Development of highway vehicle detection using background subtraction and Haar cascade methods

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ABSTRACT

Vehicle recognition is a critical component of traffic analysis and the progress of advanced transportation systems, underscoring the importance of automated, real-time methods that reduce the need for manual observation. While the field has seen notable innovations in deep learning-centric detection technologies, many of these approaches require considerable computational strength and are not well-suited for real-time application in resource-constrained environments. In response to this limitation, the present study introduces a streamlined vehicle detection framework that combines background subtraction for motion-oriented foreground extraction with a Haar cascade classifier for object identification in traffic video sequences. The system is evaluated using real-world highway traffic recordings under different illumination conditions, including both day and night scenarios. The experiment's findings show that the system achieves an overall accuracy of 82.08%, with a precision of 85.33%, a recall of 66.67%, and an F1-score of 74.86%. The system also demonstrates consistent performance across different lighting conditions. These findings indicate a trade-off between detection accuracy and computational efficiency, where the proposed approach prioritizes practical deployment feasibility. Overall, the results suggest that classical computer vision techniques remain viable alternatives for real-time traffic monitoring in environments with limited computational resources.

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1. INTRODUCTION

Intelligent transportation analysis and systems in both developed and developing countries are implemented in the form of vehicle detection [1]–[5], playing a crucial role in intelligent traffic management systems, traffic flow monitoring, incident avoidance, and traffic law enforcement [6]–[9]. Therefore, there is a growing demand for automated vehicle detection systems to reduce reliance on direct supervision and to optimize processes for more precise, cost-effective results [3], [4], [10].

Although vehicle detection is currently crucial, it remains an unusual challenge if vehicle detection is carried out in real life on highways due to the diverse types of vehicles, varying traffic volumes, constantly changing lighting conditions, and dynamic background conditions that sometimes create shadows [6], [11]–[13]. That certainly presents an obstacle that can significantly reduce the detection success rate [10], [11]. Although research on vehicle detection has made significant progress, complex research that simultaneously meets essential requirements, such as high accuracy and real-world performance, remains a challenge [4], [10], [14]. In addition, research in this field is still quite slow, as evidenced by the lack of work on the development of efficient and easy-to-apply vehicle detection systems for real traffic conditions [1]–[3].

Recently, deep learning-based approaches such as you only look once (YOLO), single shot multibox detector (SSD), and Faster Region-based Convolutional Neural Network (Faster R-CNN) have achieved high detection accuracy [15]–[17], making them widely applied for vehicle detection and identification [1], [4], [7]. These approaches provide maximum impact under pre-defined conditions and large datasets, but are less suitable for implementation in real-world situations [18], such as traffic control, where resources are limited, such as the need for high-spec computing hardware, training processes using large amounts of data, and concrete computing infrastructure [3], [4], [7]. These constraints pose significant obstacles to practical applications, particularly in edge-based traffic control systems or developing regions [18].

Traditional computer vision methodologies using video footage from stationary cameras are one alternative for vehicle detection research [10], [19], [20]. Some of these methodologies detect moving objects by distinguishing between foreground and background parts in video sequences [21]–[23]. This technique is suitable for real-time, which provides important results in terms of computational efficiency and frame-rate accuracy [21], [24]. However, the effectiveness of this technique is also often limited by several conditions that influence detection accuracy, such as noise, lighting quality, and local background motion [6], [21], [22], [25].

Haar cascade classification is another classic approach that has attracted attention, alongside background subtraction techniques, as a lightweight alternative [2] for detecting objects in an image using a series of Haar-like features trained on positive and negative example datasets [23], [25], [26]. Basically, this classification identifies objects sequentially by assessing each image in turn to recognize objects in the following image [25]–[27]. This methodology divides the image into three Red, Green, and Blue (RGB) color channels, namely red, green, and blue channels, with values ranging from 0 to 255 [23], [28]. Based on these three basic colors, the system can detect differences in various image features [23], [28]. For black-and-white images, the feature detection process will be simpler because the Haar cascade method operates on a single channel [28]. Haar cascade processes grayscale images, excluding color information, and determines the image representation [25], [29]. Therefore, under these conditions, resource-constrained areas will rely on traffic control systems that require real-time processing and operate with limited central processing unit (CPU) and memory resources (without graphics processing unit (GPU) acceleration) [18].

A basic description of the differences between deep learning-based methodologies and traditional computer vision in the vehicle detection context is presented in Table 1, which summarizes the conceptual comparison and emphasizes key aspects such as detection accuracy, computational requirements, data dependency, and real-time implementation. This provides a research basis for analyzing lightweight detection methodologies within a practical traffic control framework.

Despite the advancements in deep learning frameworks designed for the detection of automobiles, while demonstrating considerable efficacy, they typically require high computational resources, extensive annotated datasets, and enhancements via GPU technology, thereby constraining their applicability in real-time environments and scenarios with limited resources. In contrast, conventional methodologies such as background subtraction and Haar cascade illustrate notable computational efficiency; nevertheless, they often encounter a reduction in robustness when applied independently. As a result, this study advocates for a hybrid approach that integrates motion-based foreground extraction with optimized object classification to address these limitations whilst maintaining the capability for real-time operation.

Research gaps in vehicle detection, based on a review of existing studies, indicate that previous work has focused mainly on deep learning-based methods that require substantial computational resources or on the failure of traditional approaches to leverage the inherent advantages of combining the two. Furthermore, there has been no research on real-world vehicle detection under varying traffic and lighting conditions that combines motion-based foreground extraction with background subtraction using a lightweight classifier, such as a Haar cascade. This gap motivates adopting a hybrid approach to vehicle detection that balances detection accuracy, computational efficiency, and real-world implementation suitability.

Table 1. Comparison of deep learning and classical vehicle detection approaches

Aspect	Use of the method	Accuracy rate result
Detection accuracy	Generally high on benchmark datasets	Moderate and scenario-dependent
Computational requirements	High (often requires GPU acceleration)	Low (CPU-based processing feasible)
Training data	Requires large-scale annotated datasets	Required limited training data or predefined features
Model complexity	High	Relatively low
Real-time feasibility	Hardware-dependent	Suitable for real-time deployment
Suitability for resource-constrained environments	Limited	High

Therefore, this study attempts to introduce a hybrid vehicle detection framework that combines background subtraction to inhibit motion features with the Haar cascade methodology for object classification. The proposed method is designed to operate in real time using video footage captured in a road environment while maintaining minimal computational complexity. The main contributions of this study are summarized as follows:
a. Development of a real-time highway vehicle detection system by integrating background subtraction for motion-based foreground extraction with Haar cascade for object classification.
b. Evaluation of the proposed system under real-world highway traffic conditions, including varying illumination scenarios, to assess its robustness in practical deployment environments.
c. Demonstration of the feasibility of classical computer vision methods as practical and lightweight alternatives for real-time traffic surveillance in resource-constrained environments.

The subsequent sections of this manuscript are structured as follows. Section 2 delineates the proposed research methodology and the corresponding system architecture. Section 3 presents the research findings along with a critical discussion of those results. Ultimately, Section 4 provides a conclusive summary of the paper and delineates prospective avenues for future inquiry.

2. METHOD

2.1. Research framework

The research process in this study consists of several stages: data collection and needs analysis, system development, and performance evaluation of the proposed traffic vehicle detection system. The proposed system incorporates background subtraction techniques for motion-based foreground extraction and uses the Haar cascade methodology for vehicle classification. Figure 1 illustrates the overall research process adopted in this study.

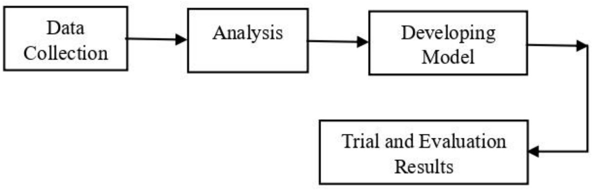


Figure 1. Research framework of the proposed vehicle detection system

The proposed framework is carefully designed to facilitate real-time vehicle recognition in road traffic visualization data while ensuring minimal computational requirements. This design aligns with the goal of deploying the system in resource-constrained environments where GPU acceleration is unavailable and real-time processing is required.

2.2. Dataset and data acquisition

The dataset collected in this study concerns vehicle traffic identification and consists of digital images, with a particular emphasis on dynamic visual representations in video. The dataset used is divided into two main components. The first dataset consists of training data for the Haar cascade model, which includes 1,000 positive images containing vehicle objects and 100 negative images without vehicles, obtained from the public dataset platform (Kaggle). This allows the Haar cascade model to learn distinguishing features between vehicle and non-vehicle objects. The secondary dataset is used for system evaluation and consists of 6 traffic video samples captured with a smartphone camera. These visual recordings exemplify authentic highway traffic conditions, and they are categorized into two distinct illumination scenarios: three videos recorded during daylight hours and three recorded at night, to assess detection performance across different environments.

2.3. System architecture and processing stages

In general, the proposed vehicle detection system sequentially processes input video frames through multiple image processing stages and an optimized pipeline to ensure real-time performance without increasing computational requirements. This architectural layout reinforces the core ideals of simplicity and operational effectiveness, making it an appropriate solution for resource-constrained traffic surveillance situations. Figure 2 illustrates the overall processing workflow of the proposed system.

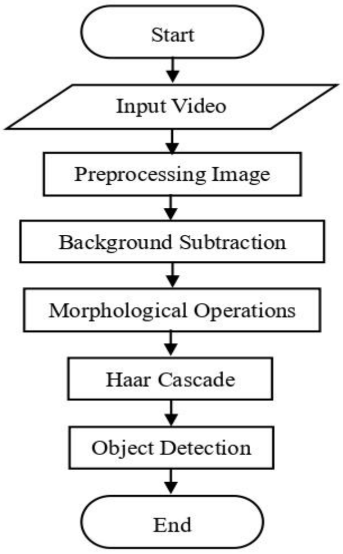


Figure 2. Overall processing workflow of the proposed vehicle detection system

Figure 2 outlines the comprehensive processing sequence of the proposed framework, beginning with the acquisition of video frames and progressing through preprocessing, motion-based foreground extraction, and vehicle classification [30]. Figures 3–5 present detailed illustrations of the key processing stages within this pipeline.

2.3.1. Preprocessing stage

In the preprocessing stage, each video frame is converted from its primary RGB format to grayscale, thereby reducing computational burden while retaining the intensity information necessary for accurate motion detection. Following this, a Gaussian blur is applied to reduce noise and subtle pixel changes often observed in outdoor roadway contexts. Figure 3 illustrates the preprocessing stage applied to the input video frames.

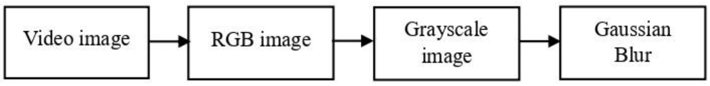


Figure 3. Preprocessing stage consisting of grayscale conversion and Gaussian blur

2.3.2. Foreground extraction using background subtraction

Post-preprocessing, background subtraction differentiates active foreground components from immobile backgrounds. This phase is integral to delineating prospective vehicle areas by leveraging motion indicators in the video sequence. Figure 4 illustrates the background subtraction process used to extract foreground regions.

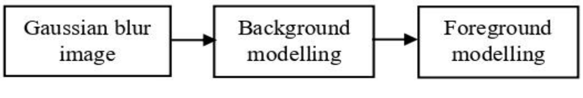


Figure 4. Foreground extraction using background subtraction

2.3.3. Foreground refinement using morphological operations

The delineated foreground area is then augmented via a systematic morphological procedure aimed at reducing noise, addressing minor disturbances, and effectively depicting the structural characteristics of the object. Figure 5 presents the morphological refinement stage applied to the foreground masks.

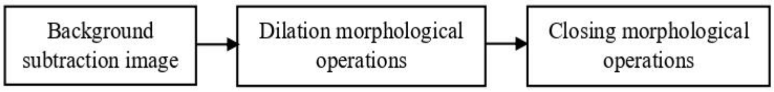


Figure 5. Block diagram of the morphological operations

2.3.4. Vehicle classification using Haar cascade

The meticulously processed foreground segments are subsequently subjected to analysis through a Haar cascade classifier, which serves to identify and categorize vehicular entities based on acquired visual characteristics. This phase of arrangement amplifies the system's talent for differentiating vehicles from various living organisms present in the area being monitored.

Through the sequential and modular organization of the detection pipeline, the proposed framework adeptly reconciles detection efficacy with computational efficiency. This architectural setup ensures trustworthy real-time vehicle recognition under assorted lighting situations while promoting practical use on CPU-oriented platforms that do not utilize GPU acceleration.

2.4. Implementation environment

The deployment of the recommended framework features elements of hardware and software. All experimental processes were run on a laptop without GPU acceleration, demonstrating the practicality of the proposed methodology in resource-constrained environments. A handheld device was used to record immediate video of vehicles on the highway [31]. The system was constructed using Python 3.12 as the primary programming language, with OpenCV for image processing. The coding workspace, identified as Visual Studio Code, enhanced the overall programming experience. The trained Haar cascade classifier was preserved in an extensible markup language (XML) file and subsequently loaded during the detection phase to facilitate real-time vehicle classification.

2.5. Performance evaluation metrics

To measure the capability of the recommended vehicle detection system, a confusion matrix served as the primary tool for performance evaluation. The confusion matrix includes four essential traits: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which demonstrate both competent and incompetent detection cases. The structure of the confusion matrix used in this study is shown in Figure 6.

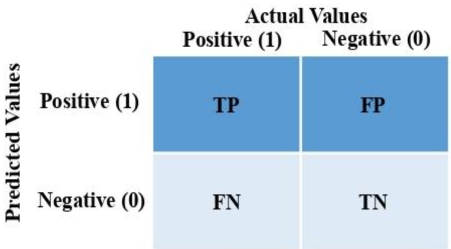


Figure 6. Structure of the confusion matrix used for performance evaluation

Using the confusion matrix as a key resource, a set of common performance metrics was developed, including accuracy, precision, recall (sensitivity), specificity, and F1 score. These metrics collectively provide a comprehensive evaluation of the system's detection performance and reliability. Formulas 1, 2, 3, 4, and 5 discussed in this test are outlined as follows [28]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall/Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

$$F1 - Score = 2\ x \frac{(Precision\ x\ Recall)}{(Precision+Recall)} \quad (5)$$

3. RESULTS AND DISCUSSION

3.1. Results of vehicle detection

This section describes the empirical findings obtained from implementing the recommended vehicle detection framework, which uses background subtraction with the Haar cascade methodology. The system assessment was conducted using six traffic video samples captured in real-world highway environments, comprising three daytime recordings and three nighttime scenarios.

To highlight the effect of pre-processing strategies on input frames, Figure 7 presents the grayscale conversion results for both nighttime and daytime environments, with examples of grayscale conversion in a nighttime environment shown in Figure 7(a) and a daytime environment shown in Figure 7(b). In addition, Figure 8 presents the Gaussian blur preprocessing results for both environments, along with the implementation of Gaussian blur on important video frames observed in both the nighttime environment shown in Figure 8(a) and the daytime environment shown in Figure 8(b). The transformation to grayscale reduces computational complexity by removing redundant chromatic data, while the Gaussian blur reduces high-frequency noise and small-pixel variance, especially in situations with lighting fluctuations.

After the preprocessing phase, background subtraction strategies are applied to extract the foreground components from the background. Figure 9 illustrates the foreground masks resulting from the background-subtraction methodology applied to selected video samples for the nighttime environment in Figure 9(a) and the daytime environment in Figure 9(b). While vehicle motion is distinctly accentuated, residual noise and discontinuities persist owing to illumination fluctuations and dynamic background components.

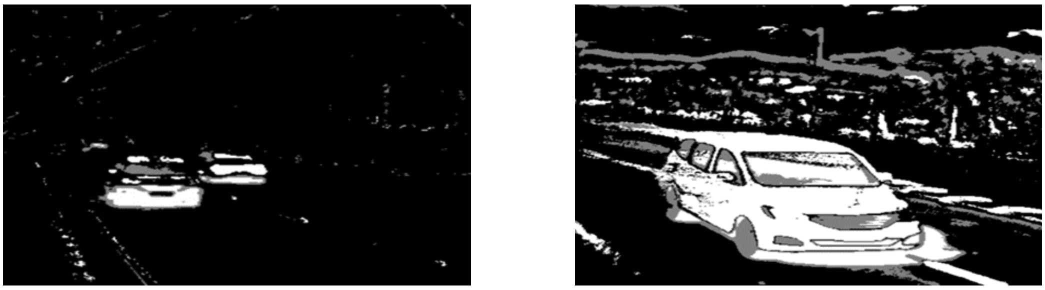
In order to enhance the delineated foreground areas, morphological closing techniques are employed. Figure 10 presents the results of morphological processing for both nighttime and daytime environments. The outcomes of these techniques are depicted in Figure 10(a) for the nighttime environment and Figure 10(b) for the daytime environment, where minor voids and fragmented regions are substantially reduced, resulting in more unified vehicle contours that are well-suited for further classification.

(a) (b)

Figure 7. Grayscale conversion results for (a) nighttime and (b) daytime

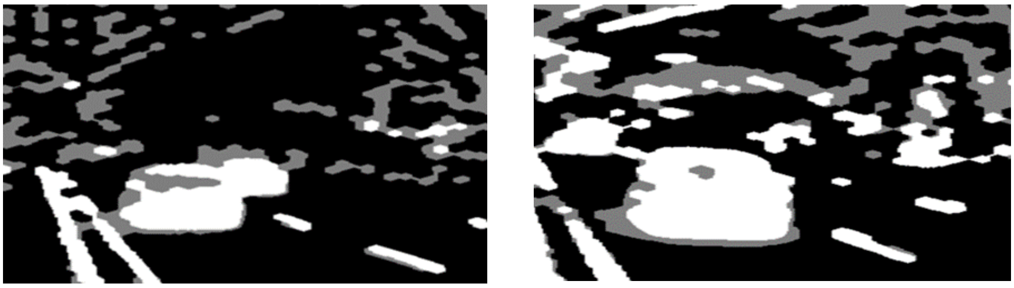
(a) (b)

Figure 8. Gaussian blur preprocessing results for (a) nighttime and (b) daytime



(a) (b)

Figure 9. Foreground extraction results using background subtraction for (a) nighttime and (b) daytime



(a) (b)

Figure 10. Results of morphological processing for (a) nighttime and (b) daytime

Figure 11 presents the vehicle detection results using the Haar cascade classifier for both nighttime and daytime environments. Displayed in Figure 11(a) are the outcomes from implementing the Haar cascade classifier for vehicle detection in a nighttime environment. Meanwhile, the results of vehicle detection in a daytime environment using the Haar cascade classifier are shown in Figure 11(b). The vehicles identified are shown as bounding boxes, indicating that the suggested system can identify vehicular entities in both day and night traffic environments.

Quantitative performance assessment is presented in Table 2, which compares system detection outcomes with manual observations for each video sample. The evidence shows that the established system meets various detection accuracy standards across different video scenarios, achieving a combined accuracy of 95.11% across the whole.

To conduct a more thorough assessment, a confusion matrix analysis was performed. Tables 3 and 4 present the metrics for allocations of TP, FP, FN, and TN results across all test videos. Assessing these metrics (TP = 64, FP = 11, FN = 32, TN = 133), the system achieved an accuracy of 82.08%, precision of 85.33%, recall of 66.67%, specificity of 92.36%, and an F1-score of 74.86%.

(a) (b)

Figure 11. Vehicle detection results using Haar cascade for (a) nighttime and (b) daytime

It is imperative to acknowledge that the mean detection accuracy of 95.11% pertains specifically to per-video detection efficacy. In contrast, the aggregate accuracy of 82.08% is obtained from an evaluation using a confusion matrix across all test videos, thereby offering a more thorough appraisal of system-level performance.

Figure 12 presents a comparative analysis of the system's performance metrics across the six test videos. Generally speaking, the system maintains a consistently high level of precision, especially in videos 3 to 6, suggesting that the majority of recognized vehicles are correctly identified.

Table 2. System performance in detecting traffic vehicles

Video	Detected	Manual	Failed	Accuracy
1	13	14	1	92.86%
2	14	18	10	77.78%
3	16	16	0	100%
4	9	9	0	100%
5	7	7	0	100%
6	8	8	0	100%
	Average accuracy			95.11%

Table 3. System performance in the success and failure of detecting car vehicles

Video	The car detection system correctly	Another object detection system is a car	Failed to detect the car	Other objects are not detected as cars correctly
1	13	1	4	12
2	11	10	3	51
3	16	0	5	34
4	9	0	7	9
5	7	0	5	11
6	8	0	4	16
Total	64	11	32	133

Table 4. Confusion matrix

Detection	Actual	
	Car	Other objects
Car	64	11
Other objects	32	133

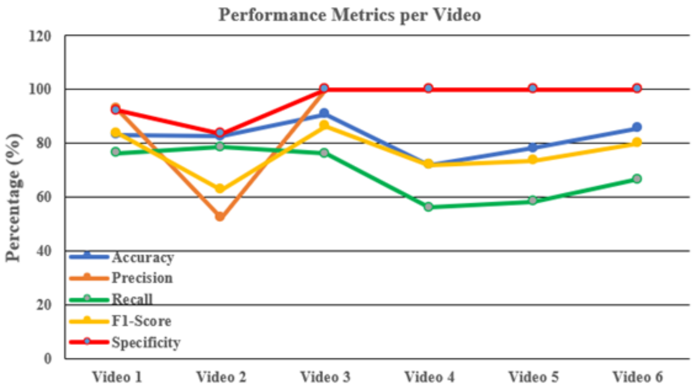


Figure 12. Comparative visualization of performance metrics across all test videos

3.2 Discussion

The analysis suggests that the advised vehicle detection methodology strikes a commendable middle ground between precision and computational speed [32]. The achieved accuracy of 82.08% and precision of 85.33% indicate that the combination of background subtraction and Haar cascade methods is effective at recognizing vehicle entities in highway traffic video footage. The notable precision-to-recall trade-off points to the system's ability to reduce false-positive rates, yet a handful of vehicle examples were not accurately detected.

Differences in the potency of various video footage can be attributed to factors such as lighting setups and the intricate features of the visuals [33]. In videos captured during daylight hours, the presence of more distinct object boundaries and enhanced contrast between vehicles and their surroundings led to improved stability in foreground extraction and detection. Observations from videos filmed at night revealed poorer contrast and higher noise levels, which negatively affected the background subtraction operation and, consequently, reduced recall effectiveness [18], [34]. Nevertheless, the system exhibited a consistent detection performance across both illumination conditions, thereby underscoring its robustness in the domain of practical highway traffic surveillance.

While techniques for vehicle detection that utilize deep learning, including YOLO, SSD, and Faster R-CNN, have exhibited high detection accuracy in prior research [1], [15], [35], their deployment often requires extensive computational resources, which consist of GPU enhancement [36] and vast training datasets [3], [18], [37]. In a different light, the advocated system highlights the feasibility and practicality of approaches in environments constrained by resources [18], [29]. By exclusively using CPU-based processing and lightweight classical computer vision methods, the proposed strategy offers a viable alternative for real-time traffic surveillance systems in scenarios where computational resources, energy consumption, or hardware accessibility are limited [18].

When measured against vehicle detection techniques rooted in deep learning, as highlighted in previous research, the introduced framework demonstrates reduced detection accuracy, yet simultaneously offers important benefits in computational efficiency and ease of implementation [18]. In analyzing the current frameworks based on deep learning methodologies, famous for their high accuracy in detection, the advised approach exhibits notable superiority in computational efficiency and easier deployment. Whereas deep learning models necessitate GPU acceleration and extensive datasets, the proposed methodology functions effectively, utilizing CPU-based processing with minimal training data, thereby rendering it more appropriate for real-time applications within resource-constrained or edge computing contexts. This highlights a trade-off between accuracy and computational efficiency, where the proposed method prioritizes practical deployment feasibility. Usually, intricate deep learning systems require comprehensive training methods and high-performance hardware, which can hinder their use in realistic traffic surveillance scenarios characterized by resource constraints [18]. Conversely, the background subtraction and Haar cascade-based methodology employed in this study imposes minimal computational demands, requires a relatively modest training dataset, and supports real-time operational performance, thereby rendering it a viable solution for highway traffic monitoring applications constrained by resource limitations [11], [18].

Notwithstanding its merits, the proposed framework is accompanied by multiple constraints. The background subtraction method may significantly affect detection effectiveness, leading to difficulties such as sudden lighting changes, dynamic shadows, and changes in background conditions [33]. Further, the Haar cascade classifier might struggle when faced with complex vehicle interference and diversity in vehicle appearance. Prospective research endeavors may investigate the incorporation of adaptive background modeling methodologies or hybrid systems that combine lightweight deep learning components with traditional techniques to enhance detection resilience while maintaining computational efficiency.

4. CONCLUSION

This inquiry has examined the development and evaluation of a real-time highway vehicle detection system, built on classical computer vision techniques, particularly background subtraction and Haar cascade classification. The architecture proposed was carefully honed, with an emphasis on computational performance and practical application, to address the immediate demand for traffic observation solutions that can operate effectively in constrained-resource settings.

Findings from accurate highway traffic recordings reveal that the advocated method achieves a vehicle detection accuracy of 82.08%, precision of 85.33%, recall of 66.67%, and an F1-score of 74.86%. These findings suggest that the system exhibits robust capability to reduce false positives while maintaining satisfactory detection efficacy across varying illumination environments, including both diurnal and nocturnal conditions.

Although methods grounded in deep learning for vehicle identification often achieve higher accuracy, their reliance on GPUs, large annotated datasets, and substantial computational power may limit their implementation in specific scenarios. Conversely, the results of the present study reveal that traditional computer vision techniques remain viable and pragmatic alternatives for real-time traffic monitoring, especially when computational resources, energy consumption, and hardware accessibility are limited. This reflects a trade-off between detection accuracy and computational efficiency, where the proposed method prioritizes practical deployment feasibility in resource-constrained environments.

Notwithstanding its efficacy, the proposed system exhibits numerous limitations. The background extraction technique is still affected by illumination shifts, shadows, and fluctuations in background subjects. In contrast, the Haar cascade classifier can struggle with challenging vehicle blockages and inconsistencies in vehicle appearance. Subsequent research could focus on enhancing system robustness by integrating adaptive background modeling methods or hybrid strategies that combine lightweight deep learning components while maintaining computational efficiency. Overall, this scholarly investigation emphasizes the persistent relevance of tested computer vision practices as sensible and efficient methods for real-time traffic monitoring in areas with limited resources.

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

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest related to this research, either financial, institutional, or personal.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, A.A., upon reasonable request.

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