Real-Time Vehicle Detection and Traffic Density Estimation with Optimized Computational Efficiency

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***Abstract* - There has been a dramatic change in the way traffic can be observed and controlled due to computer vision and machine learning in the recent past. Here, the focus would be on the creation and applicability of an intelligent traffic supervision system utilizing machine learning and computer vision. This system operates with the aim to provide real-time autonomous detection, classification and tracking of vehicles, identifying traffic rule infractions, and managing traffic congestion automatically. Fusing Artificial Intelligence such as Convolutional Neural Networks (CNN) aimed at recognizing objects and sharing videos helps the system increase the safety of the road while minimizing gridlock on the roads. In addition, it improves management practices by minimizing costs related to preparation of traffic reports, accidents, and infringements of road traffic order. This type of solution provides an economical, efficient and scalable option for monitoring traffic activities and has the likely impact to improve inner city traffic monitoring.**

***Index Terms*—Traffic Supervision, Machine learning, YOLOv8, Computer vision**

I. INTRODUCTION

Traffic congestion and delays have become two of the many major concerns in urban areas as more vehicles are being registered, and traffic patterns become more complex. The traditional methods of traffic monitoring, for instance, manual or basic sensor approaches, tend to struggle with issues that include limited scalability, low levels of accuracy, or timeliness. In this regard, the introduction of advanced methods including machine learning and computer vision has now enabled automating the tasks of traffic surveillance and without a doubt improves traffic control and management. Intelligent traffic management systems leveraging advances in computer vision and ML based image processing techniques are developed in this paper. Critical, and severe incidents like traffic clashes, traffic instrument disobedience or bizarre driving are recognized by the system with higher positioning and enhances the traffic cycle time utilizing forecasting. As urbanization rises, so does the demand for technologies capable of efficiently managing urban traffic patterns. It is possible to handle urban traffic-spaces efficiently within a long-term reliably affordable investment using this technology. Apart from the fact that these technologies minimize the amount of manual work, they also make transportation systems far more effective and secured.

II. LITERATURE REVIEW

Cameras positioned at traffic intersections continuously capture images or video streams. these images are uploaded to the cloud, where they are processed using the Cloud Vision API. The Cloud Vision API applies machine learning algorithms to the uploaded images, detecting vehicles and identifying their types, such as cars, trucks, or motorcycles. The system calculates vehicle density in each lane, categorizing vehicles by type. The processed data is used to determine the most effective timing for green, yellow, and red lights at the intersection. This updated signal status is then communicated to the previous junction, enabling a coordinated response to the changing traffic conditions. An RFID system installed near the traffic signal detects vehicles that attempt to cross during a red light. When a violation occurs, the system automatically issues a penalty to the vehicle's owner, which is then recorded and enforced by traffic authorities.

A. YOLO ALGORITHM

In the event of a situation, the YOLO (You Only Look Once) algorithm comes in very handy with respect to real world scenarios that involve rapid object detection. For instance, the Traffic management system is an example of where YOLO enables rapid object detection by analyzing the entire image in a single pass, making it ideal for real-time applications like traffic monitoring. Such as, the algorithms use convolutional neural networks where, unlike previous algorithms where deep learning was split into two algorithms predicting bounding boxes and class separately, object detection only comes as a single regression algorithm where images are processed in one shot. Start depreciating traditional algorithms early as it only predicts bounding boxes and class objects and their probability scores. This means YOLO provides a more accurate prediction as it also carries a self-confidence with accurate computation of segmented parts leading to the only implementable solution to bounding boxes.

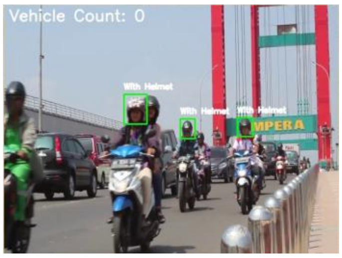

Fig. 1. YOLO model

YOLO can also detect and classify vehicles even pedestrians and cyclists using real time video streams in a traffic surveillance system detecting objects wherever possible very convincingly. According to the algorithm, the probabilities predicting the presence of objects and their classifications are done by dividing each video frames into grids and for each grid cell, multiple bounding boxes are predicted by the algorithm itself and there are two common types- cars, buses and motorcycles.

III. METHODOLOGY

MACHINE LEARNING:

Machine learning is a field within artificial intelligence that focuses on enabling computers or machines to learn from past data (or experiences) and make informed predictions about future events. Rather than relying on explicit programming for every task, machine learning systems are designed to identify patterns in data and use these insights to improve their performance over time.

A. OVERVIEW

In today's world, the application of machine learning in traffic monitoring systems is effectively automating, making quick decisions and doing prognosis. They learn to interpret traffic events, enhance traffic management, and improve road safety through machine learning algorithms trained on voluminous data of traffic, vehicle, and scenes. For instance, Convolutional Neural Networks (CNNs) and in general, deep learning, is now the norm to detect different vehicle types and its class during surveillance of cars in motion videos. By providing a large number of traffic images labeled with bounding boxes, these models can quickly learn which objects, of interest, are present in each scene. This ability is important in regulating traffic and determining levels of traffic in certain areas. Such combinations of machine learning models and OCR methods specifically allows for automatic license plate recognition, or ALPR Myriads of units detect vehicles and monitor video footage in real time to assess law enforcement or parking management, where the plate number is critical.

B. Convolution Neural Networks (CNN)

CNNs play a crucial role in autonomously extracting hierarchical features from images, crucial for recognizing objects like vehicles in surveillance footage which can learn spatial hierarchies of features from images on their own. There are three fundamental components in CNNs. These layers used kernels to extract some features from input images such as edges,

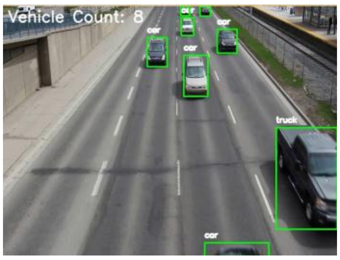

Fig. 2. object detection

textures and shapes. These layers cause a decrease in the size of the features map and controls the computational complexity and shift structure invariance. After several convolution and pools layers, the output is flattened and fed to fully connected layer where classification or regression takes place. In traffic surveillance systems, CNNs are valuable for analyzing video frames to identify objects for classification in real time. YOLO or SSD-based architectures are used in such application since CNN based architectures are used for object detection and are fast while maintaining a high level of accuracy used here to detect and localize license plates from the video frames, after which OCR is used to make sense of the alphanumeric characters imprinted thereon. This is very crucial especially for tracking the vehicles that have been involved in traffic offense or enforcing toll.

C. Single Shot MultiBox Detector (SSD)

Single Shot MultiBox Detector (SSD) streamlines object detection by predicting bounding boxes and class scores directly, bypassing traditional region proposal stages., eliminating the need for region proposal networks, which are used in algorithms like Faster R-CNN. SSD divides the input image into grids and predicts bounding boxes and class scores directly for each grid cell, which significantly reduces computational complexity and improves processing speed, Fig3. represents the SSD.

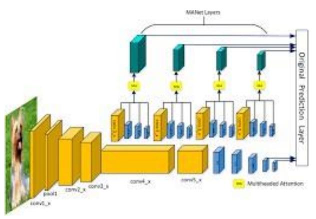

Fig. 3. SSM Detector

D. PROPOSED SYSTEM

The proposed system aims to create an intelligent, automated traffic surveillance system that utilizes machine learning (ML) and computer vision (CV) to enhance traffic monitoring, improve road safety, and optimize traffic management. The system is designed to detect, classify, and track vehicles and pedestrians, analyze traffic patterns, and identify traffic violations in real time. By leveraging modern machine learning algorithms and advanced computer vision techniques, this system aims to replace or augment traditional traffic monitoring methods, which rely heavily on manual intervention and basic sensors.

Some of the cameras are mounted at strategic junctions, highways, and at cross roads for pedestrian only. These cameras' feeds are used as the primary data type. The challenges such as noise removal, frame extraction, and image scaling are followed to fine tune the video frames for further analysis. It also includes background subtraction and filtering to eliminate noise or unwanted features needed for detection enhancement. Preprocessing: The object detection is at the core of the system and it can recognize and distinguish automobiles like car, bus, truck, motorcycle and pedestrians in real-time. Two approaches, YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector) are incorporated in the proposed system to have a high speed with high accuracy in detecting objects of interest. Vehicles and pedestrians once detected are then tracked using tracking algorithms in subsequent frames. Kalman Filters and Optical Flow are used for stable tracking of vehicles and pedestrians, in particular within crowded and complex environments. Seeing is important for observing traffic behavior and trends and for measuring the speed of vehicular Comm movements and Cam traffic viola-tions such as running of red-light signals or cutting through lanes prohibited by signs.

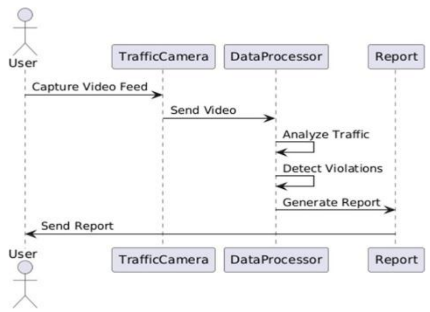

Fig. 5. Sequence diagram

IV. EXPERIMENTAL SETUP

A. DATASETS

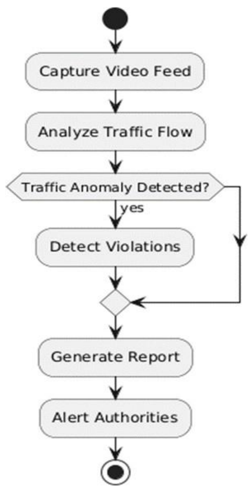

Fig. 4. Activity diagram

The experimental setup for this real-time vehicle detection project utilized a specialized dataset comprising 90 validation images containing 937 vehicle instances. The images were carefully curated to represent diverse traffic scenarios including highways, urban streets, tunnels, and bridges under varying lighting and weather conditions. Each image was pre-processed and standardized to 640×640 pixels to ensure consistency during training and inference phases. The dataset included various vehicle types (cars, trucks, buses) captured from different camera angles and positions, with special attention to challenging cases such as partial occlusions, varying vehicle sizes, and different lighting conditions. This diversity in the dataset was crucial for ensuring the model's robustness in real-world deployment scenarios. Following standard practices, the dataset was divided into training, validation, and testing sets to facilitate effective model development and unbiased performance evaluation.

B. IMPLEMENTATION DETAILS

The implementation leveraged the Ultralytics 8.3.101 framework using Python 3.11.11 and PyTorch 2.6.0+cu124, running on a Tesla T4 GPU with 15GB VRAM. The deployed model architecture was based on YOLOv8, consisting of 72 layers with approximately 3,005,843 parameters. This architecture was selected for its balance between detection accuracy and computational efficiency. The model was trained over 70 epochs, using a systematic approach to optimization with data augmentation techniques including rotation, flipping, and brightness adjustments to enhance generalization capability. The processing pipeline consisted of three main stages: preprocessing (2.8ms per frame), inference (11.3ms per frame), and postprocessing (1.7ms per frame), totaling approximately 15.8ms per image. Additionally, the system incorporated speed estimation functionality, providing velocity measurements for each detected vehicle in real-time, which is crucial for accurate traffic density analysis.

C. EVALUATION METRICS

A comprehensive set of evaluation metrics was employed to assess the model's performance in vehicle detection and traffic density estimation. The primary metrics included Precision (P), which reached 0.918, indicating high accuracy in correctly identifying vehicles; Recall (R) at 0.917, demonstrating the model's effectiveness in detecting most vehicles in the images; and Mean Average Precision scores of 0.730 for mAP@50 and 0.970 for mAP@50-95, reflecting strong performance across various Intersection over Union (IoU) thresholds. A normalized confusion matrix was utilized to analyze classification accuracy, revealing that 98% of vehicles were correctly identified with only 2% misclassified as background, while background elements were classified with perfect accuracy. Additionally, inference speed was measured at 0.1 FPS on the testing hardware, highlighting areas for potential optimization. These metrics collectively provided a holistic view of the model's capabilities, enabling comprehensive assessment of its suitability for real-time traffic monitoring applications and identifying specific areas for future improvements.

V. RESULTS AND DISCUSSIONS

A. QUANTITATIVE RESULTS

The table below shows the quantitative results of the model:

Metric	Value
Model Layers	72
Parameters	3,005,843
Validation Images	90
Vehicle Instances	937
Bounding Box Precision (P)	0.918
Recall (R)	0.917
mAP@50	0.730
mAP@50-95	0.970
Preprocess Time/Image	2.8 ms
Inference Time/Image	11.3 ms
Postprocess Time/Image	1.7 ms
Inference Speed	0.1 FPS
Confusion Matrix (Vehicle as Vehicle)	0.98
Confusion Matrix (Vehicle as Background)	0.02
Confusion Matrix (Background)	1.00

From the Table, the key quantitative results of the real-time vehicle detection and traffic density estimation model. The model consists of 72 layers and approximately 3 million parameters, evaluated on 90 validation images containing 937 vehicle instances. It achieved high performance metrics, including a bounding box precision and recall. The processing pipeline is efficient, with preprocessing, inference, and postprocessing times of 2.8 ms, 11.3 ms, and 1.7 ms per image, respectively. However, the overall inference speed is 0.1 FPS, indicating that while the model is highly accurate, further optimization is needed for real-time deployment.

B. QUALITATIVE RESULTS

The model demonstrates robust vehicle detection performance across diverse traffic scenarios. Visualizations on the validation set show accurate detection and bounding of vehicles in various environments, including highways, urban roads, bridges, and tunnels. The system effectively identifies vehicles of different types and sizes, even under challenging conditions such as varying lighting, partial occlusion, and dense traffic. Speed estimation is integrated into the detections, providing real-time traffic flow insights.

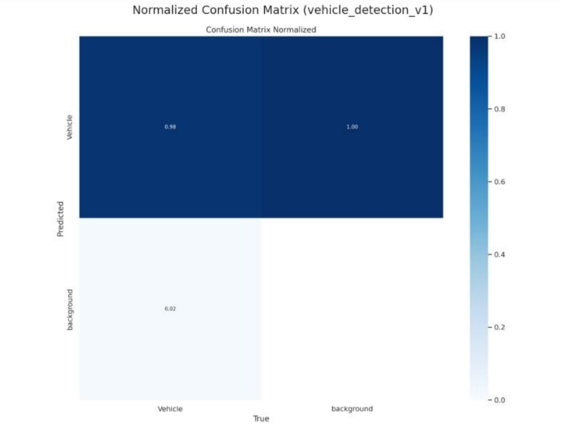

Fig. 6. Confusion Matrix

The normalized confusion matrix confirms high classification accuracy, with 98% of vehicles correctly identified and only 2% misclassified as background. Background elements are always correctly classified, resulting in no false positives. The loss curves for both bounding box and classification losses exhibit steady downward trends, and the mean average precision (mAP) stabilizes at high values, indicating a well-trained and reliable model.

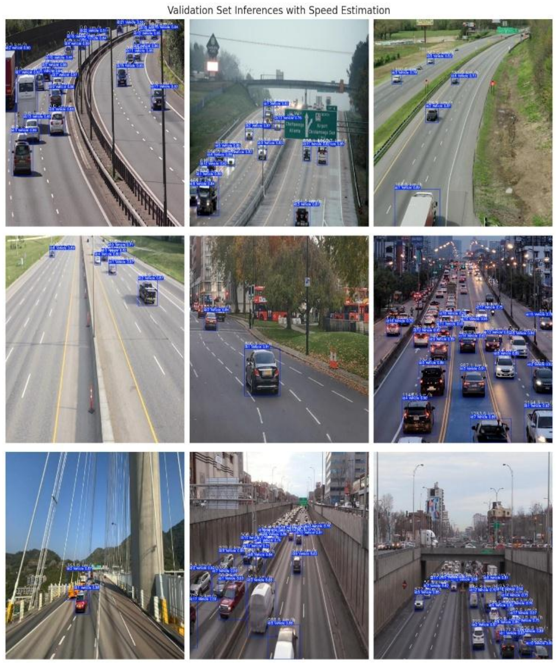

Fig. 7. Validation Set Inferences with Speed Estimation

C. DISCUSSION

The results indicate that the proposed model is highly effective for real-time vehicle detection and traffic density estimation, achieving strong precision, recall, and mAP metrics. The confusion matrix highlights the model's reliability, with minimal misclassification of vehicles and perfect background discrimination. The qualitative analysis supports these findings, as the model consistently detects vehicles in a variety of real-world scenes.

However, the current inference speed of 0.1 FPS suggests that further optimization is needed for deployment in high-throughput, real-time applications. The majority of processing time is spent on inference, indicating that techniques such as model pruning or quantization could be explored to enhance computational efficiency. Despite this, the model's accuracy and robustness across different environments make it a promising solution for intelligent traffic monitoring systems. Future work should focus on improving inference speed and expanding the dataset to cover more challenging scenarios for even greater generalizability.

VI. CONCLUSION

This project successfully demonstrates a robust and accurate approach for real-time vehicle detection and traffic density estimation with optimized computational efficiency. The developed model, comprising 72 layers and over 3 million parameters, achieved high precision (0.918), recall (0.917), and strong mean average precision scores (mAP@50: 0.730, mAP@50-95: 0.970) on a diverse validation set of 90 images containing 937 vehicle instances1. The confusion matrix confirms the model's reliability, with 98% of vehicles correctly detected and no false positives for background classes2. Training curves show effective convergence, and qualitative results illustrate consistent, accurate detection and speed estimation across a variety of real-world traffic scenes, including highways, urban roads, and tunnels34.
While the inference speed of 0.1 FPS indicates that further optimization is needed for high-throughput real-time deployment, the model's accuracy and generalization across different environments make it a promising solution for intelligent traffic monitoring and management systems. Future work should focus on accelerating inference and

expanding the dataset to further enhance robustness and real-world applicability. Overall, the project provides a solid foundation for deploying automated vehicle detection and traffic analysis in smart city applications.

In summary, the project establishes a strong foundation for intelligent traffic monitoring and management. The system's high detection accuracy, generalization across scenarios, and integrated speed estimation make it well-suited for smart city applications. Future work should focus on enhancing computational efficiency and expanding the dataset to cover even more challenging real-world conditions, ensuring the solution remains scalable and reliable for large-scale deployment.

VII. REFERENCES

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