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Nighttime Rainy Season Traffic Analysis: Vehicle Detection, Tracking, and Counting with YOLOv8 and DeepSORT

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Abstract

This research focuses on developing a reliable computer vision system for accurately tracking traffic density in India during the rainy season. The system uses deep learning-based techniques to handle the difficulties associated with vehicle detection and tracking. The three modules are vehicle detection, tracking, and vehicle counting. Vehicles are initially identified using the YOLOv8 algorithm, a state-of-the-art deep learning detector. Subsequently, the DeepSORT algorithm is utilized for multi-object tracking to ensure accurate and robust tracking of various objects, including cars, buses, trucks, bikes, and pedestrians. The importance of accurate vehicle counting and speed measurement is emphasized, especially during bad weather. An independently compiled dataset of Indian rainy conditions is used to assess the proposed computer vision system. The outcomes demonstrate the system's capability to accurately identify, track, count, and estimate the speeds of vehicles. These features offer insightful information for traffic analysis, including flow monitoring, congestion detection, and other associated traffic challenges. This study makes a contribution to the field of computer vision-based traffic monitoring and offers potential applications in transportation management systems under challenging weather conditions.

Keywords: Traffic density tracking, Vehicle detection, Vehicle tracking, Vehicle counting, YOLOv8 algorithm, DeepSORT Algorithm

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1. Introduction

Traffic monitoring plays a crucial role in various aspects of transportation management, including vehicle counting [1], accident detection, vehicle speed analysis, route planning, preventing road congestion, and assisted traffic surveillance [2]. Computer vision systems have emerged as powerful tools for tackling these tasks by leveraging image and video processing techniques. A traffic monitoring system's main goal is to identify moving objects in a video image, determine their location and speed, and offer a thorough framework for analyzing traffic conditions. Accurately measuring the number of vehicles during adverse weather conditions, particularly rainy weather at nighttime, poses significant challenges. Overcoming these challenges is essential for enabling practical applications that contribute to the advancement and effectiveness of transportation, traffic management, and parking systems [3].

In this research, focuses to create a reliable computer vision system that can precisely track traffic density in India during the rainy season. The study aims to target multiple objects, such as cars, buses, trucks, bikes, and pedestrians. The approach utilizes the YOLOv8 and DeepSORT [4]algorithms, which are state-of-the-art techniques for vehicle detection and vehicle tracking, respectively.

Vehicle detection is a crucial step in identification of the type of target objects and their localization inside them within a video frame. There are two types of object detection algorithms: traditional machine learning methods and deep learning approaches. In order to precisely recognize vehicles in adverse conditions, the research uses deep learning-based object detection algorithms, specifically YOLOv8.

The following stage after finding the vehicles is vehicle tracking, which entails re-identifying the detected objects and connecting them to their best-matched counterparts over a series of frames. With the use of vehicle tracking, the motions and trajectories of vehicles throughout time can be tracked. In this study, the DeepSORT algorithm is used, which excels at multi-object tracking, ensuring reliable and accurate vehicle tracking under challenging weather conditions.

Important components of the research include accurate vehicle counting and speed measurement. It is useful for transport systems, traffic management plans, and parking systems to have accurate estimates of the number of vehicles on the road, especially at night when it is raining. The devised method scopes to assess the effectiveness of the technique in actual and difficult conditions by utilizing the suggested computer vision system and the self-collected Indian rainy dataset. The findings from this research could advance the field of computer vision-based traffic monitoring and help improve transportation management systems in bad weather.

In the following sections, the study explores the methodology, experimental setup, results, and analysis, highlighting the contributions of the research. Additionally, the implications and potential future research directions in the domain of traffic density detection, tracking, vehicle counting, and speed measurement under rainy weather conditions is also discussed.

2. Related Work

The use of computer vision technology has become integral to intelligent traffic monitoring systems. However, adverse weather conditions and low-light environments present significant challenges in detecting and tracking moving objects, including bicycles, vehicles, buses, and motorbikes. Such difficulties are particularly pronounced during inclement weather conditions such as rain, fog, and snow. In this section, the previous research that specifically addresses the detection and tracking of vehicles, highlighting its relevance to the development of computer vision-based traffic monitoring systems is explored.

Real-time highway traffic monitoring systems are required because effective road traffic management is essential to preventing congestion, violations, and accidents [5].Provides a bounding box-based vehicle tracking technology and suggests a novel method to improve the accuracy of YOLO's vehicle categorization. In order to do this, a brand-new vehicle dataset is built, and a number of machine learning-based classifiers are trained and assessed. YOLO is then merged with the classifier that performs the best. The classification accuracy of the YOLO-based vehicle detector is dramatically increased from 57% to 95.45% by adding the best classifier. The overall performance was improved by the combination of vehicle detector 2 (YOLO + best classifier) and Bbox-based tracking (vehicle tracker 2).

The implementation of self-driving cars (SDC) and advanced driving assistance systems (ADAS) is specifically targeted by the Real-Time Vehicle Detection and Tracking (RT_VDT) technique, described in [6]. The efficient and accurate recognition and tracking of moving vehicles is the main goal of the RT_VDT technology. A strong pipeline of computer vision algorithms transforms RGB pictures into exact bounding boxes for vehicle identification to achieve this. Real-world road images and videos are used to validate the RT_VDT method's performance, showing that it consistently produces accurate results. The paper also discusses the method's apparent limitations and considers possible directions for further development.

The [7] offers a successful real-time technique that concentrates on vehicle detection and counting using fixed cameras. Utilizing convolutional neural networks and regression networks, the suggested method integrates YOLOv2 with feature point motion analysis. The approach consists of a number of steps, including the identification of the vehicle, refinement using K-means clustering and KLT tracker, and counting based on temporal data. The results of the experiments showed that the proposed system outperforms cutting-edge methods and performs better than other methods like F R-CNN and BS-CNN, especially in terms of average time efficiency.

In this research study [8] [9], a comprehensive investigation is conducted on the effectiveness of advanced object detection and tracking algorithms for the precise detection and tracking of diverse vehicle classes. To confirm the automatic vehicle counts, the researchers [8] compared them to manually counted true statistics using approximately 9 hours of traffic video data from the Louisiana Department of Transportation and Development.. The experimental findings demonstrate that the combination of CenterNet and Deep SORT, Detectron2, and Deep SORT, and YOLOv4 and Deep SORT achieves the highest overall counting percentage for all vehicle categories, helping in obtaining accurate vehicle counting statistics.

A simple single-camera solution was taken into consideration in a study by [10], making it available to a wide variety of people who own a smart-phone camera. Their main goal was to quickly and effectively process recorded videos. By concentrating on tracking each vehicle's condition throughout the film and then calculating the overall count, the process of counting vehicles was made simpler. The two sub-problems that the study tackled were object detection and multi-object tracking (MOT). For accurate object detection, notably for identifying vehicles, the YOLOv5 algorithm was used. On the other hand, the system was able to track numerous vehicles at once thanks to the use of DeepSORT for strong multi-object tracking.

A vehicle detection and tracking approach using the DeepSORT algorithm built on the YOLOv4 model was introduced in a study [11]. The number of vehicles going by within a given time period, extending from the beginning of recording to the final recorded instance, was counted by the researchers using real-time surveillance cameras installed at highways or recorded films. With an average precision (AP) of 82.08% at a 50% intersection over the union (IoU) threshold (AP50) using a customized dataset, the YOLOv4 model showed state-of-the-art performance. On a GTX 1660ti graphics processing unit (GPU), the solution demonstrated real-time processing capabilities at a speed of about 14 frames per second (FPS).

3. Methodology

The proposed process consists of three steps: detection, tracking, and counting. The state-of-the-art techniques, were extensively used in the field of computer vision to do these jobs. The proposed work uses the efficient YOLOv8 algorithm that excels in accuracy and in speed for object detection, which. In terms of object tracking, the DeepSORT, a multi-object tracking algorithm known for its ability to monitor numerous objects of different classes at the same time while maintaining real-time high processing performance is used. These sophisticated approaches are used in the proposed work to get robust and reliable results in object detection and tracking

3.1 Data Collection

A self-collected dataset acquired under the tough rainy night circumstances in Bangalore, India, is used for this study. The video has a run-time of 1 minute and 34 seconds with a frame size of 1280x720. Figure 1 shows an image from video dataset reflecting various kinds of vehicle and rainy weather. This dataset's major goal is to include a wide range of vehicles encountered in real-world circumstances. By specifically opting for this type of dataset, the significant influence of adverse weather conditions are acknowledged in the accuracy of object detection algorithms, particularly in the context of traffic events.

Figure 1. Traffic in Rainy Weather.

3.2 Vehicle Detection

The YOLO network is created from three key components: the Backbone, the Neck, and the Head. The backbone of the model is made up of a convolutional neural network that creates visual features in the images. Layers in the Neck, blend and transform these features before forwarding them to the prediction phase. The Head uses the combined features from the Neck to anticipate box and class predictions. Ultralytics [12] released YOLOv8 in 2023, as shown in Figure 2, with some architectural changes from the previous model, YOLOv5. YOLOv8 replaces the C3 module in the backbone architecture with the C2f module, which is based on Cross Stage Partial (CSP). The CSP design improves the convolutional neural network's (CNN) learning capability while lowering computational complexity. The C2f module is made up of two Conv. Modules and many BottleNecks that are linked together using Split and Concat operations. With the addition of the SPPF Module at the last layer, the remainder of the backbone architecture stays identical to YOLOv5.

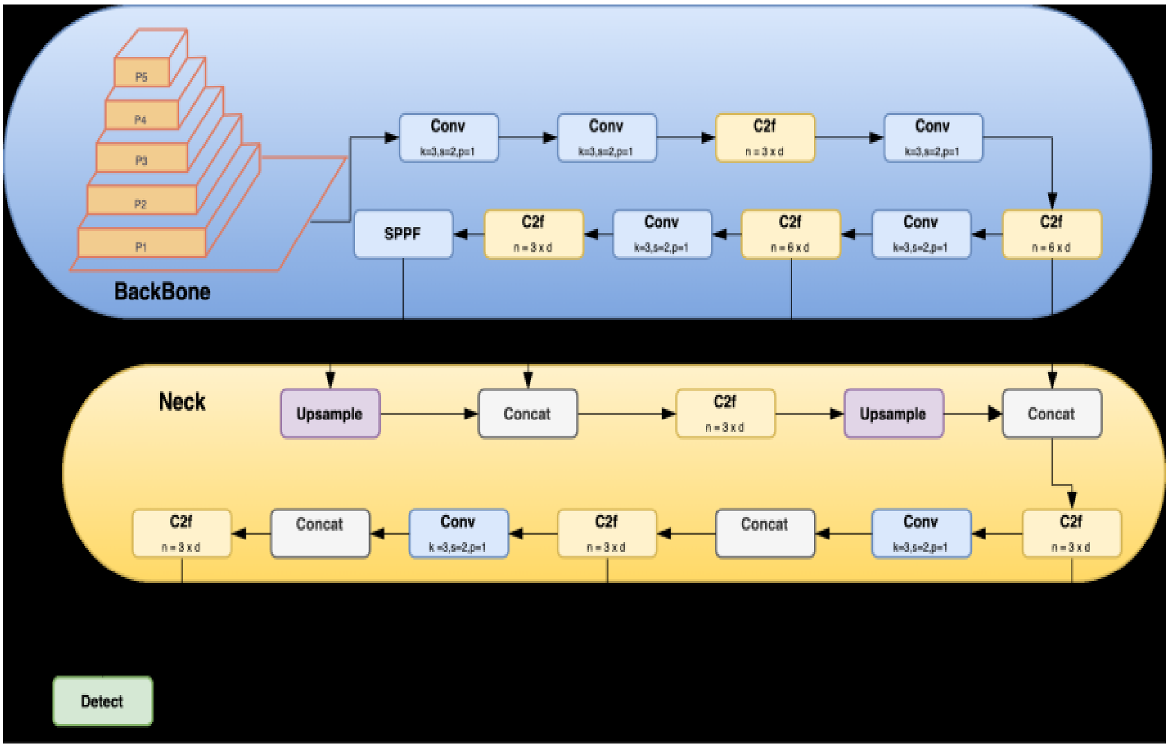


Figure 2. Architecture of YOLOv8 [13].

YOLOv8 [14] performs admirably on the COCO dataset, outperforming YOLOv5 substantially when compared to the Roboflow 100 dataset. YOLOv8 is an anchor-free model, which implies that it predicts the center of an object directly rather than computing offsets from specified anchor boxes. This anchor-free method minimizes the overall number of box predictions, resulting in quicker Non-Maximum Suppression (NMS), a sophisticated post-processing phase that filters object detections coming after inference.

3.3 Vehicle Tracking

SORT (Simple Online and Real-time Tracking) is a framework for tracking by detection developed for online and real-time tracking applications [15]. Its major goal is to recognize objects in each frame and create correlations for tracking. Simple Online and Real-time Tracking with a Deep Association metric (Deep SORT) incorporate appearance information into the tracking components to support multi-object tracking [16]. This integration is accomplished by using a combination of the Kalman Filter and the Hungarian algorithm. The Kalman Filter performs tracking in image space, but the Hungarian method permits frame-by-frame data connection with an association metric that determines bounding box overlap. A trained convolutional neural network (CNN) is used inside the framework to collect both motion and appearance information.

3.4 Vehicle Counting and Speed Measurement

In this section the vehicle counting and speed measuring techniques in a Nighttime Rainy Season Traffic Analysis is presented. Here for vehicle counting the Dequeue technique used, which stands for the double-ended queue, or DQ. DQ is opted since it outperforms the Python list in terms of quick add and pop operations. This allows us to retain the unique IDs issued to each item when it enters a frame in an efficient manner. unique ID is simply appended to the right end of the queue when an object enters into the frame and is deleted when the object departs from the frame by utilizing DQ.

the Euclidean distance formula, see Eq. 1 is used to detect vehicle speed.

$$d = \sqrt{[(x_2 - x_1)^2 + (y_2 - y_1)^2]} \tag{1}$$

where, (x_1, y_1) are the coordinates of one point, (x_2, y_2) are the coordinates of the other point, and d is the distance between (x_1, y_1) and (x_2, y_2). The idea of pixel per metre (PPM), is also incorporated. This number can be dynamically modified depending on the closeness of the item to the camera, with a greater PPM value for things closer to the camera and a lower PPM value for objects further away. The distance in meters are determined using the Euclidean distance formula and dividing the distance in pixels by the PPM. A time constant of 0.15, which is multiplied by 3.6 to convert time from seconds to kilometers per hour is also included. Finally, using Eq. 2, speed is computed by dividing the distance by the time.

$$\text{Speed} = \text{Distance} / \text{Time} \tag{2}$$

vehicle movements in the Nighttime Rainy Season Traffic Analysis are properly tracked and analysed by combining the vehicle counting system based on the Dequeue method with the speed measurement methodology based on the Euclidean distance formula. These approaches help to provide a thorough knowledge of traffic dynamics in adverse weather circumstances, providing for useful insights and informed decision-making in traffic management and road safety.

4. Experimental Setup

The proposed framework was trained as part of the experimental design for this study using the Google Colab cloud platform, which provides an effective Graphics Processing Unit (GPU) tool without the need for further preparation., As the deep sort method and the YOLOv8 pre-trained weights are used in the research work it was possible to utilize the network's learned features and accelerate the training process. The pre-trained weights and the dataset were both downloaded and made available inside the Colab environment. In order to meet the goals of this study, the proposed model was trained to detect and count vehicles from several classes, such as "car," "bus," "truck," "bike," and "pedestrian". Additionally, the speed of the detected vehicles was estimated. The Figure 3 shows the proposed workflow.

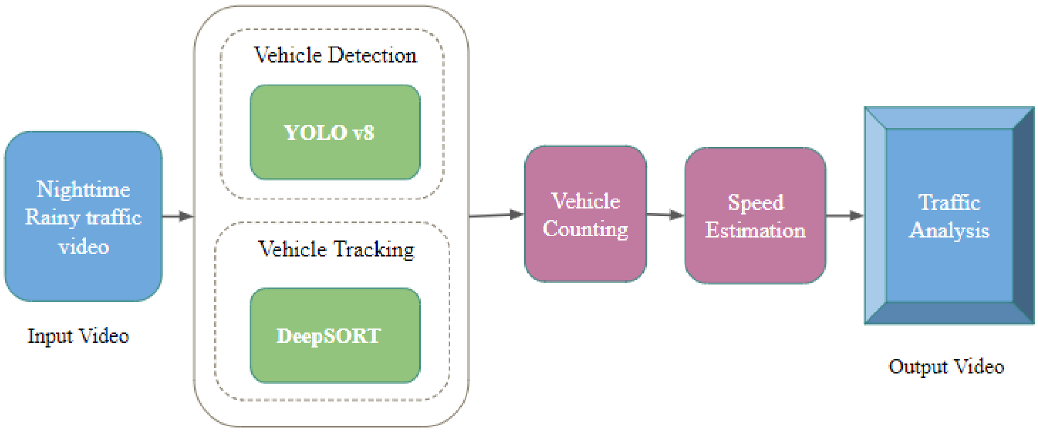


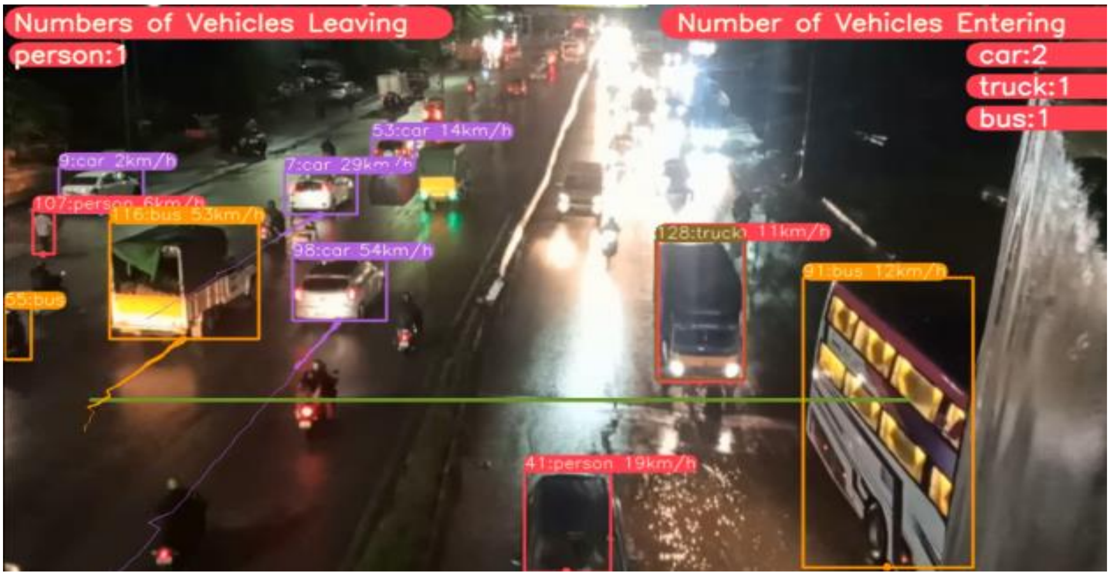
Figure 3. Our Proposed Workflow.

5. Results and Discussion

In this study, a pre-trained YOLOv8 model and the TensorFlow framework on Google Colab is used for experimental analysis. The pre-trained models were used to get around the limited quantity of data in the experimental database enabling an in-depth learning. The experiments were carried out in rainy video clips from the dataset to assess the models' performance. The surveillance footage in the collection was deliberately captured at night and in a rainy environment. With the help of this dataset, the model's performance in identifying and classifying objects in adverse conditions, notably in scenarios with night rain was evaluated.

A dynamic distance measurement approach based on the distance between objects and the camera was implemented. This involved using a formula that multiplies the pixel distance by the PPM(pixels per meter) value, multiplies the result by a constant of 3.6, and then divides the result by the frame rate per second to determine the distance in meters. A function to determine the angle and speed based on time and distance was created.

A counter code was used in the implementation to keep track of how many vehicles entered and left the region of interest area. The counter code showed the overall number of entering vehicles as well as sub-counts for each type of vehicle, such as cars, trucks, and motorbikes. a line-crossing mechanism that increases the counter whenever a vehicle passes the line as well as a speed estimating function was also designed. An indicator to notify the number of vehicles leaving was also added, to improve the performance of the system. The output result showed in Figure 4 with estimated speeds for each vehicle as well as the overall vehicle count and breakdown by kind of vehicle.



(a)

(b)

Figure 4. Results (a) and (b) with Detection, Tracking, Counting, and Speed Estimation.

The precise findings through the research, such as precise vehicle detection and segmentation, tracking IDs, and trails was acquired. As well as for properly estimating each vehicle's speed, the overall vehicle counts as well as sub-counts for various vehicle kinds were also included.

These findings demonstrate how well the suggested method works for precisely identifying, following, and counting cars as well as calculating their speeds. The effective implementation of these features demonstrates the developed system's potential for use in practical traffic monitoring and management applications.

6. Conclusion

In this study, a reliable computer vision system for accurately determining traffic density during India's rainy season—especially at night—was built. The system has shown considerable improvements in the field of traffic analysis by utilizing deep learning-based techniques, such as the YOLOv8 algorithm for vehicle detection and the DeepSORT algorithm for multi-object tracking. Through experimentation on a self-collected Indian rainy dataset, the system has shown remarkable accuracy in identifying, tracking, and counting various objects, including cars, buses, trucks, bikes, and pedestrians. The difficulties caused by adverse weather circumstances have been successfully managed by integrating YOLOv8 with DeepSORT. The advantages of deep learning algorithms over conventional methods, notably in the detection of small and low-vision objects, are further highlighted in the research. The figures and tables offer a systematic picture of which model combinations are effective in counting vehicles in adverse conditions. Because it can accurately identify vehicles in adverse conditions, the YOLOv8 system surpasses conventional machine learning.

Future research can focus on further enhancing the accuracy and efficiency of the system by exploring advanced deep-learning architectures, incorporating additional data sources, and considering real-time implementation. Integrating the system with existing traffic infrastructure and expanding its applicability to different geographic locations can broaden its practicality and impact in real-world traffic management scenarios.

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Author's biography

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