

AI AND IOT INTEGRATED SMART TRAFFIC SIGNAL MONITORING AND CONTROL SYSTEM

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ABSTRACT

Traffic congestion at urban intersections causes long waiting times, higher fuel consumption, increased air pollution, and delays for emergency vehicles. Most signals in developing cities still operate on fixed timing plans that do not change with the actual number of vehicles waiting on each approach. As a result, green time is often given to empty roads while long queues build up on busy ones. This paper presents an AI and IoT integrated smart traffic signal monitoring and control system that measures traffic conditions at an intersection in real time and adjusts signal timings according to the observed demand.

The system uses cameras mounted at each approach of the intersection together with a Raspberry Pi edge controller that runs a lightweight object detection model. The model counts cars, two-wheelers, buses, trucks, and auto-rickshaws in each lane and estimates the length of the queue. Infrared sensors placed at stop lines serve as a backup when camera visibility is poor due to rain, fog, or glare. The detected counts are converted into a weighted traffic density for each approach, giving larger vehicles a higher weight because they occupy more road space and take longer to clear.

An adaptive timing algorithm running on the controller allocates green time in proportion to the traffic density of each approach, within minimum and maximum limits that ensure fairness and pedestrian safety. The controller drives the signal lamps through a relay board connected to an Arduino or ESP32 module. When the vision model detects an ambulance or fire engine, or when a siren is detected by a sound sensor, the controller gives priority green to that approach so that the emergency vehicle can pass without stopping.

Every intersection controller publishes vehicle counts, signal states, queue lengths, and fault conditions to a cloud platform using MQTT. A web dashboard shows the live state of all connected intersections on a city map, and traffic police can override timings remotely during events or accidents. Historical data is stored and used to analyse peak hours, identify recurring bottlenecks, and train a prediction model that estimates traffic volume for the next few minutes so that timings can be adjusted in advance.

Simulation and small-scale testing with recorded traffic video showed that adaptive timing reduced average waiting time noticeably compared with a fixed-time plan, particularly when traffic was unevenly distributed across approaches. The system uses affordable hardware and can be installed on existing signal poles without major civil work. Future work includes coordination between neighbouring intersections to create

green waves along arterial roads and detection of traffic violations such as red-light jumping.

I. INTRODUCTION

The number of vehicles on city roads has grown far more rapidly than the road network itself. Intersections have become the main points of congestion, and drivers commonly spend a large part of their travel time waiting at signals. Long queues increase fuel consumption and exhaust emissions, and frustrated drivers are more likely to take risks such as jumping signals or blocking junctions. Emergency vehicles caught in these queues lose valuable minutes, which can affect the outcome for patients and the spread of fires.

Most traffic signals are controlled by fixed-time controllers that repeat the same cycle throughout the day or switch between a few preset plans for morning, afternoon, and evening. These plans are designed from traffic surveys that may be several years old, and they cannot respond to variations caused by accidents, road works, festivals, or weather. Where traffic police manage an intersection manually, the quality of control depends on the experience and alertness of the officer and cannot be sustained for long periods.

Advances in low-cost computing and computer vision now make it practical to observe traffic automatically at every intersection. Single-board computers can run compact deep learning models that detect and classify vehicles in camera images at useful frame rates. The Internet of Things provides the means to connect these controllers to a central platform so that data from many intersections can be viewed, stored, and analysed together, and so that operators can intervene when necessary.

This paper describes an AI and IoT integrated system for monitoring and controlling traffic signals. At each intersection, cameras and sensors measure the number and type of vehicles waiting, an edge controller computes adaptive green times, and a signal driver switches the lamps. Emergency vehicles are detected and given priority. All intersections report to a cloud dashboard where authorities can monitor conditions, override timings, and study historical patterns. The goal is to reduce waiting time and congestion while improving the movement of emergency services.

II. LITERATURE SURVEY

Traffic signal control has been studied for several decades, and the earliest improvements over fixed timing came from vehicle-actuated control using inductive loop detectors buried in the road surface. Studies of actuated signals showed that extending green time when vehicles were detected near the stop line reduced delay at lightly used intersections. However, loop detectors are expensive to install and maintain, since the road must be cut open and the loops are frequently damaged by resurfacing and heavy vehicles. They also provide only a count of vehicles passing a point and cannot measure queue length or distinguish vehicle types. Researchers therefore looked for alternative sensing methods, including infrared, ultrasonic, radar, and magnetic sensors mounted beside or above the road. Each of these methods was found to have particular strengths, but all of them struggled with the mixed and lane-

less traffic common in many developing cities, where two-wheelers and small vehicles move between larger ones. This limitation encouraged interest in camera-based sensing.

Vision-based traffic monitoring has become a major research area as processing hardware has improved. Early approaches used background subtraction and blob analysis to detect moving vehicles, but these methods performed poorly with shadows, lighting changes, and stationary queues. The introduction of convolutional neural networks and single-stage detectors greatly improved detection accuracy. Studies applying detectors such as the YOLO family and SSD to traffic scenes reported high accuracy in classifying cars, buses, trucks, and two-wheelers, even in dense traffic. Researchers also developed methods to estimate queue length and density from the detected bounding boxes using a region of interest drawn on each lane. Work on model compression and quantisation showed that these detectors could run on embedded devices such as the Raspberry Pi and Jetson Nano at several frames per second, which is sufficient for signal control decisions made every few seconds.

Adaptive signal timing algorithms form another important area of study. Simple methods allocate green time in proportion to the measured density of each approach, subject to minimum and maximum limits. More elaborate methods optimise cycle length and phase splits using delay models derived from traffic flow theory. In recent years, reinforcement learning has been applied to signal control, with the controller learning a policy that minimises waiting time through repeated interaction with a traffic simulator. Reported results show that learned policies can outperform fixed and simple adaptive plans in simulation. Several authors, however, point out that reinforcement learning controllers can behave unpredictably when conditions differ from those seen during training, and that transportation authorities prefer methods whose behaviour can be explained and bounded. Density-based allocation with safety limits is therefore still widely used in practical deployments.

Emergency vehicle priority has been addressed through several approaches. Some systems use radio frequency identification tags fitted to ambulances and readers at intersections, while others rely on GPS tracking of the vehicle and communication with the signal controller over a cellular network. Acoustic methods detect the characteristic frequency pattern of sirens using microphones and signal processing. Vision-based methods train detectors to recognise ambulances and fire engines by their shape and markings. Studies comparing these methods report that each has limitations, such as the need for special equipment in every vehicle or false detections from similar sounds, and several authors recommend combining two methods to improve reliability. Providing priority early enough for the queue in front of the emergency vehicle to clear is identified as an important practical requirement.

The integration of intersection controllers with IoT and cloud platforms has been examined in recent work on smart city infrastructure. Controllers publish data using lightweight protocols such as MQTT, and central servers store the data, display it on dashboards, and allow remote configuration. Studies report that centralised visibility

helps authorities respond to incidents and plan road improvements, and that stored data supports short-term traffic prediction using time series and neural network models. Authors also highlight the importance of local autonomy, so that each intersection continues to operate safely if the network connection fails. The present system follows these directions by combining edge-based vehicle detection, density-weighted adaptive timing, multi-method emergency priority, and cloud-based monitoring with local fallback operation.

III. SYSTEM ANALYSIS

The system is analysed as a network of intelligent intersection nodes connected to a central cloud platform. Each node consists of four IP or USB cameras covering the approaches, infrared sensors at the stop lines, a sound sensor for siren detection, a Raspberry Pi 4 edge controller, and an ESP32 signal driver connected to a relay board that switches the red, amber, and green lamps. The edge controller captures frames from each camera, runs a quantised object detection model, and counts vehicles by class within a lane region of interest. Counts are converted into a weighted density using passenger car equivalent factors. The timing module assigns the next green phase to the approach with the highest density and computes its duration within configured limits. Emergency vehicle detection from the camera or siren sensor causes the current phase to end safely and priority green to be given. The node publishes counts, phase states, and faults to an MQTT broker, and the cloud platform stores data, displays a city dashboard, and relays override commands from traffic police.

Existing System

Existing traffic signals in many cities operate on fixed-time controllers that repeat a preset cycle regardless of the traffic actually present. Each approach receives the same green time whether its queue is long or empty, which wastes capacity and increases waiting time. Some controllers switch between a small number of time-of-day plans, but these plans are prepared from occasional surveys and are rarely updated. During peak hours or incidents, traffic police often switch signals to manual mode and direct vehicles by hand, which is tiring and depends heavily on individual judgement. Loop detectors, where installed, are frequently damaged and not repaired. Emergency vehicles have no priority and must wait in queues or force their way through, putting other road users at risk. Signal controllers are not connected to any central system, so faults such as burnt lamps or power failures are known only when someone reports them, and no data is collected that could be used to study traffic patterns or plan improvements.

Disadvantages of Existing System

- Fixed signal timings do not respond to the actual number of waiting vehicles.
- Green time is wasted on empty approaches while other queues grow.
- Time-of-day plans are based on outdated surveys and are rarely revised.
- Manual control by traffic police is tiring and inconsistent.
- Loop detectors are costly to install and are often damaged.

- Emergency vehicles receive no priority and are delayed in queues.
- Controllers are isolated and cannot be monitored or adjusted remotely.
- Lamp and power faults are detected only when reported by the public.
- No traffic data is recorded for analysis or planning.
- Mixed traffic with many two-wheelers is poorly handled by conventional sensors.

Proposed System

The proposed system replaces fixed timing with adaptive control based on live observation of every approach. Cameras connected to a Raspberry Pi edge controller capture images of each lane, and a lightweight deep learning model detects and classifies vehicles, including cars, buses, trucks, two-wheelers, and auto-rickshaws. Infrared stop-line sensors provide backup counts when visibility is poor. The controller calculates a weighted density for each approach and allocates green time in proportion to this density, subject to minimum and maximum limits and a fixed amber and all-red clearance interval. An ESP32 module drives the signal lamps through relays and reports lamp faults. Ambulances and fire engines are identified by the vision model or by siren detection, and the controller grants them priority green. Every intersection publishes its data to a cloud platform through MQTT, where a dashboard displays live status on a city map, allows remote override, stores history, and supports short-term traffic prediction. The controller continues adaptive operation locally if the cloud connection is lost.

Advantages of Proposed System

- Green time is allocated according to the actual traffic on each approach.
- Average waiting time and queue length at intersections are reduced.
- Vehicle classification accounts for the different space needs of buses, cars, and two-wheelers.
- Emergency vehicles receive priority green and pass without stopping.
- Cameras and infrared sensors are installed on poles without cutting the road.
- Edge processing keeps decisions fast and independent of network delays.
- Traffic police can monitor and override intersections remotely.
- Lamp and controller faults are reported automatically to the dashboard.
- Stored data supports peak-hour analysis and traffic prediction.
- Reduced idling lowers fuel consumption and vehicle emissions.

IV. METHODOLOGY

The methodology begins with the collection of traffic video from local intersections at different times of day. Frames are extracted and annotated with bounding boxes for each vehicle class, and a YOLO-based detector is fine-tuned on this data before being quantised for the Raspberry Pi. A region of interest is drawn on each lane so that only waiting vehicles are counted. For every approach, detected vehicles are multiplied by passenger car equivalent weights and summed to obtain a density score. The timing algorithm selects the approach with the highest score for the next green phase, computes green duration as a base value plus a term proportional to density, and

clamps the result between fifteen and ninety seconds. Amber and all-red intervals are always applied between phases. Siren detection uses a band-pass filter and frequency pattern check, and ambulance detection uses an additional class in the vision model. The ESP32 receives phase commands over a serial link and switches relays. Data is published to an MQTT broker, stored in a time series database, and displayed on a web dashboard.

SYSTEM ARCHITECTURE

The architecture of the system is arranged in layers from roadside sensing to city-level monitoring. The Sensing Layer consists of the approach cameras, infrared stop-line sensors, and the siren sound sensor at each intersection. The Edge Vision Layer runs on the Raspberry Pi and performs vehicle detection, classification, and lane-wise counting. The Density and Timing Layer converts counts into weighted density and computes adaptive green durations within safety limits. The Emergency Priority Layer monitors vision and acoustic detections and preempts the normal cycle when an emergency vehicle approaches. The Signal Actuation Layer, built on an ESP32 and relay board, switches the lamps and reports faults. The Connectivity Layer transfers data between the intersection and the cloud using MQTT over Wi-Fi or 4G. The Cloud Storage and Analytics Layer records history and runs traffic prediction, and the Traffic Control Dashboard Layer presents live status on a city map and sends override commands, while the Alert Layer notifies maintenance staff of faults.

AI and Iot Integrated smart traffic signal monitoring and control system

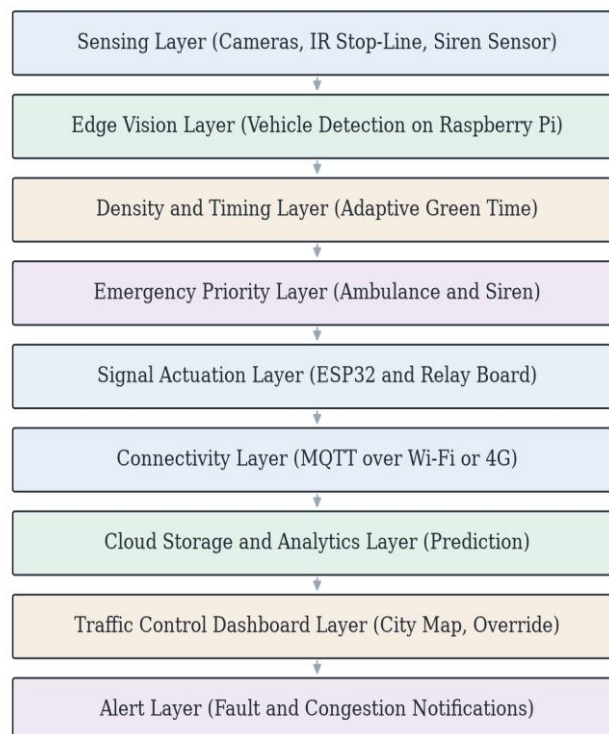


Fig. 1 System Architecture

V. RESULT AND OUTPUT



VI. CONCLUSION

This paper has presented an AI and IoT integrated smart traffic signal system that observes traffic at an intersection and adjusts signal timings according to the demand on each approach. Cameras and a compact vision model running on an edge controller provide lane-wise counts of vehicles by type, and a density-based timing algorithm distributes green time where it is most needed. This replaces the fixed timing plans that currently waste capacity and increase waiting time.

The use of vehicle classification allows the system to handle the mixed traffic found on Indian roads, where two-wheelers, auto-rickshaws, cars, and heavy vehicles share the same lanes. Infrared stop-line sensors add robustness when camera visibility is reduced. Safety limits on green time and fixed clearance intervals ensure that adaptive control never compromises the basic safety of the intersection or the needs of pedestrians.

Emergency vehicle priority based on both visual and acoustic detection helps ambulances and fire engines cross intersections quickly, which can make a significant difference in critical situations. The connection of every intersection to a cloud

dashboard gives traffic authorities a clear view of conditions across the city, lets them intervene during incidents, and alerts maintenance staff to faults as soon as they occur. Historical data collected by the system supports planning decisions and short-term prediction of traffic volumes.

Future work includes coordinating neighbouring intersections so that vehicles moving along a main road meet a sequence of green signals, applying reinforcement learning within safe limits to improve timing further, and extending the vision model to detect violations such as red-light jumping, wrong-way driving, and riding without helmets. Solar power and battery backup for the controller, and pedestrian detection for smarter crossing phases, would make the system more suitable for wide deployment across the city.

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