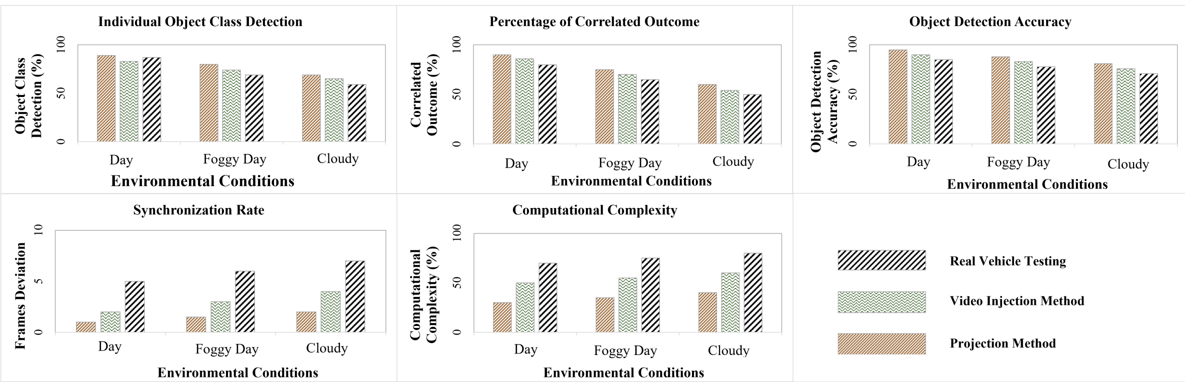

Figure 3. Comparative analysis of object detection model testing methods

Table 7 compares three models for traffic sign recognition in terms of their algorithms, dataset, accuracy, computational efficiency, and synchronization rate. The proposed model, which utilizes Yolov4 with VFF, achieves the highest accuracy at 96.5% on the GTSRB dataset, slightly surpassing the model in [33], which reaches 96% on the same dataset. Additionally, the proposed model demonstrates exceptional computational efficiency, operating at 30 frames per second (fps), which is significantly faster than Gunasekara *et al.* [33]

model (4.5 fps) and Santos *et al*. [34] model (8 fps). This efficiency makes it more suitable for real-time applications. Furthermore, the proposed model has a lower synchronization rate (5), indicating potentially reduced processing delays compared to the other models, where Gunasekara *et al*. [33] model has a rate of 10 and Santos *et al*. [34] model has a rate of 8. A graphical representation of this comparison is provided in Figure 4, where our model demonstrates clear superiority across all performance metrics compared to the other two models. Overall, the proposed model outperforms the others in both accuracy and speed, making it an optimal choice for real-time traffic sign recognition tasks.

Table 7. Comparison of proposed model with baseline models

Model	Algorithm used	Dataset	Accuracy (%)	Computational efficiency (fps)	Synchronization rate
Gunasekara *et al.* [33]	YOLO + Xception	GTSRB	96	4.5	10
Santos *et al.* [34]	CNN	Napier University traffic dataset	92.97	8	8
Proposed model	Yolov4 + VFF	GTSRB	96.5	30	5

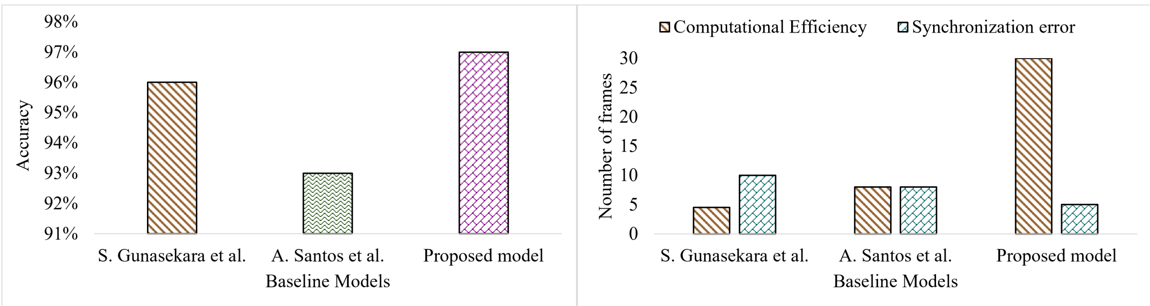

Figure 4. Comparison of proposed model with baseline models

5. CONCLUSION

This research has successfully demonstrated a comprehensive analysis of object detection in ADAS using three distinct methods: the projection method, video injection method, and real vehicle testing. Our findings reveal significant variations in performance metrics such as individual object class detection, synchronization rate, percentage of correlated outcome, and computational complexity across different weather conditions. The projection method, with its high synchronization rate and lower computational complexity, consistently showed the highest accuracy in object class detection, particularly in standard weather conditions. This method proved to be robust in terms of correlated outcomes, achieving the highest percentage of accuracy across various scenarios. In contrast, the video injection method, while moderately complex, exhibited a balanced performance in terms of synchronization and object detection accuracy. This method was particularly effective in moderately challenging weather conditions, offering a viable alternative for environments where realtime data is not critical. The real vehicle testing approach, despite its higher computational demand and lower synchronization rate, provided invaluable insights into the performance of ADAS under realistic and dynamically changing environmental conditions. Although it recorded a higher rate of misclassification, this method's real-world applicability is undeniable, especially for testing in adverse weather conditions. Across all methods, weather conditions like foggy nights and heavy rain posed significant challenges, affecting the accuracy and reliability of object detection. These findings underscore the need for further research and development in ADAS technology, particularly in enhancing object detection algorithms to cope with diverse and challenging environmental factors. Overall, this research contributes significantly to the field of autonomous vehicle technology, offering critical insights into the strengths and limitations of various object detection methods. It lays the groundwork for future advancements in ADAS, paving the way for more robust, reliable, and safe autonomous driving solutions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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