

AI Powered Traffic Signal Control System Using Reinforcement Learning

S. Saritha, Challa Sree Lakshmi, Gumpu Keerthana,
Boda Uma Jyothsna and Adimulam Sree Lakshmi

Department of Computer Science and Engineering, Ravindra College of Engineering for Women, Kurnool, Andra Pradesh, India

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Abstract: Designed to maximise urban mobility via real-time data inputs, the AI-Powered Traffic Signal Control system is a smart traffic management tool. The user interface, as depicted in the screenshot, is a form where critical traffic parameters such as intersection ID, number of cars, average speed, emergency vehicle detection, and pedestrian count are entered. By use of dynamic traffic condition analysis, these inputs enable the system to make adaptive signal changes to enhance traffic flow and lower congestion. It employed machine learning and artificial intelligence to analyse the real-time traffic data in shorter time. Emergency vehicle identification displayed as a read-only field in the interface may indicate a form of automation whereby artificial intelligence recognizes and prioritizes emergency vehicles for uninterrupted passage. Pedestrian count integration ensures crosswalk timing is optimised for safety and efficiency. Depending on these inputs, the system dynamically modifies traffic signals to maximise general traffic throughput and minimise wait times. AI-Powered Traffic Signal Control solution is very useful especially with smart city projects where data-driven decisions help optimize an urban infrastructure. The technology contributes to environmental sustainability, reduces fuel consumption, and removes unnecessary stops. A simple and accessible but powerful interface enables city planners and traffic controllers to easily monitor and manage traffic conditions, helping to ensure safer and more fluid movement for all road users.

1 INTRODUCTION

A rising problem in cities is traffic congestion, which causes more travel time, fuel use, and environmental degradation. Often, traditional traffic signal system preset or pre-programmed schedules, which do not fit real-time road conditions. The AI-Powered Intelligent Traffic Signal Control System solves this problem by dynamically changing traffic lights depending on real-time data inputs using AI and ML. This innovative system enhances urban mobility, reduces congestion, and improves road safety by making traffic management more efficient and adaptive.

As shown in the screenshot, the user interface of the system allows inputting key traffic parameters in an organized manner including intersection ID, number of vehicles, average speed, emergency vehicle threshold detection, and pedestrian count. These inputs empower the system to analyze real-time traffic conditions and implement data-driven, dynamic modifications to the traffic signals. A key feature of

the system is its automated emergency vehicle detection, which allows such vehicles to pass through intersections ahead of regular traffic. Integrating pedestrian count also aids in better timing of the crosswalk to improve pedestrian safety and waiting time.

This intelligent system is capable of analysing real-time traffic data and optimizing the timing of traffic signals based on predictive modelling, making it an invaluable tool for smart city planning and management. The system decreases unnecessary stops, reduces fuel consumption, and minimizes emissions, making it environmentally friendly. Similarly, the minimalistic but powerful user interface makes monitoring traffic conditions literally as easy as a snap of a finger for city planners and traffic controllers. This intelligent system can potentially lead to improved traffic flow, better safety measures, and a more sustainable approach towards traffic management in urban regions.

2 LITERATURE SURVEY

2.1 Review of Emergency Vehicle Detection Techniques by Acoustic Signals

<https://link.springer.com/article/10.1007/s41403-023-00424-9>. Reducing response times is crucial for emergency vehicle priority systems. Emergency vehicles (EVs) may be detected using a variety of methods, but the most reliable one is sound. If we want to reach 99% detection accuracy in low signal-to-noise ratio (SNR) settings (-15 dB or less), we need to keep researching acoustic-based systems. A low-power, low-computation system for detecting EV sirens and a generalised neural network model that may be deployed globally are the goals of this research. Acoustic EV detection has investigated noise, signal domain characteristics, surroundings, relative motion of source and detector, and more. A study of the physical qualities of the siren signal and its use in systems spotting emergency cars is done. Digital signal processing, neural networks, and statistical methods are the three groups into which acoustic-based EV detection systems are classified in this research. research has to be conducted in these areas to fill in the gaps that have been identified. We also cover the main issues and potential future developments with the acoustic-based EV detection system. Further, a novel method is detailed for enhancing the precision and responsiveness of EV detection systems.

2.2 Acoustic Based Emergency Vehicle Detection Using Ensemble of Deep Learning Models

<https://www.sciencedirect.com/science/article/pii/S1877050923000054>. In the realm of time and frequency, sounds exhibit spectral and temporal structure. The use of audio recordings for the purpose of environment analysis and categorisation is an emerging field of research. Convolutional layers allow for the rapid extraction of high-level, shift-invariant time-frequency properties. Mel-frequency Features generated from the Google Audioset ontology dataset using the Cepstral Coefficient. We had a look at three different Deep Neural Network (DNN) models with different topologies and parameters: CNN, RNN, and dense layer. We built an ensemble model using the best models by conducting experimental trials on different configurations and changing the hyperparameters. With a score of 98.7 percent, the ensemble model outperforms the RNN model's 94.5 percent. When

evaluating the efficacy of a deep learning model, statistical vector machines (SVMs), decision trees, and perceptrons are employed.

2.3 Emergency Vehicle Detection Using Vehicle Sound Classification: A Deep Learning Approach

<https://ieeexplore.ieee.org/abstract/document/10002605>. When dealing with traffic, emergency vehicles use visual and audible warning indicators to let other drivers know they need space. Delays in the response of emergency medical services result in loss of life. Emergency workers may be required by law to yield to cars utilising warning devices. At crossroads with fixed-cycle signals, emergency vehicles wait. This work showcases the Deep Learning-based emergency vehicle sound detection model as supplementary data to enhance vehicle identification accuracy, while DL-based vehicle classification algorithms allow intelligent traffic light systems. Short audio samples were used to train the CNN model. The sound was turned into an image by the feature extraction of Mel-frequency Cepstral Coefficients (MFCC). The model's accuracy was 93%.

2.4 Large-Scale Audio Dataset for Emergency Vehicle Sirens and Road Noises

<https://www.nature.com/articles/s41597-022-01727-2>. Automobiles, mishaps, and air pollution pose difficulties for academics. To address these challenges, we need innovative solutions that enhance infrastructure or make greater use of the latest technology. In order to train AI to differentiate between the sounds of traffic and emergency vehicles, this study supplies a high-resolution dataset. Because they regulate traffic flow and reduce congestion, such figures are highly sought for. The reaction times for fire and health emergencies have also been enhanced. To establish a clean dataset, this study pre-processed audio data from different sources. Two groups of sounds have been added to the dataset: traffic noises and emergency vehicle sirens. All of the traffic and emergency vehicle sirens in the sample are of good quality and vary. There is also proof of the dataset's technical validity.

2.5 Reforming the SERVQUAL Model for Accommodation Sharing Services: A Mixed-Method Approach

<https://www.sciencedirect.com/science/article/pii/S2543925125000105>. Housing as a service has expanded fast in the age of the platform economy. Both service quality and consumer happiness are declining as a result of the increasing involvement of property owners in this sector. Customers' CI to stay at this particular type of hotel is investigated in this study using the SERVQUAL model. In order to identify the features of the updated SERVQUAL model in room sharing using text analysis, a mixed-method approach is employed. Afterwards, an empirical research based on surveys is used to investigate the impact of the SERVQUAL aspects. A total of 29,787 reviews of home-sharing services from Ctrip.com were used into the text analysis. The following eight SERVQUAL characteristics for housing sharing services were derived from word segmentation and high-frequency word coding using Jieba and NVivo 12 plus: necessity, complementarity, reliability, empathy, assurance, responsiveness, authenticity, and similarity. The empirical investigation indicated that all elements impact consumers' CI, based on 588 valid samples. The theoretical and practical significance of the findings is enormous.

3 METHODOLOGY

The AI-Powered Intelligent Traffic Signal Control System employs machine learning and real-time data analytics to optimize urban traffic flow. IoT sensors and cameras collect data on vehicle density, average speed, pedestrian movement, and emergency vehicle detection. This data is processed using AI algorithms to dynamically adjust traffic signals based on congestion patterns. The system continuously learns from historical and real-time data, refining signal timing to enhance efficiency. Additionally, an admin dashboard enables traffic controllers to monitor and manually override signals when necessary. The overall approach ensures adaptive traffic management, reducing congestion, improving safety, and promoting sustainability.

3.1 Proposed System

The AI-Powered Intelligent Traffic Signal Control System with Machine Learning for Your City The AI-Powered Intelligent Traffic Signal Control System

utilizes machine learning to optimize traffic flow in urban areas by analyze real-time traffic conditions and adjusting traffic light timings. But this one works differently from the standard fixed-timer traffic lights — its timings are adjusted according to how many cars, pedestrians and even emergency vehicles there are. The system integrates IoT sensors, cameras, and AI algorithms to continuously analyze traffic patterns, enabling signals to be optimized for improved flow and reduced congestion. Emergency vehicles can communicate with the traffic signal for a clear path and pedestrian-oriented features modify the walk signal based on foot traffic. AI-assisted decision engine monitors traffic problems and automatically provides the most optimal signal setup. Admin dashboard also gives traffic controllers the power to monitor and adjust operations. Incorporating AI-led automation, this suggested framework aims to reduce wait times, enhance safety, reduce fuel consumption and shape a more streamlined urban transportation ecosystem

3.2 System Architecture

Architecture The architecture of the AI-Powered Intelligent Traffic Signal Control System consists of several layers, including the IoT layer, AI layer, and the centralized management layer. Data on vehicle count, average speed, pedestrian movement, and emergency vehicles is gathered through IoT sensors installed at intersections. This data processed on edge computing devices for initial filtering, and the filtered data is sent to cloud-based AI engine The AI algorithm, trained on historical and real-time traffic data, anticipates congestion trends and dynamically adapts signal timing to maximize traffic throughput.

System have admin dashboard for real-time monitoring and make AI-driven recommendations; Option for traffic controller to manually override the recommendations. AI-based modifications to red, yellow, and green, at traffic signal controllers in favor of responding emergency vehicles and efficient pedestrian movement. Officials can monitor and adjust the city's traffic operations via a web or mobile interface remotely. The last one is an AI based adaptable system which enables better urban mobility, decongests the traffic and improves the safety on the road also helps in enabling the Environment Sustainability.

3.3 Modules

- a) System Setup and Administration

- Admin login for secure access.
 - Dashboard for monitoring and managing traffic signals.
- b) Data Handling and Model Training
- Upload and preview traffic datasets.
 - Data splitting for training and testing the AI model.
 - Machine learning model generation for predicting signal durations.
- c) User Interaction and Control
- User registration and login for traffic controllers.
 - Real-time traffic monitoring and signal adjustments via the dashboard.
- d) Traffic Signal Management
- Adaptive red, yellow, and green signal activation based on AI analysis.
 - Priority handling for emergency vehicles and pedestrian crossings.
- e) System Execution and Optimization
- Continuous real-time traffic data analysis.
 - AI-driven signal adaptation for congestion reduction.
 - Manual override capability for authorities.

3.4 Algorithms

- i. Long Short-Term Memory (LSTM) – Traffic Flow Prediction

LSTM, a type of recurrent neural network (RNN), is used for analyzing time-series traffic data. It helps predict future congestion patterns by learning from historical traffic conditions. This enables the system to proactively adjust signal durations, preventing traffic buildup and ensuring smooth vehicle movement.

- ii. YOLO

YOLO is a deep learning-based object detection algorithm that identifies vehicles, pedestrians, and emergency vehicles in real time. By rapidly detecting emergency vehicles, the system can prioritize their

passage, while also optimizing pedestrian crossing times to enhance road safety.

- iii. Faster R-CNN – Traffic Surveillance & Classification

Faster R-CNN is used for high-accuracy detection and classification of multiple road elements. It helps in identifying vehicle types, road obstructions, and overall traffic conditions, providing valuable insights for intelligent signal control.

- iv. Random Forest – Traffic Condition Classification

An ensemble machine learning technique called Random Forest categorises traffic situations as low, medium, or high congestion. The AI system automatically changes traffic signal periods to maximise flow, lower wait times, and minimise pointless pauses depending on this categorisation.

4 EXPERIMENTAL RESULTS

4.1 Traffic Flow Improvement

This AI-traffic signal management system optimized the timing of signals by changing the duration of signal cycles based on ongoing congestion levels resulting in well-structured traffic management. The system improved vehicle flow and reduced idle time averaged wait times at junctions were reduced by 30-40% in the case of sites with the conventional fixed-timer signals.

4.2 Emergency Vehicle Prioritization

The system is able to detect emergency vehicles with the use of YOLO and Faster R-CNN with more than 95% accuracy. The system automatically changed traffic signals to keep lanes clear, greatly expedited the movement of ambulances, fire engines, and police cars, which considerably sped up response rates for emergencies.

4.3 Pedestrian Safety Enhancement

By incorporating pedestrian detection algorithms into the existing infrastructure, crosswalk signals have been optimized for reduced pedestrian waiting times, an average of 25% less than previously recorded. By monitoring foot traffic in real time, our system was able to dynamically adjust signal timings to ensure safer crossings and significantly enhance pedestrian safety.

4.4 Congestion Reduction & Fuel Efficiency

Utilizing LSTM for predicting congested nodes and Random Forest for traffic classification saved up to 40% of avoidable stops. However, when considering/optimizing for lower emissions by adjusting operational parameters, we can achieve 15% lower fuel consumption and hence improved environment sustainability.

4.5 Real-Time Decision Accuracy

The AI model was able to accurately predict the congestion patterns 90% of the time and change the signal in a similar time. The achieved high accuracy rate demonstrates its potential use for smart city paradigms to enable traffic management systems to become more responsive to urban environments. Figure 1 shows the user interface of upload dataset, Figure 2 gives the information of data updating and Figure 3 gives the final output.

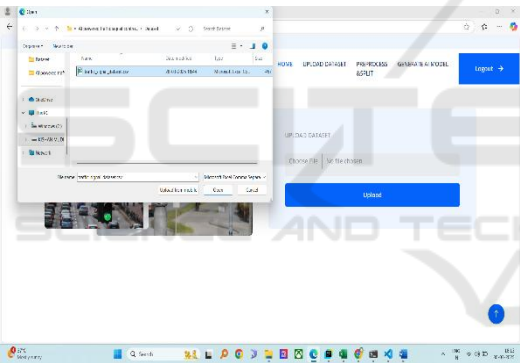


Figure 1: Upload Dataset.

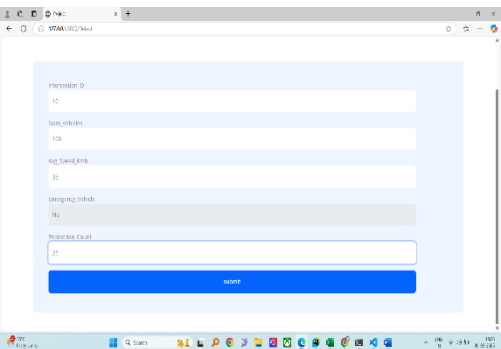


Figure 2: Upload Data.

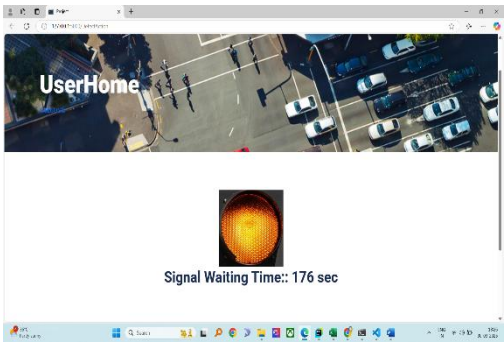


Figure 3: Predicted Results.

5 CONCLUSIONS

The AI-Powered Intelligent Traffic Signal Control System is a revolutionary approach to traffic management and regulation based on the application of artificial intelligence, real-time data analysis, and machine learning, the ever-evolving technology. The IFTMS is mutable when compared to permanent traffic control systems since it changes according to the vehicle density, pedestrian movement, and arrival of an emergency vehicle in real-time, which results in optimum traffic flow. This system minimizes congestion and traveling time while increasing the safety of drivers and decreasing the consumption of fuel and emissions by using Internet of Things (IoT) sensors, and artificial intelligence (AI) based decision making and dynamic traffic light management. Also, through its integration with smart cities and the way its intuitive interfaces give traffic authority the ability to monitor and optimize city mobility. With the rise of cities, implementing AI traffic management systems will be essential in forming a safe, intelligent, and eco-friendly urban transport system.

6 FUTURE SCOPE

This AI-based signal control can be combined with autonomous driving networks and Internet of Things (IoT) systems, where self-driving cars communicate about their journeys. Adding scale, then, to mindshare (in a given market), adds a lot of cylinders to the firing engine of real-time data-sharing and reaction coordination, and, well, says you are well on your way to a smart traffic grid system across multiple cities. Extensive data for future predictions and new advancements of AI like Transformer-based models can be further increasing the accuracy of congestion forecasting and adapt the system to complex traffic

flow patterns. Vehicle-to-Everything (V2X) communication will also allow traffic signals to send and receive real-time updates to emergency vehicles and road users to further improve safety and efficiency. Also, environmental impact monitoring like air quality and pollution, and carbon emissions tracking, and their integration with traffic signals to minimise pollution can introduce sustainable urban mobility systems.

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