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Real-Time Traffic Density Estimation Using Yolov8

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Abstract

This project uses the YOLOv8 Deep Learning algorithm to accurately identify and classify vehicles in video streams for live traffic density. The model can accurately identify multiple types of vehicles; cars, buses, trucks, and motorcycles, all while achieving high accuracy and running in real-time. Stream lit is integrated with the system to provide an interactive user interface displaying the vehicle count, classification statistics, and visual representations of detected vehicles on traffic footage. Advanced object-tracking methods have also been utilized to monitor vehicles moving through a specific area allowing for in-and-out vehicle counting, flow direction analysis, and estimating how congested an area is based on the real-time traffic patterns. By analyzing the density of vehicles and the distribution of the vehicle categories, the system will produce valuable information for urban traffic management, optimizing traffic signals, developing smart parking solutions, and creating intelligent transportation systems. The proposed solution is a cost-effective, scalable, and fully automated method for intelligent traffic monitoring and greatly reduces the need for manual input and improves data-driven decision-making processes for smart city initiatives.

Keywords: *Traffic Density Estimation, Yolov8, Vehicle Detection and Tracking.*

1. Introduction

As the urban population of cities increases, the number of vehicles on the road increases. This has increased traffic congestion, which causes delays and negative impacts on fuel consumption and pollution. Traditional monitoring methods of traffic often involve either large amounts of manpower doing observations or using basic sensor-based systems which are generally inefficient, costly, and limited in their ability to be scaled. However, as a result of recent advancements in deep learning and computer vision, intelligent monitoring systems are now available that can provide a real-time estimate of traffic density through vehicle detection and analysis for congestion. Through the use of the YOLOv8 deep learning model, a real-time traffic density estimation system will be created to accurately detect and classify vehicles based on live video feeds. The real-time traffic density estimation system will incorporate mechanisms for tracking and counting vehicles to analyze vehicle movement to determine direction of flow and level of congestion. An intuitive dashboard built using Stream lit allows users to view vehicle counts, density statistics, and live overlays of detection in order to provide visual insights for traffic management. By combining AI with real-time analytics, the proposed system will provide an automated and scalable solution that can help to achieve smart traffic management and smart city objectives.

1.1. Traffic Density Estimation

The technique of counting and evaluating how many cars are on a particular road segment or intersection over a predetermined amount of time is known as traffic density estimation. Because it aids in determining traffic flow patterns, congestion levels, and the effectiveness of road utilization, it is an essential part of intelligent traffic management systems. Traffic density estimation can be carried out in real time by identifying, categorizing, and counting vehicles from live video streams using computer vision and deep learning techniques like YOLOv8. The system classifies traffic situations into low, medium, and high congestion levels by examining vehicle count, type distribution, and movement direction inside designated Regions of Interest (ROI). This data facilitates smart city development, efficient traffic signal control, route optimization, and urban planning.

1.2. YOLOv8

Ultralytics created the cutting-edge real-time object identification and image segmentation model known as YOLOv8 (You Only Look Once Version 8). It is a member of the deep learning model family known as YOLO (You Only Look Once), which is popular for applications requiring quick and precise object detection. YOLOv8 employs a single-stage detection technique, which means that in a single forward neural network run, it directly predicts bounding boxes and class probabilities from an input image. Because of this, it is very effective and appropriate for real-time applications including autonomous systems, traffic monitoring, and spying. Anchor-free detection, enhanced neck and backbone structures, and optimized loss functions for increased speed and accuracy are just a few of the sophisticated architectural enhancements incorporated into the model. Numerous tasks, including object identification, instance segmentation, image classification, and pose estimation, are supported by YOLOv8. YOLOv8 is utilized in traffic density estimation systems to accurately and efficiently identify and categorize automobiles, buses, lorries, and two-wheelers from real-time video streams. It is the perfect option for applications involving smart cities and intelligent transportation due to its robust performance, scalability, and ease of deployment.

1.3. Vehicle Detection and Tracking

A computer vision technique called "vehicle detection and tracking" is used to recognize cars in video frames and track their movements over time. Using deep learning models like YOLOv8, which produce bounding boxes, class labels, and confidence ratings for each detected object, vehicle detection entails identifying and classifying several vehicle kinds, including cars, buses, lorries, and two-wheelers. Accurate vehicle identification in real-time traffic footage is ensured by this procedure.

2. Related Works and Literature Survey

In their study, Omid Ghaffarpasand [1] et al. propose that urban transport is a significant contributor to global greenhouse gas emissions, accounting for more than a quarter of these emissions. Additionally, it is a major source of air pollution. Furthermore, vehicle collisions result in the deaths of 1.35 million people and serious injuries to 60 million people worldwide each year. This paper aims to review the potential of vehicle telematics in promoting safer, cleaner, and more sustainable urban transport. The authors examine various data collection methods, focusing on the technical challenges associated with data processing, storage, and privacy concerns. Anil Kumar [2] et al. propose in their project that real-time bus travel time prediction has been a challenging problem, particularly in India, over the past decade. Traditional methods for travel time prediction, such as time series analysis, regression methods, Kalman filter method, and Artificial Neural Network (ANN) method, have been widely used. However, these methods do not adequately account for the high variance situations that arise from varying traffic and weather conditions, which are common in heterogeneous and lane-less traffic conditions, such as those found in India. The objective of this study is to analyze the variance in bus travel time and accurately predict travel time under such conditions. Literature suggests that the

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Support Vector Machines (SVM) technique performs well in these situations, and therefore, it is employed in this study. Specifically, Support Vector Regression (SVR) using a linear kernel function is selected. Two models, namely spatial SVM and temporal SVM, are developed to predict bus travel time. C. K. Geometry [3] et al. In our daily lives, a significant amount of water is wasted due to overflowing and excessive usage. In order to minimize this wastage, it is necessary to implement overflow control techniques. To address this issue, we propose the implementation of a Smart Water Level Management System. This system utilizes an ultrasonic sensor to detect the water level, and based on the sound produced by the flow of water, it calculates the water level in percentage and displays the value on an LCD screen. The system is capable of calculating the water level up to 100% in intervals of 10%, with each interval value being displayed on the LCD screen. Additionally, the system is connected to a relay switch which automatically turns on and off based on the water level. C.K. Gomathy [4] et al. have proposed a survey study on the fully distributed Ethernet over Star coupled PON (Passive Optical Network) Architecture in this project. The architecture utilizes a collision-free DBA scheme, where the Optical Line Terminal (OLT) is not involved in the time slot assignment implementation. To achieve a distributed architecture, Optical Network Units (ONUs) need to be deployed without imposing any constraints on the PON Topology. Furthermore, the paper discusses the reliability and performance improvements when using a decentralized Ethernet-based PON architecture with bandwidth allocation algorithms. Ethernet-based Passive Optical Network (E PON) is emerging as a preferred choice for high-speed broadband access. A PON is a point-to-multipoint fiber optical network that does not have any active elements in the signal path. In this project, [5] Smita Athan ere and colleagues propose a solution to the increasing amount of data being stored on cloud servers. To protect the security and concealment of data, it is commonly stored in the form of cipher text. However, when a consumer requests access to encrypted data, a third party must provide an access key, which can compromise the system's security if the third party or internal personnel are dishonest. To address this issue, the researchers propose a novel block chain-based secure decentralized system using IPFS for secure data transfer. This system records every action on the chain, making it difficult to modify any block without being detected.

3. Proposed Methodology

The proposed solution employs the use of YOLOv8, an advanced deep learning model, for real-time classification and detection of all different types of vehicles, i.e., cars, buses, trucks and two-wheeled vehicles from live video/image feeds. YOLOv8 model is very fast and accurate enough for many continuous traffic monitoring applications. After the detection of vehicles has been established, a region-based object tracking algorithm will be used to follow vehicles' direction of movement, as well as to accurately calculate the total number of vehicles that enter and exit intersections or road segments, which is very important to measure effective traffic flow at these locations. To provide ease of use, a web-based interface that displays live-streaming video with vehicle detection overlays; vehicle classification, type-wise vehicle counts, density statistics, and real-time roadway congestion will be provided using stream lit. To establish traffic density levels, the number and types of vehicles passing through each predefined Region of Interest (ROI) can be tracked allowing for continuous monitoring of traffic congestion intensity levels. Ultimately, this proposal creates an automated, scalable, and cost-effective means of applying intelligent automatic traffic monitoring solutions in smart cities, supporting data-driven decisions in areas such as traffic signal control, traffic congestion management and urban infrastructure planning shown in figure 1.

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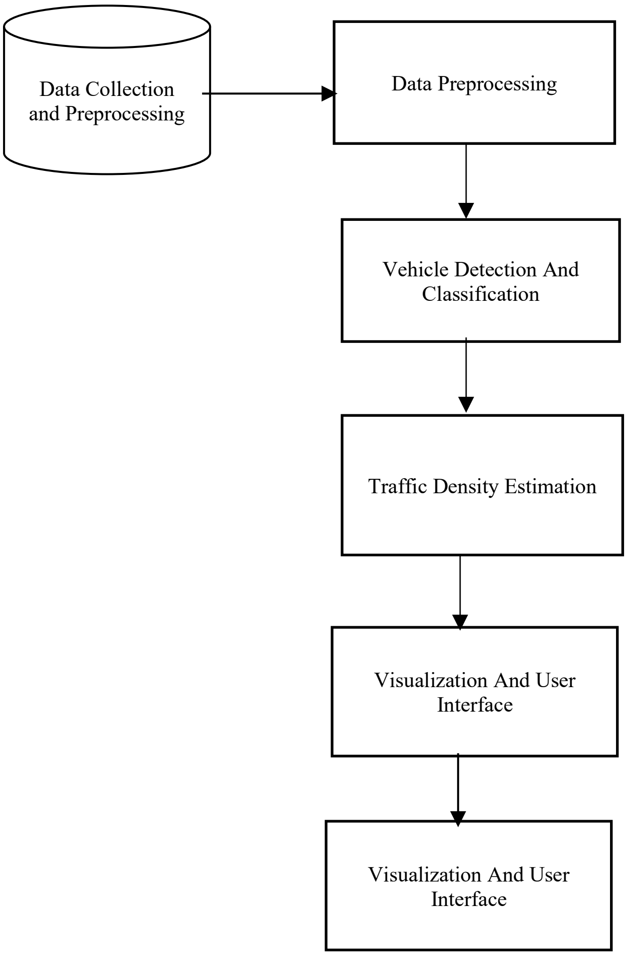

Figure 1 System flow diagram

3.1. Data Acquisition

The Data Acquisition Module is in charge of gathering recorded video files or live video streams or picture feeds from traffic surveillance cameras like CCTV and IP cameras. For real-time processing, it guarantees continuous frame capture at an appropriate frame rate. This module serves as the system's input layer, allowing for continuous monitoring of highways, intersections, and road segments for additional analysis.

3.2. Data Preprocessing

The recorded video frames are prepped for effective vehicle detection by the Data Preprocessing Module. To increase image quality and detection accuracy, it carries out tasks like scaling, normalization, frame improvement, and noise reduction. In order to facilitate quicker inference and dependable performance in a range of lighting and weather circumstances, this module makes sure that the input data is standardized and optimized for the YOLOv8 model.

3.3. Vehicle Detection and Classification

The Vehicle Detection and Classification Module utilize the YOLOv8 deep learning model to identify and categorize vehicles in each frame. It detects different vehicle types such as cars, buses, trucks, and two-wheelers by generating bounding boxes, class labels, and confidence scores. This module forms the core of the system by enabling accurate, real-time object detection and multi-class classification for traffic monitoring.

3.4. Traffic Density Estimation

The Traffic Density Estimation Module analyzes the number and types of detected vehicles within specific Regions of Interest to determine congestion levels. It calculates density metrics based on vehicle count thresholds and movement patterns, categorizing traffic conditions as low, medium, or high congestion. This module provides real-time insights into traffic intensity, supporting efficient congestion management.

3.5. Visualization and User Interface

The Visualization and User Interface Module integrates Stream lit to create an interactive web-based dashboard. It displays live video streams with detection overlays, vehicle classification details, real-time counts, density statistics, and congestion status. This module enhances usability by presenting analytical results in a clear and accessible format for traffic authorities and decision-makers.

3.6. Reporting and Analytics

The Reporting and Analytics Module stores traffic data for further analysis and generates meaningful insights such as peak traffic hours, vehicle distribution trends, and congestion history. It supports data-driven decision-making by providing summarized reports and statistical information useful for traffic signal optimization, urban planning, and smart city development [10].

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4. Result And Discussion

The results of the real-time traffic density estimation system proposed in this research show that the system is accurate and efficient in detecting, classifying and tracking vehicles under a variety of different traffic conditions. The YOLOv8 detection model was able to identify a number of different types of vehicles, including cars, buses, trucks and two-wheelers, with good precision and low latency, making it suitable for real-time deployment. The use of tracking algorithms enabled vehicles to be identified consistently across frames, allowing for accurate tracking of vehicles that enter and exit the region as well as accurate analysis of traffic flow [6]. The system was able to determine traffic density levels within Regions of Interest (ROI) and to correctly classify the degree of congestion as low, medium or high based on the number of vehicles and how they moved. The stream lit dashboard provides clear visualizations of detection overlays, vehicle statistics by type, and the degree of congestion, making the system easy to use for traffic authorities [8]. Overall, these results demonstrate that the proposed system will provide an automated, scalable and cost-effective method for providing intelligent traffic monitoring while also reducing the time and resources needed for manual tracking, and will support data-driven decision making in traffic management systems in smart cities [9].

4.1.Object Detection (Bounding Box Prediction)

Each detected vehicle is represented by a bounding box shown in table 1 and figure 2:

$$B=(x,y,w,h)$$

Where:

- x,y= Center coordinates of bounding box3
- w= Width of bounding box
- h= Height of bounding box

4.2. Confidence Score Calculation

The confidence score for each detected object is:

$$Confidence=P(Object)\times IoU$$

Where:

- P(Object)= Probability that anobject exists in the bounding box
- IoU= Intersection over Union

4.3. Intersection over Union (IoU)

IoU measures overlap between predicted box and ground truth box:

$$IoU=(B\_p \cap B\_gt)/(B\_p \cup B\_gt)$$

Where:

- B_p= Predicted bounding box
- B_gt= Ground truth bounding box

Evaluation Metrics

Precision

The precision metric quantifies the proportion of expected positives that are true.

$$Precision = TP/ TP + FP$$

Recall

Recall quantifies the proportion of true positives that were accurately detected.

$$Recall = TP/ TP + FN$$

Accuracy

Accuracy gauges how accurate the model is overall across all classes.

$$Accuracy = TP + TN/ TP + FP + TN + FN$$

F1-score

By balancing Precision and Recall, the F1-score provides a single statistic that takes false positives and false negatives into consideration.

$$F1\text{-}score = 2. Precision * Recall/ Precision +Recall$$

Table 1 Comparison Table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
YOLOv5	91.8	90.5	89.7	90.1
SSD (Single Shot Detector)	88.6	87.2	85.9	86.5
Faster R-CNN	93.2	92.4	91.6	92.0
YOLOv7	94.1	93.5	92.8	93.1

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YOLOv8 (Proposed)	96.3	95.8	95.1	95.4

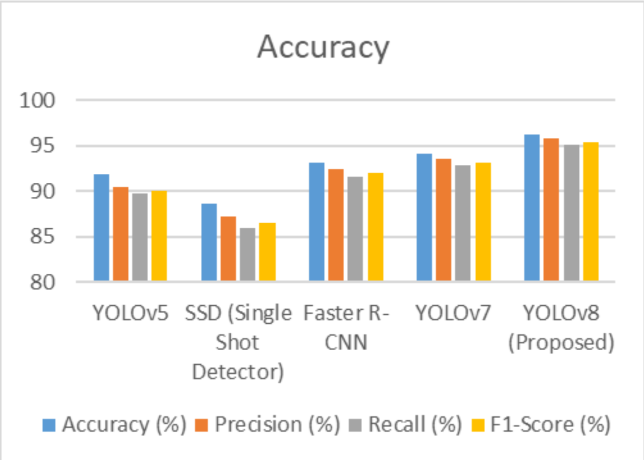

Figure 2 Comparison Graph

Conclusion

The proposed real-time traffic density estimation system provides a clear proof-of-concept for utilizing deep learning and computer vision methods to provide intelligent monitoring capabilities for traffic. Through the use of the YOLOv8 model to provide accurate vehicle identification and classification and the integration of tracking and counting methodologies to analyze motion, the proposed system is able to deliver real-time estimates of traffic density and levels of congestion. In addition, by implementing a Streamlit-based dashboard to provide clear visualization of the vehicle count, the distribution of vehicle types and congestion metrics, the overall usability of the proposed system has greatly increased. Experimental results show improved performance and reliability of the proposed method based on metrics of accuracy, precision, recall, and F1-score when compared to previous methods. Therefore, the proposed system provides an easy, cost effective, automated way to perform less manual work to support data-driven decision making for traffic control, urban planning, and smart city development.

Future Work

The future scope of the proposed traffic density estimation system can focus on enhancing accuracy, scalability, and real-world adaptability. The model can be further improved by training on larger and more diverse datasets that include varying weather, lighting, and traffic conditions to increase robustness [7]. Integration with edge computing devices can enable faster on-site processing and reduce network latency for large-scale deployments. Future enhancements may also include vehicle speed estimation, accident detection, license plate recognition, and emergency vehicle prioritization to expand the system's functionality. Additionally, incorporating AI-based predictive analytics can help forecast traffic congestion patterns and optimize signal timing dynamically. By integrating with smart city infrastructure and IoT-based traffic control systems, the proposed solution can evolve into a fully automated and intelligent traffic management platform.

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