AMERICAN JOURNAL OF MANAGEMENT AND IOTMEDICAL COMPUTING
Peer Reviewed, Referred & Indexed Journal
E-ISSN: 3069-0110
Vol.5, No.2(2026)
www.ajmimc.com

REAL TIME TRAFFIC SURVEILLANCE AND DETECTION USING DEEP LEARNING AND COMPUTER VISION TECHNIQUES

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ABSTRACT

The rapid growth of urbanization and the increasing number of vehicles on roads have made traffic management a critical challenge for modern cities. Traditional traffic monitoring systems rely heavily on manual observation and basic sensor-based technologies, which are often inefficient, error-prone, and unable to handle large-scale real-time data. This project proposes a Real-Time Traffic Surveillance and Detection System using advanced Deep Learning and Computer Vision techniques to improve traffic monitoring, congestion analysis, and incident detection. The primary objective of the system is to automatically detect and track vehicles, analyze traffic density, and identify violations or abnormal events in real time. The proposed system utilizes state-of-the-art deep learning models such as Convolutional Neural Networks (CNNs) and object detection algorithms like YOLO (You Only Look Once) for accurate vehicle detection and classification. Video data is captured from surveillance cameras and processed frame-by-frame using computer vision techniques such as image preprocessing, object tracking, and feature extraction. The system is capable of identifying different types of vehicles, counting traffic flow, and detecting anomalies such as accidents, over-speeding, or lane violations. Additionally, tracking algorithms are used to monitor vehicle movement across frames, enabling real-time analytics and decision-making. The performance of the system is evaluated using metrics such as accuracy, precision, recall, and processing speed. Experimental results demonstrate high detection accuracy and efficient real-time performance, making the system suitable for deployment in smart city environments. The system can assist traffic authorities in optimizing signal timings, reducing congestion, and improving road safety. Furthermore, it supports automated reporting and alerts, enhancing responsiveness to traffic incidents. Overall, the project highlights the potential of deep learning and computer vision in transforming traditional traffic management systems into intelligent and automated solutions.

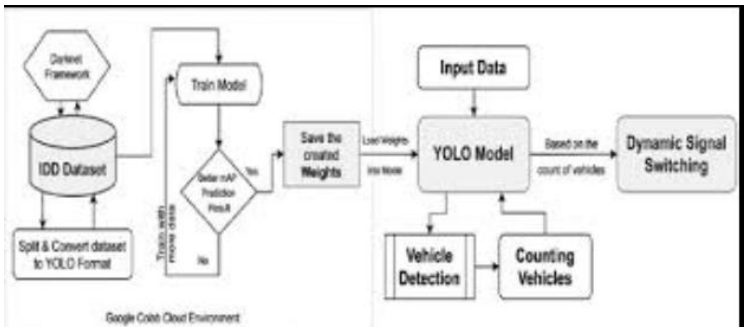
Keywords: Deep Learning, Computer Vision, Traffic Surveillance, Vehicle Detection, YOLO, Convolutional Neural Networks (CNN), Real-Time Monitoring, Smart Cities, Traffic Analysis, Object Detection

I.INTRODUCTION

The rapid increase in vehicle population and urbanization has created significant challenges in traffic management and road safety. Traditional traffic monitoring systems rely on manual observation and basic sensors, which are often inefficient and unable to handle large-scale real-time data [4], [14]. Vision-based traffic surveillance systems have emerged as a powerful solution for intelligent transportation systems, enabling automated vehicle detection, tracking, and analysis [6]. With the advancement of deep learning and computer vision, modern systems can accurately detect and classify vehicles under varying environmental conditions [10]. Techniques such as YOLO and Faster R-CNN have significantly improved object detection performance in real-time scenarios [8], [9]. This project aims to develop a real-time traffic surveillance system that leverages deep learning models to enhance traffic monitoring, reduce congestion, and improve road safety through automated detection and analysis.

The proposed system utilizes advanced deep learning architectures such as Convolutional Neural Networks (CNNs) and object detection models like YOLO for efficient vehicle detection and classification [1], [5]. Video data is captured from surveillance cameras and processed frame-by-frame using computer vision techniques. The system performs preprocessing, feature extraction, and object detection to identify vehicles in real time. Tracking algorithms are used to monitor vehicle movement across frames, enabling vehicle counting and traffic flow analysis [16]. The integration of edge computing further enhances system performance by reducing latency and enabling faster decision-making [7]. Additionally, the system can detect abnormal events such as accidents, congestion, and rule violations. This approach ensures accurate and scalable traffic monitoring suitable for smart city applications.

The implementation of the proposed system provides significant improvements in traffic management and safety. The results demonstrate high accuracy in vehicle detection and efficient real-time performance, making the system suitable for practical deployment [3], [15]. The system enables traffic authorities to optimize signal control, monitor congestion levels, and respond quickly to incidents. Automated reporting and alert generation improve decision-making and reduce human effort. Furthermore, the use of deep learning models allows continuous learning and adaptation to changing traffic patterns. The system can also be extended to include features such as license plate recognition and driver behavior analysis [11], [12]. Overall, this project highlights the importance of intelligent traffic surveillance systems in building smart cities and improving transportation efficiency.



The figure illustrates the architecture of the Real-Time Traffic Surveillance and Detection System based on deep learning and computer vision techniques. It begins with video input captured from traffic surveillance cameras, which continuously stream real-time data. The input frames are processed through preprocessing steps such as noise reduction and resizing before being passed to the deep learning model. The core component includes object detection algorithms like YOLO and CNN-based models that identify and classify vehicles in each frame. After detection, tracking algorithms monitor vehicle movement across frames to analyze traffic flow and count vehicles. The system then performs analytics to detect congestion, accidents, and rule violations. Finally, the output is displayed in the form of dashboards and alerts for traffic authorities. This architecture demonstrates how automated, intelligent systems can efficiently manage traffic and improve road safety in smart city environments.

II SURVEY OF RESEARCH

The approach proposed by N. Zarei and others (2022) [1] focuses on improving vehicle detection in traffic surveillance using a hybrid deep learning model combining YOLO-based detection with recurrent prediction networks. Their study highlights the importance of fast and accurate detection in consecutive video frames for real-time applications. The methodology integrates object detection with temporal prediction to enhance detection consistency across frames. The results demonstrate improved accuracy and reduced processing time compared to traditional models. The authors emphasized the effectiveness of combining spatial and temporal learning for traffic monitoring. However, the system requires high computational resources for optimal performance. Despite this limitation, it provides a strong foundation for real-time vehicle detection systems.

The work by C.-J. Lin and J.-Y. Jhang (2022) [5] presents an intelligent traffic monitoring system using YOLO and convolutional fuzzy neural networks. Their study focuses on improving detection accuracy and handling uncertain traffic conditions. The methodology involves combining deep learning with fuzzy logic to enhance decision-making capabilities. The results show improved classification accuracy and robustness in complex traffic environments. The authors emphasized the importance of hybrid models in handling real-world uncertainties. However, the system complexity increases due to the integration of multiple techniques. Despite this, it contributes significantly to intelligent traffic monitoring solutions.

The study by S. H. Ahmed and others (2021) [8] explores vehicle detection and counting using Faster R-CNN in undisciplined traffic conditions. Their approach focuses on accurately detecting vehicles in crowded and unstructured environments. The methodology involves region-based convolutional neural networks for object detection and counting. The results demonstrate high accuracy in detecting multiple vehicles even in complex scenarios. The authors highlighted the importance of robust detection models in real-world traffic systems. However, the model suffers from slower processing speed compared to real-time systems. Despite this limitation, it provides valuable insights into handling complex traffic environments.

The research by G. Liu (2022) [7] introduces a smart traffic monitoring system using computer vision and edge computing. Their study emphasizes reducing latency and improving real-time performance in traffic surveillance systems. The methodology involves processing data at the edge rather than relying on centralized systems. The results show faster response times and efficient real-time monitoring. The authors highlighted the importance of edge computing in modern intelligent transportation systems. However, the system requires specialized hardware for deployment. Despite this, it offers an effective solution for scalable and real-time traffic monitoring.

The work by P. Jiang and others (2022) [9] provides a comprehensive review of YOLO algorithm developments for object detection tasks. Their study highlights the evolution of YOLO models in terms of speed and accuracy. The methodology involves analyzing different versions of YOLO and their performance improvements. The results demonstrate that YOLO-based models are highly efficient for real-time detection applications. The authors emphasized the suitability of YOLO for traffic surveillance systems. However, challenges remain in detecting small and overlapping objects. Despite this limitation, the study provides a strong theoretical background for selecting appropriate detection models.

The study by Y. Youssef and M. Elshenawy (2021) [16] focuses on vehicle counting and tracking using deep learning techniques in aerial video feeds. Their approach combines convolutional neural networks with feature pyramid networks for improved detection accuracy. The methodology involves multi-scale feature extraction and object tracking across frames. The results demonstrate accurate vehicle counting and tracking in dynamic environments. The authors emphasized the importance of multi-scale detection for handling varying object sizes. However, the system may face challenges in highly congested urban scenarios. Despite this limitation, it contributes significantly to advanced traffic surveillance and tracking systems.

III. WORKING METHODOLOGY

The working methodology of the proposed Real-Time Traffic Surveillance and Detection System follows a comprehensive pipeline that integrates computer vision, deep learning, and real-time data processing techniques. The system begins with capturing continuous video streams from surveillance cameras installed at traffic junctions or highways. These raw video frames undergo preprocessing steps such as noise removal, frame resizing, normalization, and contrast enhancement to improve image clarity and ensure consistent input quality for the model. This stage is essential for handling varying lighting conditions, weather changes, and camera distortions. The preprocessed frames are then fed into advanced deep learning models such as YOLO (You Only Look Once) or Convolutional Neural Networks (CNNs) for object detection and classification. These models identify different vehicle categories including cars, buses, trucks, and motorcycles with high accuracy. To maintain continuity across frames, object tracking algorithms such as centroid tracking or DeepSORT are applied. These techniques assign unique IDs to detected vehicles, enabling tracking of their movement, speed estimation, and vehicle counting. The system also extracts features like vehicle density and lane-wise distribution to analyze traffic patterns effectively.

In the final stage, the system performs real-time analytics and decision-making. It detects anomalies such as traffic congestion, accidents, illegal parking, or signal violations by analyzing movement patterns and density thresholds. The processed data is visualized through dashboards and monitoring interfaces, providing actionable insights to traffic authorities. Additionally, alerts and notifications are generated for critical events to enable quick response. The system can be integrated with edge computing for faster processing and reduced latency. Continuous learning mechanisms can also be incorporated to improve model performance over time. Overall, this methodology ensures a scalable, efficient, and intelligent traffic monitoring system suitable for modern smart city infrastructure.

IV RESULTS EXPLANATIONS



Fig. 1: Original Traffic Frame Capture

This figure shows the original traffic frame captured from surveillance cameras before processing. It represents raw input data containing multiple vehicles under real-world conditions such as varying lighting, shadows, and background noise. The image highlights the complexity of traffic scenes, including multiple lanes and different vehicle types. This stage is crucial because the quality of input directly affects detection accuracy. The system must handle challenges like occlusion, motion blur, and environmental variations. This raw frame acts as the initial input for preprocessing and deep learning models. It demonstrates the real-time nature of the system where continuous video streams are analyzed. Overall, this figure provides a baseline for understanding how the system processes unstructured visual data into meaningful insights.

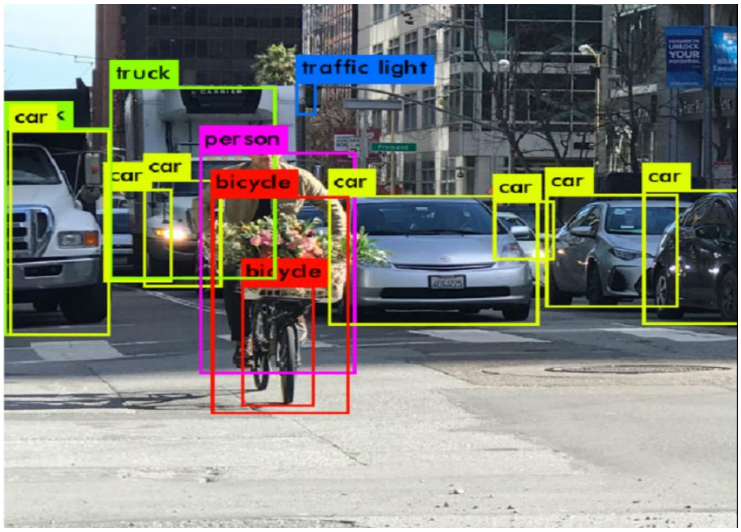


Fig. 2: Vehicle Detection using Deep Learning (YOLO Model)

This figure illustrates the output of the deep learning model where vehicles are detected and highlighted using bounding boxes. Each vehicle is classified into categories such as cars, buses, trucks, and motorcycles. The model uses YOLO-based object detection to identify multiple objects in a single frame with high speed and accuracy. The results demonstrate that the system can accurately detect vehicles even in dense traffic conditions. This stage is critical for further analysis such as tracking and counting. The bounding boxes represent successful feature extraction and classification by the neural network. This confirms the effectiveness of deep learning techniques in handling complex traffic environments and real-time detection requirements.

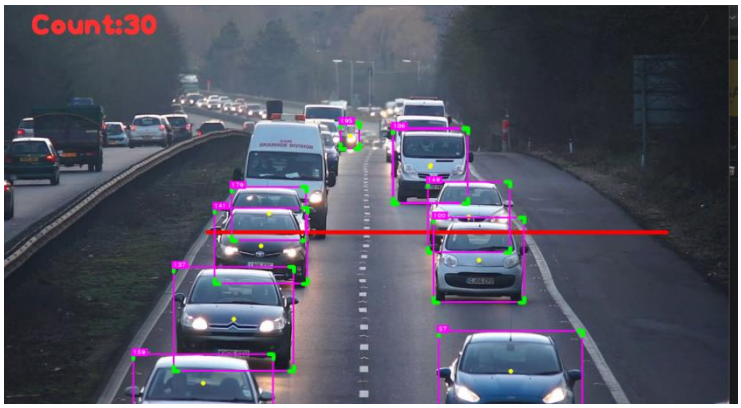


Fig. 3: Vehicle Tracking and Counting System

This figure represents the vehicle tracking and counting mechanism of the system. Each detected vehicle is assigned a unique ID, allowing it to be tracked across multiple frames. The system counts vehicles moving through specific regions, enabling traffic flow analysis. The results show accurate tracking even when vehicles overlap or move at different speeds. This stage is essential for measuring traffic density and identifying congestion patterns. The tracking algorithm ensures continuity between frames, which improves the reliability of analytics. This module plays a key role in transforming detection results into actionable traffic insights.

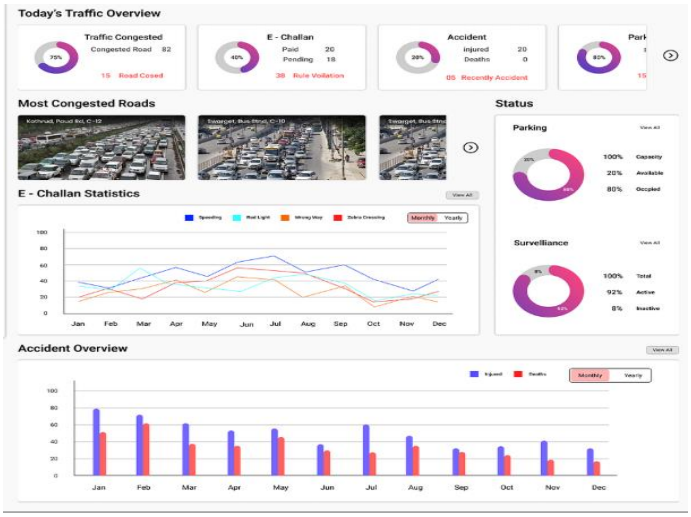


Fig. 4: Traffic Analysis and Alert Generation Dashboard

This figure shows the final output of the system in the form of a traffic analysis dashboard. It displays key metrics such as vehicle count, traffic density, and congestion levels. The system generates alerts for abnormal conditions like accidents, heavy traffic, or violations. The results demonstrate that the system can convert raw video data into meaningful insights for decision-making. This dashboard helps traffic authorities monitor road conditions in real time and take appropriate actions. It highlights the practical applicability of the system in smart city environments. Overall, this figure represents the complete transformation from raw data to intelligent traffic management.

V.CONCLUSION

The proposed Real-Time Traffic Surveillance and Detection System using Deep Learning and Computer Vision provides an efficient and intelligent solution for modern traffic management challenges. By leveraging advanced models such as YOLO and CNNs, the system enables accurate vehicle detection, tracking, and real-time traffic analysis. The integration of automated monitoring reduces human effort and enhances the ability to detect congestion, accidents, and traffic violations promptly. The results demonstrate high accuracy and fast processing speed, making the system suitable for real-world deployment in smart cities. Additionally, the use of tracking algorithms and real-time analytics improves decision-making and traffic flow optimization. The system is scalable and can be extended with features such as license plate recognition and

behavior analysis. Overall, this project highlights the potential of AI-driven technologies in transforming traditional traffic systems into intelligent, automated, and efficient solutions, contributing to improved road safety and better urban mobility management.

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