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Smart Traffic Management using Deep Learning

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Abstract: *In many major cities throughout the world, traffic congestion is a serious issue that has turned commuting into a nightmare. The traditional traffic signal system is built around a set time concept that is assigned to either side of the junction and cannot be changed to account for changes in traffic density. The designated junction times are set. When compared to the regular allocated time, extended green times are occasionally necessary due to higher traffic density on one side of the intersection. The algorithms and techniques that we are using in the system are OpenCV, Keras, Video Processing, Image Processing and CNN. To determine the number of vehicles present in the region, a contour has been produced based on the object detection in the traffic signal that has been analysed and translated into a simulator. After determining the number of vehicles, we can determine which side has a high density and according to density we will assign signal priority. Our system represents a significant step towards smarter and more effective traffic management.*

Keywords: Deep Learning, Image Processing, Feature Extraction, Segmentation, Convolutional Neural Network (CNN)

I. INTRODUCTION

Traffic congestion is a persistent problem in many cities worldwide [1]. Traditional traffic management systems have not been effective in reducing wait times at intersections, as they have focused on regulating the speed of vehicles on the road [1]. However, with advancements in technology, new methods of traffic management are being developed that offer more efficient and effective solutions [2][3]. One such solution is the application of Deep Learning, which utilizes a Convolutional Neural Network (CNN) algorithm to identify vehicles and predict their count [4]. This technology provides a means for creating a smart traffic management system that can dynamically adjust traffic signals based on real-time road conditions, allowing for optimized traffic flow and reduced congestion [5].

The key components of such a system include the ability to monitor road conditions in real-time [6], and a decision-making mechanism that can process this information to optimize traffic flow while minimizing conflict between vehicles [7]. Inspired by the success of human-led traffic management, the aim of this research paper is to create a smart traffic management system that uses Deep Learning technology to identify vehicles and predict their count, allowing for the creation of a responsive, real-time traffic management system [8]. By integrating these technologies, This system aims to create a system that can significantly reduce wait times at intersections and improve 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 order to analyse the traffic conditions for intelligent transportation systems, the technique of counting vehicles is used to determine the density of the road traffic. The widespread use of cameras in urban transportation networks has made surveillance video a key source of data. Furthermore, with the availability of handheld/mobile cameras and large data processing, real-time traffic control systems have lately gained popularity. In this study, they provide a method for counting the number of vehicles in a video of highway traffic that was shot using handheld cameras. Three steps are used to process a video: object recognition using the YOLO (You Only Look Once) technique, tracking with a correlation filter, and counting. YOLO obtained outstanding results in the object detection area, correlation filters improved accuracy, and tracking speed was competitive. As a result, they create multiple object tracking with correlation filters utilizing the YOLO framework's 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, imran menon,etl.[2] has stated that, In this paper, the research on applying various image processing algorithms to control real-time traffic is presented in this work. Images of several lanes of the roads where traffic is present are taken using a webcam. Using image processing techniques in the Matlab tool, the number of transport vehicles in each image is calculated, and the timer is allocated to lanes based on the number of vehicles in the particular image of the lane for showing the green signal to pass the vehicle. In this design, the green and red signals are displayed using LEDs, while the green signal's decrementing timer is displayed using seven segments.

Zulaikha Kadim,Khairunnisa Mohammed Johari,Den Fairol Samaon,Yuen Shang Li,Hock Woon Hon[3] has stated that, The planning and design of future traffic facilities depends on the appropriate authorities' ability to estimate road usage and traffic trends. Typically, the survey is conducted manually, requiring human observers to remain on-site throughout the survey. The method not only puts observers at risk, but it also uses a lot of resources as traffic volumes rise, as they do in metropolitan arterials. With 48 high-traffic video clips taken from cameras temporarily mounted at four chosen metropolitan arterial routes, a deep-learning-based traffic volume count method is thus proposed in this work and thoroughly tested estimated AADT more than 50,000 and 100,000). The video snippets are divided into 15-minute and 5-minute lengths for testing purposes. Then, depending on the discrepancy between the system output and the manual ground truth, each clip's correctness is assessed. The four camera viewpoints' average accuracy is 97.68 percent.

Boris A. Alpatov, Pavel V. Babayan, Maksim D. Ershov[4] has stated that, In this study, tasks related to traffic control and safety are taken into account when analyzing the road situation. The vehicle detection and counting algorithm and the road marking detection algorithm are two suggested image processing algorithms. The algorithms are made to handle pictures taken by a fixed camera. An embedded platform of smart cameras was used to implement and test the created vehicle detection and counting algorithm. The outcomes of experimental analysis of suggested algorithms are shown.

Dongfang Ma, Xiang Song and Pu Li[5] have stated that, In this research, they put out a brand-new deep-learning-based strategy for predicting daily traffic flow, where taking into account traffic flow patterns and contextual elements can be crucial. To begin with, a specific convolutional neural network is used to extract daily traffic flow patterns. The intra-day temporal development of traffic flow is then taught to long short-term memory (LSTM) units using the retrieved features. Finally, historical context is added to the prediction process to improve performance. This paper demonstrates through a real-data case study that the proposed methodology beats existing benchmark approaches by a significant margin, and that its forecasting performance is robust under multiple scenarios. It also achieves over 90% prediction accuracy

Yaohang Sun, Zhen Liu, Zhisong Pan[6] has stated that, In this study, they describe a brand-new approach to vehicle counting that makes use of traffic-related surveillance footage. They suggest a counting technique based on the regression model since the video traveling through the road has a tendency to be backed up and obstructed, moving slowly and with a high degree of regularity. To extract features from the surveillance video, they first process it. The SVM classifier is then used to confirm the vehicle density. Finally, they used actual passthrough footage to test our methodology. Our tests demonstrate that this method can count the flow more precisely and with less computing expense.

Markus Lucking, Esteban Rivera, Lukas Kohout, Christoph Zimmermann, Duygu Polad and Wilhelm Stork[7] have stated that Effective traffic monitoring is one of the key aspects of smart cities. Many monitoring strategies used today concentrate on video-processing methods using traffic surveillance cameras. However, due to limited processing resources and a range of unanticipated traffic circumstances, video analytics for traffic monitoring on edge devices like cameras is a challenging undertaking. In this paper, they created and tested a real-time vehicle counting system employing deep neural networks in an embedded device to get around these challenges. To find the ideal system configuration parameters and analyze the effects of shifting external variables on our system performance, experiments were conducted.

Shuang Li, Faliang Chang, and Chunsheng Liu[8] have stated that, It is difficult to estimate traffic flow and count vehicles using machine vision, especially in situations with thick traffic. Prior line of interest (LOI) counting techniques mainly rely on accurate tracking, and they rarely concentrate on dense settings. An LOI counting framework is suggested to address the bi-directional LOI counting challenge in dense settings without the usage of intricate tracking techniques. The key contributions are three. First off, the bi-directional traffic flow is considered as a whole rather than treating the LOI vehicle counting problem as a combination of detecting and tracking individual vehicles, and a novel spatio-temporal counting feature (STCF) is proposed for extracting bi-directional traffic flow features in dense traffic scenarios. Second, a counting network termed the counting Long Short-Term Memory (cLSTM) network is presented to perform analysis of the bidirectional STCF features and vehicle counting in succeeding video frames without relying on a multi-target tracking procedure to follow and count each vehicle. Last but not least, a model for estimation of traffic flow parameters including speed, volume, and density is created. The proposed vehicle counting method outperforms the tested representative LOI counting methods in both accuracy and speed, according to experiments conducted on the UA-DETRAC dataset and the recorded videos, and the proposed framework can effectively estimate traffic flow parameters such as speed, volume, and density in real time.

III. METHODOLOGY

In the research paper, the methodology section for 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.

3.1 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].

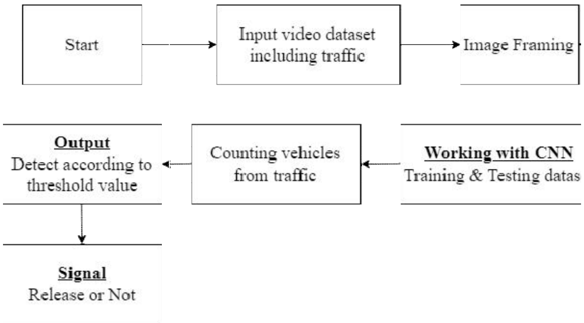

Fig 1. Workflow of Proposed System

3.2 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.

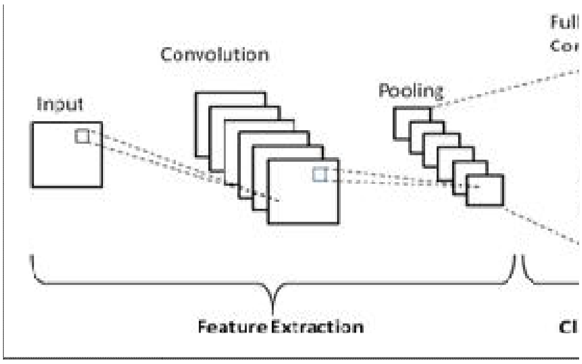

Fig 2.: CNN Architecture

Source:https://www.researchgate.net/figure/Convolutional-Neural-Network-CNN-Architecture-37_fig3_347920378

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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].

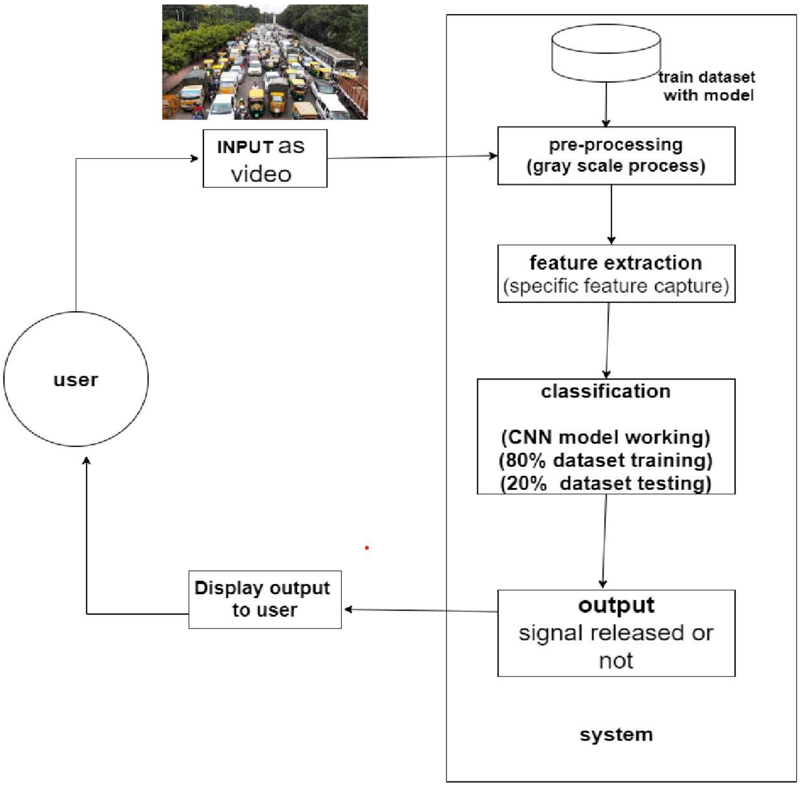

Fig 3. System Architecture

3.3 Training and Validation

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".

3.4.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.

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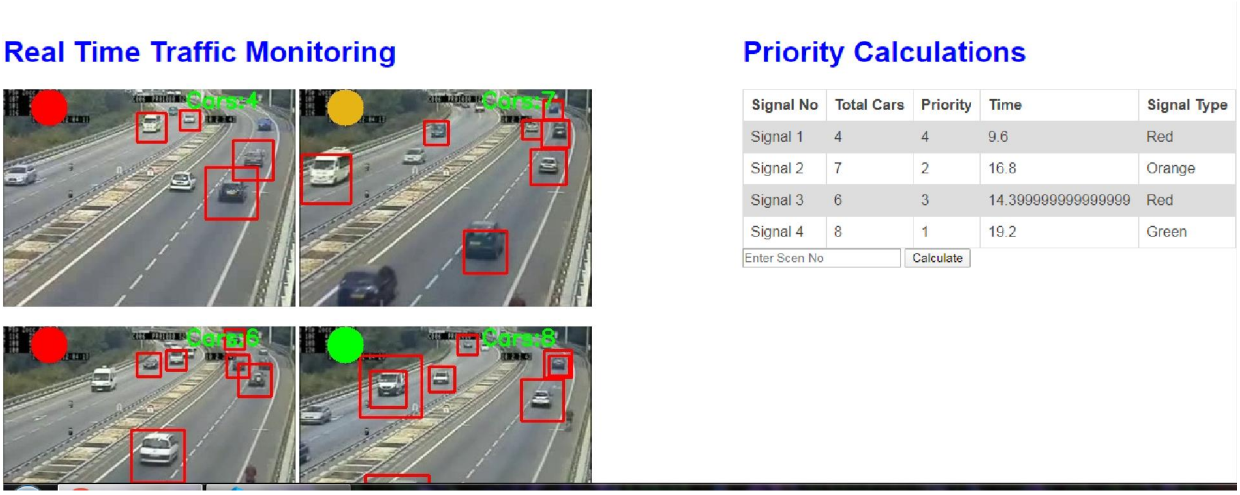
The Evaluation task is performed on the first 4 frames to detect the count of vehicles and mark the vehicles by red square brackets. and The no of vehicle count is captured by the system for further signal release calculations [fig 4]. and based on the no of vehicle count the priority calculations for signal release are performed.



Signal No	Total Cars	Priority	Time	Signal Type
Signal 1	4	4	9.6	Red
Signal 2	7	2	16.8	Orange
Signal 3	6	3	14.399999999999999	Red
Signal 4	8	1	19.2	Green

Fig 4.: Vehicle Detection and Priority Calculations

3.5 Result Discussions

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 this smart traffic management system, 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.

To accomplish this, System first determines the total number of vehicles in each lane using our CNN-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. 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.

IV. CONCLUSION

The analysis of the existing systems has revealed that some of them have implemented various strategies. The systems employ YOLO3, 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 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.

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