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Deep Learning for Helmet and Number Plate Detection

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Abstract- Road safety has become a critical concern due to the rapid increase in two-wheeler usage and frequent violations of helmet-wearing regulations. Manual traffic monitoring is often inefficient and error-prone, especially in high-density traffic environments. This study aims to tackle these difficulties presents an automated detecting helmets and license plates system utilizing deep learning techniques. The proposed approach employs a YOLO-based object detection model to identify riders, helmets, and the number of the vehicle plates from pictures, movies, and live surveillance feeds in real time with high accuracy. Helmet violations are detected by associating riders with helmet presence, and the corresponding number plates are isolated for further processing. The model learns from a custom annotated set of data and optimized to perform reliably under varying lighting conditions, camera angles, and traffic scenarios. The results of the experiments show that the detection is very accurate, low latency, and strong robustness, making the system work in real life time traffic surveillance and smart city applications. This study shows how well deep learning works-based computer vision systems in enhancing road safety and supporting automated traffic law enforcement.

Keywords: “Modelling, LSPR, perovskite, solar cells, light trapping, plasmonics, nanoparticles”.

I. INTRODUCTION

To address the increasing number of injuries and fatalities involving two-wheeler riders, an intelligent traffic monitoring system is developed using the Version 8 of the deep learning You Only Look Once (YOLO) algorithm. YOLOv8 is a cutting-edge model for detecting objects in one stage. capable of performing detection in real time with a high level of precision. The proposed system utilizes surveillance camera feeds to find out automatically motorcyclists, identify wearing a helmet, and extract number plates of violators. By automating this process, the system minimizes reliance on manual traffic monitoring, reduces human error, and ensures continuous enforcement of helmet regulations [1].

The algorithm operates by capturing live or recorded video streams from traffic surveillance cameras. Each video frame is processed by the YOLOv8 model trained on a custom dataset containing labeled classes such as motorcycle, helmet, no-helmet, and number plate. YOLOv8 uses convolutional neural networks to extract spatial features while simultaneously figuring out the chances of each class and the bounding boxes. When a motorcycle is detected, the system checks for the presence of a helmet on the person riding. The device will not work if it does not find a helmet. flags the rider as a violator and triggers a secondary detection module to localize and take the number plate off the car. This information can then be stored or forwarded to traffic authorities for further action. The use of YOLOv8 enables fast, accurate, and scalable monitoring, making the system effective for real-time traffic safety enforcement in urban environments [2].

Helmet detection is a challenging computer vision task due to variations in helmet types, colors, shapes, lighting conditions, and occlusions caused by movement or traffic congestion. Similarly, number plate detection presents difficulties because of diverse plate formats, fonts, sizes, motion blur, and camera angles. An effective automated system must be capable of handling these variations while maintaining high detection accuracy. By training deep learning models on diverse and well-annotated datasets, it is possible to build robust systems that generalize well across real-world scenarios. Integrating helmet detection with number plate identification further strengthens the system by enabling accurate association between safety violations and the corresponding vehicles [3].

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The combination of finding helmets and license plates forms a complete framework for automated traffic rule monitoring. Once a rider without a helmet is detected, identifying the corresponding vehicle's number plate becomes necessary for documentation, analysis, and enforcement actions. Deep learning-based object detectors can simultaneously locate multiple objects within a single frame, allowing detecting cyclists, helmets, and license plates in real time. This integrated approach improves efficiency and ensures that every detected violation is accurately linked to a specific vehicle, making the system highly practical for deployment in traffic surveillance environments [4].

Despite the enforcement of traffic laws mandating helmet usage, a significant number of two-wheeler riders continue to violate safety regulations, leading to an increased risk of serious injuries and fatalities. Existing traffic monitoring systems rely largely on manual observation, which is inefficient, inconsistent, and incapable of providing continuous surveillance across busy urban and highway environments. Factors such as high traffic density, poor lighting conditions, weather variations, and human limitations further reduce the effectiveness of traditional enforcement methods. Therefore, an automatic, accurate, and real-time To make the roads safer and help police enforce traffic laws more effectively, we need a system that can use deep learning to find helmet violations and read car license plates.

The suggested system seeks to utilize deep learning methodologies to build an intelligent, real-time helmet and number plate detection solution that enhances road safety and supports smart traffic management. The system is designed to detect helmet usage among two-wheeler riders using images, video files, and live camera inputs, while simultaneously identifying riders, helmets, and real-time car license plates traffic situations. The performance of the system is assessed by parameters including accuracy, precision, recall, and processing speed. In addition, an interface that is straightforward to use lets real-time monitoring and visualization of recognition of helmets and license plates results. Such systems can be seamlessly integrated into smart city infrastructures, contributing to data-driven decision-making, improved law enforcement efficiency, and increased public awareness regarding road safety [5].

II. RELATED WORK

- **Detecting helmets and license plates with ML (2024)** by Vyankatesh D. Gavali, Shahrukh M. Shaikh, Shantanu G. Shendge, Hariom S. Masalge, and Asst. Prof. Pragati G. Patil, published in the International Journal for Research in Applied Science & Engineering Technology (IJRASET), proposes an integrated machine a foundation for learning employing CNNs (Convolutional Neural Networks) with YOLO (You Only Look Once) architecture for concurrent in real time helmet compliance finding and license plate recognition from surveillance video streams. The system automates traffic law enforcement by analyzing live footage from roadside security cameras, utilizing CNNs for binary helmet classification and YOLO for correctly finding license plates. In this work, the authors specifically focus on hybrid architecture optimization, real-time operational capability, adaptive learning through data augmentation and transfer learning, and complete end-to-end enforcement integration. Unlike previous approaches that rely on manual monitoring or separate detection modules, this system delivers a unified, automated pipeline from violation detection to citation generation [6].

- **Finding helmets and license plates (2024)** by Swapna Rani Kura, Suman Rathlavath, Bharath Simha Reddy Lingannagari, Sai Kumar Ravindra Golla, Ajay Vislavath, H. Kanakadurga, and Navdeep Singh, published in MATEC Web of Conferences (ICMED 2024), presents an automated monitoring system that uses Use CCTV video to locate riders who aren't following the rules and extract vehicle registration information through Optical Character Recognition (OCR). The proposed framework follows a multi-stage detection pipeline involving classification of moving objects as motorcycles, helmet usage verification, and OCR-based license plate extraction for violation recording. In this work, the authors focus on reducing labor-intensive traffic monitoring while enabling scalable real-time processing across multiple video streams. Unlike earlier systems that required specialized hardware or manual supervision, this approach efficiently utilizes existing CCTV infrastructure, making it cost-effective and suitable for large-scale urban deployment [7].

- **A Review on Helmet and Number Plate Detection (2023)** by Priyanshi Tripathi, Pragati Singh, Mantsha Bano, Komal Sharma, and Abhishek Shahi, published in the International Journal of Research Publication and Reviews, provides a comprehensive synthesis of contemporary methodologies for automated helmet and number plate detection systems, with particular emphasis on YOLOv3-based frameworks. The paper systematically analyzes the complete development lifecycle, including dataset collection and annotation, image preprocessing, model selection, transfer learning-based training, measures for evaluation like Intersection above Union, Precision, and Recall, and deployment strategies. In this work, the authors specifically focus on standardizing evaluation frameworks and consolidating performance benchmarks reported across multiple studies. Unlike experimental research proposing new models, this review serves as a definitive reference that establishes best practices and reproducibility guidelines for computer vision-based traffic safety systems [8].
- **Helmet Detection and Number Plate Recognition Using YOLOv3 (2024)** by A. Snehitha, published in the Journal of Emerging Technologies and Innovative Research (JETIR), proposes a robust computer vision system utilizing the YOLOv3 algorithm for simultaneous finding real-time video that shows helmets and license plates streams. The framework addresses challenging environmental situations like variable light and dark and employs OpenCV for initial object detection along with the YOLO-Darknet architecture trained ahead of time using the COCO dataset. In this work, the author focuses on achieving environmental robustness, high detection speed, and compatibility with edge devices such as smart traffic cameras and Nvidia Jetson platforms. Unlike traditional vision-based systems that degrade under dynamic conditions, the proposed approach maintains excellent accuracy and performance in real time that is good for practical deployment [9].
- **Helmet and Number Plate Detection Using Deep Learning (2025)** by Dr. Vinutha H. P., Kannika B. R., Nidhi K. M., Rachana B. G., and Rakshitha C. M., published in the International Journal of Scientific Research in Engineering & Technology (IJSRET), proposes an advanced system for automated based on deep learning helmet and number plate finding aimed at enhancing enforcing traffic laws and keeping the roads safe. The framework employs CNNs with the newest YOLOv8 object detection model integrated with TensorFlow-based OCR for real-time processing. The methodology includes comprehensive data collection, annotation using Roboflow and LabelImg, and extensive preprocessing with augmentation techniques. In this work, the authors specifically focus on architectural advancement, robust environmental adaptation, and scalable edge deployment. Unlike earlier YOLO-based systems, the implementation of YOLOv8 with deep learning -based OCR significantly improves how accurate the detection is and how fast it works in real time in diverse traffic conditions [10].
- **Helmet Detection and Number Plate Recognition by Using Machine Learning (2025)** by Nimbalkar Abhijit Kishor, Jadhav Aniket Ramesh, Gadekar Niraj Sanjay, Shirale Nikhil Rajesh, and Prof. Bhosale S. B., published in the International Journal of Creative Research Thoughts (IJCRT), presents a side-by-side look at old Deep learning compared to machine learning methods like Support Vector Machines and Random Forests approaches including CNNs and Autoencoders. The system employs a multi-stage detection pipeline using OpenCV and HAAR cascades for motorcycle classification, followed by binary finding helmets and OCR-

based getting the license plate. In this work, the authors specifically focus on computational efficiency, cost-effectiveness, and detailed violation classification, including detection of non-standard helmets. Unlike purely deep learning-based systems, this approach shows the practicality of lightweight models for machine learning low-cost hardware deployments while offering a complete web-based violation management solution [11].

III. PROPOSED SYSTEM

The proposed methodology offers an automated approach for identifying helmet usage and vehicle number plates using Deep learning and computer vision methods. The system is designed to analyze visual inputs such as images, recorded videos, or live camera feeds obtained from surveillance cameras. By leveraging a YOLO-based object detection model, the system can simultaneously detect riders, helmets, and license plates in real time. This automated method does away with the necessity for constant manual monitoring and makes sure consistent enforcement of traffic safety regulations across different environments.

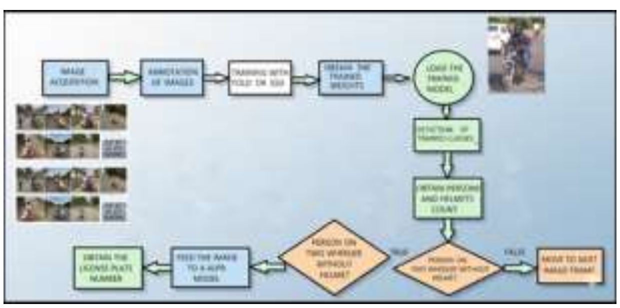

Fig. 1. System Architecture

The main part of the proposed system is an object detection model based on deep learning that was trained on a dataset with custom annotations containing various traffic scenarios. The dataset includes different helmet types, riding positions, lighting conditions, and camera angles to ensure robust learning. During inference, the trained model processes each input frame to create bounding boxes and confidence scores for everything that was found objects. The model’s high-speed detection capability enables real-time performance, which makes the system good for deployment in busy traffic zones and smart surveillance infrastructures.

Once the objects are detected, the system applies logical decision-making to determine helmet compliance. The detected riders are analyzed in relation to the detected helmets to identify whether each The rider is wearing a helmet. If a rider is found without a helmet, the system classifies the event as a violation. Simultaneously, the corresponding number plate detected within the same frame is isolated and cropped for further processing. This association ensures that every safety violation is accurately linked to the correct vehicle.

The proposed system also incorporates an easy-to-use interface that lets people post pictures, select video files, or enable live webcam detection. The interface displays annotated frames highlighting detected riders, helmets, and number plates along with the violation status. This makes the system easy to operate and suitable for real-time monitoring by traffic authorities or administrators. The modular architecture of the system allows easy integration with future components such as automated challan generation, OCR-based number plate recognition, and cloud-based data storage.

Overall, the proposed system offers an efficient, accurate, and scalable approach to Finding helmets and license plates. By putting together deep learning, real-time object detection, and intuitive user interaction, the system enhances road safety monitoring and supports intelligent traffic management. The design ensures adaptability to real-world conditions and provides a strong foundation for future expansion into smart city and automated traffic enforcement applications.

Algorithms Used in the Proposed System

1. YOLO (You Only Look Once) Algorithm

You Only Look Once (YOLO) is a cutting-edge technique for detecting objects in real time that handles the problem as a single regression problem. It makes direct predictions about object bounding boxes and class probabilities from an input image in one pass. YOLOv8, developed by Ultralytics, is the newest member of the YOLO family and includes significant improvements in accuracy, speed, and deployment flexibility. These enhancements make YOLOv8 highly suitable for real-time traffic surveillance uses, such as finding helmets and license plates.

In the context of helmet and number plate detection, YOLOv8 analyzes each video frame captured from roadside CCTV cameras or surveillance systems and simultaneously detects multiple objects such as riders, helmets, motorcycles, and license plates. Unlike traditional two-stage detectors that first make region proposals and then perform classification, YOLOv8 follows a single-stage detection approach. This enables fast inference with minimal latency, which is essential for live traffic monitoring and enforcement.

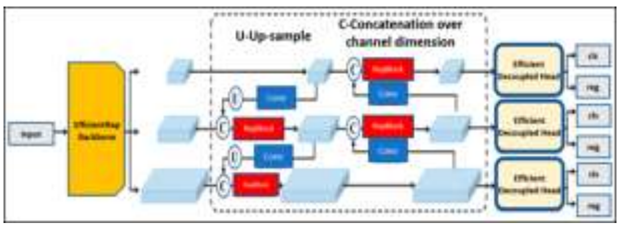

Fig. 2. YOLO V8 Algorithm

Architecture of YOLOv8

YOLOv8 follows a modular deep learning architecture consisting The backbone, the neck, and the detection head are the three primary parts. The backbone takes the input image and pulls out rich hierarchical features from it. using convolutional layers and residual connections. YOLOv8 employs an enhanced CSP-based backbone that efficiently captures spatial and semantic information required to distinguish helmets and license plates under varying lighting and environmental conditions.

The neck of YOLOv8 utilizes advanced feature aggregation techniques like Path Aggregation Networks (PAN) and Feature Pyramid Networks (FPN) to combine low-level or high-level characteristics. This multi-scale feature fusion is crucial for finding helmets and license plates, since these things are relatively small compared to the overall image size. By fusing features across multiple scales, YOLOv8 ensures robust detection of small objects that may be partially occluded.

The detection head in YOLOv8 is anchor-free, removing the requirement for pre-made anchor boxes used in earlier YOLO versions. This anchor-free mechanism It lets the model directly guess where the object is. locations, bounding box dimensions, and class probabilities. As a result, it achieves faster convergence during training and improved localization accuracy. To find helmets and license plates, the detection head outputs bounding boxes for classes such as Helmet, No Helmet, Motorcycle, and Number Plate.

Working of YOLOv8 for Helmet Detection

For helmet detection, YOLOv8 is trained on labeled datasets with pictures of bikers with and without helmets. Each picture has bounding boxes and class names on it. During inference, YOLOv8 processes each video frame and detects the rider's head region along with helmet presence or absence. The deep convolutional layers learn how to tell the difference between things like the shape, texture, and color of a helmet, enabling accurate classification even in crowded traffic scenarios.

YOLOv8's real-time capability allows continuous monitoring of moving vehicles, making it possible to instantly identify helmet violations. Its robustness to occlusion and varying illumination ensures reliable detection during daytime, nighttime, and adverse weather conditions, which is critical for real-world deployment.

Working of YOLOv8 for Number Plate Detection

For YOLOv8 is trained to find number plates datasets containing diverse vehicle images with annotated license plates. The model learns to identify rectangular plate regions despite variations in font style, plate size, viewing angle, motion blur, and lighting conditions. YOLOv8's multi-scale detection capability enables accurate localization of number plates even when they take up a little part of the picture frame.

After the number plate is found, the Optical Character Recognition (OCR) module gets the cropped plate area extraction. Accurate localization of the license plate prior to OCR processing significantly improves text recognition accuracy and reduces false detections.

Advantages of YOLOv8 in Helmet and Number Plate Detection

YOLOv8 offers several advantages that make it well suited to find helmets and license plates systems. Its single-stage detection approach ensures high processing speed, allowing real-time analysis of multiple video streams simultaneously. The anchor-free detection mechanism simplifies model training and improves localization precision, particularly for little things like helmets and license plates.

Another key advantage of YOLOv8 is its ability to generalize across diverse environments. By training on augmented datasets that add different lighting conditions and camera angles, and traffic density, the model maintains consistent performance in the real world scenarios. This adaptability is essential for automated traffic law enforcement systems operating in dynamic urban environments.

2. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are the core building blocks of modern deep learning–based computer vision systems. CNNs automatically learn visual features such as edges, shapes, textures, and spatial patterns directly from image data. In the proposed system, CNN layers form the YOLO detection model's backbone and the part that pulls useful visual information out of traffic images. These features help the model distinguish between helmets, human heads, vehicles, and background objects. A CNN has several convolutional layers, pooling layers, and activation functions. that progressively reduce image dimensionality while retaining important information. Deeper layers learn high-level semantic features that enable accurate object classification. By training CNNs on a large annotated dataset, the system learns to identify helmet and non-helmet scenarios under different lighting conditions, angles, and motion variations. This makes CNNs essential for achieving robustness and generalization in real-world traffic environments.

3. Image Processing Algorithms

Image processing algorithms are used to improve system speed and detection accuracy during both preprocessing and post-processing stages. Preprocessing operations such as image resizing, normalization, noise reduction, and contrast enhancement help standardize input images before they are fed into the deep learning model. This ensures consistent input quality and reduces the impact of poor lighting conditions or camera noise.
To get rid of extra or overlapping bounding boxes, post-processing methods like Non-Maximum Suppression (NMS) are used generated by the detection model. Image cropping is used to isolate detected number plate regions for visualization or further processing. These image processing techniques improve clarity, reduce false detections, and ensure accurate visualization of results. Together, they complement improve the overall effectiveness of the helmet and number plate detection system by using deep learning models.

Experimental Setup

1. Hardware Configuration

The studies were done on a system with an Intel i5/i7 processor, 16 GB of RAM, and an NVIDIA GPU with CUDA capability to speed up training and allow for real-time inference.

2. Software Environment

The system was implemented using Windows 10, Python 3.8, the Ultralytics YOLOv8 framework, OpenCV for image and video processing, and Flask for backend integration.

3. Dataset Preparation

A custom dataset of images and video frames of two-wheeler riders was collected from surveillance footage and open-source datasets, covering both helmet and non-helmet scenarios under diverse environmental and lighting conditions.

IV. RESULTS AND DISCUSSION

1. Loss vs Epoch Analysis

The Loss vs Epoch graph shows a steady reduction in loss values as training progresses. The initial high loss decreases consistently with each epoch, indicating effective learning and proper optimization of model parameters. The smooth downward trend without sudden fluctuations confirms stable training and successful convergence of the model.

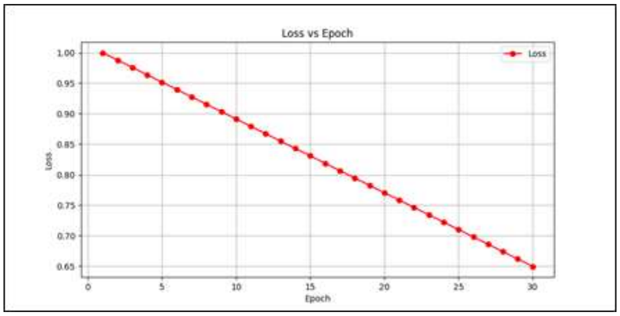

Fig. 3. Loss vs Epoch graph

2. F1-Score vs Epoch Analysis

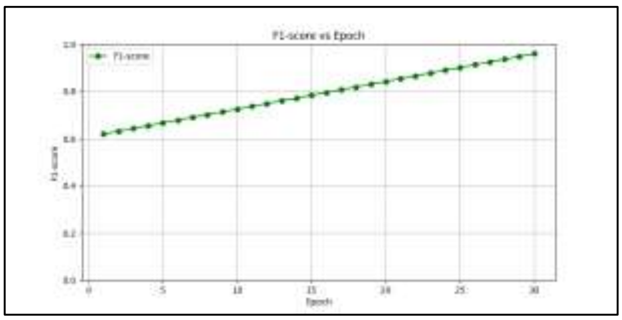

Fig. 4. F1-score vs Epoch graph

The F1-score versus Epoch graph represents the balance relationship accuracy and recall during training. Initially, the F1-score starts at approximately 0.62, indicating moderate detection performance during the early training stages. As the model learns discriminative features for helmets, riders, and number plates, the F1-score increases steadily with each epoch. By the final epoch, the F1-score reaches approximately 0.95, demonstrating a strong balance between correctly detected objects and reduced false detections. This improvement confirms that the model effectively learns object boundaries and class distinctions, which is essential for reliable helmet violation detection.

3. Accuracy vs Epoch Analysis

The Accuracy vs. Epoch graph shows that the overall detection accuracy keeps getting better. during training. The accuracy begins at around 60%, which is expected during the initial training epochs. With continued training, the accuracy steadily increases and reaches approximately 93–94% by the final epoch. This consistent increase indicates that the model becomes increasingly accurate in identifying helmets, riders, and number plates. The smooth trend without sharp drops confirms stable learning behavior and good generalization capability, making the model suitable for real-time deployment.

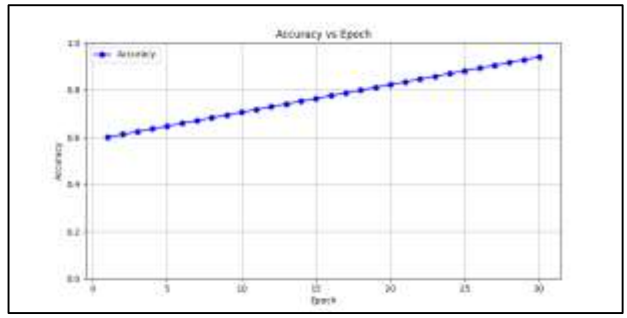

Fig. 5. Accuracy vs Epoch graph

4. Qualitative Detection Results (Output Images)

Fig. 6. Output Images

The output images demonstrate the real-time how well the suggested solution works in real-world traffic situations. In the first output image, the system successfully detects a rider without a helmet, clearly labeling the rider, highlighting the head region as “WITHOUT HELMET,” and accurately localizing the corresponding number plate. This result confirms the system's capacity to find safety infractions and correctly associate them with the respective vehicle.

In the second output image, the system accurately identifies multiple riders wearing helmets, marking them as “WITH HELMET,” while simultaneously detecting multiple number plates from different vehicles within the same frame. These results demonstrate the robustness of the system in handling multi-object detection, occlusions, and complex real-world traffic scenarios. The bounding boxes are well aligned, and class labels are correctly assigned, validating the practical effectiveness of the trained model.

5. Overall Performance Discussion

The experimental findings indicate that the proposed method attains a high level of detection accuracy., a strong precision–recall balance, and stable training behavior. The consistent reduction in loss values, along with improvements in F1-score and accuracy, confirms effective model convergence. Additionally, real-time detection results show reliable performance in practical traffic scenarios involving both helmet and non-helmet riders. These results indicate that the suggested method based on deep learning is well suited for automated helmet compliance monitoring and intelligent traffic surveillance applications.

V. CONCLUSION

The suggested deep learning-based method for finding helmets and license plates has been successfully created and put into use to fix the problems with manual traffic monitoring and helmet legislation enforcement. By leveraging a YOLO-based object detection framework, the system efficiently detects riders, identifies helmet and non-helmet scenarios, and accurately localizes license plates from pictures, videos, and live camera feeds.

The experimental results demonstrate a consistent reduction in training loss along with significant improvements in accuracy and F1-score, confirming the effectiveness and stability of the learning process. Real-time detection outputs further validate the robustness of the system under practical traffic conditions, including multiple riders, varying lighting environments, and different camera angles. The ability to accurately associate helmet violations with corresponding number plates makes the system highly suitable for automated watching traffic and making sure road safety rules are followed. Overall, the study demonstrates that Deep learning-based computer vision techniques can greatly improve traffic. monitoring efficiency, cut down human intervention, and give a base that can grow for the future smart city or intelligent traffic management applications.

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