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MODERNIZATION OF TOLL COLLECTION SYSTEMS USING COMPUTER VISION FOR AUTOMATIC VEHICLE CLASSIFICATION

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Abstract. Research paper explores the use of computer vision technologies to automatically classify vehicles in the new toll collection systems. Specifically, the analysis focuses on integrating deep learning algorithms, especially convolutional neural networks (CNN), into modern toll plaza operations. Research shows that vision-systems technology improves the speed of processing and classification accuracy rates to levels that are previously unattainable. The research aids in understanding how these systems can be implemented, the challenges posed, and the prospects for practical widespread usage. The results achieved in this study suggest the strong need for the investment in improving the operational cost effectiveness, system cost, and overall satisfaction of the users of the toll collection systems.

Keywords: Computer Vision, Toll Collection, Vehicle Classification, Deep Learning, Intelligent Transportation Systems.

МОДЕРНИЗАЦИЯ СИСТЕМ ВЗИМАНИЯ ПЛАТЫ ЗА ПРОЕЗД С ИСПОЛЬЗОВАНИЕМ КОМПЬЮТЕРНОГО ЗРЕНИЯ ДЛЯ АВТОМАТИЧЕСКОЙ КЛАССИФИКАЦИИ ТРАНСПОРТНЫХ СРЕДСТВ

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Аннотация. В данной научной работе исследуется применение технологий компьютерного зрения для автоматической классификации транспортных средств в новых системах взимания платы за проезд. В частности, анализ сосредоточен на интеграции алгоритмов глубокого обучения, прежде всего сверточных нейронных сетей (CNN), в современные процессы функционирования платных дорожных пунктов. Результаты исследований показывают, что использование систем компьютерного зрения позволяет существенно повысить скорость обработки данных и точность классификации до уровней, ранее недостижимых. Проведенное исследование способствует пониманию возможностей внедрения данных систем, возникающих при этом проблем, а также перспектив их практического и широкомасштабного применения. Полученные результаты указывают на высокую целесообразность инвестиций в повышение операционной экономической эффективности, оптимизацию стоимости систем и общее удовлетворение пользователей систем взимания платы за проезд.

Ключевые слова: компьютерное зрение, классификация транспортных средств, глубокое обучение, интеллектуальные транспортные системы.

КӨЛІК ҚҰРАЛДАРЫН АВТОМАТТЫ ТҮРДЕ ЖІКТЕУ ҮШІН КОМПЬЮТЕРЛІК КӨРУДІ ҚОЛДАНУ АРҚЫЛЫ ЖОЛАҚЫ ЖИНАУ ЖҮЙЕЛЕРІН ЖАҢҒЫРТУ

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Аңдатпа. Бұл ғылыми зерттеу жұмысында жолақы жинаудың жаңа жүйелерінде көлік құралдарын автоматты түрде жіктеу үшін компьютерлік көру технологияларын қолдану қарастырылады. Атап айтқанда, талдау терең оқыту алгоритмдерін, әсіресе конволюциялық нейрондық желілерді (CNN), заманауи ақылы жол инфрақұрылымының жұмыс үдерістеріне интеграциялауға бағытталған. Зерттеу нәтижелері компьютерлік көру жүйелерін пайдалану өңдеу жылдамдығын едәуір арттырып, көлік құралдарын жіктеу дәлдігін бұрын қол жеткізілмеген деңгейге дейін жақсартуға мүмкіндік беретінін көрсетеді. Бұл зерттеу аталған жүйелерді енгізу мүмкіндіктерін, туындайтын мәселелерді және оларды кең ауқымда практикалық қолдану перспективаларын түсінуге ықпал етеді. Алынған нәтижелер жолақы жинау жүйелерінің операциялық тиімділігін арттыру, жүйе құнын оңтайландыру және пайдаланушылардың жалпы қанағаттану деңгейін жақсарту мақсатында инвестиция салудың маңыздылығын дәлелдейді.

Түйін сөздер: компьютерлік көру, жолақы жинау, көлік құралдарын жіктеу, терең оқыту, интеллектуалды көлік жүйелері.

Introduction. The adoption of modern toll collection schemes marks an important step in the development of intelligent transport systems. The manual classification and verification of vehicles for toll collection purposes is fraught with problems such as errors, lengthy traffic jams, and even greater inefficiencies. Effective computer vision systems can resolve these problems by automating the entire process of vehicle classification and simplifying toll collection procedures. Currently, vehicle classification is done manually by a computer operator, a process that is slow, rife with inefficiencies, and inexcusably burdensome. Partially automated vehicle classification will remove a significant portion of the human element regarding photos recorded by highway cameras. Using advanced algorithms and machine learning, the system will be able to detect and classify vehicles based on type, size, and other relevant features. Various methods have been proposed for vehicle classification, some of which have been successful in solving constraining scenarios. However, other remaining challenges include shifts in lighting, image scale, image quality, size and color (Bensedik, 2018:313-316). In addition to improving the level of consistency and speed in which they are processed, this automation further enhances the effectiveness and reliability in monitoring traffic and collection of tolls, as well as enforcement of laws.

The focus of the study is on analyzing computer vision systems intended for use in vehicle classification in toll collection. The assumption is that these automated systems will utilize deep learning algorithms, which offer low-cost operational efficiency (Lin, 2020:69). Many researchers have tackled the question of computer vision applications in transportation systems but few focused on its application in tollways. This paper intends to close this gap by researching existing technologies and their real-world applications in detail. Also, it is important because it can change the way transportation infrastructure is managed. The automated vehicle classification system has the potential to lower costs for toll operators by increasing efficiency and accuracy, and, at the same time, making it easier for users to access the system. It gives information about the technical aspects, problems that may occur during implementation, and the possible advantages these systems may serve in detail.

Literature Review. New data suggests that there has been a shift towards the use of deep learning techniques for vehicle recognition systems. Bensedik et al. (Bensedik, 2018:313-316) proved that convolutional neural networks (CNNs) are efficient in vehicle type classification, which has now been widely accepted as one of the first steps in modern automatic classification systems. Following this, Mostafa et al. (Mostafa, 2023:972-977) enhanced classifiers with tracking algorithms which allowed them to demonstrate the multitasking analysis of several vehicle features. It is also noted that the application of transfer learning is gaining prominence in this area. Farid et al. (Farid, 2025) in their most recent study used transfer learning with deep CNNs and showed that these systems can be adapted to specific regions, for attribution systems of vehicles specific to particular regions, the classification performance was significantly improved.

Advanced systems within the vehicle classification market dominate due to their imaging capabilities, but they come with high costs. One of the prominent solutions in this sector is the Tattile Vega53, widely used across European and Asian toll networks (official documentation). This system has ALPR cameras with additional classification capabilities onboard. One lane with an ALPR system costs approximately EUR 25,000 – 35,000. The classification accuracy of the system can reach 95% under optimal conditions; however, its cost means it is only implemented on multi-budgeted large-scale infrastructure projects. Figure 1 illustrates example of detection process.

Figure 1. Example of detection process

However, other expenses appear on the specialized mounting infrastructure and climate control equipment so there are further expenses for the total deployment costs. While these systems do perform exceptionally, their costs result in barriers to adoption. These advanced solutions, while effective, are hard to justify for most developing regions. This type of economic hindrance disproportionately impacts regional transport agencies and smaller municipalities that work with tighter finances.

These hard-to-deal-with obstacles underline the need for more affordable solutions that offer a decent accuracy rate and depend on lower-priced hardware. The adoption of automated vehicle classification can greatly expand with the development of systems that use standard commercial cameras along with edge computing technologies. Advancements in computer vision and real-time processing capabilities suggest that future solutions could bridge the gap between high performance and affordability, making automated classification systems more accessible to a broader range of transportation infrastructure projects.

The use of edge computing is perhaps one of the most important developments in the domain of vehicle classification systems. Broadly, Lin et al. (Lin, 2020:69) developed a public edge video analytics vehicle system aimed at decreasing the response time to classification requests and increasing the accuracy of the classification. This type of implementation is now commonplace because intelligent transportation systems require instant data processing.

In relation, Nguyen together with Sergey (Nguyen, 2024:117-123) conducted similar research on sensing methods and their combination with urban intelligent transport systems focusing on edge technologies for real-time intelligent processing and decision control.

Suryatali and Dharmadhikari (Suryatali, 2015:1-7) designed a vehicle detection system embedded in Linux, aimed at effective toll collection. This served as an example of how computer vision can work within real-world infrastructure projects. Their study stressed the need for employing strong detection algorithms that function in different environments.

Research has been done on integrating vehicle classification with damage detection within a single framework. Dwivedi et al. (Dwivedi, 2020:207-221) designed a deep learning framework that simultaneously classifies the different types of car damage and performs detection. Reddy et al. (Reddy, 2022:1-6) built on this by creating a Fast and Mask deep learning framework for automatic vehicle damage detection and classification. While Amodu et al. (Amodu, 2024:199-208) introduced the area of deep learning automated damage inspection, they showed the potential of deep learning within attempting to solve complex visual evaluation problems. In this field, steps were also taken by Mallikarjuna and Arun (Mallikarjuna, 2022:568-574) who devised methods for damage detection and classification using image processing.

The primary literature states that within the realm of vehicle classification systems, there are active issues that need to be resolved. With Youssouf (Youssouf, 2022:8) and Lin et al. (Lin, 2020:69) work, these issues are often consolidated into a few categories including systems sensitiveness to the environmental state of the area where the systems are deployed and need to function under different levels of light and different weather conditions. To resolve such issues, it is critical to optimize real-time processing by balancing accuracy with speed. Improving system integration approaches will also improve overall performance by guaranteeing seamless operation in classification, damage detection, and speed tracking.

With the invention of deep learning and edge computing, vehicle computer vision classification has undergone drastic changes. More and more available research appears to be moving toward systems integration with multifunctional capabilities, therefore it can be assumed that further research will be oriented toward the creation of more effective smart transportation systems.

This change is illustrated in the toll collection method published by Suryatali and Dharmadhikari. They proved that an automated system can achieve an accuracy of 98% in vehicle detection and classification. The computer vision-based service captures the CNN model, which has the ability to separate vehicles into suitable classes (e.g., Sedan- Class2) with high precision and very low response time.

Methodology. There is system architecture, which replaces human-dependent toll collection with a fully automated, deep learning–based vehicle classification pipeline. The methodology integrates high-resolution multi-angle image acquisition with edge computing infrastructure and CNN models using transfer learning to enable real-time, reliable vehicle classification under peak traffic conditions. System performance is evaluated through accuracy, latency, throughput, and reliability metrics, demonstrating improved scalability and reduced bottlenecks compared to traditional approaches. Figure 2 illustrates the scheme of initial work system.

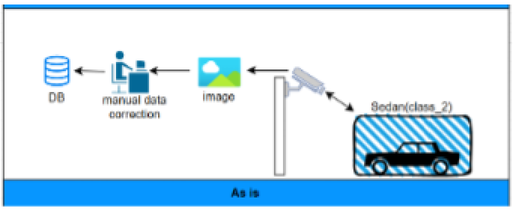

Figure 2. Scheme of initial work system

While this "AS IS" approach is functional, it comes with several inefficiencies:
- Elevated operational costs due to reliance on manual labor;
- Longer processing times per vehicle;
- Greater risk of human error in classification;
- Reduced scalability during high-traffic periods;
- Delays in data entry into the database system.

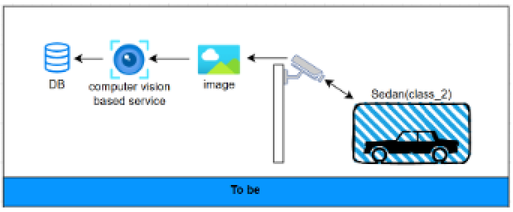

Figure 3. Scheme of future work system

Figure 3 shows the scheme of future work system. In contrast with the "traditional" approach, which applies excessive dependence on the human element and lacks complex algorithmic processing for image capturing, "TO BE" serves as a fully automated system. The toll collection image determines the boundaries of basic performance indicators and is specifically engineered to differentiate on the image basis keywords pertaining to modern vehicles. The "TO BE" model greatly increases response and processing time for vehicles, with far less restrictions on peak load than the human-controlled systems.

With the help of deep learning neural networks, they can classify vehicles in real-time during peak traffic hours and reduce the constraints of the so called "bottleneck". Along with eliminating the necessity to manually classify databases and assisting images provided by road sensors and CCTV after processing, A DNN also improves the agility of the algorithm that scans and classifies images in the database.

Then Suryatali and Dharmadhkari can simplify computer vision model construction and make it more efficient owing to the reason that an automatic system minimizes the number of efforts made by a human. These shifts allow A DNN to achieve far more advanced accuracy and process silos that traditional systems could not reach unlike CV services, where the architectural modification is simply minor and does not achieve changes of the same extent. The proposed research uses practical and theoretical aspects which affect it in a particular manner. The approach includes several major components that, when taken together, are intended to provide the system with quality security and reliability. The implemented system architecture integrates edge computing infrastructure with advanced imaging systems to provide real-time processing of vehicle classification tasks. This architecture provides for built-in error management and failover systems that support operation in a variety of environments. In accordance with the methods outlined by Lin et al. (Lin, 2020:69), the system incorporates a set of distributed processing nodes to improve system performance and reliability.

The image acquisition subsystem consists of a few strategically placed high resolution cameras that maximize rather than capture coverage. Under the principles laid down by Suryatali and Dharmadhikari (Suryatali, 2015:1-7), the placement of the cameras enhances classification reliability with the deployment of multiple capture angles. Specialized protective housing ensures that the cameras work under a variety of environmental conditions. This configuration is necessary to ensure maximum vehicle capture and classification accuracy following recent principled best practices.

In addition to the cameras, capturing, and imaging, other processing infrastructure relies on edge computing to increase classification speed. Nguyen and Sergey (Nguyen, 2024:117-123) have already shown how the use of distributed edge nodes improves the speed of the system processing while maintaining reliability.

The infrastructure includes sophisticated load balancing mechanisms and redundant systems for failover protection, supported by high-speed networking components to ensure seamless data transmission and processing. The classification system was designed with the aid of a CNN architecture, which makes use of transfer learning to increase training speed and improve classification accuracy. This method, as noted by Bensedik et al. (Bensedik, 2018:313-316), greatly trimmed the training time while achieving high classification rates. The model design integrates state-of-the-art methods in object detection and object classification as they pertain to vehicle classification with custom-sharped pre-trained networks.

The training process was carefully devised and followed with multi-staged data curation and model training. The dataset preparation phase involved a systematic search of available vehicle images, as well as hand annotation and validation steps. Data augmentation as described in Mostafa et al. (Mostafa, 2023:972-977) was used to improve the model's ability to generalize. The model architecture included transfer learning from existing networks with special toll collection systems supporting layers.

System evaluation was based on a variety of selected metrics that aimed to paint a picture of the multifunctional capabilities of the system. Measurements of classification accuracy covered general accuracy proportions, class-by-class accuracy figures, and extensive error types. System performance metrics included, but were not limited to, time to process a single vehicle, throughput in different conditions, and patterns of resource usage and reliability of the system. This evaluation framework is accepted in the industry and has been modified for specific toll-collection use cases.

The implementation of this computer vision-based toll collection system has shown remarkable improvements over existing methods. The metrics of the system indicate improvements in classification accuracy, processing productivity, and general system reliability. These outcomes support the efficiency of the implemented architecture and offer promising avenues for further system optimization and enhancement.

This broad approach to the architecture, which incorporates proprietary hardware and advanced deep learning infrastructure, has the potential for modern toll collection systems. Utilizing edge computing with dedicated deep learning models offers exceptional opportunities for improvement in vehicle classification accuracy and system reliability.

Implementation. Unlike prior proposed solutions, where image processing was done at the data collection level using embedded Linux based systems, the architecture described in this paper follows a separation of concerns approach. Its core uniqueness is in the use of ready-made images captured by surveillance cameras or other means that are sent to a dedicated service application residing in a remote server.

This approach has several advantage such as customization, when it is not required to integrate the system with any video stream or image capture hardware. Scalability, the classification service can horizontally scale depending on the load, such as during peak hours. Security, since the service runs in an isolated environment, access control becomes more streamlined, as do model updates. Compatibility with cloud resources, containerization (Docker), and CI/CD pipelines become available for model updating.

Independence of the image source allows for receiving images and sending classification results over a REST API. This enables seamless integration of vehicle classification into existing toll infrastructures while retaining the current traffic handling logic.

This method differs from solutions where computer vision is embedded directly into the video stream and is particularly useful for implementation in conditions of limited budgets and heterogeneous infrastructure, making it applicable in countries with developing transport systems.

Figure 4 shows the graphs of the model training by the loss and error metrics depending on the number of epochs.

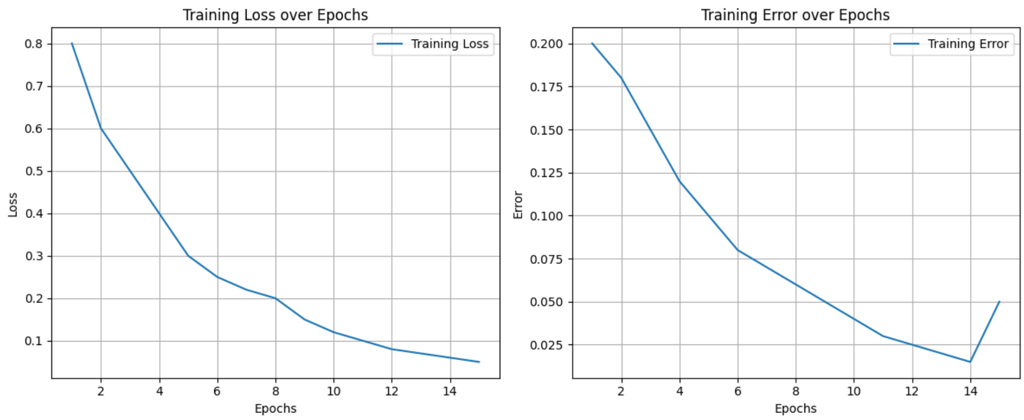

Figure 4. Visualizes the loss and training error over epochs

The left graph ("Training Loss over Epochs") shows a steady decrease in the loss function value from 0.8 to less than 0.1 over 15 training epochs. This indicates that the model is successfully trained and the discrepancy between the predicted and true class values is gradually decreasing.

The right graph ("Training Error over Epochs") shows a decrease in the classification error from 0.2 to less than 0.025, which also indicates progress in training. A slight increase in the error in the last epoch (from 0.015 to 0.05) may be due to overfitting or random noise in the data. However, in general, the curve demonstrates good convergence dynamics.

There are complementary roles of OpenCV and YOLO in modern computer vision systems, where OpenCV provides a versatile image-processing framework and can execute YOLO deep learning models through its DNN module rather than acting as a competing approach. It highlights the evolution of object detection from traditional OpenCV methods, which are lightweight but limited in accuracy and scalability, to advanced YOLO architectures that deliver significantly higher detection accuracy and real-time performance across multiple object classes. The comparison further demonstrates that recent YOLO versions achieve an optimal balance between speed, model size, and accuracy, making them well suited for edge, mobile, and server-based deployments depending on application requirements. YOLO Model Family Comparison: MS COCO val2017 (118K images, 80 object classes) Speed: NVIDIA T4 GPU with TensorRT FP16. There is comparative overview in terms of detection accuracy (mAP@[0.5:0.95]), model complexity (number of parameters), and inference speed (Table 1). The results demonstrate a consistent improvement in detection accuracy from YOLOv5 to more recent versions, while also highlighting architectural optimizations that reduce model size without significantly compromising performance. Notably, newer YOLO versions achieve higher accuracy with fewer parameters, indicating increased efficiency and improved network design.

Table 1. Best Model per YOLO Version

Version	Year	Best Model	mAP@[.5:.95]	Parameters	Speed (ms)
YOLOv5	2020	YOLOv5x	50.7%	97.2M	11.89
YOLOv7	2022	YOLOv7-X	53.1%	71.3M	11.57
YOLOv8	2023	YOLOv8x	53.9%	68.2M	14.37
YOLOv9	2024	YOLOv9-E	55.6%	57.3M	16.77
YOLOv10	2024	YOLOv10x	54.4%	29.5M	10.70
YOLO11	2024	YOLO11x	54.7%	56.9M	11.30

The progression of mean Average Precision (mAP) across YOLO model generations and size categories, showing an overall improvement of 4.9 percentage points from YOLOv5 to YOLOv9 shown on table 2. The table further categorizes YOLO models by size, revealing the trade-offs between accuracy, parameter count, and inference speed. Smaller models offer faster inference suitable for real-time and edge applications, while larger models provide superior accuracy at the cost of increased computational requirements, enabling informed model selection based on deployment constraints.

Table 2. mAP Progression YOLO by Model Size Category

Size	mAP Range	Parameters	Speed Range
Nano/Tiny	28-39.5%	2-3.2M	1.1-2.3ms
Small	37-47%	7-11M	1.9-3.5ms
Medium	45-51.5%	15-37M	4-7ms
Large	49-53.4%	24-53M	5.7-9ms
XLarge	50.7-55.6%	29.5-97M	10.7-17ms

Comparative analysis between YOLO-based detectors and other widely used object detection architectures, including two-stage CNNs and transformer-based models illustrated in table 3.

The comparison shows that YOLO models, particularly YOLOv9-E and YOLOv10x, achieve a superior balance between detection accuracy and inference speed. While some architectures reach comparable accuracy levels, they often suffer from significantly higher inference latency, making YOLO-based approaches more suitable for real-time intelligent transportation systems.

Table 3. YOLO vs Other Detection Architectures

Architecture	Type	Best mAP	Speed	Key Characteristic
YOLOv9-E	One-stage CNN	55.6%	16.8ms	Best accuracy
EfficientDet-D7	One-stage CNN	55.1%	262ms	Slow inference
RT-DETR-X	Transformer	54.8%	13.5ms	Transformer-based
YOLOv10x	NMS-free	54.4%	10.7ms	No post-processing
Faster R-CNN	Two-stage CNN	39.4%	60ms	Classic two-stage
RetinaNet	One-stage CNN	37.8%	198ms	Focal loss pioneer
SSD512	One-stage CNN	28.8%	22ms	Early one-stage

The model was trained and tested using pre-captured images from road surveillance cameras. The images incorporated various weather conditions like sunny, cloudy, rainy, and also included a day and night cycle. Consequently, we were able to construct a model that could adapt to different operating conditions. Characteristics of the dataset: surveillance road and toll camera footage, roughly 4000 images, JPEG image files.

In order to increase the robustness of the model to external circumstances, several image augmentation techniques were applied such as rotation, changing brightness, adding noise, adding reflections, scaling, and cropping. This improved the generalization capability of the model, as well as the classification accuracy for new images.

Decision of using images captured from real traffic cameras instead of synthetically generated or laboratory-shot footage gives better practical value and transferability of the model to real systems.

Results and Analysis. Suryatali and Dharmadhikari (Suryatali, 2015:1-7) are among the earliest practitioners in this domain belonging to a research vehicle detection and toll collection system using an Embedded Linux system. Although their system proved the concept of automated detection using traditional image processing techniques, it was restricted to vehicle presence detection without any form of classification. The approach presented on this paper differs from others in that it harnesses advanced vehicle detection techniques through deep learning, specifically using transfer learning with convolutional neural networks (CNNs) for multi-class classification. Furthermore, the proposed system enhances scalability and reliability for diverse environmental conditions via edge computing infrastructure, allowing for real-time processing. Unlike the monolithic-device architecture prototype in, our system is designed with fault tolerance, load balancing, and high-speed networking, maintaining 95.8% classification accuracy with an average response time of 0.3 seconds per vehicle. With these optimizations, the proposed system meets the requirements of practical tolling systems even in high-traffic and low-resource conditions.

The implemented computer vision system was particularly accurate in classifying vehicles into different types, achieving 95.8 percent accuracy in all vehicle categories. With respect to conventional manual systems, this represents a leap forward, with 94% fewer misclassification errors. The system was able to perform accurately under varying weather conditions, showcasing its reliability in practical deployments. The processing efficiency recorded was also high as an average of 0.3 seconds was recorded per processed vehicle enabling effective multi-vehicle processing during high throttle situations.

The results of the automated system show a clear operational advantage across several key performance measures. Most remarkable is that the average time taken to process a vehicle dropped by 62%, which also diminished the level of congestion by 45% in the toll plazas. Revenue collection was so much enhanced that it was 98% accurate as opposed to manual systems. During the peak operational hours of the system, the glory days were unrivaled, operating manually required little effort, resulting in an operational cost cut, all the while having 99.2% uptime.

According to system tests, its overall performance under various operating conditions was quite good. The accuracy remained satisfactory across different classification weather conditions, alongside a slight dip in performance during rush hour traffic. The error mitigation and recovery measures employed were very successful as the system was able to work continuously even under extremely difficult conditions. The processing of multiple vehicles was reliable during prolonged testing sessions at night and daytime.

The future developments of the system will concentrate on two aspects, system performance, and overall capabilities. Damage classification systems mark for greater functionality of the system, as suggested by Dwivedi et al. Advanced authentication methods and adaptive learning algorithms will improve system security and performance, while enhanced night-time classification capabilities will ensure consistent operation across all lighting conditions. Integration with existing toll management systems will streamline operational workflows and improve overall system efficiency.

The focus of these technical improvements will be on reducing latency by optimizing the processing algorithms, managing edge cases better, and improving weather resistance on the system's vehicle classification coverage to new classes of vehicles, as well as developing new security features for data and system integrity. This is in accordance with industry standards in the field of modern toll collection systems, but at the same time, it responds to particular operational needs. Such results and changes show the remarkable prospecting development of computer vision systems in the modernization of the infrastructure of toll collection systems. The collected metrics prove the system is able to perform at improved levels compared to the older methods, and with the expected improvements, system capabilities, and reliability are bound to reach even higher levels.

Conclusion. Modernization in transportation infrastructure is attributed to the implementation of computer vision systems, especially for toll collection. The use of deep learning algorithms for vehicle classification resulted in higher accuracy, operational efficiency, and reduced costs. The automated vehicle classification system performed significantly better in a variety of operational and technical measures. Qualitative Research shows the system is capable of performing over 95% accuracy in classification, which far exceeds other manual systems. Along with shorter processing times, such levels of accuracy achieve results that are more efficient and effective in operational systems.

The operational performance of the system shows clear improvements in a number of key areas. Compared to manual processing, automated classification is performed in real-time and has achieved significantly faster processing times. Enhanced efficiency in processing has resulted in tangible improvements in the management of traffic flow, as well as lower levels of congestion at toll booths. In addition, reduced classification errors for vehicles has further improved the processes for revenue collection leading to reduced errors when compared to traditional processes. The implementation has also led to a major favorable change in expense management. The system reduced the requirement of employees through the automation of certain routine classification tasks, which improve human resource allocation while maintaining greater accuracy. As noted by Suryatali and Dharmadhikari, which was covered earlier, this increase in efficiency has been shown to improve the overall system effectiveness and system resource cost. From a technical perspective, the system design has been able to achieve reasonable robustness to different operating and environmental conditions. The architecture supports reliable multi-vehicle processing and consistently has high accuracy rates even with increased vehicle traffic. Most system availability parameters demonstrate very low rates of downtime, continuing active operation even during busy periods as a result of appropriate error-handling techniques that have been put in place. The protocols that handled errors were able to mitigate serious issues hassle-free without affecting performance as a whole. Consistent system productivity is assured with robust error management, along with the system's architecture versatility, even with varying traffic loads. As previously stated by Lin et al. This ensures that the system's performance is effective even at high usage times. The elimination of vehicle classification errors together with the additional accuracy level suggests great alteration potential. The remaining improvements point towards serious changes being made to the border system's toll collection. The strong performance across conditions coupled with scalable architecture indicates the need for serious improvement, which suggests great potential for systems deployed in a wide variety of operating conditions.

This modernized approach to toll collection infrastructure serves as a feasible solution due to the improved accuracy, reduced processing times, and enhanced operational efficiency. Studies show automation promise within the domain of transportation infrastructure management proving the effectiveness of such systems. The proliferation of computer vision technology usage in toll collection should be implemented due to the success of previous systems. Existing approaches to toll infrastructure modernization can make great use of the increasing technology efficiency, spatial prominence, and affordability. Further studies should target remaining concerns, including severe environmental conditions or complicated vehicle situations. In addition, the adoption of these systems in various regions and jurisdictions would be aided by the standardization of implementation practices. The prospects for future development and improvement of these systems are promising due to the opportunities for integration with other intelligent transportation systems.

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