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A Predictive City Arteries System for Dynamic Traffic Flow Optimization and Smart Urban Mobility Planning

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KEYWORDS

Traffic Analysis, Vehicle Detection, YOLO, Traffic Density Estimation, Lane-wise Vehicle Counting, Speed Estimation, Intelligent Transportation Systems, Computer Vision, Smart Traffic Management.

ABSTRACT

The Traffic congestion is a significant problem in urban centres that causes delays, use of more fuel, and pollution of the environment. To create intelligent transportation systems and smart city solutions, effective traffic monitoring and analysis are needed. The project introduces an AI-based traffic analysis and decision support system that involves vehicle detection and traffic pattern analysis via the use of the YOLO (You Only Look Once) deep learning model on the analysed traffic videos. The intended system works with frame-by-frame processing of uploaded traffic videos to identify vehicles and assess traffic conditions. It counts cars in a lane, computes traffic density, approximates the mean and maximum vehicle speeds, and counts the total vehicles in a lane by a line-crossing algorithm. Depending on the traffic flow between the lanes, the system determines the busier lane and suggests the green signal timing to enhance traffic flow. A CSV report is also created on the analysed video that can be utilized in future planning and analysis of traffic. The system offers an automated and effective way of monitoring traffic and assist in making decisions based on data in managing traffic, congestion, and planning road infrastructure.

1. INTRODUCTION

Traffic congestion in the modern cities has been caused by the rapid rate of urbanization and the rising number of vehicles. This traffic growth not only adds more time to the travel time, but also adds to increased fuel consumption, air pollution, and road accidents. Thus, effective traffic control has turned out to be an urgent need of smart cities. Proper traffic analysis and prediction are important in enhancing transportation systems through proper planning, congestion reduction, and optimizing traffic lights operations [1]. The conventional traffic monitoring systems are based on manual surveillance or physical devices like loop detectors mounted on roads. Despite the fact that these techniques yield helpful data, they have costly infrastructure, serviceable maintenance, and cannot be scaled easily. In addition, they do not usually offer real-time and dynamic analysis in various locations [2]. With the development of artificial intelligence and computer vision, the current traffic surveillance systems have been replaced with the analysis based on the video. Object detection models based on deep learning like the YOLOv8 have demonstrated great advancements in the detection and classification of vehicles with high accuracy [3]. Such models are capable of processing real-time video streams to identify various kinds of vehicles and evaluate traffic processes effectively. Video traffic analysis is an efficient and scalable method of monitoring traffic conditions that is non-invasive. The system will be able to extract features like vehicle count, speed, and density to analyse the traffic flow patterns and help control intelligent traffic signals [4]. This facilitates the creation of intelligent traffic control mechanisms with the ability to dynamically respond to the varying road conditions [5].

2. LITERATURE SURVEY

Due to growing congestion and inefficiencies in the transportation systems, traffic forecasting and traffic control has received a lot of attention. Initial studies on traffic analysis primarily used conventional statistical and time- series models like ARIMA and regression to forecast traffic flow, as well as travel time [6]. Though these methods proved to be useful in the use of past data, they had shortcomings when it came to dealing with dynamic and complicated traffic patterns [7]. As machine learning progressed, scholars started relying on algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests to perform traffic prediction tasks [8]. Such models enhanced prediction accuracy by having learned patterns based on the traffic data including the number of vehicles and speed [9]. Nevertheless, they still needed to be manually extracted and could not be used in real-time analysis [10]. The recent advances in the field of deep learning have greatly enhanced a traffic analysis system. CNNs have been extensively applied to traffic images and video analysis, making it possible to automatically recognize and classify cars [11]. The models are better than the traditional methods in that they can deal with large and complex data [12]. Besides CNNs, Recurrent Neural Networks (RNNs) have also been employed to learn temporal relationships in traffic data, especially the Long Short-Term Memory (LSTM) networks [13]. These models work well in the sequential patterns learning and future traffic behaviour prediction [14]. CNN and LSTM hybrid models have as well been suggested to enable the models to better capture both space and time features [15]. Moreover, the most recent research is devoted to the real-time traffic monitoring based on computer vision. YOLO is one of the object detection models that have become popular because it is fast and can detect vehicles in video streams with high accuracy. Such systems facilitate real-time vehicle counting, congestion analysis and estimation of traffic density that are crucial in intelligent traffic management systems. New studies also focus on the use of a combination of data sources and intelligent technologies to better predict and improve the ability to make decisions . Such innovations help to create smart city infrastructure by making traffic more efficient and less congested . In this article, we present a deep learning-based traffic analysis system in real-time that takes video input and identifies cars and calculates traffic density. The system uses novel object detection algorithms to enhance accuracy and efficiency of tracking in traffic monitoring .

Table 1 Literature survey of some of the existing work.

S. No	Author	Description	Methodology	Results
1	Bartlett et al. [1]	Focuses on predicting traffic flow using machine learning on urban roads.	Machine learning models trained on historical traffic data.	Achieved improved prediction accuracy over traditional statistical methods.
2	Papageorgiou et al.	Discusses strategies for road traffic control and management.	Theory and modeling of traffic control systems.	Offered effective methods of managing congestion.

3	Redmon et al.	Presented YOLO to detect objects in real time.	Object detection model based on deep learning.	Achieved fast and accurate real-time vehicle detection.
4	Jiang et al.	Forecasts vehicle speed in order to analyze traffic.	SARIMA time-series model.	Good predictions of short-term speed in traffic.
5	Song et al.	Traffic prediction speed is predicted using statistical models.	Time-series analysis vs machine learning algorithms..	Machine learning outperformed traditional models.
6	Lippi et al.	Comparisons different traffic flow forecasting methods.	Statistical and machine learning models.	ML models performed well compared to the traditional approaches.
7	Ahmed et al.	Early research of traffic	Statistical time-series modeling.	techniques to predict traffic.
8	Mackenzie et al.	Compares ML models to predict traffic.	Comparison of machine learning algorithms.	Demonstrated better performance of ML models.
9	Abduljabbar et al	Examines the uses of AI in transport systems.	Overview of AI methods.	Outlined advantages of AI in traffic management.
10	Vlahogianni et al.	Surveys traffic forecasting.	Comprehensive literature review.	Determined shortcomings of conventional models.
11	Lv et al.	Predicts traffic flow with the help of deep learning.	Deep Neural Networks (DNN).	Achieved higher accuracy than ML models.
12	Szeliski	Gives basics of computer vision methods.	Image processing and vision algorithms.	Facilitated enhanced vehicle detectors.

3.PROPOSED ALGORITHM

The suggested system offers a real-time, automated traffic density estimation method based on a deep learning- based object detection system. The primary goal of the system is to use the most recent development in object recognition especially the YOLOv8 model, which has high detection precision and low latency. The system is to detect vehicles in both stationary images and live video feeds, approximate the level of traffic congestion by counting the number of objects detected, and categorize traffic congestion into low, medium, and high levels. The proposed system is completely automated and adaptive as opposed to the traditional methods that use computationally intensive region proposal methods or hard cutoffs. It uses the light and anchor-free YOLOv8n model that can do efficient real-time inference even on systems with few computational resources.

A. *Dataset Description*

The system that is proposed is not based on a conventional annotated dataset to train. Rather, it uses real-time traffic video information as provided by users. These videos are actual traffic real-life scenarios recorded by surveillance cameras or by mobile devices and most are of the MP4 or AVI format. The input videos have various vehicles traversing the road lanes with different environmental conditions such as lighting, shadows and occlusions variations. The system works with these videos by converting them into single frame videos and then each frame is analyzed as a single picture.

The system is based on a pre-trained model that is trained on large-scale datasets like COCO (Common Objects in Context). This enables the model to identify and categorize various types of vehicles, such as cars, buses, trucks, and motorcycles without the need to be trained further. In execution, the system dynamically retrieves diverse kinds of data in the input videos. These comprise of bounding box coordinates of vehicles, class labels, vehicle count per frame, vehicle distribution across lanes, vehicle movement across frames and speed estimation using displacement.

B. *Data Preprocessing*

Preprocessing of data plays an important role in making sure that the data used in its input is correctly formatted and is optimally read to detect and analyze vehicles. The system uses dynamic preprocessing on each frame prior to the detection model since the system uses real-time traffic videos. It starts with video acquisition, where the input video is either recorded or uploaded by the user. The system operates on OpenCV to get the individual frames of the video stream; a frame is a view of the traffic scenario at a specific time. The individual frames are then scaled to a standard resolution, which is usually 640×640 pixels, to the input requirements of the YOLO model. This scaling provides uniformity between frames and makes processing faster. Moreover, the model also normalizes pixel values internally, improving detection performance. The noise that can be found in real-world traffic videos is motion blur, changing lighting conditions and shadows. Even though the advanced noise filtering methods are not directly used, the strength of the YOLO model enables it to manage such differences. Frames that have very low quality are automatically disregarded during detection because of low confidence scores. Each frame is split into two areas with a defined vertical line functioning as a lane divider to study the traffic in each lane. With this segmentation, the system is able to identify detected vehicles as belonging to the left and right lane and this assists in estimating lane-specific traffic density and to optimize decisions of the traffic signal.

C. *Vehicle Detection*

The main feature of the suggested traffic analysis system is the vehicle detection. It is also in charge of recognizing and tracing the vehicles in every frame of the input video. The system makes use of the YOLO object detection model, which is famous in terms of efficiency and real-time. YOLO can process the whole image in one forward pass, and thus it is very much suitable in real-time applications. The YOLO model trained in this project can identify the typical types of vehicles like cars, buses, and trucks. The model is already trained on large-scale datasets; hence, no further training is required. After the conversion of the input video into frames with the help of the OpenCV, the frames are sent to the YOLO model to be detected. The model detects the objects in the frame, delineates bounding boxes around the identified vehicles, classifies them, and assigns confidence scores to each detection. Only the detections with a predetermined threshold of confidence are taken into consideration, in order to achieve accuracy and reduce false detections. Every identified vehicle is represented as a bounding box with coordinates (x1, y1, x2, y2). The centroid of the bounding box is computed and further analyzed such as, lane detection, vehicle tracking and speed estimation. Depending on the centroid position, the vehicles are allocated to the left or right lane. This allows the system to conduct a lane-by-lane vehicle counting and density estimation, which is essential in intelligent traffic control. The YOLO model is trained to be fast in inference, enabling the system to handle several frames per second.

D. *Traffic Density Estimation*

One of the most important functions of the suggested system is traffic density estimation because it identifies the amount of congestion on the road, depending on the number of vehicles detected. Based on the traffic of the vehicle detection module, the system uses real-time data to compute the density of traffic. On every frame that is extracted out of the video, the system counts the amount of the vehicles that have been identified which is the density of traffic at that frame. An increase in the number of vehicles means that traffic is heavy whereas a lower number means that there is less traffic. In an attempt to get a more detailed information, the system estimates the density lane by lane by splitting every frame into right and left parts. The vehicles are allocated to lanes according to their centroid positions and the system determines the number of vehicles within a particular lane. This aids in determining the busier lane at a certain time. Along with the frame-wise density, the system also calculates the mean traffic density over the entire video. This is computed by taking the total number of vehicles found divided with the number of frames processed. This mean will give a general idea of the state of traffic within the time frame of observation. According to the values of the calculated densities, the system categorises traffic conditions into low, moderate, and high congestion. Even though threshold values can change based on the use of the same, this classification assist in comprehending the traffic patterns. Intelligent traffic signal control is also based on the estimated density.

E. *Visualization & Reporting*

Visualization and reporting are important in providing the processed traffic data in a useful and comprehensible manner. The proposed system will offer real-time visual results as well as a final analysis report to support analysis of traffic conditions. In processing the annotation of each frame is done with OpenCV to show visual data regarding data on bounding boxes around the cars that are identified, a lane separation line that differentiates between the left and right sides, the numbers of cars in each lane, and frame-specific information.

This real-time visualization enables the user to see the detection model detects and tracks vehicles in real-time. The system constantly records the most important statistics of each frame, such as how many vehicles there are in each lane, and what is the average speed of the vehicles being detected. These are passed to the frontend interface via the WebSocket interface allowing real-time observation of traffic conditions. Upon completion of the whole video processing, the system would produce a detailed report on the summary that would encompass the total number of frames that have been processed, total vehicles detected, average speed of vehicles, maximum speed of vehicles, number of vehicles in a particular lane, and the most congested lane. Besides the summary report, the system produces a traffic decision report, which is based on the analyzed data. This report also contains a recommendation on how the traffic lights should be controlled like the best length of green lights per lane depending on the density of traffic and speed of the vehicles. The frontend interface is developed using the web technologies such as HTML, CSS, JavaScript which display real-time video, real-time traffic statistics, and final summarized outputs. This interactive interface makes it easier and assists the user to make informed choices on traffic management.

This is where the outcomes of the experiments carried out to determine how the suggested traffic monitoring system works are discussed. The system is tested based on the ability to identify vehicles properly, calculate the density of the traffic and its distribution in lanes and generate smart traffic signal recommendations. It will be appraised on the basis of the live video feeds of the traffic and the system performance will be measured by the number of detections, the number of vehicles in the frame, the accuracy of the lane distributions and the accuracy of the speed estimates.

A. Vehicle Detection Results

The vehicle detection model is implemented with the help of YOLO model that helps to detect the vehicles in every frame of the input video. The model is useful in determining different types of vehicles such as cars, buses, trucks and motorcycles in different traffic conditions.

A. Table 2. Sample Detection Performance

Metric	Value
Total Frames Processed	307
Total Vehicle Detections	2831

These results show that the detection model performs efficiently in identifying vehicles across frames with consistent accuracy.

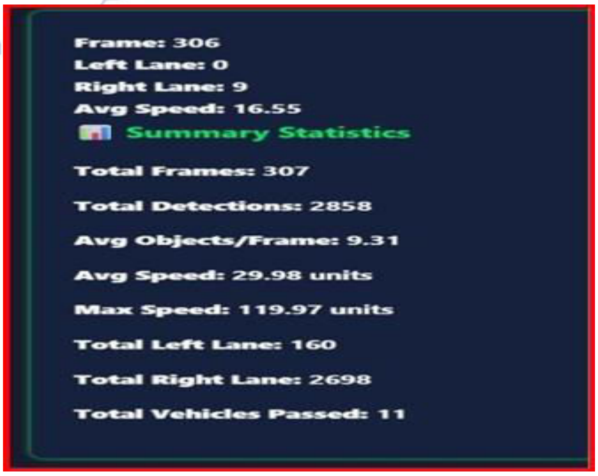

FIGURE 1: TRAFFIC ANALYSIS DASHBOARD DISPLAYING FINAL

B. Lane-Wise Traffic Analysis

The system divides each frame in two, left lane and right lane to examine traffic distribution. This division is drawn on an a priori vertical line dividing the road into two rationals. The centroid of the bounding box of each vehicle that has been detected is computed and the lane position is determined. The cars with centroids on the left side of the threshold belong to the left lane and those on the right to the right lane.

Table 3. Performance of Text Stress Detection Model

Metric	Value
Total Vehicles in Left Lane	160
Total Vehicles in Right Lane	2671

The results indicate that the right lane is significantly more congested compared to the left lane.

C. Density Estimation Results

Traffic density is obtained through counting the vehicles that are observed in a frame. The system also records the density of vehicles in every frame and averages the frame density in the video. The mean value of 9.22 vehicles per frame is moderate to high, which indicates moderate to high traffic conditions. This demonstrates that the system is able to provide an effective measurement of real-time congestion. The density prediction is dynamically adjusting i.e. it varies with each frame depending on the number of vehicles around. This helps in the implementation of the changes in traffic with time.

Table 4. Density Metrics

Metric	Value
Average Vehicles per Frame	9.22
Traffic Condition	Moderate to High

These values demonstrate that the system can effectively estimate traffic density in real-time scenarios.

D. Speed Estimation Results

The system estimates the speed of vehicles using an easy yet efficient technique of centroid tracking. The centroid motion of each vehicle identified with reference to the prior frame is computed by the system. Although the speed values are not the real world speeds (because of the absence of camera calibration), they give a relative number of vehicle movement. To improve reliability, highly high speeds because of noise detecting or sudden jumps are filtered. Although it has some errors, the speed estimation module presents valuable information on the traffic flow and movement pattern.

Table 5. Speed Metrics

Model	Value
Average Speed	28.96 units
Maximum Speed	Maximum Speed

E. The system successfully captures speed variations, although extremely high values are filtered to reduce noise.Traffic Signal Decision Results

Among the most significant contributions of the system is the possibility to come up with intelligent recommendations of the traffic signals based on the real-time information. The system takes the number of vehicles in each lane and the traffic volume to decide which lane is busier and give it green signal time.Table 6. Traffic Decision Report

Parameter	Value
Busier Lane	Right Lane
Vehicles in Left Lane	160
Vehicles in Left Lane	2671
Recommended Green Time (Left)	1.7 sec
Recommended Green Time (Right)	28.3 sec

The proposed CNN–LSTM + RoBERTa model has better accuracy than a number of traditional machine learning and deep-learning based models that are reported in the past studies

F. Discussion

Through the experiment, it is proven that the suggested traffic monitoring system can be used to analyze the actual situation on the road. The detection module based on YOLO is able to detect vehicles in other frames and in various conditions. The lane-wise analysis assists in determining the distribution of traffic whereas density estimation gives information on the level of congestion. Speed estimation module gives additional information about the motion of the vehicle, but with minor errors that may be introduced by frame differences and tracking limitations. The greatest success of the system is that it can produce intelligent recommendations of the traffic signals. This system enables the busier lane to be given a longer green signal time and therefore ease the congestion and further build on the overall flow of traffic. Overall, the proposed system will be a convenient and practical, and affordable measure to real-time monitoring of traffic and smart traffic lights control, which is why it can be adopted in the intelligent transportation systems.

5.CONCLUSION

This project has created a real-time traffic monitoring and analysis system based on deep learning and computer vision techniques. The proposed system will use the YOLO algorithm to identify vehicles in traffic video streams and conduct a detailed analysis of the traffic, such as counting vehicles, distributing vehicles by lanes, estimating the traffic density, and calculating speed. The system manages to handle real-time video feed and derive valuable information with every frame. Results of the experiment indicate that the model can identify many vehicles with high accuracy even in different conditions of the traffic. It was able to detect 2831 vehicles out of 307 frames, indicating that it was very effective in dealing with congested traffic conditions. The lane by lane analysis showed a major difference in the distribution of traffic as the right lane was found to be a lot more congested than the left lane. This points to the need to have lane-based traffic monitoring to make a better decision. The traffic density estimation module was useful in estimating the level of congestion and the speed estimation module offered more information about the movement patterns of vehicles. One of the benefits of this system is that it can be used to produce smart traffic signal suggestions. The system can dynamically assign the green signal time by examining the lane-by-lane numbers and density, so that busier lanes get a higher priority. This will be beneficial in alleviating traffic congestion and also enhancing traffic flow.

In general, the suggested system can be used to show that real-time vehicle detection, lane analysis, density estimation, and decision-making can be combined to make a significant improvement in managing traffic. The system is effective, scalable and can be deployed in smart city applications and intelligent transportation systems.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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