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Vehicle Counting and Classification from A Traffic Scene

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Abstract. *The detection and tracking approach is as follows. The moving vehicles are first extracted from the traffic scene by applying the adoptive background subtraction technique. After the background subtraction, using threshold and median filters, isolated image blobs are identified as individual vehicles. The preliminary results show that the developed system can efficiently and reliably track vehicles when unobstructed view of the traffic scene can be obtained. For optimal camera calibration, an accuracy better than 80% in counting vehicles was observed. The present system performs better with video data in which the vehicles are moving away from the camera compared to the video data in which the vehicles are moving towards the camera. The results obtained through the developed system show that with further improvements the system can be used in real-time to count and classify vehicles on busy traffic routes.*

Keywords: *You Only Look Once-(YOLO).*

1. INTRODUCTION

The rise of intelligence management systems has transformed urban mobility by enhancing automation, efficiency, and connectivity. However, this increased interconnectivity introduces new challenges in traffic monitoring and control, necessitating advanced solutions for accurate vehicle counting and classification [1]. Traditional methods struggle with dynamic traffic conditions, making it essential to explore emerging technologies such as Deep Learning (DL) for improved traffic analysis. The objective of this study is to systematically investigate and evaluate the application of DL architectures for vehicle counting and classification in traffic scenes. Urban traffic presents unique challenges, including real-time constraints, diverse vehicle types, and varying environment conditions that demand specialized solutions [2]. This paper covers various DL models, such as Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and hybrid approaches, analyzing their effectiveness, suitability for traffic scenarios, and current advancements in the field. By reviewing existing literature, the study identifies trends, challenges, and research gaps in DL -based traffic monitoring. Furthermore, this work aims to guide future research by highlighting potential areas for innovation and improvements in vehicle classification and counting. As smart cities continue to evolve, integrating cutting-edge DL techniques with intelligent transportation systems will be crucial for developing scalable, accurate, and efficient traffic monitoring solutions.

2. BACKGROUND

Object Detection in Traffic Monitoring: Object detection plays a fundamental role in intelligent traffic systems by identifying and tracking vehicles in real-time. Traditional methods rely on sensors such as inductive loops, radar, and infrared cameras to count and classify vehicles. However, these methods often require extensive infrastructure and maintenance, limiting their scalability. Recent advancements in deep learning and computer vision have paved the way for automated vehicle detection using convolutional neural networks (CNNs), enabling more accurate and cost-effective traffic monitoring solutions. YOLOv4 for Vehicle Detection and Classification: YOLOv4 is a state-of-the-art object detection model that balances speed and accuracy, making it suitable for real-time traffic monitoring applications. Unlike traditional region-based object detection methods, YOLOv4 employs a single neural network to predict bounding boxes and classify objects simultaneously, significantly reducing computational overhead. This makes it particularly effective for analyzing high-resolution traffic video streams in real-time. The model incorporates advancements such as CSPDarknet53 as the backbone, spatial pyramid pooling (SPP), and path aggregation networks (PANet) to enhance feature extraction and improve detection performance. Additionally, YOLOv4 employs techniques such as Mosaic data augmentation and self-adversarial training, which enhance the model's ability to generalize across different traffic conditions. The model's anchor-based approach ensures better localization of vehicles, even in dense traffic. Its use of cross-stage partial connections (CSP) optimizes computational efficiency while maintaining high detection accuracy. These enhancements make YOLOv4 highly effective for vehicle counting and classification across various urban and highway traffic scenarios. Challenges in Real-Time Vehicle Counting: Despite the advantages of YOLOv4, several challenges remain in implementing real-time vehicle counting and classification systems. Variations in lighting conditions, occlusions, and weather conditions can impact detection accuracy. Furthermore, real-time processing requires optimized hardware and efficient computational techniques to maintain high frame rates without compromising accuracy. Addressing these challenges is crucial for deploying YOLOv4-based traffic monitoring solutions in diverse environments. Additional challenges include the need for large annotated datasets for model training. The presence of multiple vehicle types with varying sizes and orientations further complicates classification tasks. Furthermore, motion blur caused by high-speed vehicles can degrade detection accuracy. Ensuring real-time performance requires leveraging hardware accelerators, such as GPUs or TPUs, which may not always be cost-effective. Addressing these limitations will be key to improving YOLOv4's performance in large-scale traffic management systems.

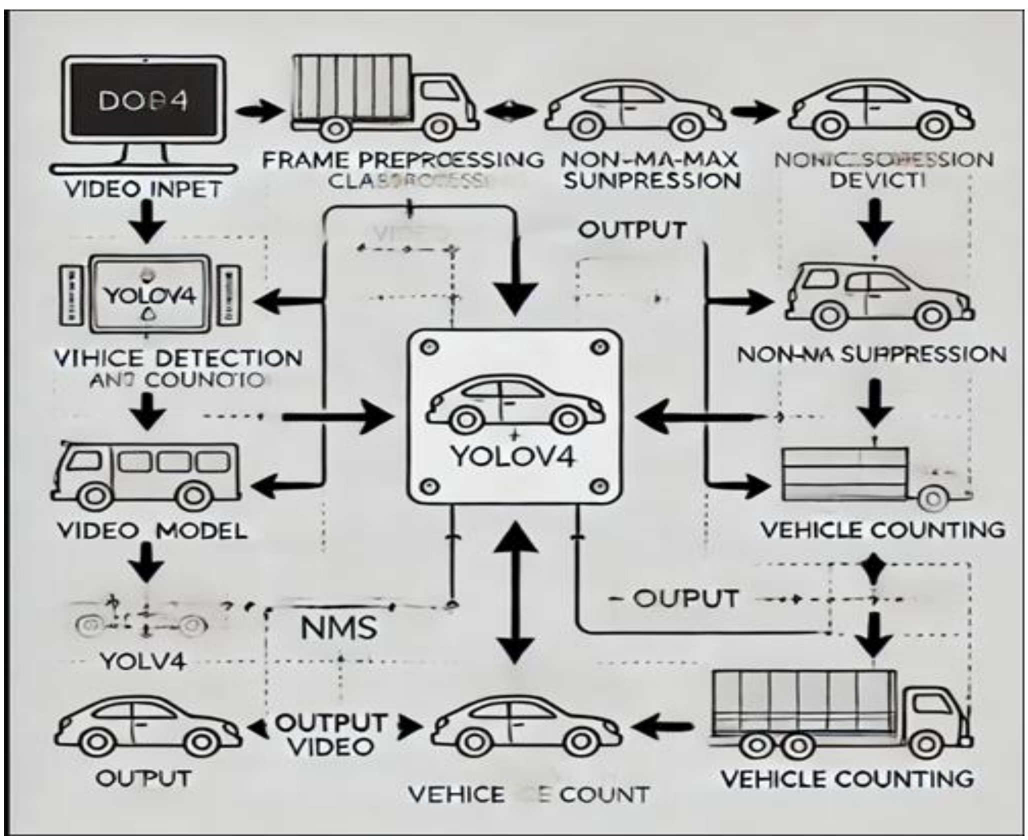

FIGURE 1. Data Flow Diagram

3. LITERATURE REVIEW

Numerous research studies have focused on vehicle detection and counting systems for real-time traffic monitoring. These studies have evolved from traditional image processing techniques to advanced deep learning-based approaches, improving accuracy and efficiency. A study published in 2018 introduced a vehicle detection and counting system using Background Subtraction (BS). This approach worked by identifying changes in pixel intensities across video frames to detect moving objects. While BS is a widely used method in computer vision, it has several limitations, such as high sensitivity to environmental changes, poor scalability, and a high false positive rate. The system struggled in dynamic environments with varying lighting conditions, shadows, and background clutter, leading to inaccurate vehicle detection. Additionally, BS-based systems require continuous recalibration to maintain accuracy, making them less effective for large-scale traffic monitoring applications. To overcome these drawbacks, a study published in 2021 proposed a more advanced approach using YOLO (You Only Look Once) and Virtual Detection Zones. YOLO, a state-of-the-art object detection framework, significantly improved the efficiency of vehicle counting and classification by processing entire images in a single forward pass of a neural network. The Virtual Detection Zones concept further enhanced the accuracy of vehicle tracking by defining specific regions of interest within the video feed, ensuring better localization of moving vehicles. The YOLO-based system demonstrated several advantages over traditional methods, including higher accuracy, faster detection speeds, and the ability to classify multiple vehicle types simultaneously. However, the study also highlighted several challenges that remain unaddressed: Occlusion Handling: Vehicles blocked by other objects or overlapping vehicles could lead to misclassification and inaccurate counts. Lighting Variations: Performance was affected under low-light conditions, such as nighttime surveillance or extreme weather scenarios. Latency Issues: Real-time traffic monitoring requires fast processing speeds, but high-resolution video feeds and deep learning computations increased processing delays. In comparison, research studies have also evaluated other deep learning-based approaches such as Faster R-CNN and SSD (Single Shot MultiBox Detector) for vehicle detection. While these models offer competitive performance, YOLOv4 has been found to achieve a better balance between speed and accuracy, making it more suitable for real-time applications. Despite advancements in deep learning, several gaps still exist in current vehicle detection systems. Future research is focusing on integrating tracking algorithms (e.g., DeepSORT) to improve counting accuracy in dense traffic scenarios, optimizing models for edge computing, and enhancing robustness against motion blur and extreme environmental conditions. Additionally, the development of multi-camera traffic monitoring systems is being explored to expand the coverage of vehicle detection across multiple intersections and road networks.

TABLE 1

Year	Title of the Paper	Algorithms	Drawbacks
2018	Vehicle detection and counting system for real-time traffic surveillance	Background Subtraction (BS)	Sensitivity, Scalability, False Positives
2021	A Real-time Vehicle Counting, Speed Estimation, and Classification System Based on Virtual Detection Zone and YOLO	YOLO (You Only Look Once), Virtual Detection Zones	Occlusion, Lighting, Latency

4. FINDINGS AND LIMITATIONS

The implementation of vehicle counting and classification systems using YOLOv4 has shown promising results in terms of accuracy and real-time detection. However, despite its advancements over traditional traffic monitoring methods, certain limitations still hinder its effectiveness in practical applications. These limitations primarily stem from environmental factors, computational constraints, scalability challenges, and the complexity of vehicle classification. Addressing these challenges is crucial for enhancing the system's performance and ensuring seamless traffic monitoring in real-world scenarios. One of the most significant limitations of the existing system is its accuracy under various environmental conditions. While deep learning models like YOLOv4 are designed to generalize well across different datasets, they often struggle when faced with challenging real-world scenarios such as poor lighting, adverse weather conditions, or complex traffic environments. Factors like fog, heavy rain, and nighttime surveillance can significantly reduce the model's ability to detect and classify vehicles accurately. This is because the neural network relies on visual features extracted from images, and when visibility is reduced, its ability to distinguish vehicles from the background is compromised. Furthermore, glare from headlights, reflections on wet roads, and shadows cast by large objects can introduce false detections, leading to inaccuracies in the vehicle counting process. Another major challenge is achieving real-time processing while maintaining high accuracy. Deep learning-based object detection models require substantial computational power to process high-resolution video feeds in real-time. The YOLOv4 architecture, although optimized for speed, still demands powerful GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units) to ensure smooth operation. In practical deployments, traffic monitoring systems often need to process multiple video feeds simultaneously, which increases the computational burden. As a result, implementing the system on low-resource edge devices, such as embedded systems or IoT devices, can be problematic due to hardware limitations. To address this, optimization techniques such as model pruning, quantization, and hardware acceleration are being explored to enhance processing efficiency without compromising detection performance. The scalability and adaptability of the system also pose significant challenges. Traffic conditions vary across different locations, requiring models to be fine-tuned or retrained for each specific environment. For instance, a model trained on urban traffic may not perform well on highway traffic or rural roads, where vehicle density and movement patterns differ. Additionally, factors such as road infrastructure, camera angles, and regional vehicle variations influence the detection accuracy. Traditional approaches often rely on manually annotated datasets for training, which can be time-consuming and resource-intensive. To overcome this limitation, researchers are exploring self-supervised learning and domain adaptation techniques that allow models to adapt to new environments with minimal human intervention. Another critical limitation is the complexity involved in vehicle classification. While YOLOv4 excels at detecting vehicles, differentiating between similar vehicle types (e.g., distinguishing between a sedan and a hatchback) or identifying specific vehicle attributes (such as color, make, or model) remains a challenge. The presence of occlusions, where one vehicle partially blocks another, further complicates the classification task. In dense traffic conditions, where multiple vehicles are closely packed, the system may fail to correctly assign class labels to individual vehicles. To improve classification accuracy, integrating multi-frame analysis, tracking algorithms (e.g., DeepSORT), and feature extraction techniques can help in distinguishing vehicles more effectively over time. In summary, while YOLOv4-based vehicle counting and classification systems offer significant improvements over traditional methods, several limitations need to be addressed for widespread real-world deployment. Issues related to accuracy in diverse conditions, computational efficiency, scalability, and vehicle classification complexity must be tackled through further research and optimization. Future advancements in deep learning architectures, dataset augmentation, and edge computing are expected to enhance system performance, making it more robust, adaptable, and efficient for intelligent traffic monitoring applications.

5. FUTURE DIRECTION

Although the current system is functional and effective, there are several areas for future improvements and enhancements that can significantly enhance its performance and applicability in real-world scenarios. One key area of improvement is the implementation of more sophisticated tracking algorithms such as Kalman filters, SORT (Simple Online and Realtime Tracker), or Deep SORT (Deep Learning-based SORT). These tracking methods can help maintain object identity even during occlusions, where vehicles may be temporarily hidden behind other objects or overlap in dense traffic. By improving tracking consistency, the system can reduce counting errors and ensure more precise vehicle identification over time. Another crucial enhancement is real-time performance optimization, which involves optimizing the code and leveraging hardware acceleration techniques such as GPU processing and TensorRT optimization. These improvements can significantly enhance the frame processing speed, making the system capable of operating seamlessly in real-time traffic monitoring applications without significant delays. Additionally, the integration of multi-sensor fusion techniques can enhance the system’s robustness by incorporating data from multiple sensors such as radar and LiDAR alongside traditional camera-based object detection. This approach will improve the accuracy of vehicle detection and tracking, especially in adverse weather conditions such as heavy rain, fog, or low-light environments where camera-based systems alone may struggle. Multi-sensor fusion will also provide depth perception and improved motion tracking, allowing for better classification of vehicles moving at different speeds and distances. Another area of development is the incorporation of advanced deep learning models for object detection and classification. While YOLOv4 is already effective, newer models such as YOLOv5, YOLOv8, EfficientDet, or SSD (Single Shot MultiBox Detector) could further enhance the accuracy of vehicle detection, especially in complex scenarios such as dense urban traffic, high-speed highway monitoring, or lowvisibility conditions. These models offer improved feature extraction and classification techniques, which can make vehicle identification more precise and reliable. Furthermore, a significant enhancement to the system would be its integration with smart traffic management solutions to enable real-time decision-making for automated traffic control. By linking the system with intelligent traffic lights, adaptive congestion management strategies, and connected vehicle networks, authorities can optimize road usage dynamically, reduce traffic congestion, and improve overall transportation efficiency. Real-time data collected from the vehicle counting and classification system can be leveraged to adjust traffic signals, reroute vehicles, and provide traffic flow predictions for better urban planning. Overall, these future enhancements will make the system more scalable, efficient, and adaptable to diverse real-world conditions, ensuring its successful deployment for smart city applications and intelligent transportation infrastructure development.

6. CONCLUSION

The vehicle detection, classification, and counting system demonstrates a reasonable level of accuracy in identifying and tracking vehicles across a variety of traffic conditions. By employing adaptive background subtraction, morphological operations, and centroid-based tracking, the system efficiently detects vehicles and maintains an accurate count as they cross predefined lines. These techniques enable it to function effectively in standard scenarios, making it a valuable tool for real-time traffic monitoring and analysis. However, certain challenges remain, particularly in low-light environments, where reduced visibility can impact detection accuracy. Additionally, in densely packed traffic, occlusions and overlapping vehicles may lead to misclassifications or counting errors. Occasional false detections further indicate the need for refinement in object recognition and tracking. Despite these limitations, the system serves as a robust solution for traffic management applications, providing valuable data for urban planning and congestion control. By incorporating more advanced filtering techniques, such as Kalman filters or deep learning-based object tracking, the system's reliability and accuracy could be significantly improved. Enhancing adaptability to challenging conditions would further strengthen its performance, making it a more comprehensive and efficient tool for intelligent transportation systems.

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