SINERGI Vol. 29, No. 3, October 2025: 771-778
http://publikasi.mercubuana.ac.id/index.php/sinergi
http://doi.org/10.22441/sinergi.2025.3.018

Car seatbelt monitoring system using a real-time object detection algorithm under low-light and bright-light conditions

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Abstract
Seatbelt usage is essential for minimizing injury risk during vehicular accidents. The monitoring seatbelt system in modern vehicles can be easily tricked into not displaying the warning alert. Car seatbelt detection, utilising real-time object detection, is employed to monitor seatbelt usage. However, the accuracy of such systems needs to be further evaluated under low-light and bright-light conditions. This study aims to develop a car seatbelt monitoring system using a real-time object detection algorithm, which will be tested in low-light and bright-light scenarios. The system integrates a trained YOLOv5 model into embedded hardware, which interfaces directly with the vehicle's ignition system, enabling or disabling engine start based on seatbelt usage. Notifications are also delivered through LEDs, a buzzer, and Telegram messages. This system has an accuracy of 95.75%, precision of 99.1%, recall of 96.2%, and an F1-score of 97.2%. The results show that the system can generate a better confidence score under bright-light conditions than under low-light conditions. This work offers tangible proof of the efficacy of applying intelligent object detection models for real-time driver monitoring, particularly in enhancing compliance through physical intervention and IoT-based alerts.

Keywords:
Internet of Things;
Monitoring;
Seatbelt;
You Only Look Once;

Article History:
Received: December 5, 2024
Revised: April 22, 2025
Accepted: April 30, 2025
Published: September 3, 2025

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INTRODUCTION

Safety in driving is an essential aspect of using transportation, as road traffic accidents remain a significant public health concern. In [1] have shown that accident-prone road segments are often associated with poor road conditions, inadequate signage, and environmental factors that increase collision rates. However, many drivers still neglect it, including the use of seatbelts. The use of seatbelts in motor vehicles is useful in minimizing the risk of injury or death in the event of a traffic accident. An ideal driver is said to always use a seatbelt when driving. However, many drivers of four-wheeled vehicles are unwilling to use seatbelts. They merely fasten it to the buckle to silence the warning buzzer without actually wearing it on their bodies. Using a combination of lap and shoulder seatbelts is an efficient way to minimize the seriousness and mortality rate of injuries caused by vehicle collisions [2].

The absence of seatbelt use among new drivers, particularly those aged 15 to 17, significantly increases the risk of morbidity and mortality in motor vehicle accidents, with studies showing over 20% greater odds of mortality and nearly two-thirds of pediatric spinal fractures occurring without seatbelts [3]. In 2020, only 49% of vehicle passengers were using seatbelts during accidents [4]. Therefore, a driver monitoring system is needed to ensure the proper use of seatbelts.

An object detected by a camera requires an algorithm to process it. Algorithms such as Faster R-CNN use two stages in object detection, which results in longer processing times but higher accuracy [5][6]. Additionally, object detection algorithms like YOLO and SSD tend to excel in speed, while R-CNN and its variants perform better in terms of accuracy [7]. The RetinaNet algorithm has a slower speed due to its more complex architecture, which results in higher accuracy for detecting small objects [8]. For object detection systems that require speed, the use of the YOLO algorithm is a suitable choice. YOLO can detect objects quickly while maintaining accuracy because it uses a simpler architecture, requiring only a single pass of the image through the network [9].

The ETLE (Electronic Traffic Law Enforcement) system, which can monitor driver behavior, has been implemented. The penalties issued are diverse, including violations of seatbelt usage while driving [10]. However, this method is still not effective, as the monitoring cameras are not installed in all locations and are only present at certain points [11]. The YOLO algorithm has been applied in various fields, including ETLE systems. The YOLO algorithm in ETLE systems can detect riders who are not wearing helmets [12].

Several studies have explored seatbelt detection using different algorithmic approaches and environmental conditions. The work in [13] applied YOLOv5 to identify seatbelt usage from frontal images of drivers, while the author in [14] developed a model resilient to weather-related lighting variations using the S-AlexNet architecture. Other approaches incorporated hybrid feature modeling, such as local-global predictors and shape modeling processes [15], or emphasized detection performance under varying light conditions, particularly in the context of autonomous vehicles [16]. Detection frameworks have also evolved to support multi-class classification of seatbelt states, such as properly worn, worn incorrectly, or absent, enabling more granular analysis for occupant monitoring systems (OMS) and driver monitoring systems (DMS) [17][18]. However, these implementations remain constrained to laboratory environments or image-level validations, with limited integration into physical vehicular systems or evaluation under diverse real-world lighting conditions.

This study develops a comprehensive car seatbelt monitoring system that integrates the YOLOv5 object detection algorithm into embedded hardware for real-time deployment. In addition to recognizing seatbelt usage under varying lighting conditions, the system is directly linked to the vehicle's ignition circuit, thereby enabling automated enforcement of seatbelt compliance. It also incorporates a dual-alert mechanism through visual/auditory signals and remote Telegram messaging. By validating the system under actual driving conditions, this work demonstrates a practical advancement over previous approaches that were limited to algorithmic evaluation or simulation-based implementation.

METHOD

This study employs the YOLO (You Only Look Once) algorithm, which uses a Convolutional Neural Network (CNN) to perform real-time object detection by dividing an image into an $S \times S$ grid, with each cell predicting bounding boxes and confidence scores, resulting in an output tensor of $S \times S \times (B \times 5 + C)$ [19]. The system was developed using hardware, including a Lenovo Ideapad Slim i5 laptop, Raspberry Pi 4, relay, buzzer, LED, LM2596 step-down module, cables, smartphone, HD 1080DPI webcam, and 64 GB micro SD card. Software tools such as Google Colab, Raspberry Pi Imager, VNC Viewer, Roboflow, and Telegram supported the process. A dataset of 1,617 images featuring seatbelts and face objects was used, sourced from Roboflow and a manual collection of simulated drivers with and without seatbelts, accessible at: https://universe.roboflow.com/face-seatbelt/seatbelt-monitoring/browse?queryText=&pageSize=50&startingIndex=0&browseQuery=true

Research Workflow

Based on Figure 1, the research workflow starts with dataset collection, labeling, and splitting into training, validation, and testing sets, followed by pre-processing and model training. If object detection testing fails, it loops back to data collection. Once successful, device components are assembled and tested in a car environment.

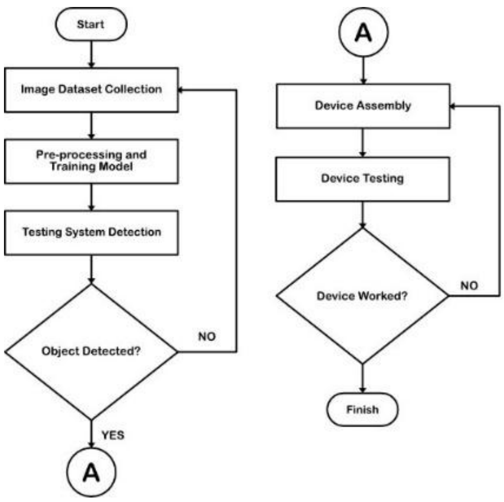

Figure 1. Car Seatbelt Detection Research Workflow

Dataset Collection

This research used a raw dataset of 1,617 images from Roboflow and manual collection, showing individuals with and without seatbelts. Images were manually annotated and labeled in Roboflow with bounding boxes and two classes: "seatbelt" and "face." The dataset was then split into training (70%), validation (20%), and testing (10%) sets.

Pre-processing

The dataset underwent pre-processing in Roboflow, including resizing to 640x640 pixels, auto-orienting, and augmentation (vertical flip, 15% grayscale, and ±25% saturation). This enhanced data quality and increased the dataset to 2,749 images: 2,264 for training, 323 for validation, and 162 for testing.

Training Model

This research uses the YOLOv5s model, a lightweight yet effective variation suitable for low-capability devices [20], offering a good balance between complexity and model size [21]. Training parameters include a 640x640 image size, batch size of 64, and 100 epochs, where larger image sizes improve accuracy but demand more resources, and more epochs allow deeper learning. The training took 1.294 hours, producing a model to detect face and seatbelt objects. The YOLOv5s training process produced strong performance metrics: precision of 0.962 (96.2%), recall of 0.97 (97%), and a mean Average Precision (mAP) of 0.985 (98.5%). A performance graph, shown in Figure 2, further illustrates the model's effectiveness.

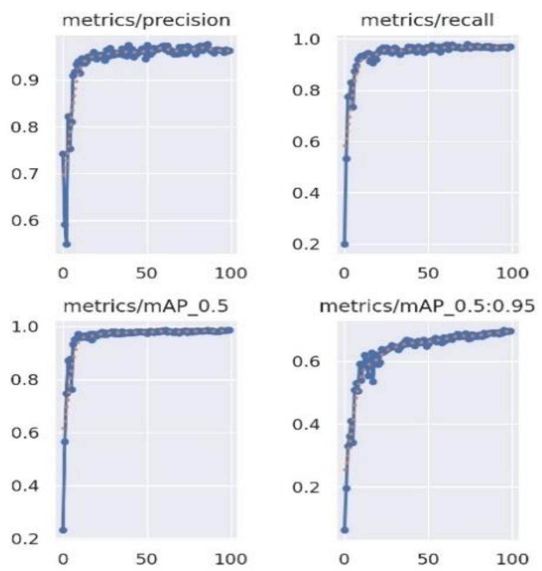

Figure 2. YOLOv5s Training Model Results

Device Assembly

The monitoring design, as shown in Figure 3, is powered by the car battery via the ignition switch and uses a Raspberry Pi 4 for object detection. A connected webcam detects the presence of a face and a seatbelt. If a seatbelt is detected, the LED and buzzer remain off, and the relay stays closed, allowing engine start. If not, the LED and buzzer activate, the relay opens, and the engine is blocked. Additionally, Telegram alerts are sent to the driver every 5 minutes if the seatbelt is not detected, ensuring reminders without excessive disturbance.

Testing and Evaluation

System testing includes detection, monitoring, device, and Telegram notification tests. Detection testing evaluates accuracy, precision, recall, and F1-score using test data and a confusion matrix (1). The matrix shows TP (true positive), FP (false positive), FN (false negative), and TN (true negative), with evaluation calculated using (1) – (4) [22]. Table 1 shows the confusion matrix used to assess model performance.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\text{-}Score = 2\,x \left(\frac{Precision\ x\ Recall}{Precision+Recall}\right) \quad (4)$$

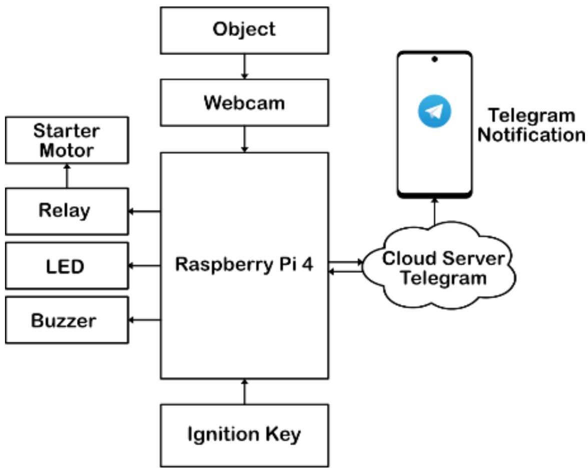

Figure 3. Monitoring Device Design

Table1. Confusion Matrix

		Actual	
		Positive	Negative
Predicted	True	TP	FP
	False	FN	TN

Accuracy, precision, recall, and F1-score are used to evaluate prediction performance, with error percentage calculated using (5).

$$\%Error = (1 - \text{Accuracy}) \text{ x } 100\% \qquad (5)$$

For monitoring, device, and Telegram testing, the system is directly connected to the car's ignition to assess its ability to respond to seatbelt usage and light intensity inside the vehicle.

RESULTS AND DISCUSSION

Detection System Testing

The detection system was tested on 162 images containing seatbelt and face objects using a confidence threshold of 0.5 and an IoU threshold of 0.45 to balance precision and recall [23]. As shown in Figures 4 and 5, the images were resized to 640×640 pixels, and object detection results were displayed with bounding boxes, class labels, and confidence scores. An error is observed in Figure 5(b), where the system failed to detect a worn seatbelt, highlighting a limitation in model performance. Evaluation was conducted using confusion matrix values (TP, FP, FN, TN), as shown in Table 2. The accuracy, precision, recall, and F1-score derived from these counts are summarized in Table 3.

(a) (b)

Figure 4. (a) Before being Detected (b) After being Detected

(a) (b)

Figure 5. (a) Before being Detected (b) After being Detected

Table 2. Confusion Matrix

No	Object	TP	FN	FP	TN
1	Face	219	0	4	11
2	Seatbelt	171	14	0	21

Table 3. Evaluation Matrix

No	Object	Accuracy	Precision	Recall	F1-Score
1	Face	0.983	0.982	1	0.984
2	Seatbelt	0.932	1	0.924	0.96
Average		**0.9575**	**0.991**	**0.962**	**0.972**

Car Seatbelt Monitoring Device Testing

The monitoring system is tested by observing the detection performance of the seatbelt and face based on the light intensity inside the car in real-time. The tests are conducted under two conditions, with each condition being tested ten times. In the first condition, which is bright-light, the performance results are displayed in Table 4. The installation of the car seatbelt monitoring device on the car dashboard is shown in Figure 6.

Based on Table 4, during bright-light testing at 11:19 AM, the system achieved an average confidence of 90.3% for face detection and 85.5% for seatbelt detection, with an average light intensity of 4334.2 lux and a detection speed of 1513.81 ms. The results are shown in Figure 7. Under low-light conditions (Table 5), tested at 5:59 PM, face and seatbelt detection confidences were 87.7% and 83.6%, respectively, with 2295.8 lux light intensity and 1512.29 ms detection speed, as shown in Figure 8.

Figure 6. Placement of The Monitoring Device

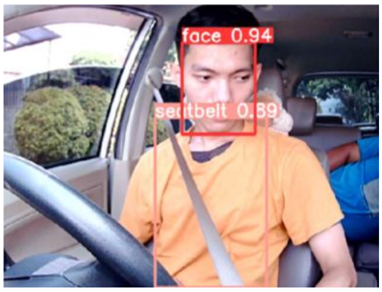

Figure 7. Bright-light Test Sample

Table 4. Bright-light Test Results

Conf. Seatbelt	Conf. Face	Light Intensity	Detection Speed	Test Time (s)
94	89	5081	1495.6	11.19
95	80	4645	1518.3	11.19
94	82	4305	1528.4	11.19
95	90	4879	1506.6	11.19
96	92	4550	1520.6	11.19
78	94	3926	1500.8	11.19
71	96	3735	1524.6	11.19
65	94	3617	1522.0	11.19
88	94	4341	1518.6	11.19
79	92	4263	1502.6	11.19

Table 5. Low-light Test Results

Conf. Seatbelt (%)	Conf. Face	Light Intensity	Detection Speed	Test Time (s)
83	89	2552	1418.8	17.59
79	90	2592	1457.9	17.59
80	87	2146	1461.3	17.59
78	83	2354	1439.9	17.59
85	93	2103	1441.1	17.59
88	89	2313	1592.8	17.59
90	94	2480	1488.2	17.59
85	79	2260	1568.5	17.59
83	94	1975	1788.4	17.59
85	79	2183	1466.0	17.59

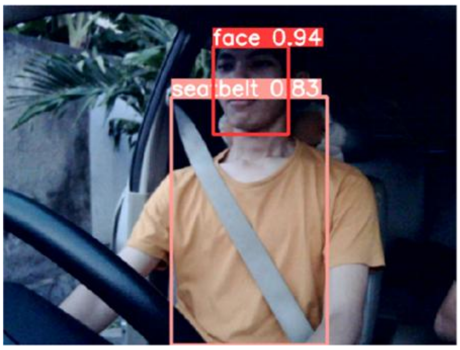

Figure 8. Low-light Test Sample

A test is performed to assess the car seatbelt monitoring response, which includes the relay, buzzer, LED, and Telegram notifications, based on the driver's detection status. Table 6 shows system response when the system detects the seatbelt and face, the LED and buzzer notification components are off, the relay condition that was initially open becomes closed, and the driver's smartphone does not receive a Telegram notification. During testing in the car, the driver can start the engine by activating the starter motor via the ignition switch. The average confidence value for seatbelt detection is 81.4%, while the average confidence value for face detection is 94.4%. All these tests were conducted with an average light intensity of 4124.6 lux, performed during the daytime at 13:25. The results of the test, when the driver is using the seatbelt, are shown in Figure 9.

Table 6. Test Result with Seatbelt

Conf. Seatbelt	Conf. Face	Light Intensity	Notification	LED & Buzzer	Relay	Time (s)
89	94	3758	Not Sent	Off	Close	13.25
80	95	3843	Not Sent	Off	Close	13.25
82	94	3925	Not Sent	Off	Close	13.25
90	95	4436	Not Sent	Off	Close	13.25
92	96	4606	Not Sent	Off	Close	13.25
78	94	4246	Not Sent	Off	Close	13.25
71	96	3827	Not Sent	Off	Close	13.25
65	94	3789	Not Sent	Off	Close	13.25
88	94	4631	Not Sent	Off	Close	13.25
79	92	4185	Not Sent	Off	Close	13.25

Figure 9. Result of Test Using Seatbelt

Table 7. Not Use Seatbelt

Conf. Seatbelt	Conf. Face	Light Intensity	Notification	LED & Buzzer	Relay	Time (s)
-	94	3974	Sent	On	Open	13.30
-	89	3914	Not Sent	On	Open	13.31
-	95	3735	Not Sent	On	Open	13.32
-	94	3891	Not Sent	On	Open	13.33
-	95	4341	Sent	On	Open	13.35
-	96	4263	Not Sent	On	Open	13.36
-	95	4550	Not Sent	On	Open	13.37
-	93	4645	Not Sent	On	Open	13.38
-	95	4305	Not Sent	On	Open	13.39
-	94	4167	Not Sent	On	Open	13.40

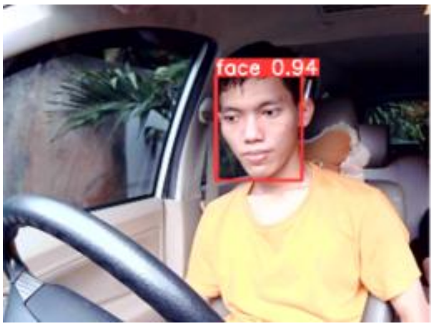

Figure 10. Result of Test Without Seatbelt

Table 7 shows the test results when the driver is not wearing a seatbelt. In 10 trials, the system consistently detected the face (with an average confidence of 94%) without errors, under an average light intensity of 4178.5 lux. When the seatbelt was not detected, the LED and buzzer activated, the relay remained open, Telegram sent alerts every 5 minutes, and the car's engine could not be started via the ignition. A sample result is shown in Figure 10.

Telegram Notification Testing

Telegram notifications are sent when the driver is detected not wearing their seatbelt. The system automatically sends notifications to the driver's smartphone via the Telegram application. Notifications are sent every 5 minutes while the driver is not detected wearing the seatbelt. The format of the Telegram notification received on the smartphone is shown in Figure 11.

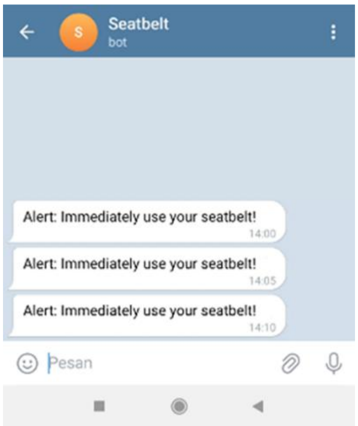

Figure 11. Telegram Notification

Result Analysis

Based on Table 3, from 162 test images, the system achieved 95.75% accuracy, 99.1% precision, 96.2% recall, and a 97.2% F1-score. Detection performance was higher for faces than for seatbelts. Face detection reached 98.3% accuracy, 98.2% precision, 100% recall, and 98.4% F1-score, with a 1.7% error rate. Seatbelt detection scored 93.2% accuracy, 100% precision, 92.4% recall, and 96% F1-score, with a 6.8% error rate.

Face detection outperforms seatbelt detection in accuracy, recall, F1-score, and error rate, but lags in precision. Seatbelt detection only excels in precision. This discrepancy may stem from dataset imbalance—1237 seatbelt objects vs. 2539 face objects—making seatbelt detection more challenging under varying conditions. Seatbelt objects are larger and include more background noise, while face objects are smaller and consistently captured due to camera placement. Although data augmentation was applied, further techniques like SMOTE, GANs, color space transformation, or noise injection [24] are needed to improve balance and detection performance.

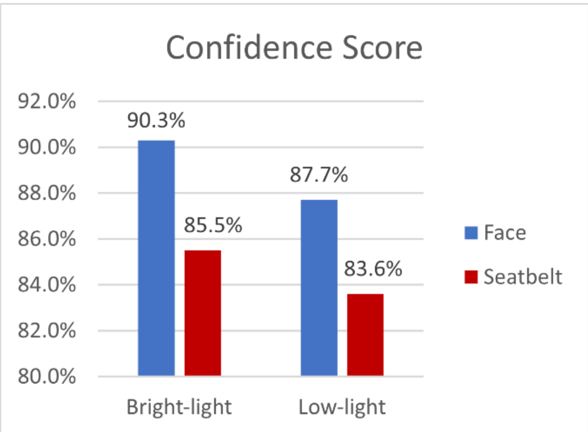

Figure 12. Confidence Score Comparison

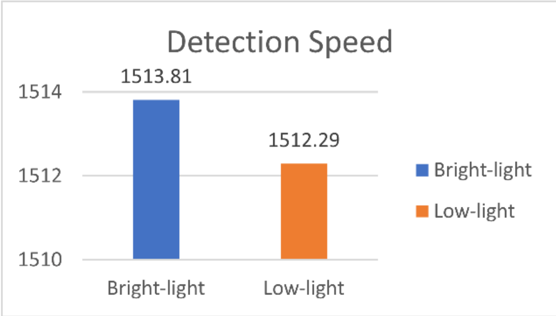

Figure 13. Comparison of Detection Speeds

The average intensity of light entering the car in the evening is lower (low-light) at 1512.29 lux compared to during the day (bright-light), which is 4334.2 lux. This can be a factor for the lower confidence scores produced in the low-light conditions compared to during the bright-light conditions, as the reduced light entering the car affects the object detection results [25].

Based on the monitoring tests under bright-light and low-light conditions, the confidence values for object detection fluctuate due to factors like the driver's movement and the seatbelt being blocked by the driver's hand [26]. As shown in Figure 12, the system detects face objects more confidently than seatbelt objects. In bright-light conditions, the average confidence is 90.3% for faces and 85.5% for seatbelts; in low-light conditions, it is 87.7% for faces and 83.6% for seatbelts. This may occur because face objects are smaller and less obstructed, while seatbelt objects are more often blocked or partially visible during driving.

As shown in Figure 13, object detection speed remains consistent across 10 tests, with only a 1.72 ms difference between bright-light (1513.81 ms) and low-light (1512.29 ms) conditions. This stability is due to the use of the same model and image size, which influences Raspberry Pi's processing efficiency. When the driver wears a seatbelt, the system detects both face and seatbelt, resulting in the relay closing, no activation of the LED/buzzer, and no Telegram alert, allowing the engine to start normally.

Discussion

This study shows that YOLOv5 detects faces better than seatbelts due to dataset imbalance. A larger number of face annotations leads to higher performance. As supported by [27] and [28], dataset balance and representativeness are crucial for achieving accurate object detection results. In [13], an achieved 89% precision and 81% recall using YOLOv5 under bright light. In contrast, the proposed system performs better with 99.1% precision, simpler implementation, and includes hardware-based alerts and Telegram integration. Therefore, the proposed monitoring system demonstrates improved results compared to the referenced study. In [29], implemented YOLOv7 for seatbelt detection using Jetson Nano, buzzer, and display, achieving a 98% F1-score and high precision, though not integrated with the vehicle's electrical system. Meanwhile, the proposed system achieves slightly lower F1-score (97.2%) but uses more datasets (1617 compared to 1240), integrates with car electronics, includes Telegram alerts, and reaches 100% seatbelt precision, indicating enhanced functionality. The monitoring system in this study demonstrates better performance under bright-light conditions than in low-light environments. This aligns with the findings of [30], which observed a decline in detection accuracy under low-light settings. The system in this study was tested without applying advanced preprocessing techniques (such as low-light enhancement or adaptive histogram equalization) in order to reflect the original image conditions from the camera. However, the use of these techniques is believed to improve detection performance under various lighting conditions. Therefore, future research is recommended to integrate these methods and compare the detection results to evaluate their impact on system performance.

CONCLUSION

This study developed a car seatbelt monitoring system using the YOLOv5 algorithm to detect seatbelts and face objects. The system is tested under low-light and bright-light conditions. The system achieved 95.75% accuracy, 99.1% precision, 96.2% recall, and a 97.2% F1-score. Average confidence scores were 90.3% (face) and 85.5% (seatbelt) in bright-light (4334.2 lux), and 87.7% (face) and 83.6% (seatbelt) in low-light (1512.29 lux), with detection speeds of 1513.81 ms and 1512.29 ms, respectively. The device connects to the car's ignition and sends Telegram alerts every 5 minutes. Future work should expand the dataset, optimize for speed and accuracy, integrate law enforcement notifications, and test across diverse vehicles and conditions.

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