Smart Traffic Decongestion

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Abstract— Urban traffic congestion remains one of the chronic factors that contribute to delays, escalation of fuel consumption, and pollution of the environment. The immediate problem is that intelligent systems have to be feedback controlled in relation to current traffic congestion in the metropolitan cities. In this regard the present article proposes the concept of Smart Traffic Decongestion, where it proposes the development of systems for signaling optimization in predictive mode based on live active object trackers. The camera system will use object detection model for generating heat maps of traffic congestion levels. Data on the external world is captured and processed in real time which allows for changes to be made to the signal timings in order to relieve congestion while maintaining a desired traffic flow. This approach resolves particular aspects of the urban traffic problem through enhanced detection methods, real-time solution provision and promotes extendability.

Keywords— Urban Traffic, Object Detection, YOLOv8, MobileNetV2, Traffic Decongestion, Heatmap, Real-time Traffic Analysis

Introduction

The swift rise of cities and urbanization, in general, has created challenges to control traffic, particularly, the menace of congestion. Roads are progressively becoming crowded leading to more time spent on the road, wastage of fuel, and more carbon emissions released into the environment. However, the typical traffic control systems that operate on pre-set timings even for signals are poorly integrated with traffic patterns that are inherently peak and different from normal situations, particularly rush hour. Instead, such systems usually magnify the existing difficulties. With the majority of cities aiming to enhance their physical constructs, there is a growing need for traffic management systems that are more advanced, smart, and flexible to the changing environment.

Intelligent transport systems promote the smart control of the traffic with the help of state-of-the-art technologies which use machine learning, computer vision and data management systems all in a real-time environment. These do not stick to the traditional approach but rather dynamic ones that alter the traffic control mechanisms in a real time basis allowing for normal flow of traffic. Adaptive traffic management systems are based on such advanced technologies, with the ultimate goal of enhancing the efficiency of road networks while minimizing the impact of roads on the environment.

This paper focuses on a specific Technology called Smart Traffic Decongestion which employs state of the art object detection techniques to address traffic Issues. The main aim is to come up with a heat map that will show where vehicles are on the road using live traffic camera feed.[10] Such heat maps allow for intelligent control of the timing of traffic lights, thereby enabling non-static control of the system. This reduces the waiting time and smoothens traffic in case of traffic jams to some extent.

The technique suggested depends on cutting-edge object detection system. In this study, the two models known as YOLOv8 and MobileNet V2 have been adopted. These particular models offer great precision and efficiency thereby making them suitable for real-time usages. Using their functionalities with a simple heatmap generation process enables the system to offer real-time practical solutions for traffic management. The combination of these technologies with city infrastructure has the ability to make cities more habitable and ecologically friendly.

I. Literature Survey

A. Adaptive Traffic Signal Control with AI, Optimization

There has been numerous research and new approaches on traffic signal control, and in the recent past most traffic management systems have included more advanced technologies including artificial intelligence, reinforcement learning as well as optimization techniques for the effective management of urban traffic. Most of the traditional control measure of traffic signal systems employing fixed time such as timers that have to be set manually are useless especially when it comes to peak periods. Real-Time Traffic Control for Traffic Signal Systems Reinforcement Learning (RL)[1] Uses basic data like vehicle numbers and speeds and real time controls traffic signals effectively. Continuous in–situ experiments and mathematical models allow the RL systems learn the proper timing of signals and therefore integrate very well with the management of the urban traffic even in developing countries.

Moreover, the application of the GA approach for signal timing optimization in oversaturating conditions has also rendered reduction of traffic congestion. The neural networks for example modify the critical parameters such as cycle length, green split and phase sequence to limit delays and enhance vehicle flow[6] even in optimally saturated networks. Results of simulations have confirmed that systems whose optimization is based on genetic algorithms are superior to conventional models characterized by fixed timing in the aspect of vehicle throughput, which is the speed at which vehicles enter and leave the intersection on the average. This has further demonstrated the promise of such approaches for controlled traffic signalling.[4]

B. Multi-Objective Optimization in Traffic Signal Control

There has been a lot of interest in the traffic signal optimization technique which includes mobility, safety and environmental aspects in the present day. In multi-objective optimization techniques, the evolutionary algorithms are employed to address such conflicts of interest elegantly. This is to say that signal timings will not only improve the traffic but also cause less fuel and emissions. For instance, it has been noted that the structure of these optimization models that mobility simulation (VISSIM), conducting safety evaluation (SSAM), and assessing the mitigation of traffic emissions (CMEM) combined, fuel was saving and safety was improved without affecting the traffic throughput.[8]

Sustainability considerations are also prioritized nowadays when traffic signals are optimized. Most of the recent work has focused on the integration of these environmental aspects, such as the reduction of emissions and fuel use, into the optimization routines. Through the reduction of the resulting delays and the optimization of the signals with a view to sustainability, it is possible to enhance this safety by as much as 50% of vehicle emissions – emphasizing the need for sustainable practices even in traffic flow optimization.[7]

C. Real-Time Traffic Optimization with Soft Computing, Data-Driven Systems

Adaptive Traffic Signal Control has been researched onto soft computing techniques such as fuzzy logic, clustering, and neural networks.[9] The systems are based on recurrent models which calculate optimal signal timings from observed traffic patterns and implement it in the course of the day as the traffic conditions change. By employing real-time traffic sensors data, soft computing models can take care of abnormalities in the traffic flow, therefore enabling better and faster traffic management.

In addition to soft computing[3], it is also possible to use cloud-based systems for effective real time traffic optimization. The vehicle and traffic sensor data is analyzed within these systems where in vehicles can communicate with their central traffic control TCC. The figures forecast the degree of congestion through a mapping network in order to enhance routing and decrease the congestion levels within the indiscriminate traffic networks. In cloud only systems traffic delays were cut down during congestion periods by as high as 19%, indicating its relevance in smart city traffic control deployment.

D. Person-Based Traffic Signal Control in Multimodal Networks

The traffic signal optimization techniques from the person-centered perspective do not consider the vehicles as the primary focus – rather aims at public transport and high occupancy vehicles. MIP models optimize certain parameters of traffic signals, with emphasis on passengers and timing schedules of transit vehicles, thus facilitating easier movement of public transport and lowering the movement of individual vehicles with high passenger numbers.[2] Such approach is proven to be much more effective than the traditional vehicle-oriented approach when used in highly congested multimodal systems with heavy rail and bus traffic.

By introducing dynamic approaches or systems where traffic is adjusted by occupancy or giving system, transit traffic, giving systems have been shown to enhance the traffic performance of urban corridors. These systems which are more concerned about the traditional means of transit ensure that transit facilities are given first consideration and thereby improving traffic flow. In view of this, both vehicle and passenger addressed, it can be said that these systems provide a holistic approach to urban traffic management[5] .

II. *MATERIALS AND METHODS*

A. Pre-trained Models Overview

In this project, we seek to implement the use of pre-learned deep learning models in dealing with smart traffic management and signal optimization. More specifically, we apply YOLOv8 and MobileNet V2 models that have been trained on high-quality generic datasets and adapted some for traffic purposes. These models are not project specific and do not need a project-related dataset since they offer a means of accessing their knowledge to classify and localize vehicles in a video stream of an on-going traffic with no training.

YOLOv8 architecture is designed in a manner that can recognize many types of vehicles which include cars, trucks, buses, two wheelers etc. at the same time with a single image processing which is useful in analyzing traffic in real time. MobileNet V2 is light and has great performance which carries its deployment focus on edge devices and systems with limited processing power. These pre-trained models have enabled the identification of the vehicles which contribute to the traffic, eliminating the need for extensive data collection and labeling.

B. Model Description and Architecture

YOLOv8 (You Only Look Once): The YOLOv8 is an object detection neural network that utilizes a single forward pass over the complete image. This makes it highly efficient for use in live systems such as traffic monitoring. The network divides the input image into a number of grid cells and makes predictions of bounding boxes and class probabilities using the information in each grid cell. For its speed and accuracy YOLOv8 is well suited for real time traffic signal control, where adjustments need to be made based on current traffic conditions.

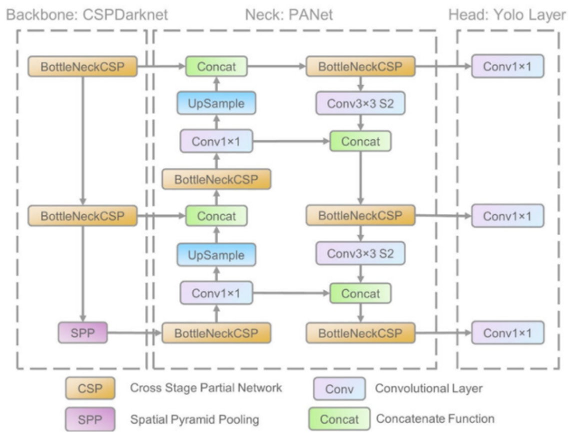

Figure 1: Architecture of YOLO

MobileNet V2 : MobileNet V2 model is light, swift and made for performing object detection quickly in an efficient way. It captures an image and uses a single shot to predict multiple bounding boxes for the image hence making it applicable to the detection of several vehicles in a certain frame. As MobileNet V2 has been trained on various large object detection datasets it is perfectly suitable for hardware constrained environments.[11] It can also recognize vehicles and people which are essential for determining traffic density accurately. Thanks to the efficiency of MobileNet V2, this model can be recommended for real time traffic monitoring systems in particular edge computing environments.

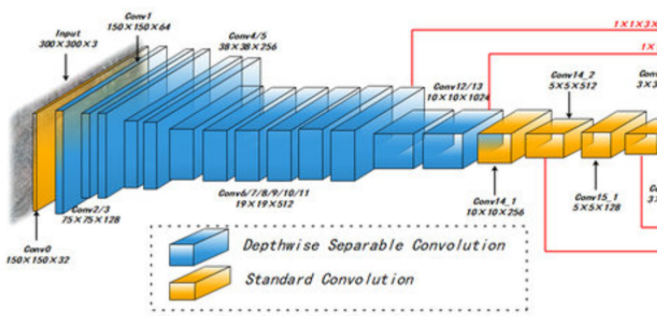

Figure 2: Architecture of MobileNet

In conjunction with vehicle count and traffic density, these pre-trained models are also used to generate traffic heat maps. The heat maps indicate areas of peak traffic concentration and are then used to recalibrate the traffic signal timing in real-time, thus improving the traffic conditions and lowering the congestion level.

C. Approach Employed

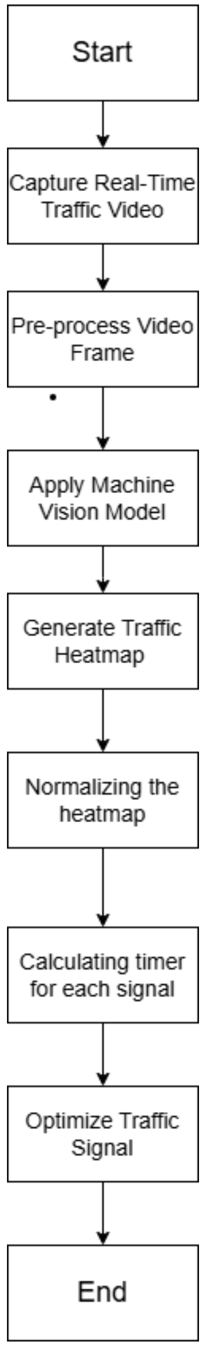

Figure 3: Flowchart of search engine

The system captures real-time traffic video by setting cameras at strategic locations, including very busy intersections. Such real-time video footages are considered the principal inputs into the system and monitor the movement of vehicles constantly. After capturing the video they are broken down it into frames, which further undergo resisizing to conform to restrictions of deep learning model .

Once the frames are resized, pre-trained machine vision model is applied to them.The model then detects the vehicles in the video frames.The model then draws bounding boxes around detected objects, and classifies them into different class, and provide confidence scores for each detection. The results from these models form the basis for further analysis and traffic management.
By employing the results of machine vision models, a heatmap is created to illustrate the amount and movement of vehicles in the surveyed region. Regions of heavy traffic are indicated in warm colors such as red and orange . For purposes of uniformity and definiteness, the heat map is subjected to normalization which re-scales and redistributes intensity values within a fixed set range and also tends to smoothen the data so that the observable patterns are enhanced. This normalization of heatmaps allow for the useful evaluation of traffic congestion at different intervals on different roads.
Using the data indicated by the heatmap, the system determines the best possible signal timings for each junction. Traffic signals are dynamically adjustable based on traffic load with higher green light duration for high traffic directions. This is achieved using the formula:

Signal Timing = Base Time + (Density Factor × Alpha) (i)

Where:

- **Base Time** = 90 seconds (default time for a clear traffic signal),
- **Density Factor** = A normalized value representing the traffic density, calculated based on the heatmap intensity (the total number of vehicle detections or heatmap pixel intensity),
- **Alpha** = A scaling factor = 0.00001.

This optimization process helps in controlling traffic thereby reducing the waiting times of vehicles and helps to avoid the accumulation of traffic at the crossing. Finally, the developed signal plans are put into operation in real time making it possible to oversee and manage the traffic situation in a proactive manner. This cycle helps establish a traffic control system that is flexible and works effectively, increasing the efficiency of the transport network while decreasing fuel use and emissions.

III. RESULTS

A. *Model Resource Comparison*

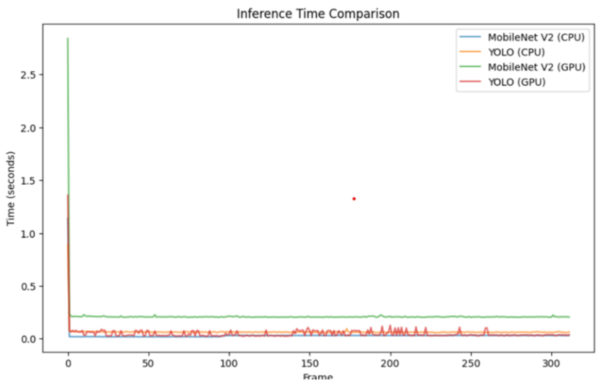

Figure 4: Inference Time Comparison

This graph shows the comparison of various configuration regarding inference time. MobileNet V2 on GPU has the highest inference time, followed by YOLO on CPU, while the usage of GPU for YOLO demonstrates more prevalent spikes sobering higher usage sprints. On the other hand, MobileNet on CPU has the lowest inference time, making it the least resource-consuming configuration.

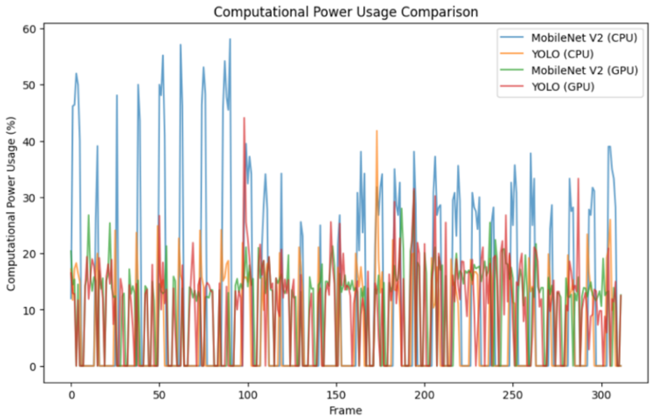

Figure 5: Computational Power Usage Comparison

MobileNet V2 on CPU vs YOLO on CPU: When it comes to power usage on the CPU, MobileNet V2 always utilizes more resources than YOLO. The power consumption for MobileNet V2 on the CPU has more spikes occurring more frequently, which means that its system requirements for rendering certain frames are quite high. In contrast, YOLO's power usage on the CPU remains much constant and less indicated by the more energy efficient software processes which require such power.

MobileNet V2 on GPU vs YOLO on GPU: Both models, when executed on a GPU, exhibit less fluctuation in the power consumed compared to a CPU. YOLO running on GPU indicates moderate power utilization which suggests well-suited optimization for parallel processing. MobileNet V2 when run on GPU also exhibits power spikes quite often, but the power spikes are not as sharp as that of the CPU version.

The comparisons show that computationally Intensive tasks such as object detection benefits from the incorporation of GPUs. YOLO on the GPU further emerges as the most efficient in terms of power usage, among other computation demands of the four combinations, hence making it favourable for use in applications where such as in traffic management systems.

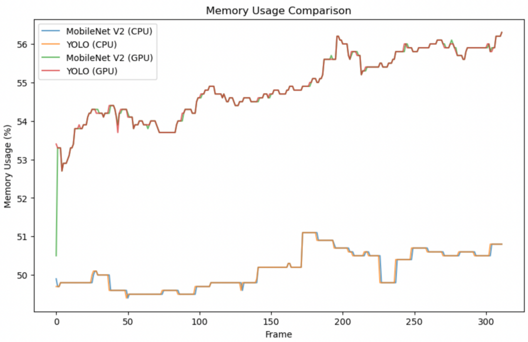

Figure 6: Memory Usage Comparison

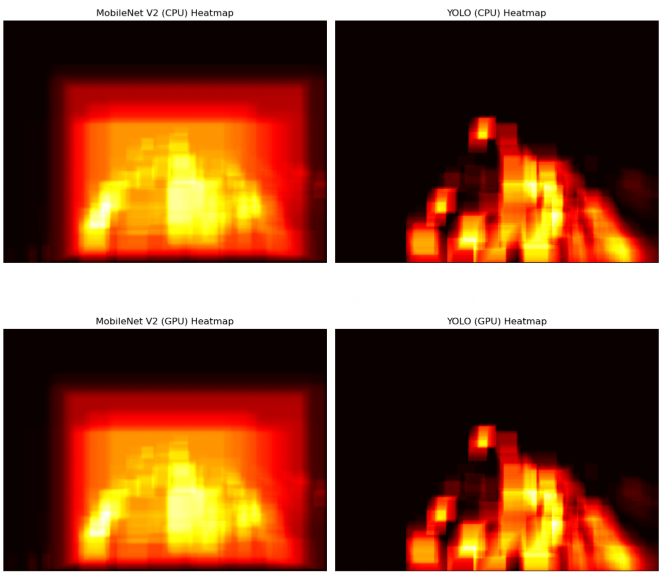

Figure 7: Heat Map

MobileNet V2 (CPU) Heatmap: The heatmap displays a more even spread of activations from concentrations of many yellow and orange patches.

It indicates that the model tends to utilize more area suggesting possible consistent but low usage.

YOLO (CPU) Heatmap: The activations seem to be concentrated more with few high levels (darker yellow and orange) section.

This implies that the YOLO model focuses computational resources on specific regions, likely due to its complex detection requirements.

MobileNet V2 (GPU) Heatmap: Similar to the CPU version but appears slightly smoother, with better distribution and more consistent activation across the heatmap.

The smoother gradients may indicate that the GPU handles computations more efficiently, distributing the load uniformly.

YOLO (GPU) Heatmap: The heatmap generated for the YOLO model when using a GPU is seen to be more sharper and has clearer areas of high intensities.Ist highlights the YOLO model's capability to leverage GPU resources for complex, focused computations.

B. Lane Signal Dynamic Timing

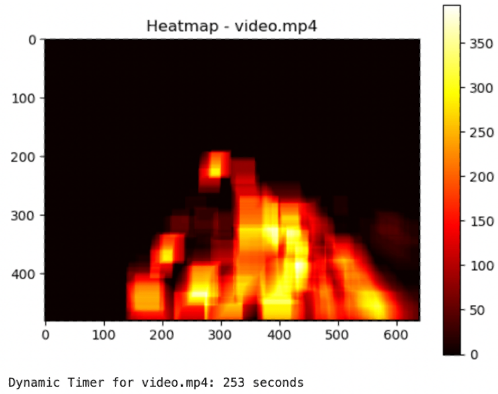

Figure 8: YOLO Traffic Heat Map 1

This heatmap reveals a higher traffic density distributed over a wider area, with intense congestion in certain regions. Consequently, the dynamic timer is set to 253 seconds, reflecting the need for a longer green light duration to manage the increased traffic load in this simulated scenario.

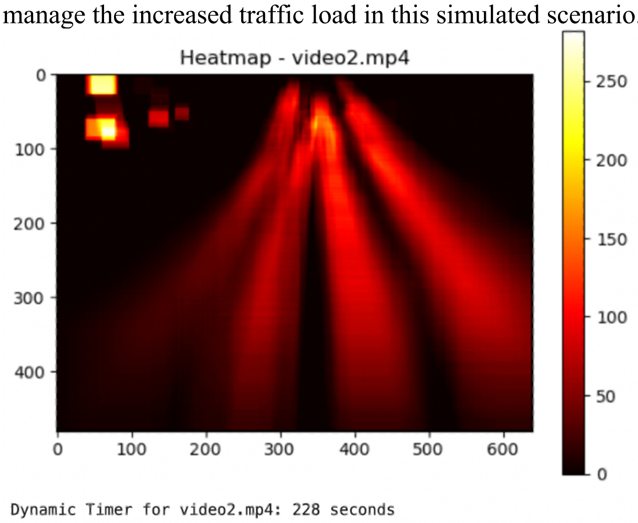

Figure 9: YOLO Traffic Heat Map 2

The heatmap shows that traffic tends to be moderate within certain lanes giving a moving average timer of 228 seconds. The image shows tamed congestion in this simulation.

IV. Conclusion

To sum up, this project showcases the benefits of using prior deep learning models such as YOLOv8 and MobileNet V2 for the purpose of smart signaling and traffic management. In this case, the two models were able to process an input video and identify as well as categorize vehicles within it, allowing for efficient, real time control of traffic lights. Of the two models tested, it was found that YOLOv8 was the better model capable of producing detailed and accurate traffic heat maps which are important in determining congestion levels and adjusting the signals' timings accordingly. This coupled with its power of detecting objects in real time, even under high quantity of moving objects and using low latency GPU's makes this model appropriate for city applications demanding real time execution.

Even though MobileNet V2 is still a helpful choice for lightweight applications with lesser computation capabilities, the findings of this study show that the heatmap accuracy and granularity, which are crucial in the optimization of traffic flow, were less compared to that of YOLOv8. This distinction highlights the importance of choosing a model appropriately for the system specifications and application scenarios.

In terms of developments relating to the project, more functionalities could be added, for instance, a pedestrian detection module, a vehicle type classification module, as well as a module for identifying and providing priority to emergency/high-priority vehicles. The system could be made more precise and efficient if more IoT sensors and connected vehicles were used. In addition, the development of the traffic management system could take an advantage of the principles of reinforcement learning which would help to make the system more robust with respect to changing and unpredictable traffic situations. Implementation of the system in a suitable urban setting would also help to understand the system better by obtaining performance testing and scalability testing results. That would allow understanding its impact on traffic congestion, better travel times, and less fuel consumption more fully.

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