Grenze International Journal of Engineering and Technology, June Issue

Smart Control of Traffic Lights using Artificial Intelligence

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***Abstract*— The increasing number of vehicles and urban population has made traffic congestion a serious problem. In addition to creating traffic jams and driver frustration, this issue raises fuel consumption and pollutes the air. Although congestion is a problem everywhere, megacities get the worst of it. The increasing traffic volume emphasizes how crucial real-time road traffic density estimations are to improved signal control and effective traffic management. The management of traffic flow is largely dependent on traffic controllers, and in order to keep up with demand, traffic control systems must be optimised. Our suggested method uses artificial intelligence (AI) and image processing to determine traffic density utilising real-time video feeds from traffic intersections. It also concentrates on creating algorithms to modify traffic light timings according to vehicle density, which will lessen traffic, facilitate quicker transit, and cut down on pollution.**

I. Introduction

In India, traffic is expanding at a rate four times faster than the population. Many countries worldwide are currently grappling with traffic congestion issues, which have significant repercussions on urban transportation and pose substantial challenges. Despite the adoption of automatic traffic systems to replace traffic officers and supervisors, effectively optimizing heavy traffic congestion remains a formidable challenge, especially at multiple junction nodes.

Traffic congestion gives rise to various critical issues and problems that directly impact daily human lives and can sometimes even lead to fatalities. For example, there is an increased danger that a vital patient won't arrive at the hospital in time if an emergency vehicle, such an ambulance, is stuck in traffic. Thus, in order to avoid collisions, accidents, and traffic congestion, it is essential to create an advanced traffic system that intelligently manages traffic.

Consider the following scenario: if one route experiences low traffic while another route encounters high traffic, but both are allocated the same duration of green light, it results in a squandering of available time and inefficiency. In these situations, it is important that the route with more traffic be given a longer green signal than the route with less traffic.

This approach entails calculating traffic density by analyzing live traffic images and comparing them to reference images. A notable disparity in traffic density indicates heightened congestion. However, addressing traffic issues

Grenze ID: 01.GIJET.10.2.71

is intricate due to the involvement of numerous factors and parameters.

The complexity of the traffic problem arises from various factors. Firstly, traffic flow varies according to the time of day, with peak hours typically occurring in the morning and afternoon. Weekends generally see lighter traffic, while Mondays and Fridays often experience heavy traffic as people commute between urban centers and their outskirts. Additionally, seasonal changes, such as foliage and summer, also impact traffic patterns.

Additionally, contemporary traffic light systems often depend on hardcoded delays, employing fixed time slots for light changes that fail to adjust to real-time traffic flow. Furthermore, the status of one traffic light junction can impact traffic flow at neighboring junctions.

Ensuring unhindered passage for emergency vehicles like ambulances, rescue vehicles, fire brigades, police, and VIPs is another vital aspect of traffic management. Unfortunately, in the current traffic system, these priority vehicles frequently face delays and obstructions.

Enhancing the conventional traffic system is crucial for mitigating severe traffic congestion, tackling transportation challenges, reducing traffic volume and wait times, minimizing overall travel duration, and bolstering health, economic, and environmental advantages. This paper puts forward a straightforward, cost-effective traffic light control system designed to tackle many of these deficiencies and enhance traffic management.

II. Literature Survey/ Existing System

A review of literature concerning the intelligent control of traffic lights through artificial intelligence (AI) highlights an expanding field of study aimed at utilizing cutting-edge technologies to tackle urban traffic issues. Many studies underscore the promise of AI algorithms in streamlining traffic flow and alleviating congestion. Researchers frequently emphasize the flexibility of AI systems in responding to changing traffic conditions, enabling on-the-fly adjustments to signal timings according to variables like traffic density and patterns. These insights underscore the importance of AI-based traffic light management in optimizing transportation systems' effectiveness and reducing the adverse effects of congestion on both vehicle and pedestrian traffic [1].

Moreover, the literature underscores a significant focus on safety aspects when integrating AI into traffic management systems. Scholars delve into how AI can detect and address potential safety risks, such as pedestrian crossings and emergency vehicle maneuvers. This safety-oriented approach aligns with the overarching objective of developing intelligent transportation systems that prioritize the safety of all road users. Additionally, the literature examines the fusion of AI with various sensor technologies, surveillance cameras, and communication networks to establish a cohesive and interconnected urban infrastructure capable of enhancing road safety measures [2]. Environmental sustainability is a prominent focus in the literature review, where researchers explore how AI-driven traffic light management can aid in cutting emissions and fostering eco-friendly transportation. Research demonstrates the ability to optimize traffic flow to reduce fuel consumption, thereby lessening the environmental footprint of urban travel. This combined emphasis on efficiency and sustainability underscores AI's pivotal role in shaping environmentally aware and resource-efficient urban transportation networks [3]. Furthermore, the literature review highlights the broader implications of integrating intelligent traffic light control within larger smart city initiatives. Scholars investigate the potential synergies of merging traffic data with information from various sources, including public transportation systems, weather conditions, and special events. This interdisciplinary approach to urban planning, facilitated by AI, promises more comprehensive and data-informed decision-making processes, enhancing the overall resilience and adaptability of contemporary urban infrastructure [4]. The literature review uncovers a multifaceted examination of intelligent traffic light control using AI. Researchers explore traffic flow optimization, safety considerations, environmental sustainability, and the integration of AI with broader smart city initiatives. As this field continues to progress, the literature suggests that AI-driven traffic management holds significant potential in reshaping urban transportation for the better.

III. Proposed System/ Implementation

Using object detection and image processing, our suggested method uses CCTV camera footage at intersections to calculate traffic density in real time. The Vehicle Detection module, the Signal Switching Algorithm, and the Simulation module are the three main modules that make up this system [5]. Traffic density is first determined by first processing the input image through the vehicle recognition algorithm, which employs YOLO to count the number of vehicles in several classes, like cars, bikes, buses, and trucks. The This density is used by the signal switching algorithm, in conjunction with other criteria, to modify the red signal times in accordance with the adjustments made to the green signal timer for each lane [6]. The green signal time is limited to the maximum and minimum values to avoid lane starvation. To further illustrate the system's efficacy and contrast it with the current static system, a simulation is created.

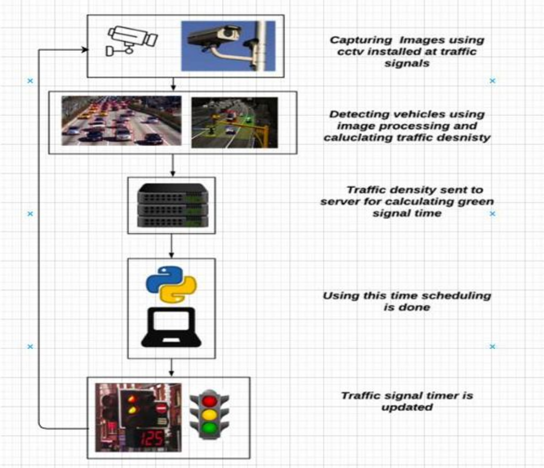

Figure.1 PROPOSED METHOD

A. Vehicle Detection Module

For vehicle detection, the system makes use of YOLO (You Only Look Once), which offers the required precision and processing effectiveness [7]. Specifically trained for vehicle detection, a modified YOLO model recognizes many vehicle types, including automobiles, bikes, heavy vehicles (such buses and trucks), and rickshaws. Using LabelIMG, a graphical tool for image annotation, pictures from Google were gathered and manually labeled to provide the dataset that the model was trained on.

The model was then trained using pre-existing weights that were retrieved from the YOLO website. The.cfg file that was used for training was modified to conform to the specifications of our particular model. By modifying the 'classes' variable, the final layer's output neuron count was adjusted to correspond with the number of classes the framework was expected to identify. This involved four classes in our system: Car, Bike, Bus/Truck, and Rickshaw. In addition, the formula 5*(5+number of classes) was used to adjust the number of filters, which in our case came to 45.

Following these setup changes, training was applied to the model until the loss fell dramatically and did not show any more decline. The training process was considered finished when this criterion was satisfied, and the weights were adjusted to meet our unique needs.

The weights were then incorporated into the code and used with the OpenCV library to detect vehicles. The lowest degree of confidence needed for successful detection is known as a threshold. After the model has been loaded and given a picture, the output is generated in JSON format and consists of key-value pairs, where labels are the keys and the corresponding confidence levels and coordinates are the values. Once more, bounding boxes surrounding the collected labels and coordinates may be drawn using OpenCV and superimposed onto the images.

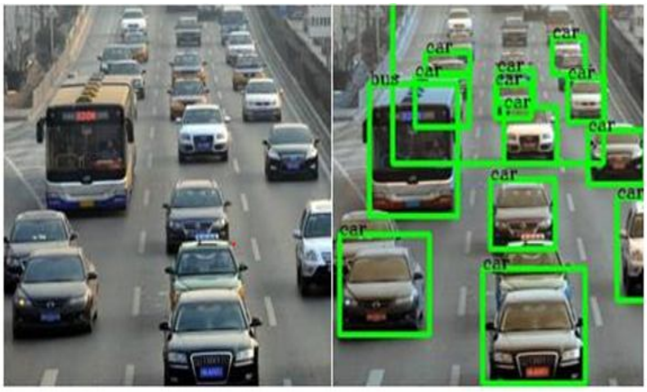

Figure.2 VEHICLE DETECTION METHOD

B. Signal Switching Algorithm

The vehicle recognition module detects traffic density, and the Signal Switching Algorithm dynamically adjusts the duration of green signal timers. Based on this information, it subsequently synchronizes the red signal timer modifications for additional signals. Moreover, the algorithm is cyclical in nature, switching between signals based on the timers' instructions.

As mentioned in the section above, the algorithm consumes data about identified vehicles from the detection module. The confidence level and coordinates are the values, while the label of the identified object serves as the key in this JSON-formatted data set. The algorithm parses this information when it is received to determine the total number of vehicles in each class. Then it determines and assigns the signal's green signal duration while simultaneously modifying the red signal durations for other signals as needed. The technique is additionally made to scale smoothly to support any number of signals at an intersection.

The algorithm's development took into account the following factors:

To effectively manage traffic flow, several factors are considered:

1. Processing Time:This determines when to acquire the image based on the time required to calculate traffic density and green light duration.

2. Number of Lanes: This influences traffic volume and density at the intersection.

3. Vehicle Counts: Data on the number of vehicles in each category informs traffic density calculations.

4. Traffic Density: Derived from factors such as vehicle counts and lane numbers, it guides signal timing decisions.

5. Time Considerations: Lag experienced by vehicles during startup and its non-linear increase for trailing vehicles affect green light duration.

6. Average Vehicle Speed: Different vehicle classes have varying speeds at the start of the green light, impacting the time needed to clear the signal.

7. Minimum and Maximum Time Limits: Setting these limits ensures that green light durations prevent signal starvation while optimizing traffic flow.

By considering these factors, the system can dynamically adjust signal timings to manage traffic effectively and minimize congestion.

C. Working

The default time for the first signal of the first cycle is specified during the algorithm's initial execution. The timings of every other signal in the first cycle and every signal in the cycles that follow are then calculated by the algorithm. Each direction's vehicle detection is handled by a different thread, while the main thread manages the timer for the active signal. The detecting threads take a picture of the future direction as the green light timer for the current signal (or the red light timer for the next green signal) approaches zero seconds. After that, the timer for the next green signal is set and the acquired data is processed.To ensure flawless timer assignments and avoid any delays, the whole procedure runs in the background as the main thread counts down the timer for the current green signal. The following signal turns green for the length of time decided by the algorithm once the current signal's green timer ends.

When the countdown meter for the signal that will turn green next reaches zero seconds, the picture is taken. This gives the system five seconds to process the image—the same amount of time as the yellow signal. During this period, the system counts the number of cars in each class that are visible in the picture, determines how long the green signal should last, and then modifies the timings of the current signal and the next red light based on that number.

To calculate the optimal green signal duration based on the vehicle count for each class at a signal, we utilized data on the average speeds of vehicles at startup and their acceleration rates. This information enabled us to estimate the average time needed for each vehicle class to cross an intersection. The green signal duration is then determined using the formula provided below.

$$GST = \frac{\sum_{vehicleClass} (NoOfVehicles_{vehicleClass} * AverageTime_{vehicleClass})}{(NoOfLanes + 1)}$$

- GST stands for Green Signal Time.
- "noOfVehiclesOfClass" indicates the number of vehicles detected for each vehicle class by the vehicle detection module.

- "averageTimeOfClass" signifies the typical duration taken by vehicles of a particular class to traverse an intersection.
- The term "noOfLanes" indicates the quantity of lanes available at the intersection.

The duration for vehicles of different classes to cross an intersection can be personalized based on several factors, including location parameters like region, city, locality, or even specific intersections. This customized strategy seeks to optimize traffic management effectiveness. Utilizing data from transportation authorities can facilitate the analysis and customization of these parameters.

The traffic signals follow a cyclical pattern instead of favoring the direction with the highest traffic density initially. This mirrors the existing system, where signals systematically switch to green in a predetermined sequence, eliminating the necessity for individuals to alter their behavior or causing any potential confusion. The signal sequence remains unchanged from the current system, with provisions in place for yellow signals as well.

Order of signals: Red → Green → Yellow → Red

IV. RESULTS AND DISCUSSIONS:

The successful implementation and testing of the Smart Traffic Light Control System using Artificial Intelligence are highlighted in this section. It outlines the key findings obtained throughout the project, demonstrating the system's effectiveness and operational capabilities.

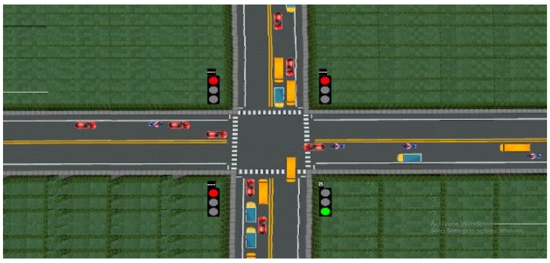

Figure.3 RESULTS

V. Conclusion

In essence, the proposed system adapts green signal durations in real-time according to traffic density at each signal. This ensures that intersections prioritize heavier traffic flows, aiming to minimize delays, ease congestion, and ultimately reduce fuel consumption and pollution. Simulation findings show a noteworthy 23% increase in the number of vehicles passing through intersections compared to the existing system, signifying a substantial advancement. Further improvements in system performance can be achieved through refining the model using real-world CCTV data.

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