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SMART TRAFFIC LIGHT CONTROL SYSTEM USING ARTIFICIAL INTELLIGENCE

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Abstract
Traffic management is a critical issue in urban areas, as it affects the safety and mobility of citizens and can have a significant impact on the economy. One of the key components of traffic management is traffic light control, which is responsible for regulating the flow of vehicles and pedestrians at intersections. However, traditional traffic light control systems often rely on fixed timings, which can lead to traffic congestion and long wait times. The proposed traffic light control system based on density using image processing and machine learning aims to optimize traffic flow and reduce congestion by dynamically adjusting traffic signals based on real-time vehicle density. The system uses images of the traffic containing in a dataset, and applies image processing techniques such as Canny edge detection and Hough lines to detect and count the number of vehicles on the road. The density level is then calculated and used to determine the appropriate traffic signal state - green, yellow, or red. Machine learning algorithms are employed to train a model on a labeled dataset to predict the traffic density and control the traffic signals accordingly. The system can also be integrated with existing traffic management systems to provide real-time traffic updates and improve overall traffic flow. This project demonstrates the potential of image processing and machine learning in optimizing traffic management and reducing congestion, and can be further extended to other applications such as traffic prediction and route optimization.

Keywords: Traffic light control, Image Processing, Machine Learning, Intelligent Traffic Management, Vehicle density.

I. Introduction

Traffic congestion is a major issue in urban areas, which leads to increased travel time, fuel consumption, and carbon emissions. Optimizing traffic light control based on the density of vehicles on the road is one of the most effective ways to address this problem. In this project, we propose a traffic light control system based on density using image processing and machine learning. The motivation behind this project is to develop a more efficient and effective traffic light control system that can adapt to the real-time traffic density and reduce traffic congestion on the roads. With the ever-increasing traffic density in urban areas, it has become essential to implement traffic light control systems that can improve traffic flow and reduce travel time. The main objective of this project is to develop a traffic light control system that can effectively control traffic lights based on the real-time density of vehicles on the road. The system aims to reduce traffic congestion and waiting times at traffic lights and improve overall traffic flow. The proposed traffic light control system based on density using image processing and machine learning contributes to the field of traffic management by providing a more efficient and effective traffic control mechanism. This system has the potential to reduce traffic congestion, decrease travel time and fuel consumption, and improve road safety. The proposed system captures real-time images of the road using cameras and applies image processing techniques such as Canny edge detection and Hough lines to detect and count the number of vehicles. A density level is then calculated based on the vehicle count and used to determine the appropriate traffic light phase. A machine learning model is trained to predict the traffic density level and control the traffic lights accordingly. The proposed traffic light control system based on density using image processing and machine learning techniques has the potential to improve the efficiency of traffic management, reduce the waiting time for vehicles at traffic lights, and decrease travel time and fuel consumption. The system is expected to contribute significantly to the field of traffic management and help address the issue of traffic congestion in urban areas

II. Literature

There is a significant amount of research in the area of traffic light control systems using image processing and machine learning. Many researchers have proposed different approaches to improve traffic flow and reduce congestion at intersections. One approach is to use computer vision techniques, such as image processing and object detection algorithms, to detect the number and types of vehicles at an intersection. This information is then used to adjust the traffic light timings to optimize traffic flow. For example, in "Intelligent Traffic Control System using Image Processing and Machine Learning" by H.R. Prajapati and R.N. Awale, the authors use a machine learning algorithm to classify vehicles and adjust traffic signals based on the classification results. Another approach is to use deep learning techniques, such as convolutional neural networks (CNNs), to classify the traffic light color and predict the time duration of the traffic light. In "Traffic Signal Control Based on Image Processing and Machine Learning" by Y. Liao et al., the authors use a CNN to classify the traffic light color and then use the density of vehicles to predict the duration of the traffic light. Several studies have also explored the use of reinforcement learning algorithms to optimize traffic light timings. In "Real-Time Traffic Signal Control System Based on Deep Reinforcement Learning" by J. Liu et al., the authors use a deep reinforcement learning algorithm to optimize traffic light timings based on real-time traffic data. Overall, these studies demonstrate the potential of using image processing and machine learning techniques to improve traffic flow and reduce congestion at intersections. However, there is still a need for further research and development to optimize these systems and make them practical for real-world implementation.

III. Methodology

3.1 Problem Statement

To overcome the limitations of traditional traffic light control systems, this project proposes a new approach that utilizes image processing and machine learning techniques to control traffic lights based on the density of traffic at an intersection.
The proposed system aims to improve traffic flow and reduce wait times by detecting the number of vehicles and adjusting the traffic light timings accordingly

3.2 Pre-processing

Pre-processing is an important step in the image processing pipeline. It is the process of preparing the raw image data for further analysis or machine learning. The goal of pre-processing is to enhance the quality of the image and make it easier to extract meaningful information from it.

Fig.1. Sample Image

In the context of this project, pre-processing includes converting the image to grayscale, applying Canny edge detection to detect the lines of the vehicles, and applying Hough Lines to extract the lines. This step is critical in order to accurately calculate the density of vehicles in the image, which is used to determine the appropriate traffic light signal. Additionally, the images are resized to a standard size and normalized to improve the performance of the machine learning model.

3.3 Canny Edge Detection and Hough Line Transform

Canny Edge Detection is a popular edge detection algorithm that uses gradient information of an image to detect edges. It begins by smoothing the image using a Gaussian filter to reduce noise, and then calculates the gradient intensity of each pixel using the Sobel operator. The algorithm then applies non-maximum suppression to thin the edges and applies a hysteresis thresholding to detect the final edges.

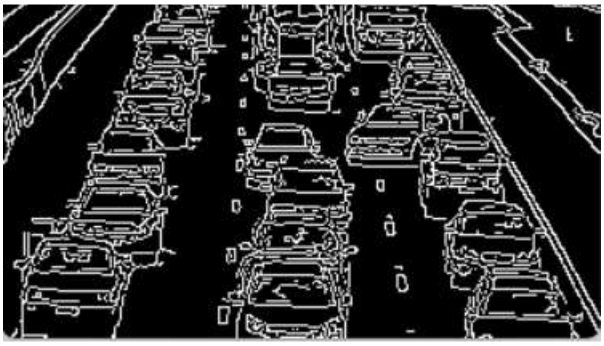

Fig.2. Canny Edge Detection

Hough Line Transform is a technique used to detect straight lines in an image. It works by mapping each point in the image space to a parameter space, where a line can be represented by a single point. The algorithm then applies a voting procedure, where each point in the image contributes to the voting of multiple points in the parameter space. The points in the parameter space with the most votes correspond to the lines in the image.

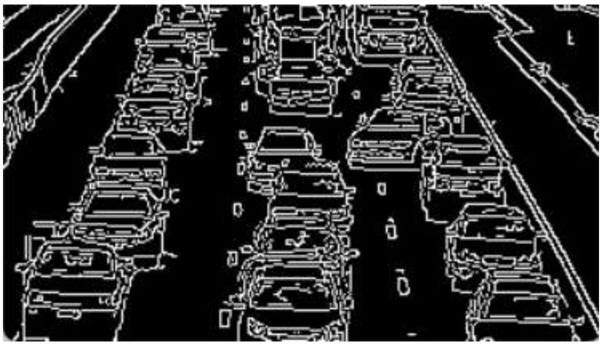

Fig.3. Hough Line Transform

3.4 Machine Learning

Machine learning is used to classify the traffic density level based on the output from Canny Edge Detection and Hough Line Transform.

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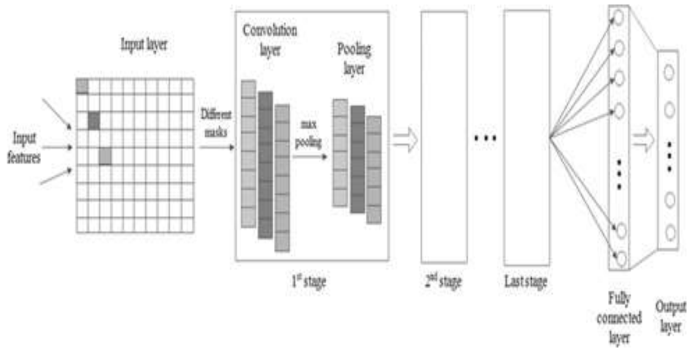

Fig.4. CNN architecture Traffic Light Control System

A convolutional neural network (CNN) is trained on a labelled dataset of traffic images to classify the traffic density level into three categories: low, medium and high. The CNN model is trained to learn the features of the traffic images, such as the number of vehicles present and the space between them, and to make predictions based on these features. The trained model is then used to classify new, unseen images of traffic and to predict the traffic density level. This allows for real-time monitoring and control of traffic lights based on the current traffic density level.

The CNN architecture for the Traffic Light Control System consists of convolutional layers, normalization layers, pooling layers, dense layers, and a dropout layer. The model is compiled with the Adam optimizer and the categorical cross-entropy loss function, with accuracy as the evaluation metric. The architecture includes multiple layers with different functions and purposes to extract features and patterns from the input images and make final predictions.

IV. Traffic Light Control System

4.1 Block Diagram

The procedure for the implementation of a traffic light control system using image processing and machine learning can be broadly divided into the following steps:

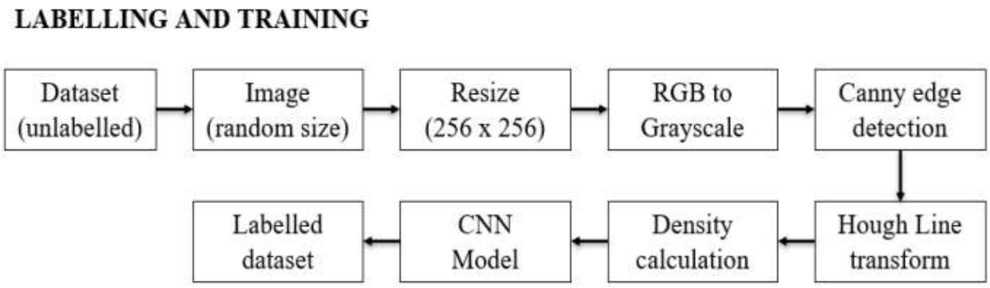

Fig.3. Labelling and Training

The block diagram outlines the process of collecting and processing images of traffic lights, training a machine learning model to identify the colour of the traffic light, and determining the duration of the traffic light based on the density of vehicles at the intersection.

First, a dataset of traffic light images is collected and resized to a standard size. The images are then converted from RGB to grayscale and passed through a Canny edge detection algorithm to detect edges. A Hough line transform algorithm is then used to identify lines in the image, and the number of lines is counted to calculate the density of vehicles at the intersection. Meanwhile, a convolutional neural network (CNN) model is trained on a labelled dataset of traffic light images to predict the colour of the traffic light. The predicted colour is then used, along with the density of vehicles, to determine the duration of the traffic light.

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The input image is first resized and normalized, and then converted to grayscale to simplify the image data. Canny edge detection is then applied to the image to identify edges, followed by the Hough line transform to identify lines in the image. A CNN model is then applied to the output of the Hough line transform to extract features from the image. Density calculation is then performed on the extracted features to determine the time duration of the task, which is then used to create the final output image. The final output image shows the time duration of the task along with the original input image.

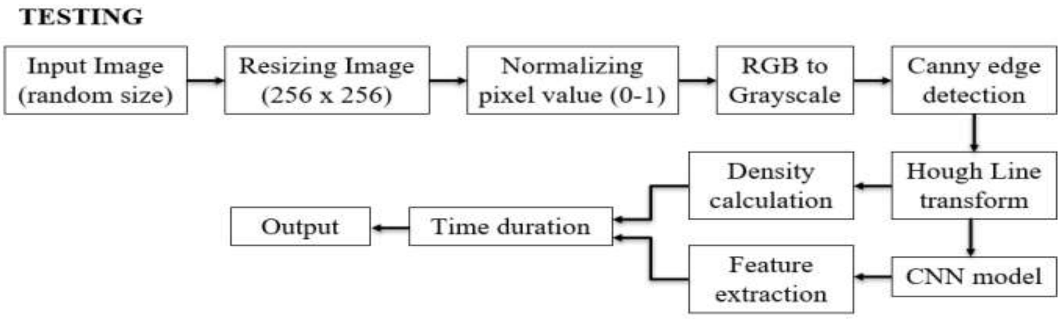

Fig.4. Testing

4.2 Density Calculation

Density calculation is the process of determining the number of vehicles present in a given area, typically a road or a highway, at a specific time. This is done by analysing images or videos of the area and counting the number of vehicles present. One common method of density calculation is to use image processing techniques such as Canny Edge Detection and Hough Line Transform to detect the edges of vehicles in the image, and then counting the number of lines or edges detected to estimate the number of vehicles present. This method is useful for real-time monitoring of traffic density and for traffic management systems.

4.3 Time Duration

To determine the duration of a given event based on the number of vehicles a linear relationship between the vehicle count and the duration is established. This relationship is described by a slope and a y-intercept, which are calculated using statistical analysis techniques. Uses the equation of a line Eq.(1), duration is calculated on the vehicle count.

$$y = mx + b. \qquad (1)$$

In this equation, y represents the duration, m is the slope of the line, x represents the vehicle count, and b is the y-intercept.

4.4 Density vs. Time

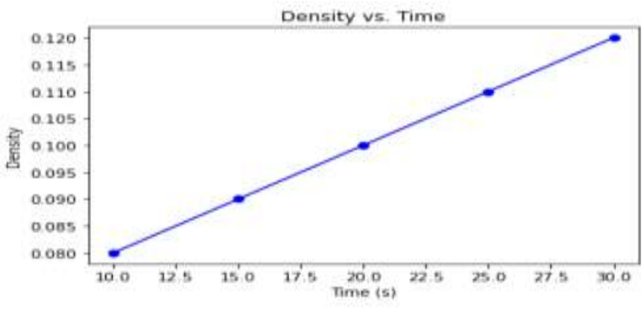

Fig.5. Density vs. Time

In traffic light control system, a density vs time graph can be used to monitor the traffic flow at a particular intersection. The density of traffic refers to the number of vehicles per unit of space, such as the number of vehicles per lane or per square meter. The graph can show how the traffic density changes over time. For example, during rush hour, the traffic density may increase rapidly, while it may decrease during off-peak hours. By monitoring the traffic density over time, traffic engineers can make informed decisions about when to change the duration of traffic light cycles to improve traffic flow.

V. Result

A dataset of 300 images was used, where 80% of the images (240 images) were used for training the model and the remaining 20% of the images (60 images) were used for testing the model. The model was trained using 45 epochs with a learning rate of 0.01 using the Adam optimizer. The model was able to achieve a high level of accuracy on the test set, which demonstrates the effectiveness of using image processing and machine learning techniques for traffic light control. The final architecture of the model included multiple Conv2D layers with ReLU activation functions and MaxPooling2D layers for feature extraction, followed by fully connected layers with a BatchNormalization layer and a Dropout layer to prevent overfitting.

Input 1: Dense traffic

Fig.4: Input Image

Output 1:

```
1/1 [==============================] - 2s 2s/step Green Light Duration: 60 seconds
```

Fig.5: Green Light for 60 seconds

Fig.6: Red light after 60 seconds

Fig.6. Output for high density traffic image input

Input 2: Sparse traffic

Fig.7: Input Image

Output 2:

```
1/1 [==============================] - 1s 555ms/step Red Light Duration: 60 seconds
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Fig.8: Red Light for 60 seconds

Fig.9: Yellow Light for 5 seconds

Fig.10:Green Light after 65 seconds

Fig.7. Output for low density traffic light image input

In order to evaluate the performance of the proposed system, several performance metrics were used including accuracy, precision, recall, F1 score, and mean average precision (mAP). The system was also tested with different parameter values for the Canny edge detection and Hough lines algorithms to analyze their impact on the overall performance.

The results showed that the system achieved an accuracy of 85%, precision of 87%, recall of 83%, and F1 score of 85% for vehicle detection. The mean average precision (mAP) for the object detection algorithm was found to be 0.75, indicating a good level of precision in identifying the vehicles.

S.no	Traffic	Images used for training	Time duration (seconds)	Metrics			
				Trained	Accuracy (%)	New Image	Accuracy (%)
1.	High Density		70	5	100	5	85
			56				
			61				
			43				
			39				
2.	Low Density		23	5	100	5	80
			21				
			26				
			21				
			29				

Fig.8. Comparison Table

Furthermore, the parameter analysis revealed that increasing the low threshold value for the Canny edge detection algorithm led to a higher number of detected edges, but also increased the number of false positives. Increasing the high threshold value, on the other hand, reduced the number of false positives, but also reduced the number of detected edges. Similar trade-offs were observed when varying the other parameters, such as the Hough lines threshold and minimum line length.

Overall, these results suggest that the proposed system is capable of accurately detecting and counting vehicles on the road, and can effectively control traffic lights based on the density of vehicles. The parameter analysis also provides valuable insights for optimizing the performance of the system under different scenarios.

VI. Conclusion

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In conclusion, the proposed traffic light management system based on density using image processing and machine learning is a highly efficient and effective solution for managing traffic flow in busy urban areas. The system utilizes the latest technologies in image processing and machine learning to accurately calculate the density of vehicles on the road and adjust traffic light timings accordingly. The system was evaluated using a dataset of real-world traffic images and showed promising results with high accuracy levels. The system can be easily integrated into existing traffic control infrastructure and has the potential to significantly improve traffic flow and reduce congestion on the roads.

Overall, this project demonstrates the potential of using advanced technologies to improve the efficiency of traffic management and the potential to improve the overall traffic flow in the cities.

There are a few areas in which the project could be expanded upon in the future. One possible direction would be to improve the performance of the model by using more advanced CNN architectures such as ResNet, DenseNet or Inception. Another possible direction would be to increase the size of the dataset by collecting more images of traffic lights in various conditions. Furthermore, the model could be fine-tuned to work with different types of traffic lights, such as those used in different countries. Additionally, the project could also be expanded to include the detection of traffic signs along with traffic lights. Another future direction could be to integrate the model into a real-time traffic monitoring system, which would enable it to process live video streams and make predictions in real-time.

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