International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

REAL-TIME TRAFFIC VEHICLE DETECTION AND CLASSIFICATION SYSTEM

[1] V Sumalatha, [2] Y Sindhura Devi, [3] J Soumya Sri, [4] M Rakesh
[1]AssistantProfessor, [234]Students
Department of IOT
Siddhartha Institute of Technology & Sciences, Narapally
dr.sumalatha@siddhartha.org.in, 23tq1a6914@siddhartha.co.in, 23tq1a6944@siddhartha.co.in, 23tq1a6938@siddhartha.co.in

Abstract

The rapid growth of urban populations has resulted in a significant increase in the number of vehicles on roads, creating challenges related to traffic congestion, road safety, and transportation management. Traditional traffic monitoring systems often depend on manual observation or basic sensors that provide limited information about individual vehicles. To address these challenges, the Real-Time Traffic Vehicle Detection and Classification System is proposed as an intelligent computer-vision-based solution. The system automatically detects vehicles from live traffic video streams and classifies them into different categories such as cars, buses, trucks, motorcycles, and other road vehicles.

The proposed system uses deep-learning-based object detection techniques to identify vehicles accurately from video frames. A trained object detection model processes each frame and determines the location and category of detected vehicles using bounding boxes and confidence scores. Image-processing techniques are applied to improve the quality of input frames and support reliable detection under different traffic conditions. The system can process video obtained from surveillance cameras, traffic cameras, webcams, or prerecorded traffic footage.

In addition to vehicle detection, the system performs vehicle classification to determine the type of each detected vehicle. This information can be used to calculate traffic density, monitor vehicle distribution, and analyze traffic patterns. The system can also maintain vehicle counts and generate statistical information about different vehicle categories. Real-time processing enables traffic authorities to obtain immediate information about current road conditions without depending entirely on manual monitoring.

The system is designed to support intelligent transportation applications such as congestion monitoring, traffic flow analysis, road surveillance, and traffic management. The collected information can be displayed through a dashboard containing live video, vehicle counts, classification results, and traffic statistics. Alerts can also be generated when traffic density exceeds predefined thresholds or when unusual traffic conditions are identified.

I. Introduction

Traffic congestion has become one of the major problems in rapidly developing cities. The increasing number of private vehicles, public transportation vehicles, commercial vehicles, and two-wheelers has placed considerable pressure on existing road infrastructure. Traffic authorities require accurate and timely information about vehicle movement to manage congestion and improve road safety. Conventional monitoring methods often require personnel to continuously observe CCTV footage, making the process expensive, time-consuming, and difficult to scale.

Computer vision has emerged as an important technology for automated traffic monitoring. A camera-based system can continuously capture road scenes and use image-processing algorithms to identify objects present in the environment. With the development of deep learning, modern object detection models can recognize multiple vehicles within a single frame and determine their positions. This allows traffic monitoring to move from manual observation toward automated real-time analysis.

Vehicle classification is another important component of intelligent traffic management. Different types of vehicles occupy different amounts of road space and have different effects on traffic flow. For example, a truck or bus may have a greater impact on congestion than a motorcycle. Identifying the categories of vehicles present on a road can therefore provide more useful information than simply counting the total number of vehicles.

The proposed **Real-Time Traffic Vehicle Detection and Classification System** uses deep-learning-based object detection to identify and classify vehicles from live or recorded video. The system captures video frames, preprocesses the images, detects vehicles, classifies them into predefined categories, and displays the results in real time. Bounding boxes and labels can be placed around detected vehicles so that users can visually verify the system's predictions.

The main objective of the system is to provide an efficient and automated traffic-monitoring solution that can operate with minimal human intervention. The information generated by the system can assist traffic authorities, smart-city applications, transportation researchers, and road-management organizations. By integrating real-time detection with traffic statistics and visualization, the proposed system can contribute to improved traffic monitoring and data-driven transportation management.

II. Literature Survey

Early traffic-monitoring systems primarily depended on manual observation, road-side sensors, magnetic loops, and other hardware-based technologies. These systems could provide information such as vehicle presence, traffic volume, or road occupancy, but they often required dedicated infrastructure. Hardware sensors can also be expensive to install and maintain, particularly when monitoring needs to cover a large road network. Camera-based monitoring introduced a more flexible alternative because existing surveillance infrastructure can potentially be used for traffic analysis.

Traditional computer-vision approaches for vehicle detection commonly used techniques such as background subtraction, frame differencing, edge detection, contour analysis, and feature extraction. These methods could detect moving vehicles under controlled conditions but often experienced difficulties with changing

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

illumination, shadows, rain, occlusion, camera movement, and dense traffic. Handcrafted features also required significant engineering effort and generally lacked the adaptability of modern deep-learning methods.

The introduction of convolutional neural networks significantly improved object-recognition performance. CNN-based approaches automatically learn visual features from training images rather than depending entirely on manually designed features. Two-stage object detectors can first generate candidate regions and then classify those regions, while one-stage detectors perform detection more directly. These deep-learning approaches have become widely used for detecting objects in complex visual environments, including roads and traffic scenes.

Modern real-time object detection architectures have further improved the balance between detection accuracy and processing speed. Models in the YOLO family, for example, are designed for fast object detection and have been widely applied to real-time video-analysis tasks. Such models can identify multiple objects in individual frames and provide bounding boxes, class labels, and confidence scores. Their ability to process video at high speed makes them suitable for traffic-monitoring applications.

Research in intelligent transportation has also explored vehicle tracking, counting, speed estimation, and traffic-density analysis. Object tracking algorithms can associate detected vehicles across consecutive frames, allowing a system to estimate movement and avoid repeatedly counting the same vehicle. Combining detection and tracking can therefore provide more detailed traffic information than frame-by-frame detection alone.

Recent traffic-analysis systems increasingly integrate deep learning with dashboards, edge computing, cloud platforms, and smart-city infrastructure. These systems can provide real-time traffic statistics and support automated decision-making. However, challenges such as occlusion, low-light conditions, camera quality, computational requirements, and model generalization remain important. The proposed system focuses on real-time vehicle detection and classification while providing a foundation that can later be extended with tracking, speed estimation, and other intelligent transportation features.

III. System Analysis

The proposed system analyzes live or recorded traffic video to automatically identify vehicles and determine their categories. The system begins by receiving video input from a CCTV camera, traffic camera, webcam, or stored video file. Individual frames are extracted from the incoming video stream and passed to an image-preprocessing module. The preprocessing stage can resize frames and perform basic normalization to prepare them for detection. A deep-learning object detection model then analyzes each frame to identify vehicles and generate bounding boxes. Each detected object is assigned a class label such as car, bus, truck, motorcycle, or other supported categories. The model also produces a confidence score representing the estimated reliability of each detection. A filtering mechanism removes detections that fall below a predefined confidence threshold. The system can count detected vehicles according

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

to their categories and calculate traffic-density statistics. The processed frames are displayed with bounding boxes and labels over the original video. The results can be stored in a database for later analysis and reporting. A dashboard can present live vehicle counts, category distributions, and traffic conditions. The overall system therefore converts raw traffic video into useful real-time transportation information.

Existing System

Existing traffic-monitoring systems commonly depend on manual surveillance, basic traffic sensors, CCTV observation, and conventional image-processing methods. In manual monitoring, traffic personnel continuously observe roads or camera feeds to estimate traffic conditions. This approach requires significant human effort and can be affected by fatigue and human error. Sensor-based systems can detect vehicle presence and traffic volume but often require specialized hardware installed at particular locations. Traditional CCTV systems provide video footage but generally require humans to interpret the information. Earlier computer-vision approaches used background subtraction, motion detection, and handcrafted visual features to identify moving vehicles. These approaches can work in controlled environments but may perform poorly when vehicles overlap or lighting conditions change. Conventional systems may also provide limited vehicle classification capabilities. In many cases, they cannot reliably distinguish between cars, buses, trucks, and motorcycles. Real-time analysis can also be difficult when processing high-resolution video using computationally expensive techniques. These limitations demonstrate the need for an intelligent system capable of automatically detecting and classifying multiple vehicles in real time.

Disadvantages of Existing System

- High dependence on manual traffic monitoring.
- Human observation can result in errors and inconsistent measurements.
- Continuous CCTV monitoring requires significant manpower.
- Traditional sensors require additional physical infrastructure.
- Hardware installation and maintenance can be expensive.
- Conventional image-processing methods are sensitive to lighting conditions.
- Shadows and reflections can affect detection accuracy.
- Vehicle occlusion can cause missed or incorrect detections.
- Limited ability to classify different vehicle categories.
- Difficult to process large-scale traffic video automatically.
- Limited real-time analytics and visualization.
- Difficult to generate detailed historical traffic statistics.
- Traditional systems may not adapt well to complex traffic environments.

Proposed System

The proposed system introduces a deep-learning-based approach for real-time vehicle detection and classification from traffic video. The system accepts live video or prerecorded footage as input and extracts frames for analysis. Each frame is preprocessed and passed to a trained object detection model. The model identifies vehicles and predicts their bounding boxes, class labels, and confidence scores. Detected vehicles are classified into categories such as cars, buses, trucks, motorcycles, and other relevant vehicle types. A confidence threshold is applied to remove unreliable predictions and improve the quality of the displayed results. The system can count vehicles by category and calculate traffic-density information in real time. Bounding boxes and class labels are overlaid on the video so that users can visually monitor the detection process. A tracking module can optionally be integrated to maintain vehicle identities across consecutive frames. The processed information can be stored for historical traffic analysis and reporting. A dashboard can display live video, vehicle counts, classification percentages, and traffic statistics. The proposed architecture can be deployed on suitable computing hardware near the camera or on a centralized server depending on performance requirements. The system can later be extended with speed estimation, accident detection, license-plate recognition, and intelligent traffic-signal applications.

Advantages of Proposed System

- Provides automated real-time vehicle detection.
- Reduces dependence on manual traffic monitoring.
- Classifies vehicles into multiple categories.
- Provides bounding boxes and confidence scores.
- Supports live CCTV and prerecorded video.
- Enables real-time vehicle counting.
- Provides traffic-density information.
- Improves monitoring efficiency.
- Can process multiple vehicles in the same frame.
- Supports historical traffic-data collection.
- Provides visual results through a dashboard.
- Can be integrated with smart-city applications.
- Can be extended with vehicle tracking and speed estimation.
- Reduces repetitive human observation work.

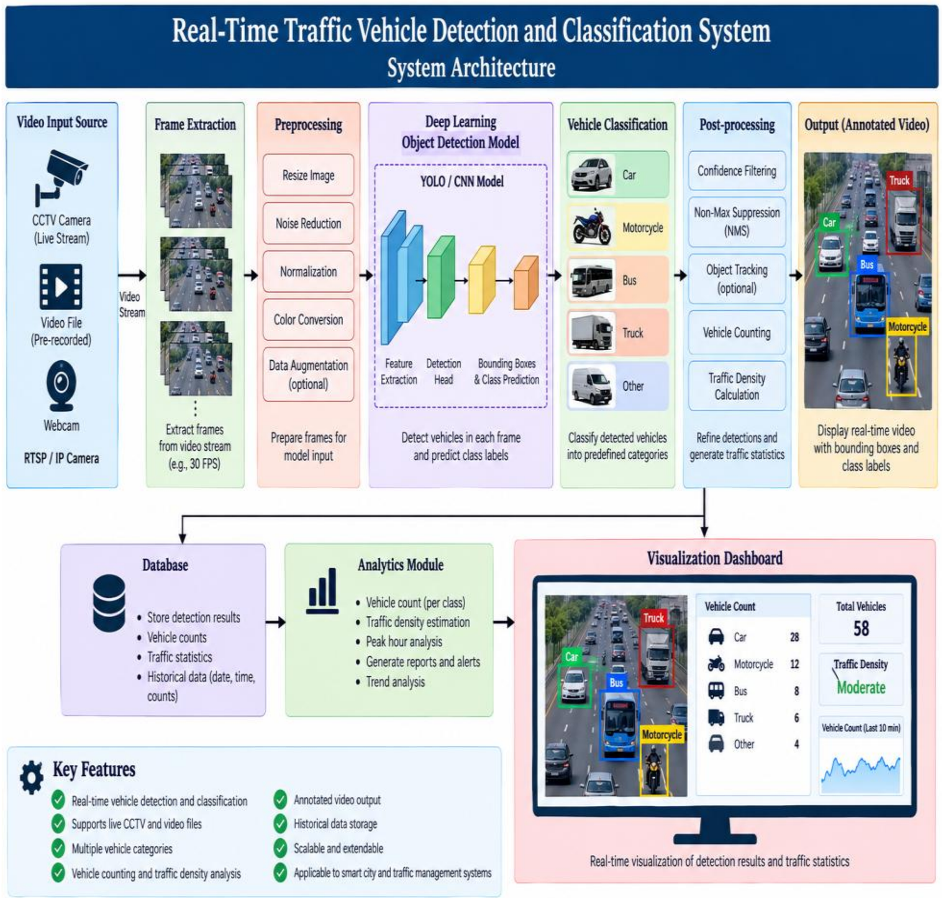
IV. Methodology

The methodology of the proposed system consists of several stages beginning with video acquisition and ending with real-time traffic analysis. The first stage is **video acquisition**, where traffic footage is collected from CCTV cameras, webcams, or stored video files. In the second stage, the video stream is divided into individual frames for processing. The frames are resized and normalized during the preprocessing stage to provide a suitable input format for the detection model. A deep-learning object detection model is then loaded with trained weights capable of recognizing different vehicle categories. Each frame is passed through the model, which predicts bounding boxes, class labels, and confidence scores for detected objects. A confidence threshold is applied to eliminate low-probability detections. The remaining detections are classified into vehicle categories such as cars, buses, trucks, and motorcycles. Vehicle-counting logic calculates the number of detected vehicles and can maintain category-wise statistics. Optional object-tracking techniques can associate vehicles across consecutive frames and prevent repeated counting. The processed frames are annotated with bounding boxes and class labels and displayed as real-time output. Traffic statistics can be stored in a database or generated as reports for further analysis. Finally, a dashboard presents the processed video, vehicle counts, classification results, and traffic-density information to the user.

System Architecture

The system architecture consists of several interconnected modules including the Video Input Module, Frame Extraction Module, Image Preprocessing Module, Deep Learning Detection Model, Vehicle Classification Module, Confidence Filtering Module, Tracking and Counting Module, Database, Analytics Module, and Visualization Dashboard. The process begins when a CCTV camera or video file provides traffic footage to the system. The video input module transfers the stream to the frame extraction component, which generates individual frames for processing. The preprocessing module resizes and normalizes the frames before sending them to the deep-learning detection model. The detection model identifies vehicles and generates bounding boxes, class labels, and confidence scores. The classification module determines the type of each detected vehicle based on the model's predictions. The confidence filtering module removes detections that do not meet the required confidence level. The tracking and counting module can associate vehicles between frames and calculate category-wise vehicle counts. The resulting information is sent to the analytics module, where traffic density and vehicle-distribution statistics can be calculated. Relevant data can be stored in a database for historical analysis and reporting. The visualization dashboard displays annotated video frames, vehicle counts, vehicle categories, and traffic statistics to users. This architecture provides a complete pipeline from **traffic video input → frame processing → vehicle detection → classification → tracking/counting → analytics → real-time visualization**.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper



V. Result and Output

VI. Conclusion

The Real-Time Traffic Vehicle Detection and Classification System provides an intelligent and automated approach to monitoring road traffic using computer vision and deep learning. The system can process live or recorded traffic video and automatically detect vehicles without requiring continuous manual observation. By identifying the location and type of vehicles, it provides useful information for understanding real-time traffic conditions.

The proposed system uses deep-learning-based object detection to classify vehicles into categories such as cars, motorcycles, buses, trucks, and other vehicles. It can also calculate vehicle counts and traffic density, making the collected information more useful for traffic management and analysis. The use of confidence filtering and optional tracking can further improve the reliability of detection and counting results.

The system can significantly reduce the workload associated with manual traffic monitoring while providing faster and more consistent traffic information. A visualization dashboard can present detected vehicles, vehicle counts, classification statistics, traffic-density levels, and historical information in an easily understandable format. This makes the system useful for traffic authorities, smart-city applications, transportation planning, and road-safety monitoring.

Overall, the proposed system demonstrates how Artificial Intelligence, Computer Vision, and Deep Learning can be combined to create an efficient real-time traffic-monitoring solution. In the future, the system can be enhanced with vehicle speed estimation, license-plate recognition, accident detection, traffic-rule violation detection, vehicle tracking, emergency-vehicle identification, and intelligent traffic-signal control, making it a more comprehensive intelligent transportation system.

References

[1] Kumar, R. D., Prudhviraj, G., Vijay, K., Kumar, P. S., & Plugmann, P. (2024). Exploring COVID-19 through intensive investigation with supervised machine learning algorithm. In Handbook of Artificial Intelligence and Wearables (pp. 145-158). CRC Press.

[2] Swathi, B., Vijay, K., Sushanth Babu, M., & Dinesh Kumar, R. (2024, November). Machine Learning Techniques in Cloud Based Intrusion Detection. In The International Conference on Artificial Intelligence and Smart Environment (pp. 557-564). Cham: Springer Nature Switzerland.

[3] Sv satyakrishna, shirisha rangu ,bhargavi nalacheruve.(2024) Prospective investigation on colorectal cancer with SMOTE on machine learning Algorithm

[4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.

[5] V. N. S. Manaswini, K. K, C. Nigam, S. S. Ali, R. Niranjana, and Suman, “Real-Time Object Detection in Drone Surveillance Using YOLOv5,” in Proc. 2025 3rd Int. Conf. IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2025, pp. 1–6, doi: 10.1109/ICICAT68430.2025.11414670.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

[6] B. Soundarya, V. N. S. Manaswini, M. Ayyakrishnan, R. D. Kumar, "Contextual Analysis of Big Data Analytics in Intelligent Transportation Frameworks," in Intersection of Artificial Intelligence, Data Science, and Cutting-Edge Technologies: From Concepts to Applications in Smart Environment, Lecture Notes in Networks and Systems, vol. 1353, Cham: Springer, 2025, doi: 10.1007/978-3-031-88304-0_79.

[7] R. D. Kumar, V. N. S.Manaswini, "Applications of blockchain in smart cities: detecting fake documents from land records using blockchain technology," in Blockchain for Smart Cities, Elsevier, 2021, pp. 105–117, doi: 10.1016/B978-0-12-824446-3.00017-X.

[8] Tejavath Veeramma, Badarla Anil, Guguloth Ravinder, "An advanced movie recommender using collaborative filtering and sentiment analysis," International Research Journal of Modernization in Engineering Technology and Science, vol. 7, no. 7, July 2025, doi: 10.56726/IRJMETS81618.

[9] Ravi Kumar Banoth, Ramana Murthy B V, "Automatic crop recommendation system using LightGBM and decision tree machine learning models," Journal of Machine and Computing, vol. 5, no. 1, pp. 343, Jan. 2025, doi: 10.53759/7669/jmc202505026.

[10] Ravi Kumar Banoth, Dr. B.V. Ramana Murthy, "Smart agriculture through IoT and machine learning for analyzing carbon footprints," in Proc. Int. Conf. Computer Science and Communication Engineering (ICCSCE), Apr. 2025.

[11] Ravi Kumar Banoth, B. V. Ramana Murthy, "Soil image classification using transfer learning approach: MobileNetV2 with CNN," SN Computer Science, vol. 5, art. no. 199, 2024, doi: 10.1007/s42979-023-02500-x.