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TrafficEZ: Optimizing Traffic Monitoring through a Novel Two-Tier Edge Computing Model Integrating Advanced Computer Vision Algorithms

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Abstract

This research introduces a novel two-tier edge computing model to optimize video processing for traffic monitoring systems, focusing on balancing computational tasks between edge nodes near traffic cameras and a centralized Traffic Management Center (TMC). The system integrates advanced computer vision models, including Perspective Transformation, MOG2 Background Subtraction, Convex Hull Detection, and Morphological Noise Reduction, to significantly improve vehicle detection and traffic density estimation. The model was rigorously tested through a real-world deployment in El Salvador City, Misamis Oriental, Philippines, where it demonstrated superior performance over traditional cloud-only and edge-only solutions. Key results include the accurate approximation of traffic density and dynamic traffic signal management, visualized through various figures, such as the system's real-time processing capabilities and the successful integration of convex hull tracking. These outcomes highlight the system's effectiveness in managing complex traffic scenarios, underscoring its potential as a robust solution for intelligent transportation systems. The research presents significant advancements in edge computing applications for smart city infrastructure, particularly in real-time traffic monitoring and management.

***Keywords**:* computer vision algorithms, edge computing, intelligent transportation systems, traffic density estimation, traffic monitoring

1. Introduction

Urban traffic congestion poses a significant challenge in modern cities, impacting economic productivity (Victoria Transport Policy Institute, 2020), environmental sustainability (Ewing and Rong, 2008), and quality of life (Stutzer and Frey, 2008). The rising complexity of urban traffic management demands systems that can adapt dynamically to varying traffic patterns while ensuring minimal latency and high accuracy. Traditional traffic management solutions, often centralized and dependent on fixed signal timings, struggle to accommodate the variability of traffic volumes and patterns, leading to inefficiencies and increased congestion. While artificial intelligence-based traffic systems have shown promise in improving traffic flow, they often require prohibitive costs (Koch, 2022) and lack sufficient real-time adaptability (Genitha *et al.*, 2023).

This study addresses these gaps by introducing TrafficEZ, a novel two-tier edge computing model designed to optimize video processing for traffic monitoring systems. Unlike conventional cloud-based solutions or purely edge-centric systems, TrafficEZ strategically balances computational tasks between edge nodes near traffic cameras and a centralized Traffic Management Center (TMC). Decentralized computing enables reduced latency and more responsive traffic flow management, making the system highly suitable for real-time urban traffic scenarios (Kiani *et al.*, 2018).

The TrafficEZ system integrates advanced computer vision algorithms, including Perspective Transformation, MOG2 Background Subtraction, Convex Hull Detection, and Morphological Noise Reduction, to enhance vehicle detection and traffic density estimation. These techniques ensure robust performance across diverse scenarios, such as low-light conditions or variable weather, which are critical for real-world applications (Kunekar *et al.*, 2023). Moreover, while previous studies have explored vehicle detection and tracking methods, many fail to address the scalability of these solutions in larger urban environments or their adaptability to fluctuating traffic conditions (Brahmi *et al.*, 2013). This study fills this gap by presenting a system capable of handling diverse urban settings while maintaining accuracy and efficiency.

Additionally, while delay and video quality have been highlighted as key challenges in real-time traffic monitoring (Tubaishat *et al.*, 2009), the TrafficEZ system is designed to mitigate these challenges through localized processing and the integration of predictive analytics. Real-world testing in El

Salvador City, Misamis Oriental, Philippines, demonstrated the system's capability to improve traffic flow management by accurately estimating traffic density and detecting congestion in dynamic urban environments.

By bridging the gap between centralized and fully decentralized traffic management systems, TrafficEZ sets a benchmark for future innovations in smart city infrastructure. This paper provides a comprehensive discussion of the system's design, deployment, and evaluation, including metrics such as traffic density approximation, vehicle detection accuracy, and video quality considerations, to highlight the system's real-world effectiveness.

2. Methodology

2.1 Computer Vision/Technology Algorithm Implementation

The algorithm design focuses on optimizing the allocation of green light time at intersections using real-time traffic density and flow data. The time for the incoming green light t_G is computed using Equation 1, which considers the traffic densities during previous red-light k_{R-1} and green-light k_{G-1} instances.

$$t_G = T(k_{R-1}) + T(k_{G-1}) \tag{1}$$

where:

t_G = allocated green light time (seconds);
$T(k_{R-1})$ = a function determining green light duration based on prior *red-light* density (seconds);
$T(k_{G-1})$ = a function determining green light duration based on prior *green-light* density (seconds);
k_{R-1} , k_{G-1} = traffic density during respective instances (in vehicles $/\text{m}^2$).

To determine the traffic density during the previous red-light instance k_{R-1}, a single frame instance (screenshot at the beginning of the red-light) is captured. A machine learning-based vehicle detection system then processes this input. The YOLOv4 object detection model, retrained to recognize vehicles specific to the local deployment area (e.g., jeepneys, tricycles, etc.), is employed for this task. TensorFlow Lite (v2.10, 2022) will be used on edge devices to perform predictions of the number of vehicles (n) within a specified region of interest (inside the lane) during the red-light phase. This prediction facilitates the calculation of k_{R-1} using Equation 2.

$$k_{R-1} = \frac{n}{l \cdot w} \tag{2}$$

where:

n = number of vehicles inside the region of interest (in vehicles);
l = length of the lane (in meters);
w = width of the lane (in meters).

However, to determine the traffic density during a green-light instance, this has to be estimated in a roundabout matter, seen in Equation 3. This is because during a green-light, vehicles enter and exit the camera image area at different rates and speed.

$$k_{G-1} = \frac{\bar{q}_{G-1}}{\bar{v}_{G-1} \cdot w} \tag{3}$$

where:

$\bar{q}_{G-1}$ = average traffic flow (vehicles crossing a reference line) during the previous green-light instance (in vehicles/second);
$\bar{v}_{G-1}$ = average velocity parallel to the lane during the previous green-light instance (in meters/second), w is the width of the lane (in meters).

The number of vehicles crossing a reference line at specific intervals is counted to determine the traffic flow. To do this, two possible computer vision algorithms can be used for motion estimation: Background Subtraction (BS) and Optical Flow (OF).

In BS, the Mixture of Gaussian algorithm (MoG) *is* employed and in OpenCV, it is provided by the *cv.createBackgroundSubtractorMOG2()* function (KaewTraKulPong and Bowden, 2001). Vehicle identification is based on contour detection in an area above a certain threshold. The tracking of these contours is calculated frame-by-frame, determined by their centroids and the Euclidean distance between previous and current frames. Additionally, the velocity of each vehicle is derived (in units of pixels/frame converted to meters/second upon calibration). Simplifying the calibration of the image plane pixel to meters involves positioning the camera parallel to the lane, thereby reducing the problem to basic trigonometric equations.

The second, method OF, can determine vehicles' traffic flow and velocity out of the box. The Dense Optical Flow algorithm of Gunnar-Farneback (Farneback, 2003) is utilized for this purpose. This is more computationally heavy than the BS method but can provide a more robust and reliable estimation. The vehicles will be detected as the blobs of grouped pixels that are moving from frame to frame, and their corresponding velocity would be that blob's vector field that is parallel to the lane. Although this requires more CPU power, the selected edge device can perform this computation efficiently.

2.2 Operating Traffic Parameters and Success Metrics

Efficient traffic management systems require robust parameters and metrics to evaluate their performance in real-world scenarios. This study adopts vehicle count and traffic density as primary operating metrics due to their direct relationship with traffic flow efficiency. As Shingate *et al.* (2020) outlined, adaptive traffic light systems employing object detection models like YOLO can provide reliable vehicle counting within simulated traffic environments. Building on such methodologies, this research extends their application to real-world intersections, incorporating dynamic adjustments based on real-time traffic conditions.

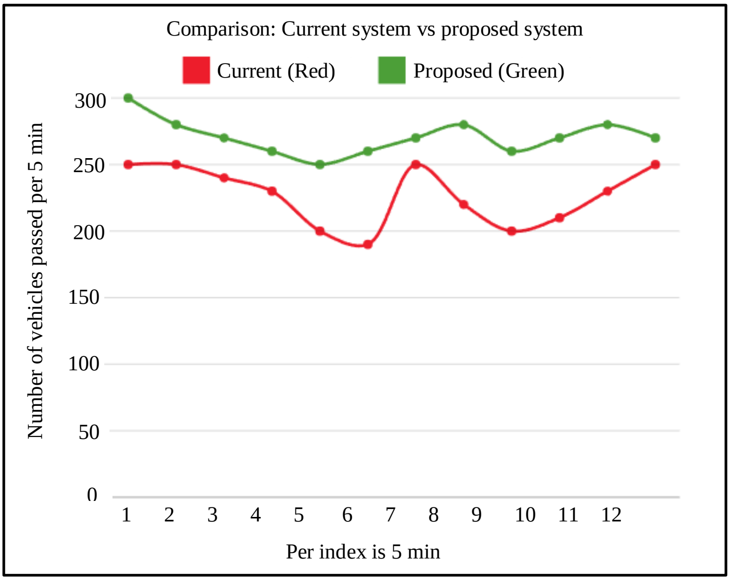

Figure 1. Comparison of current static system and proposed adaptive system

Figure 1 illustrates the superiority of the proposed adaptive system over traditional static systems. The graph demonstrates a marked increase in vehicles passing through intersections under the adaptive system, emphasizing its ability to manage varying traffic volumes dynamically and efficiently. The Flow-Density Relationship (Treiber and Kesting (2013), as depicted in Figure 2, provides a fundamental framework for understanding traffic flow dynamics. At lower densities, vehicles move freely, resulting in a proportional increase in flow.

As density approaches the critical threshold (K_c), the flow reaches its maximum efficiency (q_{max}). Beyond this point, congestion begins to form, causing a decline in flow rates. At jam density (k_j), and traffic flow ceases entirely, representing a state of gridlock. This relationship underpins the TrafficEZ system's approach to optimizing traffic signal timing, ensuring operations around critical density to maximize flow while minimizing congestion.

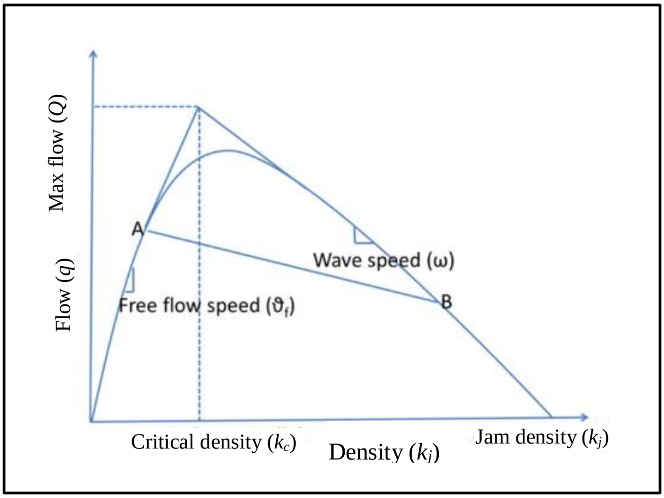

Figure 2. Flow-density relationship

The TrafficEZ system dynamically adjusts green-light durations based on vehicle count and density data by leveraging real-time data collection and analysis. This adaptability enables consistent traffic flow efficiency across various junctions. For example, Figure 1 shows how the system optimizes throughput during peak traffic hours, significantly improving traffic flow compared to the current static system.

The system's design also addresses the inherent variability in urban intersections. Different traffic patterns and conditions necessitate localized optimizations to maintain flow efficiency. Integrating predictive analytics and advanced computer vision models allows the system to identify critical density thresholds and adjust traffic parameters accordingly, maximizing throughput and reducing congestion.

These metrics and visualized results from Figures 1 and 2 highlight the TrafficEZ system's scalability and adaptability to diverse urban traffic conditions. The system ensures robust performance and efficient traffic management by operating near critical density levels, as shown in the Flow-Density graph. This data-driven framework establishes a scalable solution capable of addressing the dynamic nature of modern traffic environments.

2.3 Application of Centroid-based Tracking for Traffic Flow Estimation

The You Only Look Once (YOLO) algorithm, developed by Redmon and Farhadi (2018), is employed to identify vehicles in a single frame during the red-light phase. The importance of tracking across multiple frames is recognized; however, continuous tracking is not required for this phase. Tracking algorithms such as Simple Online and Realtime Tracking (SORT) or DeepSORT (Wojke *et al.*, 2017) have not been integrated with YOLO for the red-light phase.

For the green-light phase, tracking is implemented with a different purpose. A centroid-based object tracker calculates the Euclidean distance between objects across frames. This tracker is not utilized to maintain continuous vehicle identification but rather to estimate vehicle speed and traffic flow during the green-light phase. The performance of this tracker in consistently following objects is not critical in this application, as the primary objective is to extract speed and flow data rather than maintaining a continuous track of individual vehicles.

2.4 Communication System for TrafficEZ

The communication system deployed in the proposed edge computer vision solution is critical to the effectiveness of the traffic management system. This system involves a combination of Wireless Sensor Networks (WSNs) and Internet of Things (IoT) technologies.

WSNs, consisting of distributed, self-configured, and independent devices (nodes), were used to monitor physical or environmental conditions such as traffic density and vehicle speed. These nodes contained sensors that wirelessly communicated with each other, forming a mesh network for data exchange and coordination.

As part of deploying edge computing, these nodes also possessed some level of computational power, allowing for data processing at the source. This approach reduced latency, saved bandwidth, and ensured quicker response times, which were critical factors for effective traffic management.

The WSN was designed to support a robust, bidirectional communication system that ensured the constant flow of information between the sensors and the traffic control system. Data collected at the edge of the network was processed locally, and any pertinent information was transmitted back to a centralized system or Traffic Management Center (TMC). This allowed the TMC to have an overview of the entire traffic network and make informed decisions based on comprehensive, real-time data.

For IoT integration, standard IoT communication protocols such as MQTT (Message Queuing Telemetry Transport) or CoAP (Constrained Application Protocol) were considered, as these protocols ensured reliable data transmission and provided mechanisms for secure communication, which was paramount for our system.

Additionally, the expertise of collaborators at the University of Science and Technology of Southern Philippines, along with the partnering IoT-based company RSpot Solution, was leveraged to build a scalable, robust, and secure communication system that seamlessly integrated into the proposed traffic management solution.

2.5 Design Thinking with El Salvador City's Mayor and its Traffic Management Division

In a prior meeting with officials from El Salvador City, Misamis Oriental, Philippines, several key issues and requirements were identified, emphasizing the need for a proposed Lightweight Edge Computer Vision Solution for a Smart, Decentralized, and Efficient Traffic Management project. El Salvador City has expressed an urgent demand for a responsive and decentralized traffic light system. The current system, which is centralized and timing-based, fails to adapt to real-time traffic conditions or prioritize safety for vulnerable populations such as senior citizens and pedestrians. This inefficiency often results in prolonged waiting times and missed opportunities for optimal traffic flow, particularly at critical conduits like Laguindingan International Airport. A decentralized traffic management system would address these challenges by allowing traffic lights to operate autonomously based on real-time data, improving safety and efficiency at intersections. This approach ensures that traffic lights function harmoniously within a broader network, adapting dynamically to changing traffic and pedestrian demands.

City officials highlighted specific requirements for the new system: it must seamlessly integrate with existing traffic lights and infrastructure to minimize transition costs and avoid disruptions; it must be cost-effective to address resource constraints while delivering high functionality; and it must include robust data management capabilities, as there is currently no effective mechanism to capture and analyze traffic patterns for decision-making and urban planning. A robust data management framework is vital to harness and leverage real-time traffic data effectively. This project addresses these gaps by leveraging cutting-edge edge computing and IoT technologies to provide a scalable and sustainable solution. By incorporating design thinking principles, the project focuses on creating a system that adapts to the city's specific needs while aligning with its long-term urban development goals.

2.6 Camera Positioning Considerations

For successfully implementing a traffic monitoring system that uses computer vision, the positioning of the camera is crucial. A poorly placed camera can lead to inaccurate results and hinder the system's effectiveness. To ensure optimal functionality, the camera should be mounted sufficiently to provide a clear, unobstructed view of the area of interest. This often involves mounting the camera on a traffic light post or a purpose-built pole. Additionally, the camera should be angled downward slightly to capture vehicles and pedestrians clearly. This positioning helps reduce the impact of sunlight and other lighting conditions, which could otherwise cause glare on the lens. Proper camera placement is essential to maximize the accuracy and reliability of the traffic monitoring system.

3. Results and Discussion

The TrafficEZ system deployed multiple models and algorithms to enhance vehicle detection, tracking, and traffic flow monitoring in real time. The results highlight the efficiency and adaptability of each model, contributing to an overall robust traffic management system. This section discusses the performance of each model and its significance in achieving accurate, real-time traffic monitoring.

3.1 Model 1: Perspective Transformation

The Perspective Transformation model is a critical component of the system, designed to standardize the camera's field of view. By converting skewed footage into a bird's-eye view, this model provides a top-down perspective that is essential for accurate spatial analysis. Figure 3 illustrates this transformation, showing how warped views are corrected to facilitate better measurement of vehicle dimensions and movement. This standardization enables consistent calculations of traffic density and flow by ensuring that pixel coordinates in the video are mapped accurately to real-world distances.

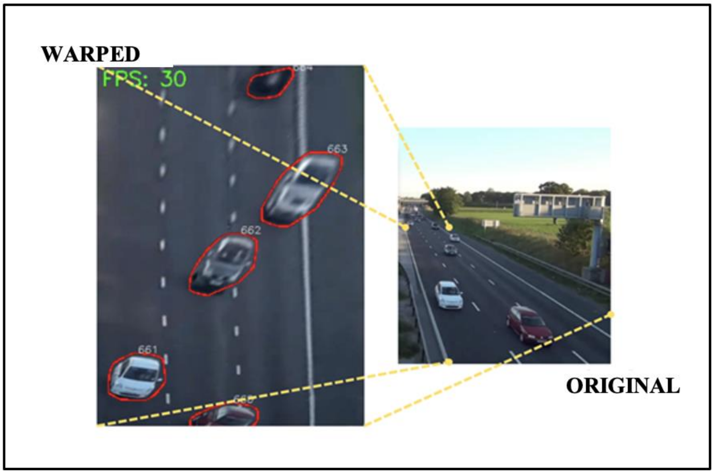

Figure 3. Snapshot of the application of perspective transformation

The significance of this transformation lies in its ability to remove visual distortions caused by the camera angle, which could otherwise compromise the accuracy of vehicle tracking and density estimation. As seen in Figure 3, the Perspective Transformation model enhances the system's ability to process traffic data accurately, making it a foundational step for subsequent algorithms. This model ensures that the TrafficEZ system can reliably measure and analyze traffic patterns, providing valuable insights for real-time traffic management.

3.2 Model 2: MOG2 Background Subtraction

The MOG2 Background Subtraction algorithm is a critical component of the TrafficEZ system, enhancing vehicle detection by isolating moving vehicles from the static environment. Figure 4 illustrates how this algorithm processes input video frames, effectively distinguishing moving objects from the background to create a clean, isolated image for further analysis. This approach significantly improves the accuracy and efficiency of subsequent traffic monitoring and data extraction tasks.

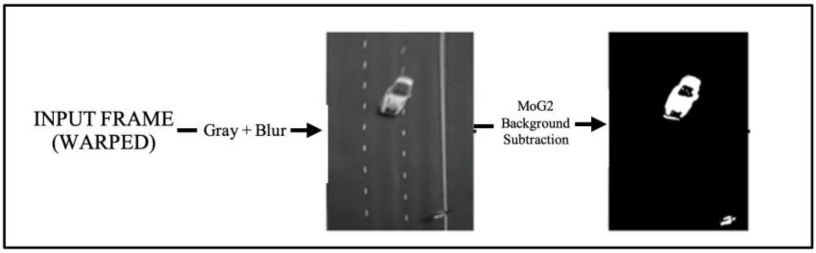

Figure 4. Snapshot of the application of background subtraction

The function of the MOG2 algorithm lies in its ability to isolate moving objects, ensuring that only relevant entities, such as vehicles, are detected and tracked. Its significance is further highlighted by its adaptability to varying environmental conditions, including changes in lighting and weather. The algorithm remains reliable across diverse traffic scenarios by consistently processing grayscale video frames to distinguish vehicles from the background. This capability is crucial for maintaining accurate traffic monitoring during different times of day or weather patterns.

The robustness of the MOG2 algorithm ensures high accuracy in identifying vehicles, paving the way for more detailed analysis in subsequent tracking stages.

3.3 Model 3: Convex Hull Detection and Tracking

The Convex Hull Detection and Tracking model is an essential component of the TrafficEZ system, focusing on encapsulating vehicle shapes and tracking their movement across frames. Figure 5 illustrates the step-by-step application of this model, showing how it integrates with the Perspective Transformation and MOG2 Background Subtraction models to enable precise vehicle monitoring. This model analyzes vehicle contours and movements, providing valuable insights for estimating traffic flow and density in dynamic environments.

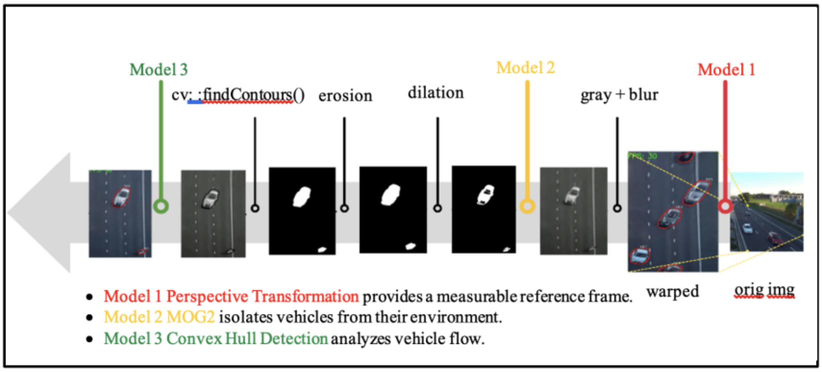

Figure 5. Snapshot of the application of convex hull detection and tracking

The primary function of the Convex Hull Detection and Tracking model is to detect and outline vehicle contours, ensuring that even irregularly shaped vehicles are accurately identified and monitored. By creating convex hulls around detected shapes, this model provides a reliable mechanism to track vehicles as they move through the monitored area. Its significance lies in its ability to maintain accurate tracking of vehicles over time, even when shapes are distorted due to perspective changes or motion blur. By analyzing the space occupied by each vehicle, the system estimates traffic density and flow with high precision.

This model is particularly valuable for analyzing complex traffic patterns, as it allows the TrafficEZ system to handle distortions and shape variations effectively. By leveraging convex hulls, the system ensures accurate and consistent tracking, enabling better traffic management and decision-making processes.

3.4 Integration of the Models

The synergy between the three models forms a comprehensive traffic monitoring system. Each model contributes a specific function to the overall traffic detection pipeline:

1. Perspective Transformation establishes a measurable frame of reference by correcting the camera's viewpoint.
2. MOG2 Background Subtraction provides a clean foundation by isolating moving vehicles from the static background.
3. Convex Hull Detection and Tracking accurately tracks vehicle movement and helps estimate traffic density.

This integrated approach ensures the system is scalable and adaptable to various traffic conditions, making it suitable for real-time urban traffic management. The system's adaptability to different environments and its computational efficiency position it as a promising solution for smart city infrastructure.

Table 1 provides a comprehensive overview of each algorithm, detailing their purpose, key features, and specific applications within the study. By summarizing the functionality of the models, this table highlights their individual contributions to the overall effectiveness of the TrafficEZ system.

Table 1. Comprehensive overview of each algorithm, including their purpose, key features, and specific application within the study

Algorithm	Purpose	Features	Implementation in the study
Warping Algorithm for Perspective Transformation	Transforms skewed footage to a bird's-eye view for accurate spatial analysis.	Uses strategic points for transformation matrix creation; essential for consistent spatial analysis.	Selected specific points in traffic footage to create a transformation matrix, successfully converting angles to a top-down view.
MOG2 Background Subtraction Algorithm	Segregates moving vehicles from static backgrounds, focusing on dynamic scene elements.	Applies a Gaussian Mixture Model to grayscale frames; adaptively responds to lighting and weather changes.	Applied to grayscale video frames to isolate moving vehicles, effectively adapting to different environmental conditions.

Table 1. Continued.

Convex Hull Detection and Tracking Algorithm	Encloses detected vehicles in polygons for tracking and traffic density estimation.	Handles distorted vehicle contours; crucial for vehicle identification and flow analysis.	Used to draw polygons around vehicles, regardless of shape irregularities, and track their movement over time.
Morphological Noise Reduction Algorithm	Refines vehicle detection by eliminating noise and small objects.	Employs dilation and erosion techniques; maintains integrity of vehicle shapes.	Implemented to clean up the image by reducing noise and refining the identification of vehicles.
Contour Analysis Algorithm for Vehicle Identification	Identifies and differentiates vehicles based on unique contours.	Analyzes shapes from convex hulls; facilitates accurate vehicle counting and classification.	Analyzed vehicle shapes post convex hull application for accurate vehicle identification and counting.

3.5 System Optimization and Scalability

The integration of these algorithms enabled the TrafficEZ system to manage and monitor traffic flow across multiple intersections efficiently. The use of Perspective Transformation improved the accuracy of spatial analysis, ensuring that vehicles were correctly tracked in real-world distances. Background Subtraction allowed the system to effectively isolate moving vehicles, providing a clean and reliable input for further analysis. Finally, Convex Hull Detection enabled the system to track vehicles accurately, even in complex traffic conditions.

Morphological Noise Reduction and Contour Analysis enhanced the system's performance, refining the vehicle detection process and ensuring precise, distinct contours for accurate tracking. The real-time adaptability of these models makes TrafficEZ an attractive solution for intelligent traffic management systems, with the potential for wide-scale deployment in urban environments.

4. Conclusion and Recommendation

The findings of this study highlight the effectiveness of the TrafficEZ system as a robust and scalable traffic management solution. The system successfully enhances vehicle detection, tracking, and traffic flow estimation by integrating advanced models such as Perspective Transformation, MOG2 Background Subtraction, and Convex Hull Detection and Tracking. These components collectively improve real-time traffic monitoring, adaptability to diverse urban environments, and the potential for smart city integration. The study underscores the importance of combining edge computing and machine learning in addressing traffic management challenges, paving the way for more efficient and responsive systems.

Based on the study's findings, several recommendations are proposed to enhance the TrafficEZ system further. First, expanding edge computing capabilities by integrating more powerful devices and GPU-accelerated technology can improve real-time performance and accuracy. Second, the system could incorporate additional traffic metrics, such as pedestrian flow and public transport, for a more comprehensive traffic management solution. It is also recommended that adaptive machine learning models be included that continuously learn from traffic patterns to optimize performance over time. Strengthening security protocols, including encryption and tamper detection measures, is crucial as the system scales. Pilot testing in diverse urban environments will ensure the system’s adaptability to various traffic conditions. At the same time, continued collaboration with Local Government Units (LGUs) and innovative city initiatives will aid in large-scale deployment. Finally, integrating predictive analytics will enable proactive traffic management, enhancing the system’s ability to adjust signals before congestion occurs. These recommendations will support the ongoing development and scalability of TrafficEZ for effective traffic management.

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