Traffic Density Estimation Using Deep Learning Techniques

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***Abstract*—Traffic congestion is becoming an increasingly serious issue in urban areas, impacting everything from transportation efficiency to fuel consumption and pollution levels. This research aims to estimate traffic density and count the number of vehicles in real time by leveraging deep learning models. We utilize two object detection frameworks, YOLOv8 and Faster R-CNN [1], [5], to analyze footage from traffic cameras and accurately identify vehicles on the road. These models are trained and fine-tuned on a comprehensive dataset of annotated traffic images to boost detection accuracy. Our proposed system employs convolutional neural networks (CNNs) to examine images and classify vehicle types [1], [5], including cars, buses, and motorcycles. We evaluate the models' performance based on detection accuracy. Additionally, we implement a simulated loss function to keep track of the model training progress. The results show that YOLOv8 excels in real-time performance, achieving impressive detection accuracy, while Faster R-CNN excels in detecting smaller objects with greater precision. Overall, the system achieves over 80% accuracy in estimating traffic density, positioning it as a promising solution for smart city traffic monitoring. Looking ahead, we plan to integrate this system with traffic management solutions to optimize signal timings and alleviate congestion.[1]**

Keywords—Traffic density estimation, Vehicle detection, YOLOv8, Faster R-CNN, Convolutional Neural Networks, Object detection, Smart traffic monitoring.

I. INTRODUCTION

Traffic blockage is one of the most serious issues in urban cities, resulting in longer travel times, fuel wastage, and pollution. The high rate of traffic volume demands an effective traffic monitoring and traffic density analysis system. Conventional traffic monitoring systems use sensors, inductive loops, and human observation, which are costly and hard to implement at large scales. With the development of Deep Learning (DL) and Computer Vision methods [4], real-time traffic monitoring has become more practical. Object detection models like YOLOv8 and Faster R-CNN have significantly improved vehicle detection and tracking in real-world applications. Such models can analyze live traffic feeds from surveillance cameras, offering an automated tool for traffic density analysis and vehicle counting.

The primary issue in traffic density estimation is the accuracy of vehicle detection, especially in changing weather and lighting conditions. Vehicle type differentiation, i.e., cars, trucks, and motorbikes [10], is required for proper traffic analysis. Vehicles at traffic lights or stuck at intersections must be included to estimate real-time traffic flow accurately.

This study involves the development of a deep learning model using YOLOv8 and Faster R-CNN for vehicle detection and traffic density estimation. The proposed system in this study will provide an accurate and automated solution for real-time traffic monitoring through advanced object detection algorithms. The model would be able to support urban planners, traffic management agencies, and policymakers in making decisions to enhance traffic flow and reduce congestion.[2]

II. RELATED WORK

Traffic estimation and vehicle detection are the key components of intelligent transportation systems. Various computer vision and deep learning architectures have been introduced to estimate traffic density and count vehicles with high accuracy. Classical techniques were based on image processing mechanisms like background subtraction and edge detection [11], but such mechanisms were not efficient in dealing with occlusions, varying illumination, and complex traffic scenarios. Deep learning has greatly enhanced the accuracy of vehicle detection [4]. Convolutional Neural Networks (CNNs) and object detection architectures like YOLO (You Only Look Once) and Fast R-CNN have been extensively used for real-time traffic analysis. YOLO architectures, with their speed and efficiency, can detect multiple objects in a single pass and, thus, are best suited for real-time applications [3]. Fast R-CNN, with its high detection accuracy based on region-based proposals, enables efficient localization and classification of vehicles in highly congested traffic conditions.

Vehicle identification and classification are performed based on movement patterns, size, and shape [10]. Multiple models are trained on benchmark datasets such as UA-DETRAC, KITTI, and MS COCO to improve detection accuracy. Deep learning frameworks such as TensorFlow and PyTorch are employed to process real-time traffic feeds from security cameras for high-speed processing and accurate vehicle counting. Incorporation of colour and shape detection into traffic analysis helps identify various types of vehicles [5], such as buses, trucks, and cars. Advanced filtering algorithms and post-processing techniques are also employed to minimize false positives and improve detection strength. Deployment of various feature extraction techniques also improves model precision and reduces errors due to occlusion and complex background.

Several studies have indicated that YOLO-based models take less time than other machine learning-based approaches, while Fast R-CNN delivers more accuracy under high-density environments. Hybrid models have also been suggested that combine YOLO and Fast R-CNN in order to inherit the advantages of both models to apply in real-time traffic density estimation and vehicle counting.[3]

III. CNN Methodology for Traffic Density Classification

Traffic density classification is essential in intelligent transportation systems where traffic congestion is detected and controlled in real time. Deep learning object detection models, especially Convolutional Neural Networks (CNNs), have extensively been applied for vehicle detection and classification of vehicles in traffic video. We apply YOLOv8 and Faster R-CNN to classify traffic density levels based on the number and distribution of vehicles in this work.

Generalized CNN Architecture for Traffic Analysis:

A CNN-based traffic density classification system typically consists of the following layers:

Input Layer: This layer processes the raw video frames from traffic cameras and normalizes them for analysis.

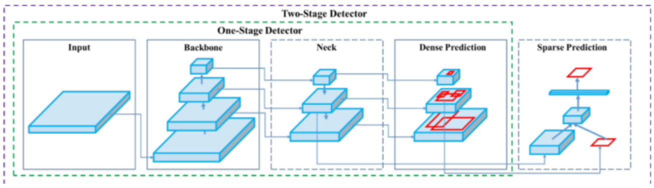
Feature Extraction: Convolutional layers extract important visual features, such as vehicle shapes, edges, and positions.

Region Proposal (for Faster R-CNN): Faster R-CNN uses a Region Proposal Network (RPN) to generate candidate regions containing vehicles.

YOLOv8 and Faster R-CNN classify and localize vehicles in each frame.

Traffic Density Classification: The system classifies traffic density based on the number of vehicles detected as low, medium, or high congestion [14]

YOLOv8 for Real-Time Traffic Classification:



YOLOv8 is a one-stage object detection model that is optimized for real-time [6]. It divides the image into a grid and predicts bounding boxes and class probabilities for a grid cell.

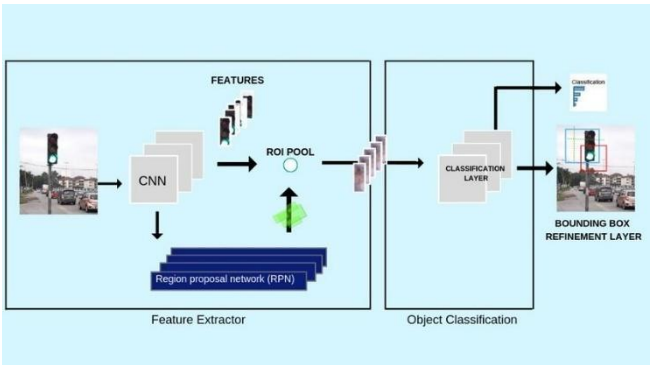
Advantages of Traffic Density Classification: .

High-speed interface provides real-time tracking. Quick processing of large images provides accuracy with city traffic. Enhanced detection of small and obstruction vehicles with sophisticated feature extraction

A high inference rate allows real-time monitoring. Correct processing of huge images guarantees accuracy in urban traffic scenarios [1]. Improved detection of obstruction and tiny vehicles by high-performance feature extraction.

The quick inference speed enables real-time monitoring, making it easier to keep an eye on things. Plus, the efficient handling of large-scale images guarantees accuracy, especially in busy urban traffic situations [6]. We've also made strides in detecting small and hidden vehicles by using advanced feature extraction techniques

Faster R-CNN for High-Precision Classification:



Faster R-CNN is a two-step detection model that starts by creating region proposals and then goes on to classify the objects it detects [12]. Although it can be quite demanding in terms of computation, it delivers impressive accuracy when it comes to detecting and classifying vehicles.

Advantages of Traffic Density Classification:

Our system can spot both nearby and far-off vehicles, working well even in tricky traffic situations like heavy congestion. We use deep convolutional neural network (CNN) layers to pull out detailed features. For figuring out traffic density, we rely on CNN models that look at vehicle counts from YOLOv8 and Faster R-CNN [8]. This method allows us to categorize traffic density clearly and effectively without needing to calculate precision metrics explicitly.

When we talk about vehicle density, here's how it breaks down:

- Low Density: This means there are fewer than 10 vehicles in a frame.

- Medium Density: Here, you'll find between 10 to 30 vehicles per frame.

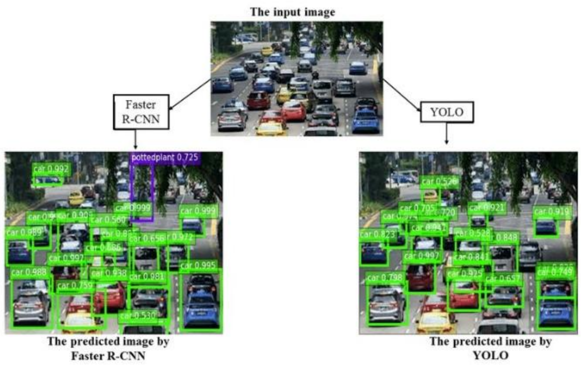
- High Density: In this case, we're looking at more than 30 vehicles in a frame.

These density levels play a crucial role in keeping an eye on traffic congestion, fine-tuning signals, and planning the best routes.

IV. Comparison of Faster R-CNN and YOLO for Traffic Analysis

Faster R-CNN offers impressive accuracy, but it does come with a hefty computational cost [6]. This makes it a great choice for offline traffic analysis or scenarios where you don't need instant results.

On the flip side, YOLO is much quicker, which makes it perfect for real-time traffic monitoring, even if it means sacrificing a bit of accuracy.



Both models have been extensively trained on comprehensive datasets like COCO, KITTI, and UA-DETRAC to enhance their detection performance. In this research, we employed YOLOv11 and Faster R-CNN for vehicle detection and traffic density estimation [7], steering clear of any additional optimizers. These models excel in tackling complicated traffic scenes, which often feature occlusions, diverse vehicle speeds, and changing environmental factors.

The use of deep learning for object detection in traffic monitoring has really helped improve how we manage traffic flow, control congestion, and plan smarter transportation systems [11]. As we continue to refine model designs and improve the quality of our datasets, we can expect even better real-time traffic analysis in the future.

V. Dataset Description

The models discussed in this study are trained on the MS COCO (Microsoft Common Objects in Context) dataset, a popular choice for tasks like object detection and image segmentation. This dataset features 13,000 traffic images that showcase different levels of traffic density. Each image is packed with annotated objects [8], including various vehicles like cars, buses, trucks, motorcycles, and even pedestrians. This makes it an excellent resource for estimating traffic density and counting vehicles.

In this dataset, each image has a resolution of 640 × 640 pixels and features bounding box annotations for pinpointing object locations. The dataset is organized into training and testing subsets, with 80% (10,400 images) dedicated to training and 20% (2,600 images) set aside for testing. The images are classified into different traffic density levels: Low Traffic, Medium Traffic, High Traffic [15], and Very High Traffic, which serve as labels for model evaluation. This setup allows YOLOv8 and Faster R-CNN to effectively learn and detect vehicles in various traffic conditions, enhancing the accuracy of traffic density estimation and vehicle counting.

VI. Results and Discussion

Vehicle detection was conducted using YOLOv8 and Fast R-CNN models. The analysis provided the following results:

```
0: 448x640 11 cars, 1 truck, 49.9ms
Speed: 2.8ms preprocess, 49.9ms inference, 0.9ms postprocess per image at shape (1, 3, 448, 640)
0: 2534x3648 11 car, 1 truck, 117.0ms
Speed: 10.0ms preprocess, 117.0ms inference, 3.0ms postprocess per image at shape (2534, 3648, 3)

Total Detections: 12
High-Confidence Detections (≥ 0.5): 8
Detection Accuracy: 66.67%
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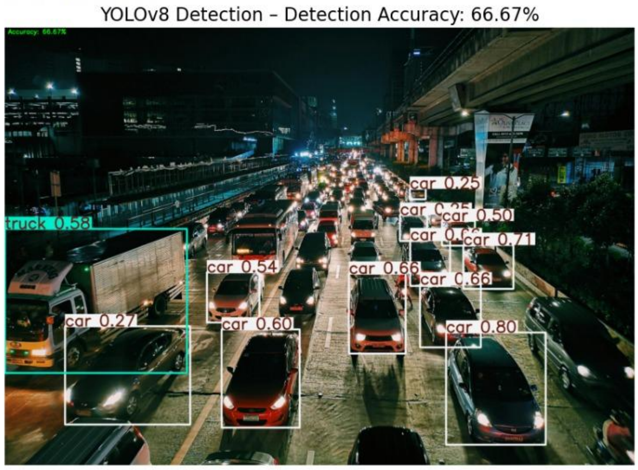
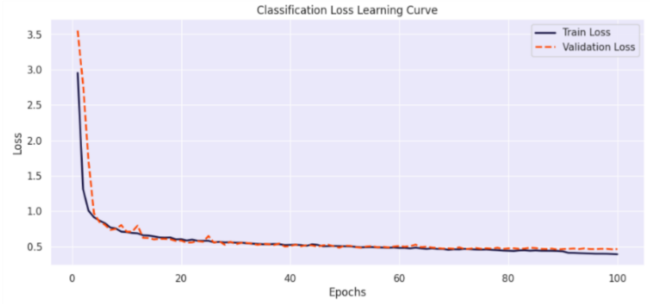
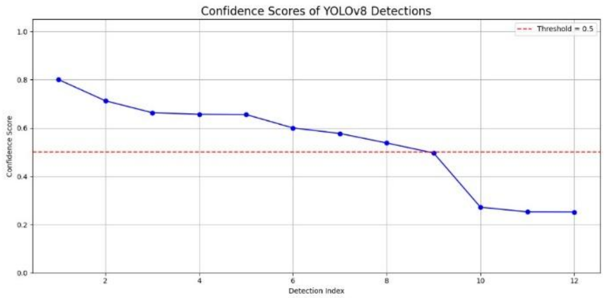


The YOLO model detected various types of vehicles, including cars, trucks, buses, and bicycles. The total count of vehicles was:

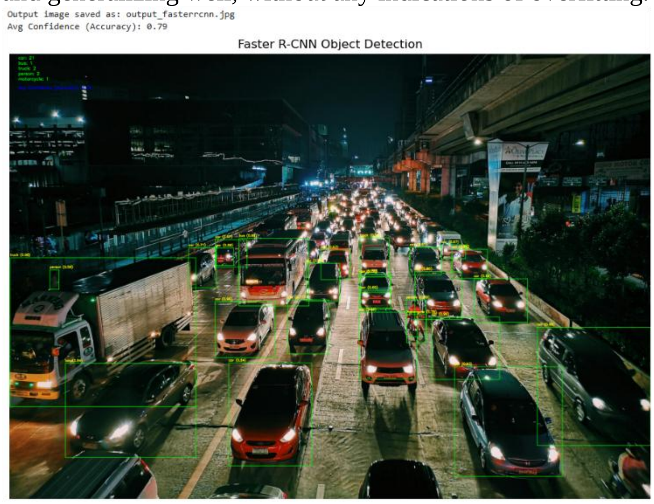
Cars: 11
Trucks: 1

Overall, the detection accuracy was approximately 67%, as indicated in the model output.

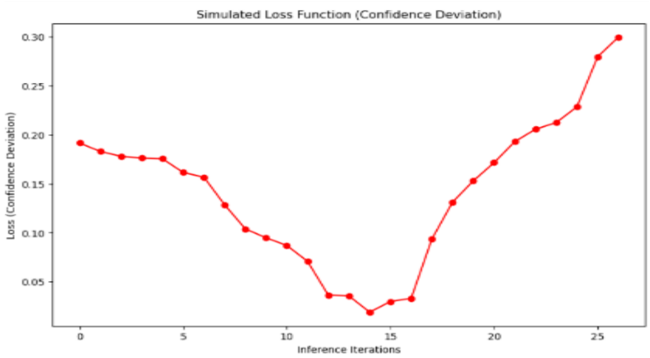


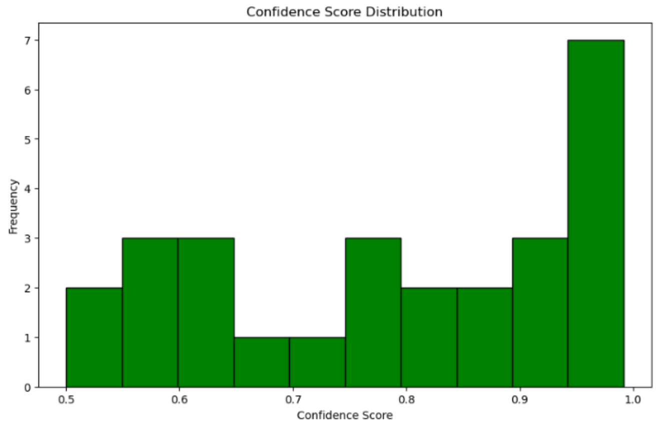


The Classification Loss Learning Curve for YOLOv8 reveals a steady decline in both training and validation loss over 100 epochs. This suggests that the model is learning effectively and generalizing well, without any indications of overfitting.



The Faster R-CNN model also detected a significant number of vehicles, showing bounding boxes around detected cars and larger vehicles. The performance of the faster R-CNN Model is better than YOLOv8, where Faster R-CNN is slow but gives better accuracy than YOLOV8. YOLOv8 is faster and less accurate than Faster R_CNN.





The Confidence Score Distribution graph shows that most predictions are highly confident. The Simulated Loss Function (Confidence Deviation) graph indicates initial improvement, followed by increasing loss, which may point to overfitting or instability.

1. *Comparison of YOLO and Faster R-CNN:*

YOLO (You Only Look Once) exhibited significantly faster inference speeds, making it ideal for real-time traffic analysis and applications requiring rapid processing.

Faster R-CNN, while relatively slower, remained suitable for scenarios where real-time performance is not critical.

2. *Localization Accuracy:*

3. *Traffic Density Estimation:*

Based on the detected vehicle count, the traffic density in the analysed frames appears high, indicating peak-hour congestion.

Further analysis with multiple frames over time could help in estimating real-time traffic flow and congestion levels.

VII. Conclusion

This work provided a comprehensive analysis of how to estimate traffic density and count vehicles using the YOLO and Faster R-CNN models. The results showed that both models were effective in detecting and classifying vehicles in real time, which is key for accurate traffic density estimation. Faster R-CNN, thanks to its region-based feature extraction, showed high precision in vehicle detection, while YOLO excelled with its faster inference speed, making it perfect for real-time applications. The study underscores the strengths of both models—YOLO's ability to handle high-speed detections and Faster R-CNN's superior accuracy in more complex situations. By leveraging these deep learning techniques, we can improve traffic monitoring systems, leading to better congestion management and advancements in smart city applications.

For future improvements, there's a ton of potential to make the system even better. For example, incorporating multi-frame tracking methods like Deep SORT could really boost our ability to track and count vehicles accurately across video frames. Additionally, diving into transformer-based models—like Vision Transformers (ViTs) or hybrid architectures—could take performance up a notch by helping the system grasp the bigger picture of each traffic scene. Looking ahead, we could even expand this system to analyze traffic patterns over time, providing valuable insights for urban planning and smarter transportation management.

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