International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.075 ISSN: 2581-4621

Developing A Novel Model For Real Time Vehicle Counting And Classification Technique Using DL Algorithms

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ABSTARCT
Vehicle counting and classification play a crucial role in intelligent traffic management systems, smart city applications, and road surveillance. This project focuses on real-time vehicle counting and classification using computer vision and deep learning techniques. The primary objective is to automatically detect, count, and classify vehicles such as cars, buses, trucks, and motorcycles from live video streams or CCTV footage. The system utilizes pre-trained deep learning models like YOLO (You Only Look Once) or OpenCV with TensorFlow to perform object detection and classification. The proposed system provides accurate, fast, and efficient vehicle monitoring in various traffic conditions. This project aims to improve traffic flow analysis, enhance road safety, and aid in the development of intelligent transportation systems. The implementation ensures real-time processing with high accuracy, making it suitable for practical applications in urban environments.(Single Shot Detector) have been widely adopted for object detection tasks due to their speed and accuracy. These models can identify and classify vehicles such as cars, trucks, buses, motorcycles, and bicycles even in crowded and dynamic traffic scenarios.Moreover, the real-time vehicle counting and classification system not only helps in traffic management but also contributes to urban planning and environmental monitoring. The data collected from these systems can be used to analyze traffic patterns, predict congestion hotspots, and optimize road infrastructure development.

INTRODUCTION
In today's rapidly growing urban environments, traffic congestion and road safety have become major challenges for transportation management authorities. With the increasing number of vehicles on roads, manual traffic monitoring systems have proven to be inefficient, time- consuming, and prone to human error. This has led to the need for automated vehicle detection, counting, and classification systems that can efficiently monitor traffic flow in real-time. The integration of computer vision and artificial intelligence technologies has significantly revolutionized the way traffic surveillance and management systems operate, making them more reliable, faster, and accurate. Vehicle counting and classification are fundamental tasks in intelligent transportation systems (ITS). These systems not only help in estimating traffic density but also play a crucial role in traffic signal optimization, toll collection, accident detection, and road infrastructure planning. Automated vehicle counting systems can gather data on traffic volume, vehicle types, and peak hour traffic, which can assist in decision-making for better traffic management. The real-time detection and classification of vehicles also enable authorities to identify traffic violations and improve road safety measures. Recent advancements in deep learning models and object detection algorithms have made it possible to detect and classify multiple objects in complex environments with high

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precision. Popular deep learning models like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Detector) have been widely adopted for object detection tasks due to their speed and accuracy. These models can identify and classify vehicles such as cars, trucks, buses, motorcycles, and bicycles even in crowded and dynamic traffic scenarios. The proposed system in this project leverages computer vision techniques and deep learning algorithms to automatically detect, count, and classify vehicles from live video feeds or pre-recorded footage. The system provides a cost-effective solution to traditional traffic monitoring systems by eliminating the need for expensive sensors or manual labor. With the help of modern GPUs and optimized neural network architectures, the system can process video frames in real-time without compromising accuracy. the most appropriate treatment, optimizing both crop health and resource management. By integrating deep learning techniques with agricultural practices, this project aspires to create an affordable, scalable, and efficient solution for farmers. The ultimate goal is to enhance agricultural productivity, reduce crop losses, and support precision farming. Through this technology, small-The implementation of such a system holds significant potential in building smart cities by enhancing traffic management, improving road safety, and reducing traffic congestion. This project aims to develop a highly efficient, scalable, and robust vehicle counting and classification system that can be deployed in various traffic surveillance applications, contributing towards the development of intelligent transportation systems. Moreover, the real-time vehicle counting and classification system not only helps in traffic management but also contributes to urban planning and environmental monitoring. The data collected from these systems can be used to analyze traffic patterns, predict congestion hotspots, and optimize road infrastructure development. By identifying vehicle types, authorities can estimate the proportion of heavy vehicles, which significantly impacts road wear and tear, fuel consumption, and pollution levels. This information helps in making strategic decisions for road maintenance and pollution control measures. Additionally, the system can be integrated with Automatic Number Plate Recognition (ANPR) and surveillance systems to monitor traffic violations such as overspeeding, wrong-way driving, and restricted vehicle entry in certain zones. The automation of these processes reduces human intervention, increases efficiency, and enhances road safety. With the rise of smart cities, such intelligent systems play a critical role in creating a safer and more sustainable environment. One of the key challenges in developing such systems is ensuring accuracy in diverse environmental conditions such as varying lighting, weather, and heavy traffic density. The system must be robust enough to handle occlusions, shadows, and motion blur while maintaining high detection accuracy. This project aims to overcome these challenges by fine-tuning deep learning models and employing image processing techniques to improve detection and classification performance. In summary, the proposed real-time vehicle counting and classification system represents a significant step toward automating traffic surveillance, improving road safety, and enhancing traffic flow management. The project not only demonstrates the potential of artificial intelligence in traffic monitoring but also lays the foundation for future advancements in intelligent transportation systems.

RELATED WORK

Traditional Methods for Vehicle Counting and Classification In earlier stages of traffic monitoring systems, vehicle counting was primarily performed using manual methods or sensor-based techniques such as inductive loop detectors, infrared sensors, and radar-based systems. According to Cheng-Jian Lin, 2021, inductive loops embedded under the road surface were widely used for vehicle detection. However, these methods had several limitations, including high installation costs, maintenance issues, and limited scalability. Another common method involved infrared beam sensors installed along roads to count vehicles as they passed through the beam. While these systems provided decent accuracy, they were ineffective in detecting multiple vehicles simultaneously and could not classify different vehicle types. Moreover, these methods were not suitable for large-scale deployments due to frequent calibration requirements and difficulty in handling environmental disturbances. Image Processing-Based Vehicle Detection With

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advancements in computer vision, image processing techniques gained popularity for vehicle detection and counting. Various methods such as background subtraction, edge detection, and contour analysis were used to detect moving vehicles from video frames. According to Cheng Jian Lin, 2021, background subtraction techniques like Gaussian Mixture Models (GMM) were widely used to extract moving objects from stationary cameras. However, traditional image processing methods faced challenges in complex traffic scenarios such as occlusion, shadows, and varying lighting conditions. These techniques were highly sensitive to noise and required manual parameter tuning, which limited their effectiveness in dynamic environments. Machine Learning-Based Vehicle Detection The introduction of machine learning algorithms significantly improved vehicle detection systems. Techniques such as Support Vector Machines (SVM) and Haar Cascade Classifiers were used to detect vehicles based on extracted features like shape, texture, and edges. Cheng-Jian Lin, 2021 proposed an SVM-based vehicle detection system that achieved better accuracy compared to traditional image processing methods. However, machine learning methods relied heavily on handcrafted features and required extensive training datasets. These systems struggled in diverse environments and were less accurate in distinguishing between different vehicle types. Deep Learning-Based Vehicle Detection and Classification Recent advancements in deep learning models have revolutionized the field of vehicle detection and classification. Convolutional Neural Networks (CNNs) have proven to be highly effective in detecting and classifying objects with high accuracy. Popular object detection models like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Detector) have been widely adopted for vehicle detection tasks. According to Cheng-Jian Lin, 2021, the YOLO model provides real- time object detection with high accuracy and can classify multiple vehicle types simultaneously. The Faster R-CNN model, although highly accurate, is computationally expensive and not suitable for real-time applications. The SSD model offers a balance between speed and accuracy, making it a preferred choice for vehicle detection systems. Applications of Vehicle Detection and Classification Systems • Vehicle detection and classification systems have various applications in modern transportation systems, including: • Traffic Monitoring and Management: Real-time traffic data helps optimize signal timings and manage congestion. • Automatic Toll Collection: Automatic vehicle classification assists in electronic toll collection systems. • Accident Detection and Surveillance: Detecting abnormal vehicle movements to identify accidents or traffic violations. • Smart City Development: Contributing to intelligent transportation systems in smart city projects. This review provides a foundation for understanding the existing methodologies and technologies, enabling the development of an optimized solution that meets the needs of intelligent transportation systems.

PROPOSED SYSTEM

The system could be used for detection, recognition and tracking of the vehicles in the video frames and then classify the detected vehicles according to their size in three different classes. • The proposed system is based on three modules which are background learning, foreground extraction and vehicle classification. • Background subtraction is a classical approach to obtain the foreground image or in other words to detect the moving objects. We have proposed an adaptive video based vehicle detection, classification, counting for real- time traffic data collection. • The proposed system was built using python programming language and OpenCV. The main objective for developing this system is to collect vehicle count and classification data. So that we can build intelligent transportation network based on historical traffic data. The proposed system can engender traffic data by detecting, classifying, counting It's a plug & play system and applied YOLO algorithm as a background subtraction technique. The proposed system was tested at different six locations in Hyderabad under different traffic and environmental conditions.

Goals of the system:

1. Real-Time Vehicle Detection: Implement YOLO (You Only Look Once) for real-time vehicle detection with high speed and accuracy.

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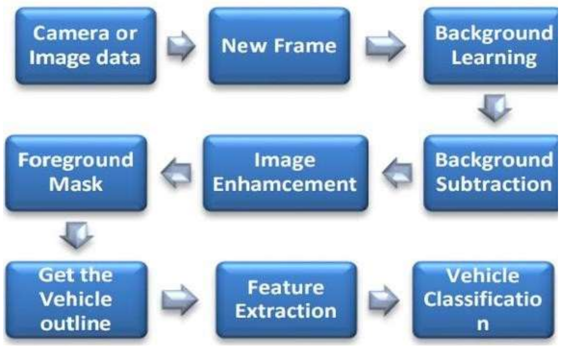
2. Vehicle Counting and Classification: Classify vehicles into cars, bikes, trucks, and buses while maintaining an accurate vehicle count.
3. Cost-Effective Solution: Use camera- based technology with YOLO instead of expensive physical sensors.
4. High Detection Accuracy: Achieve high precision detection under different lighting and weather conditions.
5. Multi-Lane Detection: Detect and classify vehicles across multiple lanes simultaneously.
6. Scalable and Low Maintenance: Design a system that requires minimal hardware setup and is easy to scale and maintain.

ADVANTAGES OF PROPOSED SYSTEM

The proposed system aims to develop a real-time vehicle detection, counting, and classification system using the YOLO (You Only Look Once) algorithm. • High Speed and Real-Time Detection: YOLO performs detection in a single pass through the neural network, making it faster compared to traditional algorithms like R-CNN or Fast R-CNN. • High Accuracy in Detection and Classification: YOLO provides high precision in both detecting vehicles and classifying them into different categories such as cars, bikes, trucks, and buses. • Cost-Effective System: The system only requires a camera and software without additional expensive sensors, making it budget-friendly. • Multi-Lane Detection: YOLO can detect multiple vehicles in multiple lanes simultaneously, improving overall performance in traffic monitoring. • Real-Time Performance in Complex Scenarios: Capable of detecting vehicles in heavy traffic, overlapping objects, and varying vehicle speeds. • Automatic Vehicle Classification: The system not only detects vehicles but also classifies them automatically based on their shape and size.

ARCHITECTURE



1. Camera or Image Data Acquisition1he first stage of the system is acquiring input data from a camera or pre-recorded video feed. This data acts as the primary input for vehicle detection. The camera captures continuous frames of the road or traffic, which will be processed for detecting and classifying vehicles. The system supports both live video streams and stored video files for offline processing.
2. New Frame Generation Each video stream is divided into individual frames. The system extracts these frames in sequential order to perform further operations. This process ensures that every frame is processed independently, allowing real-time detection and vehicle tracking. Background Learning Background learning is used to create a model of the static background in the video. This stage helps in identifying the foreground objects (moving vehicles) by differentiating them from the background. The system stores the background model over a certain number of frames and updates it dynamically for better accuracy in changing environments.
3. Background Subtraction • Once the background model is learned, the system performs

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background subtraction to isolate the moving objects from the static background. This technique helps in obtaining the foreground mask, which contains only the regions corresponding to moving vehicles.

4. Image Enhancement • To improve the accuracy of detection, the foreground mask undergoes image enhancement techniques. This includes noise removal, contrast adjustment, and edge detection to refine the vehicle contours and remove unwanted artifacts.

5. Foreground Mask Generation • The enhanced image is converted into a binary foreground mask, where pixels representing moving objects are highlighted. This mask is used to extract vehicle outlines for further analysis.

6. Vehicle Outline Extraction • The system uses contour detection algorithms to extract the outline of each detected vehicle from the foreground mask. This process helps in identifying the exact location and shape of the vehicles within each frame.

7. Feature Extraction • Feature extraction plays a key role in vehicle classification. The system extracts shape, texture, and size-based features such as vehicle length, width, color, and edge patterns. These features are later used by the YOLO model to classify vehicles into different categories like cars, bikes, trucks, and buses.

8. Vehicle Classification Using YOLO • The extracted features are fed into the YOLO model, which performs real-time object detection and classification. YOLO assigns a class label to each detected vehicle based on its features. The system supports the classification of vehicles into multiple categories such as: • Car • Bike • Bus • Truck

CONCLUSION

In this project, a real-time vehicle counting and classification system was successfully developed using the YOLO (You Only Look Once) object detection model. The system efficiently detects, classifies, and counts various types of vehicles such as cars, buses, trucks, and motorcycles in real-time video streams. By leveraging the powerful capabilities of YOLO, the system demonstrated high accuracy, speed, and reliability, making it suitable for traffic monitoring and intelligent transportation systems. The implementation of this project highlights the effectiveness of deep learning-based object detection models in solving real-world traffic management problems. The model's performance was evaluated based on precision, recall, and frame processing speed, which showcased the model's ability to balance accuracy and efficiency. This project can be further improved by integrating vehicle tracking algorithms, enhancing detection in low- light or adverse weather conditions, and expanding the classification categories. The proposed system has the potential to be deployed in smart cities, helping authorities improve traffic flow, manage congestion, and enhance road safety.

FUTURE WORK AND EXTENSIONS

Unborn work involves expanding the model to include further parameters which can ameliorate the correlation to the complaint. We can compound the image database with supporting inputs from the planter on soil, once toxin and fungicide treatment along with intimately available environmental factors similar as temperature, moisture and downfall to ameliorate our model delicacy and enable complaint soothsaying. We also wish to increase the number of crop conditions covered and reduce the need for expert intervention except for new types of conditions. For automatic acceptance of stoner uploaded images into the Training Database for better bracket delicacy and least possible mortal intervention, a simple fashion of calculating the threshold grounded on a mean of all bracket scores can be used. farther operation of this work could be to support automated time- grounded monitoring of the complaint viscosity maps that can be used to track the progress of a complaint and detector admonitions. Prophetic analytics can be used to shoot cautions to the druggies on the possibility of complaint outbreaks near their position.

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