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# Smart Traffic Management Using Transfer Learning Approach for Improve Urban Mobility

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ARTICLEINFO	ABSTRACT
Article History: Accepted: 01 March 2024 Published: 15 March 2024	The increase in congestion on traffic lanes is a major problem hindering the development of an urban city. The reason for this is the increasing number of vehicles on roads leading to large time delays on traffic intersections. To overcome this problem and to make traffic control systems dynamic, several methods and techniques have been introduced throughout the years. The static
<b>Publication Issue</b> Volume 10, Issue 2 March-April-2024 <b>Page Number</b> 156-164	traffic control systems worked on fixed timings which were allocated to each traffic lane and were not able to be altered. Also, there was no provision for counting and detection of pedestrians on the zebra crossings as well as the detection of emergency vehicles in traffic. We will explore several machine learning and deep learning models for the detection of vehicles and pedestrians in this review article, evaluate their viability in terms of cost, dependability, accuracy, and efficiency, and add some new features to improve the performance of the current system.
	Keywords: Traffic Congestion, Traffic Control Systems, Vehicle Detection, Deep

Learning, Pedestrian Detection.

### I. INTRODUCTION

Properly functioning transportation system [16] is very important for the development of an urban city. But, also, at the same time traffic congestion is a major problem. There are numerous reasons for the sudden surge in traffic. One of the main reasons is the everincreasing population which leads to increase in number of vehicles causing more road congestion. Some of the other reasons leading to road congestion are ineffective management of capacity, insufficient infrastructure, poor road conditions etc. The general diagram of a traffic intersection is displayed in Fig. 1.

The average time spent by a person waiting at a traffic junction is increasing day by day. In most of the places, the traffic signal is monitored either manually or with the help of timers. Manually handling the traffic with the help of a traffic policeman is equivalent to inadequate application of manpower. On the other hand, timers are allotted based on the average traffic which are not automated. For instance, even if the traffic density is less or more, only a fixed timer of 30

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seconds will be allotted. This wastes a lot of time and fuel of the commuters. Eventually, people lack patience waiting at the signals and this leads to an increase in the number of accidents.

The general diagram of a traffic intersection is displayed in Fig. 1.



Figure 1. General traffic intersection

Based on the survey of current methods, it has been noted that the traffic control systems [23] using wireless technology like object detection algorithms and adaptive traffic signals, are becoming popular as they help in avoiding the congestion, reduce the average waiting time and prioritize emergency vehicles. The road transportation has become better nowadays but there are still some problems which are not being addressed. There is no provision for pedestrian detection and counting of humans for zebra crossings. Also, the detection and counting of intersecting vehicles and humans is unaddressed. The detection and counting of vehicles in different weather conditions is also a major task.

There is a rise in road traffic congestion along with the population growth. By cutting down on the amount of time it takes for cars to travel and decreasing the number of times they must stop, traffic control systems [16] guarantee a smooth flow of traffic. A strategic plan for the ease of flow of cars without any congestion is known as a sustainable urban mobility plan (23), which ensures a smooth traffic flow. The safety of everyone in and around the traffic is one of the primary goals of a traffic management system. An uncontrolled traffic system leads to more accidents and injuries. The road would be significantly riskier if there were no guidance or guidelines. There must be traffic control equipment to guide cars when there is a junction of traffic [17]. At junctions and in particular regions, anarchy would result from a lack of traffic management. Controlling vehicle movement makes sure that efficiency and safety come first. Carbon emissions increase with a vehicle's time on the road. Traffic management shortens the amount of time that cars are on the road. This contributes to a brighter future for society as well as keeping traffic organised.

Urban traffic control has historically focused on traffic signal control. Urban crossroads with insufficiently efficient and adaptable traffic management often have obstructions in the flow of traffic, which always results in congestion. Urban traffic management presents several challenges, including how to handle traffic more intelligently. There is currently no provision for pedestrian road crossing safety or monitoring automobiles that are crossing in front of them. The suggested system focuses on monitoring people and cars on the traffic lanes to decrease waiting times, identify and avoid traffic congestion, and recommend other routes in order to solve this issue.

## **II. LITERATURE SURVEY**

Yalong Pi et., in [1] have created a system that uses films for input and output, counting the amount of traffic and displaying junction turning patterns. This framework combines a CNN model with an object tracking algorithm to recognise and track cars in the camera's pixel view. The traffic counts and turn calculations may be done once the spatial-temporal data from the vehicle is projected onto an orthogonal real-scale map. The techniques indicate a high accuracy of 96.91 percent for traffic volume counting. Finally, some of the drawbacks include the absence of research into difficult weather conditions like rain, which may influence the aesthetic appeal of cars. On



zebra crossings, there is no facility for counting or detecting pedestrians.

Chandrasekhara, et., in [2] have presented a method for creating a real-time, density-based traffic signal control system that is efficient and adapts to the flow of traffic. The two main components of this study are an artificial neural network (ANN) model to forecast outcomes considering real-time data and image processing to acquire real-time data. By selecting the best features and reducing their dimensionality, they employed principal component analysis to train a neural network model. Finally, taking into account various weather circumstances is one of this study's weaknesses. Weather conditions like rain and fog may affect the image quality. Also, the Neural Network (NN) method can be broadened to a multi- agent network to test its efficiency in a multi-intersection model.

Satya Prakash Sahu, et., in [3] have suggested a deep reinforcement learning model to address the concerns of vehicle wait times and fuel waste by controlling the traffic signal cycle. Sensor networks gather traffic information from junctions and display it as state-level grids of little squares. Later, a Markov decision technique is used to map the duration variations of traffic lights. These produced states are then used by a convolutional neural network to map rewards (CNN). To expand the behaviour of the method, a dualling network that consists of the prioritised experience replay, the target network, and the Double Q-Network (DQN), is also employed. The Simulation on Urban Mobility (SUMO) simulator for cycle control of traffic lights is then used to evaluate the model. Future applications of this technology may include challenging road intersections with heavy traffic flow.

Yanzhao Zhu, et., [4] have put a YOLOv5 model experiment into practice. For Traffic Sign Identification (TSR), which is appropriate for visual object recognition in deep learning, they employed the YOLOv5 model on their own dataset. Regarding identification speed, the YOLOv5 model performs better than the Single Shot multibook Detector (SSD) technique. They chose the YOLOv5 as one of their NZ-TSR models for this project. Four components make up the whole model: input, backbone, neck, and prediction layers. They have used 2,182 traffic sign photos from a bespoke dataset with 8 classifications for their investigation. The experiment was then put into practice on Google Colab because of its powerful processing power. When YOLOv5 and SSD are put side by side, YOLOv5 exhibits more accuracy-up to 97.70—than the other. One of the approach's potential future directions is to expand the datasets to include all categories of traffic signs. Additionally, the authors will seek to create new visual object identification models such the Mask R-CNN, CapsNet, and Siamese neural network.

Umesh Kumar Lilhore, et., in [8] have shown how an Adaptive Traffic-Management system (ATM) based on IOT and ML was implemented and designed. Infrastructure, vehicles, and events are its three most important components. The suggested solution employs the DBSCAN clustering technique as well for anomaly detection. The ATM model is continuously updated based on traffic numbers and movements from neighboring crossings. On the MATLAB simulator, the suggested model was put into practice. To confirm the correctness and effectiveness of the ATM model, several traffic scenarios for linked autonomous vehicles (LAVs) were developed. Future development will include security and energy-efficient technologies into the suggested system. Rather of using data produced by a simulator, the suggested model might be validated using real-time traffic flow data.

Salah Bouktif, et., in [9] have put out a design for a hierarchical decision-making structure for next stages of traffic lights. They have created a Parameterized Deep Q-Networks specifically for this (P-DQN). They've developed a hybrid Deep Reinforcement Learning system that will be capable of both discrete



and continuous decision-making. The average wait length and vehicle travel time may be cut by 22.20 percent and 5.78 percent, respectively, thanks to the suggested design. They have Deep Q-Networks (DQN), Dueling-DQN, and Double- DQN DRL designs for this. The phase selection and its length might be managed by the suggested method. Future plans for this system include centralized and decentralized coverage of many intersections. They would also use real-time information from crossings in the real world to guide their simulations of the future.

Quadri Noorulhasan Naveed, et., in [10] have put out a wireless sensor network (WSN) and visual analytics framework integration-based traffic control solution. Their study's objective was to examine average network performance, average energy use, and average delay. The network lifespan, energy consumption, access ratio, delivery ratio, and communication cost are the factors utilized to assess the proposed system. The study's suggested method is cheap, unstable, and doesn't call for extensive installation labor. Future studies should include incorporate queue length, occupancy, and traffic classification type. Additionally, there are issues with double parking and busy roadside activity.

Dakshayani Ijeri, et., in [11] have suggested a technique that will use image processing to determine the traffic lane density. Later, utilizing image processing methods, the lane with the highest traffic flow in comparison to the other lanes will be granted a green light and the maximum timeframe will be allocated. Four collected and four reference photos of four separate lanes are used as input by the suggested method. Road photographs are the ones that are taken, while reference images are those of vacant roads. After converting RGB photos to grayscale, edge detection and image enhancement will be carried out. Following comparison, traffic density and image matching are computed. After computing the traffic density, the timer will finally be assigned. Future applications of the suggested technology might include traffic intersections with more than four lanes.

Mihir Gandhi, et., in [12] have proposed a system which aims to design a traffic light controller which can adapt with the current traffic situations using computer vision. The proposed system will be taking live images and perform traffic density calculation and set the green signal time accordingly. The vehicle detection algorithm they have used includes YOLO. The signal switching algorithm uses density as its parameter and along with the green signal timer, it also updates the red signal timer. Along with YOLO, a single CNN is used which simultaneously predicts multiple bounding boxes and their class probabilities. After testing the vehicle detection module, an accuracy of about 75-80 was achieved. As a future scope, the project could be further expanded to identify the vehicles violating the traffic rules, accident detection, adapting to emergency vehicles and traffic signal synchronization at multiple intersections.

Belinda Chong Chiew Meng, et., in [13] have suggested an image processing-based adaptive traffic light control system that measures the density of the roadways. Additionally, other edge detectors including Canny, Sobel, Log, and Roberts were employed for comparison. Using high quality 1080px cameras, the initial phase is image acquisition to get four lane pictures. Then, MATLAB software is used to process these pictures. Later, the RGB images will be converted to grayscale images and a dilation operation will be applied to fill in the discontinuing edge segments. Lastly, the features of both, reference image and test image willbe compared and percentage of image matching will be calculated. The future scope of this proposed work is to use edge detectors other than Canny edge detector. Also, this proposed system could be applied on a more than four lane traffic junction.

Syed Shah Sultan Mohiuddin Qadri, et., in [14] have suggested a study to evaluate the various



Computational Intelligence (CI) based simulation methods for improving Traffic Signal Timing (TST) and Traffic Signal Control (TSC) systems, as well as to provide insights and recommendations for future research. The future works of this study include the counting and detecting of pedestrians on the streets. Also, it would be useful to analyse he effects of driver behaviours on the proposed model.

Luiz Fernando Pinto de Oliveira, et., in [15] have proposed a traffic control system (TCS) which can be operated remotely using wireless communication technology. As it is a wireless system, it would be simpler to install new traffic lights. This proposed system would also be flexible to apply at various intersections as it is wireless. The future scopes of this system are to add sensors for the detection of vehicular flow on the lanes. Another scope is to develop an algorithm which would be able to adjust to the traffic light cycles for the operation of green wave coordination.

## III.PROPOSED METHODOLOGY

In this section, the tentative approach is presented in the form of a graphic flow diagram. It can be said that this type of system will work batter for future research. The flow diagram consists of mainly two detection methods for pedestrian and vehicles. In vehicle there is further sub class is included. Figure 2 shows the workflow of the provisional framework. In a nation like India, a more sophisticated method of monitoring and regulating traffic has long been discussed. Urban crossroads with insufficiently efficient and adaptable traffic management often have obstructions in the flow of traffic, which always results in congestion. We have suggested a framework by changing a pre-trained object identification model [30] based on transfer learning method to handle this traffic more intelligently. The framework begins by taking a monitoring video as input [37] and breaking it down into individual frames. Any personally identifying

information, such as human faces and license plate numbers, is later removed during pre-processing of these frames.

The next stage is to feed every frame of the video to a CNN model for vehicle recognition termed YOLOv5 (you-only-look-once version 5). [38] The items in a digital image are contained by bounding boxes created by the CNN model YOLO. The selection of YOLOv5 was influenced by two things. One of its most recent variants, YOLOv5, is capable of effectively achieving mean average accuracy (mAP) on the testing dataset. This version of YOLO delivers better outcomes than previous incarnations and rival CNN algorithms. The second rationale is that the YOLOv5 model may analyze photos at real- time or near to 20 real-time speeds, depending on the hardware.



Figure 2. Proposed Workflow

After the processing of the images, the objects will be classified as humans and vehicles. After the categorization of the objects, the detection will be refined for the intersecting objects. In the case of intersecting objects, the outlines of these objects are overlapping each other. To detect the objects properly it is necessary to refine their outlines and treat them as different individual objects. After refining the outlines of the objects, these objects will be counted and based



on their count, a density map will be developed. A density map will point out the number and volume of vehicles on a particular lane. Based on density of each lane, decision will be made for traffic management. The lane with the highest density will be prioritized first and be given the maximum timer.

Lastly, the tentative model will be compared with other models based on parameters like Accuracy, Sensitivity and Specificity. For the implementation of the proposed framework, the model will be trained on Google Collab because of its high-range GPU performance. The code development will be done on Spyder Anaconda distribution as it can easily search and install thousands of Python packages and access a vast library of community content and support. The python libraries which will be helpful in the code development are: TensorFlow, Keras, OpenCV, Scikitlearn, Matplotlib and NumPy. The proposed framework will be capable of adapting to the realworld data and benefitting the traffic management system.

## IV. RESULTS



Figure 3. Screen short of implemented work Web-App







Figure 5. Run Code



Figure 6. Car Detection

## V. CONCLUSION & FUTURE SCOPE

The creation of an adjustable, real-time, and densitybased traffic signal management system is the primary objective of the preliminary research. This has given developers of a system to manage traffic at junctions a broad notion. A tracking algorithm and object identification model (i.e., YOLO) will be used in particular to track objects like cars and people in video frames. The suggested framework will be more practical, flexible, and cost-effective than current



traffic monitoring methods, which rely on GPS data, in-person human observation, and traffic sensors. One may argue that the suggested system would accurately identify and count the movement of items and cars on the traffic lanes. Additionally, it would be feasible to find and count items that cross each other.

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