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Real Time Traffic Management Using Machine Learning

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Abstract: *The goal of the project is to create a dynamic traffic light system based on density.Upon detecting the level of traffic at the intersection, the signal time adjusts automatically. In many major cities throughout the world, traffic congestion is a serious issue that has turned commuting into a nightmare. The traditional traffic light system is based on the idea that each side of the junction has a defined amount of time.*
This cannot be adjusted to accommodate changing traffic volumes. The designated junction timings are set. Sometimes a side of the junction with a higher traffic density requires a longer green time than the normal allocated time. The traffic signal's object detection is analysed, converted to a simulator, and then the threshold is determined using that information to determine the contour. After determining the number of vehicles, we'll be able to: which signals will be assigned to a specific side depending on which side has a high density.

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I. INTRODUCTION

In the past few decades, traffic congestion in the major cities has gotten significantly worse. The motorization of society and the widespread use of the automobile, which has raised the demand for transportation infrastructure, are particularly linked to congestion.

But the availability of transport infrastructure has frequently lagged behind the expansion of mobility. Specifically as traffic numbers approach a road's capacity, traffic congestion difficulties include incremental delays, vehicle operational costs including fuel consumption, pollution emissions, and stress that results from interference among vehicles in the traffic stream. More individuals than ever before are stuck in traffic jams around cities.When demand exceeds the capacity of the roads, traffic congestion results. There are various factors that contribute to congestion; the majority of them diminish the road's capacity at a certain location or over a specific distance, such as when people park on the road or when the number of vehicles increases. Traffic signals also contribute to traffic congestion. When there is little to no road traffic, the traffic light still displays the same traffic time, which causes other lanes' traffic to increase and cause traffic congestion. Due to this issue, sometimes ambulances, police vans, and fire trucks are late getting to their destinations.

II. RELATED WORK

Xiaoyuan Liang, Xusheng Du in this research, investigate how to choose the duration of traffic signals based on the data gathered from various sensors and vehicle networks. For the purpose of managing the traffic signal, we suggest a deep reinforcement learning model. By gathering information and subdividing the entire intersection into small grids, we can represent the complex traffic scenario as states in the model. A high-dimension Markov decision process is used to mimic the timing changes of traffic lights. The cumulative waiting time difference between two cycles is the reward. A convolutional neural network is used to map the states to the rewards in order to solve the model.

Lisheng Jin, current vision-based driving assistance systems are built to function in a variety of weather scenarios. In order to improve the effectiveness of vision improvement algorithms, classification is a process used to identify the kinds of optical features that are present. A multi-class weather model is needed to enhance machine vision in inclement conditions A classification approach based on numerous meteorological features and supervised learning is provided. From many traffic scene photos, the underlying visual features are first extracted, and the feature is then expressed as an eight-dimensional feature matrix. Second, classifiers are trained using five supervised learning techniques. The investigation demonstrates that the features that were extracted can effectively express the semantics of a picture, and the classifiers have a high rate of recognition accuracy and adaptability.

Caixia Zheng, Fan Zhang, Huirong Hou, this study offers a fresh paradigm for classifying various weather conditions. The suggested technique has the following advantages over other algorithms. First off, our method extracts from photos both the physical properties of the nonsky region and the visual appearance attributes of the sky region. As a result, the retrieved features are more extensive than some of the current methodologies, which simply take into account the features of the sky region. Second, we adopt discriminative dictionary learning as the classification model for weather, which might solve the constraints of earlier efforts, in contrast to other methods that used traditional classifiers (e.g., SVM and K-NN). In order to avoid using a large number of labelled samples to train the classification model in order to get good performance of weather recognition, the active learning approach is also added into dictionary learning.

Hamid Reza Riahi Bakhtiari, in order to extract several road types from high-resolution remote sensing photos, this research suggests a semi-automatic method. The strategy is based on the mathematical morphology method, SVM, and edge detection. First, using a Canny operator, the road's outline is found. Next, adjacent segments are combined using the Full Lambda Schedule merging approach. The complete image was subsequently categorised as a road image using Support Vector Machine (SVM) and several spatial, spectral, and textural features. Finally, morphological operators are used to raise the detection quality of roadways. On a variety of satellite photos from Worldview, QuickBird, and UltraCam aerial photographs, the algorithm was methodically assessed. The accuracy evaluation's findings show that the suggested road extraction approach can extract various types of roads with high accuracy.

III. PROPOSED WORK

- **Gathering and analysing needs:** In this waterfall step, we determine the different requirements that are necessary for our project, such as the databases, interfaces, and necessary software and hardware.
- **System Design:** In this phase of system design, we create a system that is user-friendly and simple to understand for end users. In order to comprehend the system flow, system modules, and order of execution, we construct several UML diagrams and data flow diagrams.
- **Implementation:** During the project's implementation phase, we successfully implemented the various modules needed to achieve the desired results at the various module levels. The system is initially built in tiny programmes known as units with input from the system design, and is then combined in the following phase. Unit testing is the process of developing and testing each unit for functionality.
- **Testing:** Various test cases are run to see if the project module is producing the desired results within the anticipated time frame. Following the testing of each unit created during the implementation phase, the entire system is merged. The entire system is tested for errors and failures after integration. 5. System Deployment: After functional and non-functional testing, the product is either released to customers or deployed in their environments. 6. Maintenance: The client environment encounters a few problems. Patches are published to address certain problems. Additionally, improved versions of the product are issued. To bring about these changes in the surroundings of the consumer, maintenance is performed.

The progression is seen as flowing smoothly downward through each phase, like a waterfall, in a cascade to one another. The "Waterfall Model" gets its name because the following phase doesn't begin until the prior phase's established set of goals have been met and it has been approved. Phases in this model don't cross over.

IV. PROPOSED METHOD

In accordance with vehicle density, the first proposed model will be presented, and vehicle number will determine the second proposed model.

- **The earliest proposed model, which was based on the density of vehicles**

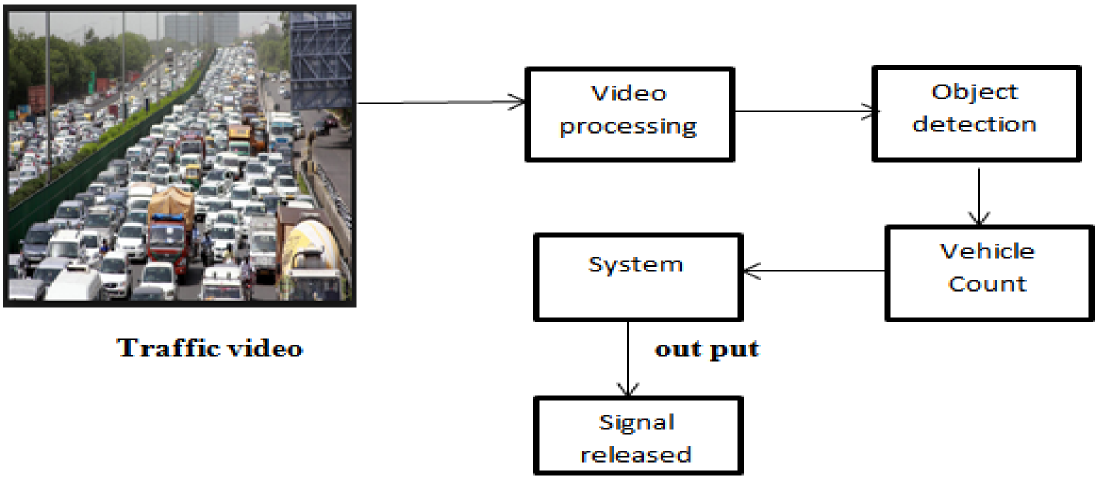
The suggested model works as follows: initially, it shows the crossroad's traffic conditions in each direction.

The picture is used as a reference image on the Raspberry Pi board for each orientation. The Raspberry Pi is then given ready photographs from traffic control cameras on each side or images of the current traffic conditions captured by a web camera mounted in each direction. Images on the Raspberry Pi are processed for each direction by removing the edges from the original image. White pixels are then tallied after the edge image is displayed in white and the image's background is made black. As a result, the instantaneous traffic image's percentage of overlap with the reference image is determined. The scheduling algorithm is then provided information to use in making a decision about when to turn on the green light for each direction. Finally, the connected path is given an acceptable allocation of the green light signal schedule. Additionally, according to the on-site network platform, the traffic data can be delivered to the traffic control room or to any other location for monitoring and controlling traffic and obtaining path traffic statistics using a Raspberry Pi. An overall flowchart of the suggested approach using image processing is shown in Fig. 1.

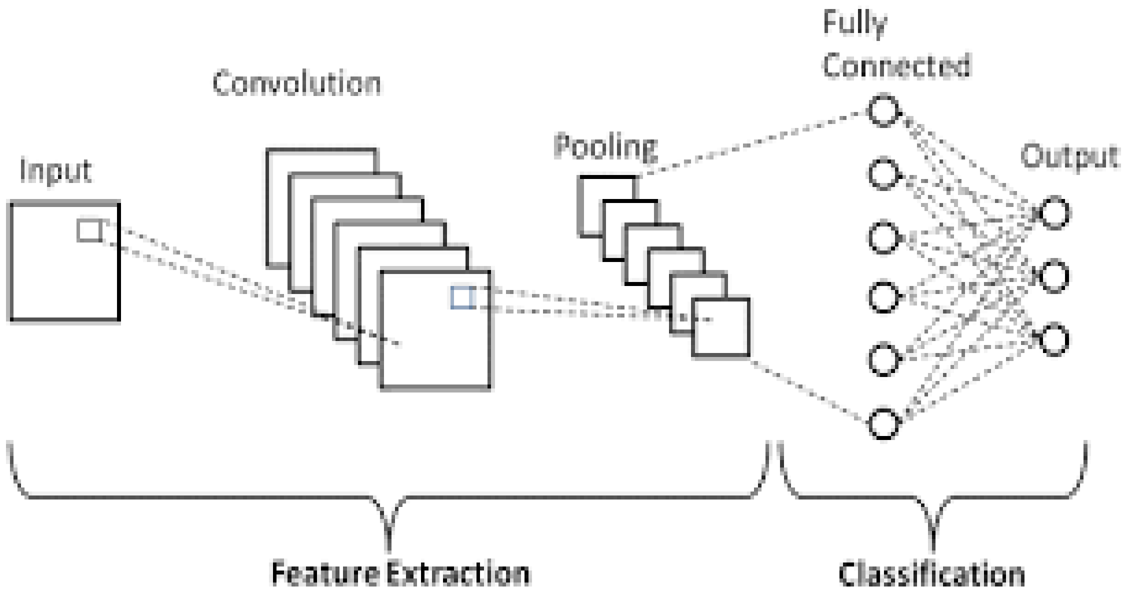
- **The second model based on the quantity of cars proposed**

In order to calculate the number of vehicles going through the key streets leading up to the crossroads, this model processes live video. As a result, the camera used to count the number of vehicles is situated distant from the intersection and along the road that leads there. The Raspberry Pi offers videos in all directions. The video

processing is then carried out utilising the video backdrop removal technique. Filters are used to separate the moving vehicle from the rest of the video and display it as white stains.
When a vehicle first enters the video frame, it is given a unique identifier. As soon as the vehicle crosses the first stimulation line and is stimulated, the motion direction is tracked. When the vehicle crosses the second stimulation line, which is placed appropriately apart from the first stimulation line, it is indicated for movement, and the counter for the number of vehicles rises by one. As a result, the quantity of passing cars is calculated. The scheduling algorithm uses this data to determine when to schedule the signal for the green light. Finally, the corresponding traffic light receives a suitable allocation of the computed time. Additionally, the camera can be used to count the number of vehicles moving in both the up-down and down-up directions.

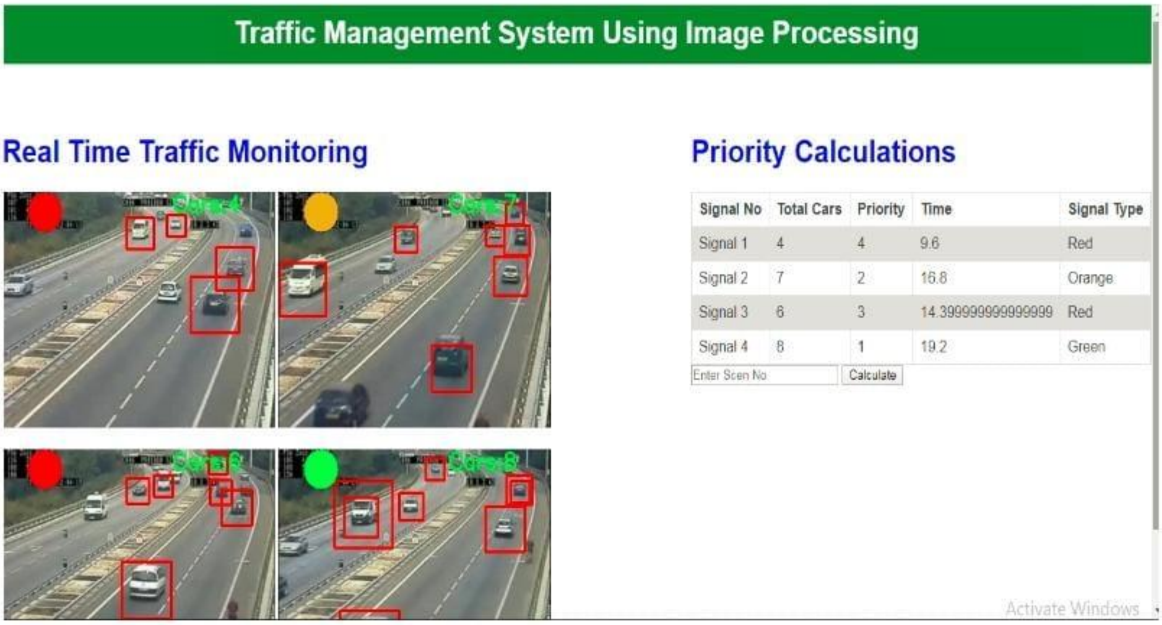


CNN Model: A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input image, give various elements and objects in the image importance (learnable weights and biases), and be able to distinguish between them. Comparatively speaking, a ConvNet requires substantially less pre-processing than other classification techniques. ConvNets have the ability to learn these filters and attributes, whereas in primitive techniques filters are hand-engineered.



V. RESULTS

We can see on the output that those lane where the volume and density of vehicle is high will show the green signal and the one with low density and volume of vehicle will show the red light.



VI. CONCLUSION

We may combine our system with a programme that analyses the official traffic signal so that real-time notifications of traffic conditions can be recorded. In the worst situation, our system will be able to alert users to traffic-related events concurrently with the console's display of the results on the websites. Additionally, we are looking at the possibility of integrating our system with a more intricate traffic sensing infrastructure. Both sophisticated physical sensors and social sensors, such as streams from social media, may be a part of this infrastructure. Particularly in regions (such as urban and suburban) without standard traffic sensors, social sensors may offer a low-cost wide coverage of the road network.

This paper offers a clever approach to managing and control the traffic at the intersections utilising the Internet of Things for smart cities and image and video processing techniques. According to the proposed models, the amount and density of cars going through the principal streets leading to the crossroads determines when the traffic lights should turn green and red. The suggested algorithms were put into practise. The replies, the state of the path, and the cars waiting at the crossing are all reasonably correlated. In the original model, choices were decided solely based on how congested the junction was. Although it is not clear from the camera frame, traffic congestion cannot be seen at a distance far from the crossroad.

In the decision-making model based on the density and number of vehicles, decisions were made based on the measurement of the vehicles density at the crossroad and distances far from the crossroad in terms of the number of vehicles passing within a given interval. This significantly contributed to preventing traffic jams at the crossroad and direction at the same time.

Future priorities will be given to protective situations like the passage of governmental authorities as well as emergency vehicles like ambulances and fire engines. Additionally, this approach can be utilised to guide drivers in selecting the best route given the available traffic.

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