AI-based traffic management system

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Abstract—In cities, traffic congestion is becoming a bigger problem that leads to delays, financial losses, and environmental issues. In this paper, object detection methods like YOLO and COCO SSD are used to investigate an AI-driven approach to traffic congestion analysis. Our objective is to develop an intelligent system that uses real-time traffic data, including vehicle count, lane distribution, signal time, and congestion levels, to assist transportation authorities in optimising traffic flow. The study looks at the literature on traffic management with reinforcement learning, deep learning, and the Internet of Things. The study also discusses key object detection methods, emphasising their application in monitoring and assessing traffic congestion. The effectiveness of the model is evaluated by considering performance metrics such as mAP, IoU, FPS, and latency. The findings demonstrate the importance of artificial intelligence and deep learning.

Index Terms—**[COCO-SSD, Performance Metrics, Traffic Congestion Analysis, YOLO]**

I. INTRODUCTION

Traffic congestion in urban areas is growing as fast as technology is growing in the construction world. Although most of the cities are metropolitan, traffic congestion is still a major issue faced in various situations. Most of the people spend hours on the roads themselves stuck in traffic. This is the problem that is not faced in India itself but is faced worldwide e.e.e. To overcome this problem, first there should be some system that can analyze the congestion by considering different parameters like time, width, location, number of vehicles by its subclass, total number of lanes, and signal time. These different parameters can be used for developing a model that can predict the congestion and analyze the congestion in a good manner. These analyses can be used by the Road and Transportation Department and Police Department so that they can help them with the reduction of the traffic congestion in many cities. Mostly this analysis can be done at toll plazas, traffic signals, cross-junctions, and near religious places.

II. LITERATURE SURVERY

With the advancement of deep learning, vehicle detection and intelligent traffic management have become critical areas of research. Models such as *YOLO (You Only Look Once)* and *Single Shot MultiBox Detector (SSD)* are widely used due to their real-time processing capabilities. Zhang et al. (2020) explored the efficiency of YOLO in vehicle detection, highlighting its real-time performance and high accuracy compared to conventional object detection methods [1]. Similarly, Liu et al. (2021) compared *YOLO and SSD* for vehicle detection in complex urban environments, noting that SSD performs better for small object detection, whereas YOLO is superior for high-speed recognition [2].Kumar et al. (2022) investigated the *COCO dataset's impact* on vehicle detection accuracy, showing that using pre-trained COCO models enhances object recognition in varying weather conditions [3]. Wang et al. (2023) applied YOLOv5 for traffic monitoring, demonstrating that it reduces false positives and increases detection efficiency [4]. Jiang et al. (2022) integrated *YOLO-based vehicle detection* with aerial imagery, proving its effectiveness in drone-based traffic surveillance [5]. Another study by Patel et al. (2023) focused on *YOLOv7*, achieving superior performance in nighttime vehicle detection [6].

Signal optimization plays a key role in improving urban mobility. Wang et al. (2021) proposed *AI-driven signal optimization, which dynamically adjusts traffic light timings based on real-time congestion levels, leading to a **30\% improvement in traffic flow* [7]. Gupta and Sharma (2023) examined *reinforcement learning for adaptive traffic signal control*, showing reduced wait times and enhanced road efficiency [8].

Chen et al. (2020) introduced a *hybrid approach combining YOLO-based vehicle detection with AI-driven signal optimization*, proving that integrating detection with dynamic signal control significantly reduces congestion [9].

Other studies have focused on traffic density estimation. Singh et al. (2022) utilized *YOLOv4 for vehicle count estimation, achieving a **95\% accuracy rate in real-time scenarios* [10]. Further, *machine learning techniques* have been applied to optimize traffic systems. Ahmed et al. (2021) developed a *deep reinforcement learning-based traffic signal control, achieving a **40\% reduction in average delay per vehicle* [11] . Similarly, Roberts et al. (2023) proposed *a deep Q-learning-based approach* for optimizing intersection traffic lights [12]. Recent work by Lee et al. (2022) integrated *computer vision with IoT-based sensors* to detect real-time vehicle movements and adjust traffic signals accordingly, achieving enhanced urban traffic management [13]. Santos et al. (2023) highlighted *the importance of integrating edge computing with vehicle detection systems, reducing latency and enhancing processing efficiency [14]. Lastly, Sharma et al. (2021) developed a **multi-camera YOLO-based vehicle tracking system*, proving useful in large-scale traffic monitoring applications [15].

III. PROPOSED METHODOLOGY

Traffic nowadays has become a major issue in several cities. Some of the factors that are there that affect the congestion directly are the urbanisation of towns, an increase in the count of heavy vehicles, and several other factors. Mostly the traffic is caused near traffic signals; sometimes it takes hours and hours to clear the traffic and congestion. One of the main reasons for the congestion is the signal time provided for each lane; usually the same time is provided equally for each of the lanes in a junction, usually 20 seconds for green, 5 seconds for orange, and 45 seconds for red. This equal distribution of the signal time is leading to an increase in the number of vehicles. Usually in a junction, 2 or 3 lanes probably have more congestion; providing equal time leads to an increase in more traffic, and the lane with the least traffic or vehicles gets a larger amount of time, which is not really required. So the proposed solution handles the traffic in an efficient manner. The first important step is to identify the number of vehicles in each of the lanes with its subclass type and later need to do an analysis on the total vehicles in each of the lanes. Then we need to check the congestion level and each of the lane and provide the respective signals according to the density of the vehicles.

The proposed system involves the following steps:

A. Data Collection:

Data collection is an important and crucial step in machine learning and artificial intelligence. Mostly here our aim is to collect necessary images and videos related to our target object. The images that we consider or train the model on should be captured in different conditions like lighting, angle, and background.

B. Object Detection:

YOLO and COCO SSD are used to detect and classify vehicles in real time.

C. Feature Extraction:

It is one of the important steps that need to be followed while developing AI-based applications. It helps in identifying the key features, patterns, and characteristics of the image, which further helps in differentiating the objects that are detected and helps in increasing the classification accuracy, which plays a major role in detection. Mostly convolutional neural networks are used for the feature extraction. Edge detection is one of the methods used, which uses techniques like Sobel filters and Canny edge detection for identifying the boundaries. Histogram of Orientated Gradients (HOG) is used to capture the gradient-based features to detect structures and shapes. In models like YOLO and SSD, feature extraction occurs through multiple convolution layers, which helps in accurate classification and prediction.

D. Model Selection:

Mostly two different Models are used for the detection of the vehicles COCO SSD and YOLO

IV. OBJECT DETECTION TECHNIQUES

A. COCO SSD:

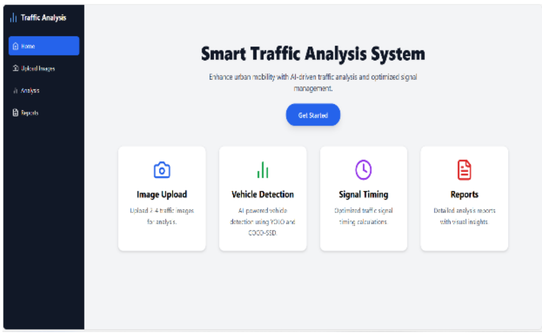
It usually stands for Single Shot MultiBox Detector, it is trained on a dataset named COCO dataset. Unlike traditional two-stage detectors like Faster R-CNN, which first generate region proposals and then classify them, SSD performs both tasks simultaneously, making it significantly faster. The dataset COCO stands for Common Objects Content that contains a set of objects, which includes vehicles, animals, people, and some items. It generally uses some series of the convolution layers for the extraction of the features. Mostly this COCO SSD is used widely in traffic monitoring, autonomous driving.

B. YOLO:

YOLO stands for "YOU ONLY LOOK ONCE. It is a real-time object detection model that is used to process images in a single forward pass of a deep neural network, making it one of the best and most efficient object detection architectures. Unlike region-based methods such as Faster R-CNN, which first generate region proposals and then classify them, YOLO divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell simultaneously. This end-to-end approach significantly reduces computational complexity, enabling real-time performance while maintaining high detection accuracy. YOLO has different versions like YOLOv3, YOLOv4, and YOLOv5, which provide better efficient results with good accuracy.

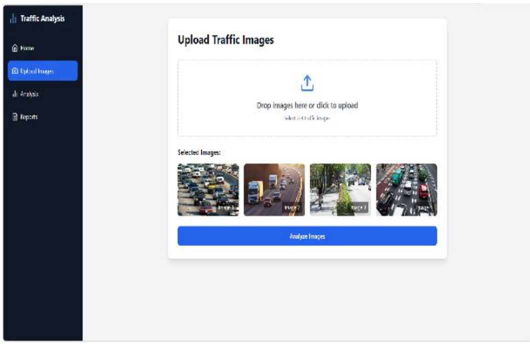
V. INTERFACE

C. Home page



The home page serves as the entry point to the Smart Traffic Management System, providing a seamless and intuitive user experience "Get Started" button allows users to quickly access the platform's core functionalities. The page highlights four key features: an image upload option that supports 2-4 traffic images, vehicle detection using YOLO and COCO-SSD models for accurate recognition, optimised signal timing based on real-time vehicle analysis, and detailed reports with visual insights to enhance traffic management decisions. A navigation menu on the left side of the page enables users to easily explore different sections, including Home, Upload Images, Analysis, and Reports.

D. Upload page



This is the Upload Traffic Images page of a smart traffic management system. The interface has a clean and intuitive design, with a sidebar navigation panel on the left, providing quick access to different sections such as Home, Upload Images, Analysis, and Reports. Users can easily upload 2 to 4 traffic images by dragging and dropping them into the designated upload area or clicking to select files manually. Below the upload section, selected images are displayed with clear labels for easy identification. Once the images are uploaded, users can proceed by clicking the prominent Analyze Images button, which initiates the traffic analysis process. This streamlined workflow enhances user experience by ensuring smooth navigation and efficient image management.

E. Analysis page

The Analysis page gives a clear and concise conclusion and overview about the processed traffic, and a valuable insights for efficient traffic management. By using AI based detection algorithms, this page offers detailed information about the traffic situation, helping authorities make data-driven decisions to optimize traffic flow and minimize congestion.

The Analysis Results page displays crucial metrics including:

- Total Number of Vehicles**:** Reports page gives a clear count of all the detected vehicles in the image.
- Detected Lanes: It finds the number of lanes that are accurately identified, ensuring proper lane management and also facilitates better traffic signal management.
- Vehicle classes**:** All the detected vehicles are classified into different categories such as cars, trucks, buses, motorcycles, and bicycles.
- Congestion Level**:** The system finds the congestion level based on the number of vehicles and number of lanes. This insight is needed for real-time traffic control and long-term planning.

F. Report page

The Report Page provides a detailed analysis of all the uploaded traffic images. It identifies key factors such as the total number of vehicles, detected lanes, and vehicle classes in the uploaded images. The image with the highest vehicle count is highlighted that help for further review. Users can view detailed comparisons and summaries to understand traffic patterns effectively. Additionally, the report can be downloadable, offering a complete breakdown of the analysis, including visual representations and data insights. This feature streamlines decision-making for traffic management, helping to optimize signal control and reduce congestion.

- Total Number of Vehicles in the Images: This counts and provides an overall view of traffic density.
- Detected Lanes and Vehicle Types**:** Comparing results across different locations or timeframes can reveal trends in vehicle movement and lane usage.
- Congestion Trends**:** By tracking congestion levels across images, authorities can identify recurring bottlenecks and areas requiring intervention.

Report page identifies the image with highest vehicle count among all the uploaded images. The image is highlighted as there is a change for severe traffic jam or any abnormal congestion in that particular lane. So, by analysing all the summary and by the insights the officials can take decisions accordingly, authorities can pinpoint problem areas and devise targeted solutions.

VI. PERFORMANCE METRICS

I. Mean Average Precision (mAP):
Mean Average Precision (mAP) is the most widely used metric for evaluating object detection models. It measures the accuracy of a model by considering both precision and recall at different confidence thresholds.
II. Intersection over Union (IoU):
Intersection over Union (IoU) measures the overlap between the predicted bounding box and the ground truth bounding box. It is a fundamental metric used to determine whether a detection is correct.
III. Latency:
The time required to process an image and generate detections.
IV. Frames Per Second (FPS):
Determines the speed of the detection model

VII. FUTURE SCOPE

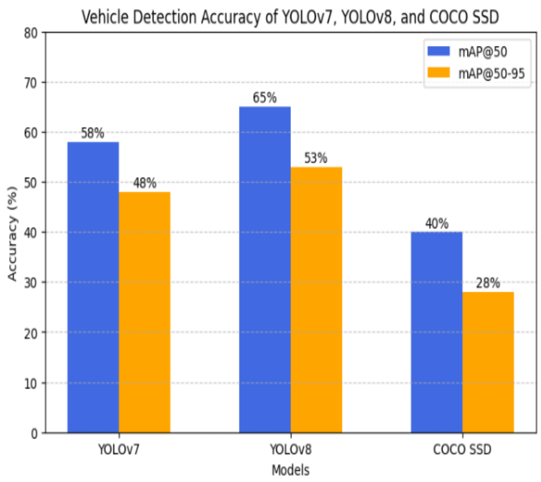
In the future, we can further add some more features to the application. We can integrate IoT and smart sensors for accurate vehicle detection; we can do real-time adjustments of signal timings based on vehicle congestion and patterns identified in the image or video captured using sensors. Also, in the future, we can add Vechile to infrastructure communication, which enables communication of vehicles and traffic lights to reduce waiting time. Also, we can implement emergency vehicle privatization to ensure smooth passage of ambulances. We can also implement smart traffic analysis that analyzes the live data that is fetched using sensors, due to which we can analyze the traffic and take necessary precautions related to it.

VIII. RESULTS

YOLOv8 provides the highest accuracy for vehicle detection, making it the best choice for precision-based applications. YOLOv7 offers a balance between speed and accuracy, making it ideal for real-time detection. COCO SSD, while less accurate, is lightweight and suitable for mobile or edge devices. YOLOv8 outperforms in mean average precision (mAP), especially in complex environments. YOLOv7 is optimized for fast inference, making it efficient for traffic monitoring systems. COCO SSD is useful for low-power applications but struggles with smaller objects. Choosing the right model depends on the trade-off between accuracy, speed, and hardware limitations. Overall, YOLOv8 leads in performance, but YOLOv7 and COCO SSD have their own advantages in specific scenarios.

MODEL	MAP@50 (\%)	MAP@50-95 (%)
YOLOv7	58	48
YOLOv8	65	53
COCO SSD	40	28

PERFORMANCE COMPARISON OF OBJECT DETECTION MODELS.



IX. CONCLUSIONS

This study presents an smart traffic management system that utilizes advanced object detection techniques like YOLO and COCO SSD. By analyzing key parameters such as time, location, vehicle types, and signal duration, the model provides accurate congestion predictions, aiding in traffic optimization. The literature survey highlights the effectiveness of deep learning, IoT, and AI in intelligent traffic management. The integration of real-time monitoring and predictive analytics demonstrates the potential for improving urban traffic flow. With performance metrics ensuring efficiency and accuracy, the proposed system serves as a scalable and adaptive solution for mitigating congestion in urban environments. Future advancements can focus on integrating reinforcement learning and multi-modal data sources to enhance traffic forecasting and control strategies.

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