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Deep Learning Techniques for Real-time Traffic Analysis and Optimization

Prof. Saraswati Nagtilak[1], Parth Jadhav[2], Shreyas Chaudhari[3], Pratik Bhosale[4],Om Godase[5]

[1]Assistant Professor, IT, Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

[2,3,4,5]Student, IT, Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

Abstract: *Traffic congestion is a pressing issue in major cities worldwide, causing significant challenges for daily commuters. Conventional traffic signal systems rely on fixed time intervals, lacking adaptability to changing traffic conditions. In some cases, longer green times are required to accommodate high traffic density on specific sides of intersections. To address this, our system incorporates advanced algorithms and techniques such as Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) approach, along with OpenCV, Keras, Video Processing, and Image Processing. By leveraging these technologies, our system utilizes object detection within traffic signals to generate contours. These contours are then analyzed and translated into a simulator, enabling accurate determination of the number of vehicles present in a given region. This vehicle count facilitates the identification of areas with high traffic density, allowing for the prioritization of signal timings accordingly.Our system combines the power of CNN and YOLO approaches to enhance the efficiency of traffic management systems. By integrating real-time object detection and adaptive signal control, we aim to optimize traffic flow and alleviate congestion in urban environments. This research contributes to the development of intelligent transportation systems and represents a significant step towards more effective and sustainable traffic management strategies.*

Keywords: *Deep Learning, Image Processing, Feature Extraction, Segmentation, Convolutional Neural Network (CNN), You Only Look Once (YOLO).*

I. INTRODUCTION

Congestion caused by heavy traffic is an enduring challenge experienced in numerous urban centers worldwide [1]. Traditional approaches to traffic management have predominantly focused on regulating vehicle speeds, which have yielded limited success in alleviating intersection wait times [1]. However, advancements in technology have paved the way for innovative traffic management techniques that offer superior efficiency and effectiveness [2][3]. Among these advancements, Deep Learning has emerged as a promising solution, employing a Convolutional Neural Network (CNN) algorithm to accurately detect and estimate the number of vehicles present [4]. This transformative technology enables the development of intelligent traffic management systems capable of dynamically adjusting traffic signals in response to real-time road conditions, ultimately leading to optimized traffic flow and reduced congestion [5].

An effective smart traffic management system comprises essential components such as real-time road condition monitoring [6] and a decision-making mechanism capable of optimizing traffic flow while minimizing vehicle conflicts [7]. Taking inspiration from the accomplishments of human-led traffic management, the objective of this research paper is to develop a responsive, real-time traffic management system by harnessing the potential of Deep Learning technology for vehicle identification and count prediction [8]. Through the integration of these cutting-edge technologies, the envisioned system aims to substantially reduce intersection wait times, thereby enhancing the overall efficiency and sustainability of urban transportation [1].

II.RELATED WORK

Asha C S, A V Narasimhadhan[1] has stated that, in this paper, in the realm of intelligent transportation systems, vehicle counting serves as a crucial technique for analyzing traffic conditions. The ubiquity of cameras in urban transportation networks has elevated surveillance videos to a pivotal data source. Furthermore, the advent of handheld/mobile cameras and advancements in data processing have fueled the growing popularity of real-time traffic control systems. In this study, a novel approach is presented for accurately counting vehicles in highway traffic videos captured using handheld cameras. The video processing entails three distinct steps: object recognition employing the YOLO (You Only Look Once) technique, correlation filter-based tracking, and vehicle counting. The YOLO framework demonstrates exceptional performance in object detection, while correlation filters enhance accuracy, and tracking speed remains competitive. Consequently, the study achieves the creation of multiple objects tracking utilizing correlation filters within the framework of YOLO. Produced bounding boxes. An experimental study of actual video sequences demonstrates the accuracy with which the suggested technique can recognise, track, and count the car.

Muhammad hanif tunio, imranmenon, et al.[2] has stated that, in this paper, this work focuses on investigating the application of diverse image processing algorithms for real-time traffic control. The research involves capturing images of multiple lanes with traffic using a webcam. Utilizing image processing techniques within the Matlab tool, the number of vehicles present in each image is calculated. Subsequently, lane-specific timer allocations are determined based on the vehicle count within the corresponding lane image. These timer allocations regulate the display of green signals to facilitate vehicle passage. The signaling system incorporates LEDs for displaying green and red signals, while a seven-segment display is employed to indicate the decrementing timer associated with the green signal. This design approach combines image processing algorithms with efficient signaling mechanisms to enable effective real-time traffic management.

Zulaikha Kadim,Khairunnisa Mohammed Johari,Den FairolSamaon,Yuen Shang Li,Hock Woon Hon[3] has stated that, Accurate estimation of road usage and traffic trends is crucial for the planning and design of future traffic facilities. Traditionally, such surveys have relied on manual methods, necessitating the presence of human observers at survey sites. However, this approach poses risks to the observers and becomes resource-intensive as traffic volumes increase, particularly in metropolitan arterials. To address these challenges, this study proposes a deep-learning-based method for traffic volume counting, which was extensively tested using 48 high-traffic video clips captured from temporarily mounted cameras at selected metropolitan arterial routes. The estimated Average Annual Daily Traffic (AADT) for volumes exceeding 50,000 and 100,000 vehicles was thoroughly evaluated. For testing purposes, the video clips were segmented into 15-minute and 5-minute durations. The accuracy of each clip was assessed by comparing the system's output with the manually obtained ground truth. The average accuracy across the four camera viewpoints was found to be 97.68 percent, demonstrating the effectiveness and reliability of the proposed method.

Boris A. Alpatov, Pavel V. Babayan, Maksim D. Ershov[4] has stated that, in this study, when analyzing the condition of roads, various tasks associated with traffic control and safety are considered. In this context, two image processing algorithms are proposed: a vehicle detection and counting algorithm, and a road marking detection algorithm. These algorithms are specifically designed to process images captured by fixed cameras. To implement and assess the effectiveness of the vehicle detection and counting algorithm, an embedded platform consisting of smart cameras is utilized. The experimental analysis results of the suggested algorithms are subsequently presented, providing insights into their performance and efficacy.

Dongfang Ma, Xiang Song and Pu Li[5] have stated that, in this research, introduces an innovative approach based on deep learning for predicting daily traffic flow, emphasizing the importance of considering traffic flow patterns and contextual factors. Initially, a dedicated convolutional neural network is employed to extract essential daily traffic flow patterns. Subsequently, the temporal evolution of traffic flow within a day is captured by training long short-term memory (LSTM) units using the extracted features. Additionally, historical context is incorporated into the prediction process to enhance overall performance. Through a comprehensive case study using real-world data, this research demonstrates the superiority of the proposed methodology over existing benchmark approaches, showcasing its robust forecasting capabilities across various scenarios. Notably, the methodology achieves a remarkable prediction accuracy exceeding 90%.

Yaohang Sun, Zhen Liu, Zhisong Pan[6] has stated that, in this study, presents a novel approach to vehicle counting utilizing surveillance footage from traffic-related sources. Recognizing that video captured on roadways often encounters congestion and obstructions, resulting in slow and regular movement, the authors propose a counting technique based on a regression model. To extract relevant features from the surveillance video, a pre-processing step is performed. Subsequently, a Support Vector Machine (SVM) classifier is employed to verify the vehicle density. The proposed methodology is then evaluated using actual footage of vehicle passages. The experimental results showcase the method's ability to achieve more accurate flow counting with reduced computational overhead, thereby demonstrating its practical effectiveness.

Markus Lucking, Esteban Rivera, Lukas Kohout, Christoph Zimmermann, DuyguPolad and Wilhelm Stork[7] have stated that Effective traffic monitoring is one of the key aspects of smart cities. Contemporary monitoring strategies in traffic management primarily rely on video processing techniques utilizing traffic surveillance cameras. Nevertheless, the task of video analytics for traffic monitoring on edge devices, such as cameras, poses challenges due to constrained processing resources and unpredictable traffic conditions. Addressing these challenges, this paper presents the development and evaluation of a real-time vehicle counting system that leverages deep neural networks on an embedded device. By utilizing this approach, the system aims to overcome the limitations associated with edge devices. To ensure optimal performance and assess the impact of changing external factors on system performance, comprehensive experiments were conducted, enabling the identification of ideal system configuration parameters. The results of these experiments shed light on the effectiveness and adaptability of the proposed system.

Shuang Li, Faliang Chang, and Chunsheng Liu[8] have stated that, counting vehicles and estimating traffic flow using machine vision, particularly in dense traffic situations, poses challenges. Existing line of interest (LOI) counting techniques often rely on complex tracking methods and lack focus on dense settings. To address the challenge of bi-directional LOI counting in dense scenarios without relying on intricate tracking, this study proposes an LOI counting framework. The framework introduces three key contributions. Firstly, it considers the bi-directional traffic flow as a whole, presenting a novel spatio-temporal counting feature (STCF) for extracting features in dense traffic scenarios. Secondly, a counting Long Short-Term Memory (cLSTM) network is introduced, enabling analysis of bidirectional STCF features and vehicle counting across consecutive video frames without the need for multi-target tracking. Lastly, a model is developed to estimate traffic flow parameters, including speed, volume, and density. Through experiments conducted on the UA-DETRAC dataset and recorded videos, the proposed vehicle counting method outperforms representative LOI counting methods in terms of accuracy and speed. Additionally, the proposed framework demonstrates effective real-time estimation of traffic flow parameters such as speed, volume, and density. These results highlight the superiority and practicality of the proposed approach in tackling dense traffic scenarios and providing accurate and timely traffic flow information.

III.METHODOLOGY

The Smart Traffic Management System using Deep Learning project can be approached in two ways: utilizing Convolutional Neural Networks (CNN) and using the YOLO 3 (You Only Look Once) simulation model. The CNN approach involves training the system on a large dataset of images to identify and classify different types of vehicles, pedestrians, and traffic signals. It requires significant processing power to extract features and patterns from images and classify them accurately. On the other hand, the YOLO 3 simulation model is an object detection system that detects and tracks objects in real-time, making it ideal for monitoring traffic flow. It uses a single neural network to predict the locations of different objects, making it fast and efficient for real-time applications.

In the first CNN approach, the system conducts a count of all signalized vehicles from all sides, and assigns priority to the signal with the highest density of vehicles. Subsequently, signals are assigned in descending order. In the YOLO approach, signal priorities remain the same, but the duration of signal count depends on the number of vehicles at that particular intersection. This means that the system assigns the signal duration with the number of vehicles present, such that it remains green for a longer time if there are more vehicles and vice versa.

1. CNN Approach:

In the research paper, the smart traffic management system would describe the specific steps taken to train a CNN using a video dataset to determine which traffic signal to release and for how long. Dataset Collection and Pre-processing: The first step in this system was to collect a large video dataset of traffic intersections. This dataset was pre-processed by cleaning the videos and removing any blurriness to ensure that the images were clear and ready for analysis [fig 1].

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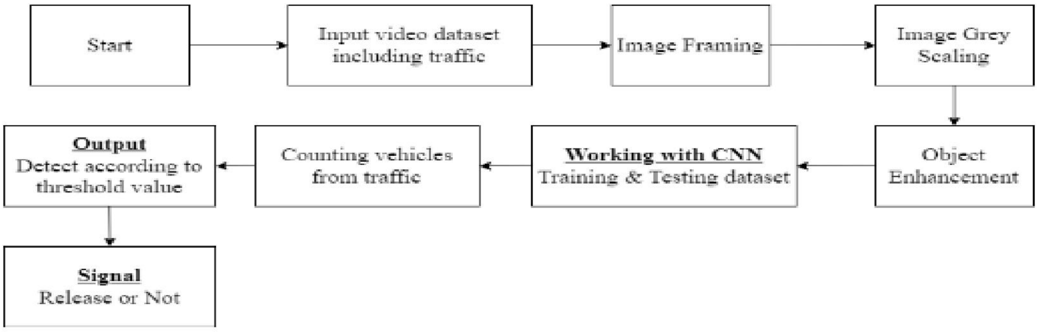

Figure 1: Workflow of Proposed System

Model Architecture Design: The next step in the system was to design the CNN architecture that would be used to analyze the video dataset. The input layer was set to accept video frames of a specific size, while the convolutional layer was used to extract relevant features from each frame. A pooling layer was then used to reduce the dimensionality of the feature maps, followed by a fully connected layer to make the final prediction. Convolutional filters, also known as kernels or weights, are an essential component of CNNs. They are used to extract features from the input data by applying a sliding window over the input matrix and performing a dot product between the kernel and the corresponding sub-matrix of the input. The output of this operation is a new feature map that represents the presence or absence of specific features in the input data. We will be using a (3x3) filter as it is the most commonly used filter size because it is computationally efficient and it can capture important local features such as cars,bikes,trucks on the road [fig 2].

The CNN model was then trained on the pre-processed video dataset, using a combination of stochastic gradient descent and backpropagation algorithms. The model was validated by splitting the dataset into training and validation sets, and then assessing the accuracy of the model on the validation set [fig 3].

System utilized a neural network consisting of 19 convolutional and 2 fully connected layers for our vehicle detection approach. Our training data was a video dataset that we collected and labeled ourselves. It is important to note that the accuracy of our vehicle detection model is dependent on both the total number of frames as well as the diversity of labeled frames, such as varying camera field of view. To train and evaluate our model specifically for vehicle detection applications, we collected and labeled a dataset of 180,805 frames. For this particular dataset, we merged the classes for cars and trucks into a single class called "vehicle".

2.YOLO Approach:

In this paper, the simulation system is based on computer vision and machine learning to optimize traffic signal phases based on collected data, primarily queue density and waiting time per vehicle. The system utilizes a state-of-the-art, real-time object detection system called You Only Look Once (YOLO) based on deep Convolutional Neural Networks.

Our proposed system takes an image from the CCTV cameras at traffic junctions as input for real time traffic density calculation using image processing and object detection. This system can be broken down into 3 modules: Vehicle Detection module, Signal Switching Algorithm, and Simulation module. As shown in the figure below, this image is passed on to the vehicle detection algorithm, which uses YOLO.

The number of vehicles of each class, such as car, bike, bus, and truck, is detected, which is to calculate the density of traffic. The signal switching algorithm uses this density, among some other factors, to set the green signal timer for each lane. The red signal times are updated accordingly. The green signal time is restricted to a maximum and minimum value in order to avoid starvation of a particular lane. A simulation is also developed to demonstrate the system's effectiveness and compare it with the existing static system.

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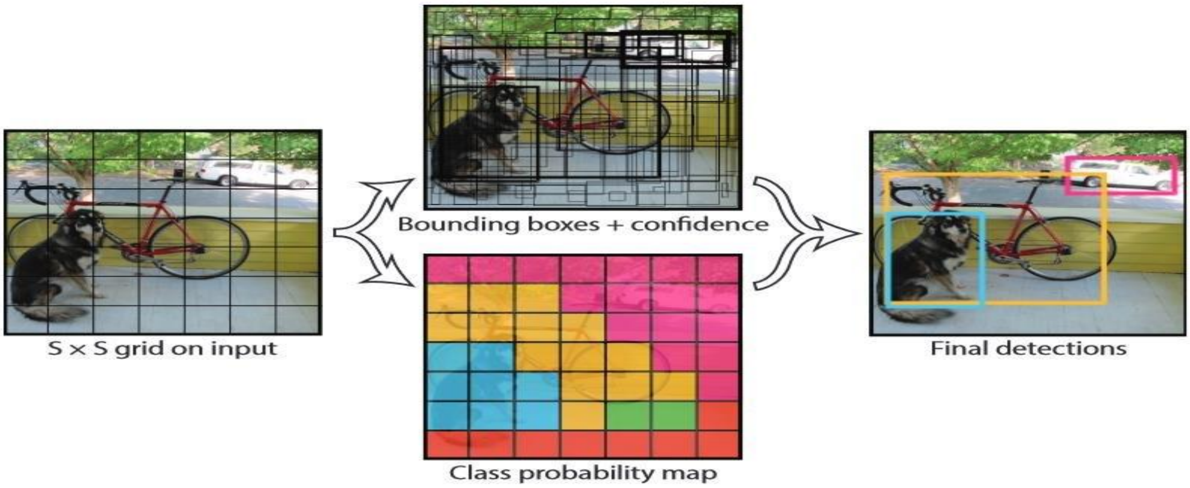

Figure 2: YOLO Detection System

This project can be broken down into 3 modules:

1.Vehicle Detection Module:

- The proposed system uses YOLO (You only look once) for vehicle detection, which provides the desired accuracy and processing time. A custom YOLO model was trained for vehicle detection, which can detect vehicles of different classes like cars, bikes, heavy vehicles (buses and trucks), and rickshaws.
- The dataset for training the model was prepared by scraping images from google and labeling them manually using LabelIMG, a graphical image annotation tool.
- Then the model was trained using the pre-trained weights downloaded from the YOLO website. The configuration of the .cfg file used for training was changed in accordance with the specifications of our model. The number of output neurons in the last layer was set equal to the number of classes the model is supposed to detect by changing the 'classes' variable. In our system, this was 4 viz. Car, Bike, Bus/Truck, and Rickshaw. The number of filters also needs to be changed by the formula 5*(5+number of classes), i.e., 45 in our case.
- After making these configuration changes, the model was trained until the loss was significantly less and no longer seemed to reduce. This marked the end of the training, and the weights were now updated according to our requirements.
- These weights were then imported in code and used for vehicle detection with the help of OpenCV library. A threshold is set as the minimum confidence required for successful detection. After the model is loaded and an image is fed to the model, it gives the result in a JSON format i.e., in the form of key-value pairs, in which labels are keys, and their confidence and coordinates are values. Again, OpenCV can be used to draw the bounding boxes on the images from the labels and coordinates received

Following are some images of the output of the Vehicle Detection Module:

2.Signal Switching Algorithm:

The Signal Switching Algorithm sets the green signal timer according to traffic density returned by the vehicle detection module, and updates the red signal timers of other signals accordingly. It also switches between the signals cyclically according to the timers.

The algorithm takes the information about the vehicles that were detected from the detection module, as explained in the previous section, as input. This is in JSON format, with the label of the object detected as the key and the confidence and coordinates as the values. This input is then parsed to calculate the total number of vehicles of each class. After this, the green signal time for the signal is calculated and assigned to it, and the red signal times of other signals are adjusted accordingly. The algorithm can be scaled up or down to any number of signals at an intersection.

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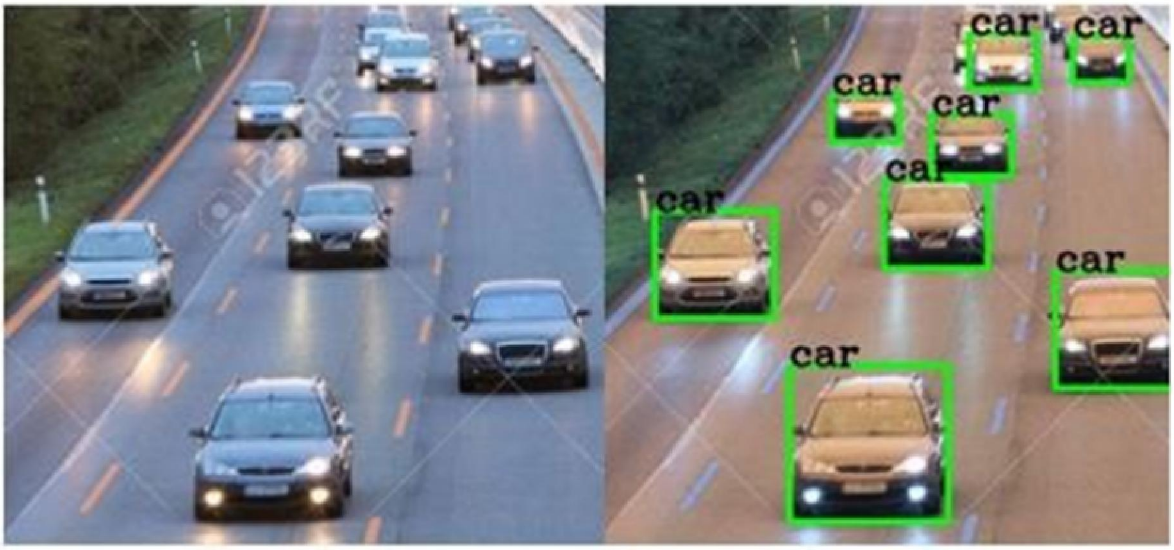

Figure 3: Vehicle Detection Module

The following factors were considered while developing the algorithm:

- The processing time of the algorithm to calculate traffic density and then the green light duration – this decides at what time the image needs to be acquired
- Number of lanes
- Total count of vehicles of each class like cars, trucks, motorcycles, etc.
- Traffic density calculated using the above factors.
- Time added due to lag each vehicle suffers during start-up and the non-linear increase in lag suffered by the vehicles which are at the back
- The average speed of each class of vehicle when the green light starts i.e., the average time required to cross the signal by each class of vehicle
- The minimum and maximum time limit for the green light duration - to prevent starvation

3.Simulation Module:

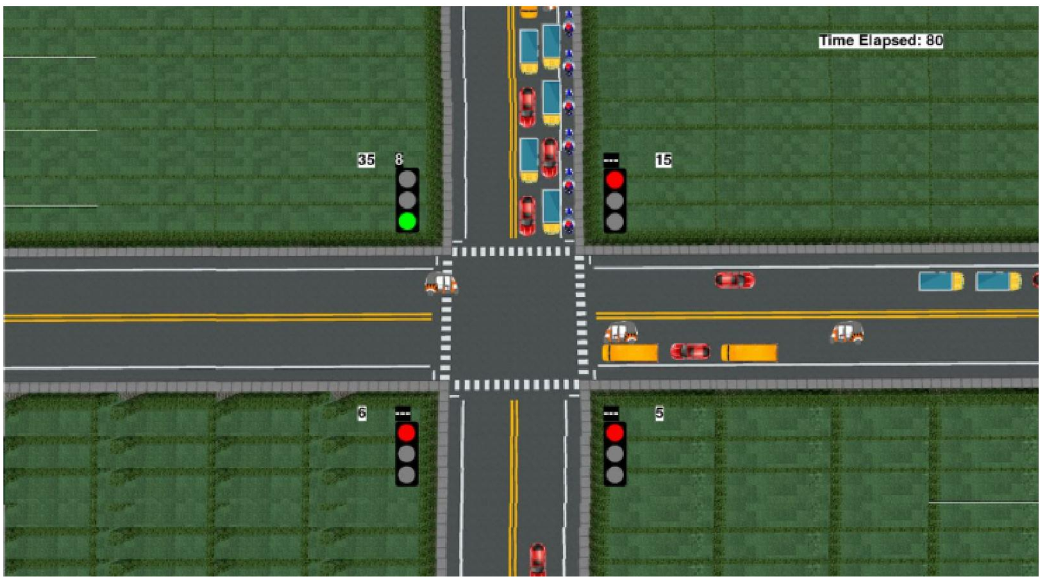

Figure 4: Simulation Module

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A simulation was developed from scratch using Pygame to simulate real-life traffic. It assists in visualizing the system and comparing it with the existing static system. It contains a 4-way intersection with 4 traffic signals. Each signal has a timer on top of it, which shows the time remaining for the signal to switch from green to yellow, yellow to red, or red to green. Each signal also has the number of vehicles that have crossed the intersection displayed beside it. Vehicles such as cars, bikes, buses, trucks, and rickshaws come in from all directions. In order to make the simulation more realistic, some of the vehicles in the rightmost lane turn to cross the intersection. Whether a vehicle will turn or not is also set using random numbers when the vehicle is generated. It also contains a timer that displays the time elapsed since the start of the simulation and other traffic-related factors.

IV.TESTING AND EVALUATION

Once the CNN model was trained, it was tested on a separate dataset of traffic video to evaluate its performance. The accuracy of the model was evaluated by comparing the predicted signal release times with the actual release times in the test dataset. And also, the road marking efficiency is greater than existing systems which is 85% approximate[8]. For evaluation of the system cascade classifiers are being used on the "car_detect.xml" file, the .xml file gives the text-based data format for exchange of the structural data.

The Evaluation task is performed on the first 4 frames to detect the count of vehicles and mark the vehicles by red square brackets. and the number of vehicle count is captured by the system for further signal release calculations [fig 4]. and based on the number of vehicles count the priority calculations for signal release are performed.

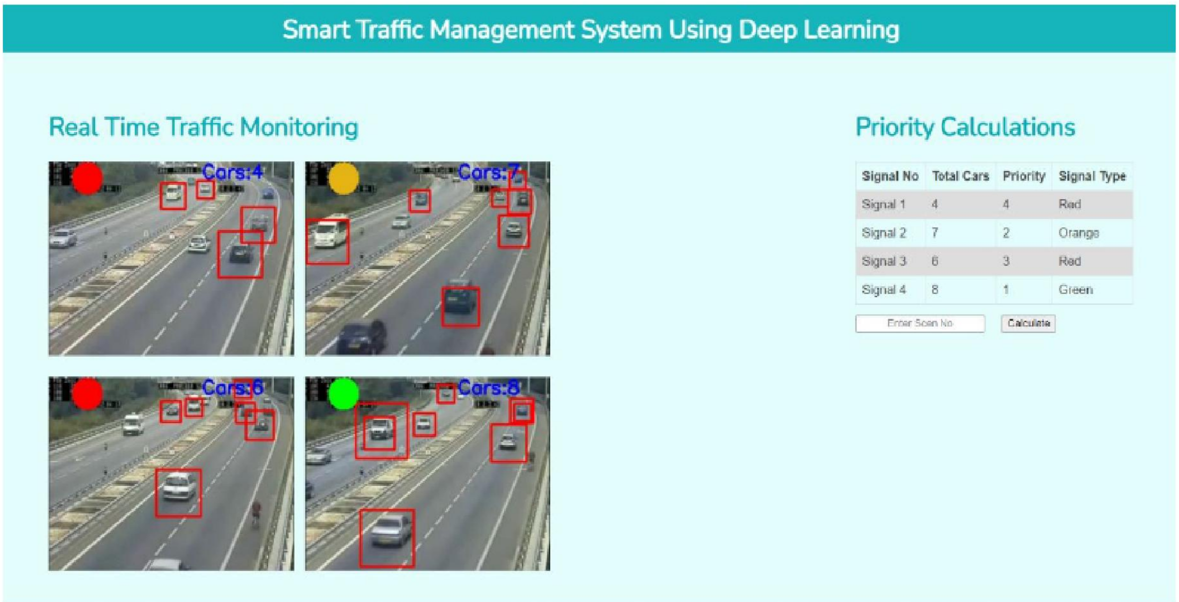

Figure 5: Vehicle Detection and Priority Calculations

V.RESULT DISCUSSION

The results of the system were analyzed and presented, including the accuracy of the model and any insights gained from the analysis of the traffic videos. The paper also discussed any limitations of the system and potential areas for future research.

In the CNN based model, we have implemented a priority calculation algorithm that determines the order in which traffic signals should be released based on the total number of vehicles present in each lane. This algorithm assigns higher priority to the lane with the highest vehicle count, and releases the signal for that lane first, thereby reducing traffic congestion and improving traffic flow.

And referring to the YOLO model a signal adaptation process takes place with reference to the count of the vehicles and by using the YOLO approach, we were able to achieve similar objectives as the CNN-based vehicle detection and counting method mentioned earlier. The YOLO algorithm allowed us to detect and locate vehicles in traffic videos with high accuracy, even in challenging scenarios such as heavy traffic and varying lighting conditions.

One of the key advantages of the YOLO approach is its efficiency. Unlike traditional methods that require scanning the image or video multiple times to detect objects, YOLO performs detection in a single pass. This makes it much faster and suitable for real-time applications like traffic management systems.

To accomplish this, System first determines the total number of vehicles in each lane using our CNN and YOLO based vehicle detection and counting approach. The lane with the highest number of vehicles is given the highest priority and is released first are shown in the table format [fig 4]. Moreover, this lane is also allotted a higher signal release time to accommodate the increased traffic volume. On the other hand, if the total number of vehicles in a particular lane is lower than the other lanes, it is given a lower priority, and the signal release time for that lane is reduced accordingly. This ensures that traffic flow is optimized based on the actual traffic volume and reduces the waiting time for vehicles at traffic signals.

We observed a significant increase in the accuracy of vehicle counting compared to traditional methods. As we use both approaches for wherever it is necessary The CNN model was able to accurately count the number of vehicles passing through a specific area of interest, even in complex scenarios such as heavy traffic and varying lighting conditions. And the YOLO model determines the count of vehicles with higher speed but with less accuracy.

VI. CONCLUSION

The analysis of the existing systems has revealed that some of them have implemented various strategies. The systems employ computer vision, Otus method, COCO detection, IVRT, LSTM, SVM classifier, SSD, and STCF among other techniques. By implementing these strategies, it is possible to identify flaws in the current systems that set them apart from the proposed system. These systems shortcomings include variations in accuracy, poor handling of traffic noise, poorer accuracy, poor feature extraction, overfitting issues, and numerous others. To tackle these existing flaws, we proposed our system with higher accuracy and better traffic management using CNN and YOLO algorithm applying on the real time traffic datasets and as a great impact to the society it also minimizes the human requirements and solve the traffic congestion problem in an efficient manner.

The development of a smart traffic management system using Deep Learning can greatly improve transportation efficiency and reduce traffic congestion. Our project utilized two different approaches, CNN and YOLO, to improve the accuracy of vehicle detection in smart traffic management. The YOLO approach included the simulation of a traffic signal system, which determined when to release a signal based on the number of vehicles present. On the other hand, the CNN approach calculated the traffic density of all signals and then assigned priority to a particular signal based on that information. The implementation of this smart traffic management system offers several benefits. Firstly, it improves the accuracy of vehicle detection, which can lead to better traffic flow management, reduced congestion, and ultimately, fewer accidents. Additionally, the system can reduce the environmental impact of traffic by reducing the amount of time vehicles spend idling in traffic. And also, the road marking efficiency is greater than existing systems which is 85% approximate[8]. Overall, our project represents an innovative and practical solution to modern traffic management challenges.

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