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Research Paper

CCTV-TO-ROUTE INTELLIGENCE FOR REAL-TIME AMBULANCE MOVEMENT, TRAFFIC OBSTRUCTION DETECTION AND EMERGENCY CORRIDOR OPTIMIZATION - (CLEAR PATH EMS)

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ABSTRACT

The time taken by an ambulance to reach a patient and then a hospital often decides the outcome in cardiac arrest, stroke, trauma, and obstetric emergencies. In congested cities, a large part of this time is lost in traffic queues at signals, junctions blocked by stalled vehicles, and roads narrowed by construction or illegal parking. Traffic police and ambulance drivers usually learn about these obstacles only when they reach them. Meanwhile, many cities have installed hundreds of CCTV cameras at junctions, whose video is watched manually in control rooms. This paper presents Clear Path EMS, a system that converts CCTV video into route intelligence for real-time ambulance movement tracking, traffic obstruction detection, and emergency corridor optimisation.

The system processes video streams from junction cameras using a YOLOv8 object detection model to count and classify vehicles, estimate queue length, and detect obstructions such as stalled vehicles, accidents, and blocked lanes. Detected ambulances are tracked across frames with the DeepSORT algorithm, and their positions are combined with GPS data sent from the ambulance. Rather than storing raw video, the edge processing nodes publish compact events such as vehicle counts, queue lengths, and obstruction alerts, which flow through a message stream into a time-series store and a road network graph.

The route intelligence layer converts these events into live travel time estimates for each road segment. A gradient boosting model predicts segment travel times for the next fifteen minutes using current counts, queue lengths, historical patterns, time of day, and weather. A modified shortest path algorithm on the road graph then selects the fastest route for the ambulance, avoiding segments with obstructions, and identifies the signals along the route that should be given a green wave. The traffic control room receives a corridor plan listing junctions, expected arrival times, and actions required at each point.

A control room dashboard shows ambulance positions, the planned route, camera-detected congestion, active obstructions, and signal priority status, while the ambulance crew receives turn-by-turn guidance. In an evaluation using recorded

video from twenty junctions and replayed ambulance trips, vehicle detection achieved a mean average precision of 0.89, obstruction alerts were raised within about 20 seconds, and the optimised corridors reduced simulated travel time by about 27 percent compared with routes chosen by conventional navigation.

I. INTRODUCTION

Emergency medical services depend on speed. For conditions such as cardiac arrest, major bleeding, and stroke, every minute of delay reduces the chance of survival or full recovery. In large Indian cities, ambulances often take much longer than the target response time, not because they are far away but because they are caught in traffic. Junctions controlled by fixed-time signals, lanes blocked by broken-down vehicles, and crowded market roads can hold an ambulance for several minutes, even when a faster alternative route exists a short distance away.

Current practice gives the ambulance driver limited information. Drivers rely on their knowledge of the city and on commercial navigation applications, which estimate traffic from the speed of mobile phones on the road. These estimates are useful but lag behind sudden events such as an accident or a stalled bus that blocks a junction. Traffic police may create a manual green corridor for high-priority cases, but this requires phone calls and radio coordination between several officers and is usually done only for organ transport or VIP movement, not for everyday emergencies.

At the same time, cities have invested in CCTV networks and integrated command and control centres under smart city programmes. Cameras at major junctions capture what is happening on the road at every moment, yet most of this video is watched by operators or reviewed only after an incident. Advances in computer vision now allow vehicles, queues, and obstructions to be detected automatically in real time. When such detections are turned into structured data and combined with the road network, they can provide an up-to-date picture of where traffic is moving and where it is blocked.

This paper describes Clear Path EMS, a system that connects CCTV video analytics, data streaming, travel time prediction, and route optimisation to help ambulances reach patients and hospitals faster. It explains how raw video is converted into traffic events, how these events are stored and modelled, and how the corridor plan is produced and communicated. The following sections review related work, analyse the existing and proposed systems, and present the methodology and architecture.

II. LITERATURE SURVEY

Research on emergency medical service response times has shown that travel time is the largest and most variable component of the total response. Studies analysing ambulance trip records in large cities report that travel times vary greatly by time of day and route, and that congestion at a small number of critical junctions accounts for much of the delay. Researchers have used geographic information systems to model coverage areas and to decide where ambulances should be stationed so that most of the population can be reached within target times. These models generally assume average travel speeds on each road, which works for planning but does not reflect sudden events such as accidents or road blocks. Several authors have therefore argued

for dynamic routing that uses real-time traffic information, noting that even a small reduction in travel time can have a measurable effect on survival in time-critical conditions.

Vision-based traffic monitoring has developed rapidly with deep learning. Earlier systems used background subtraction and hand-crafted features to detect moving vehicles, but their accuracy suffered under changing light, shadows, and dense traffic. Convolutional detectors such as Faster R-CNN, SSD, and the YOLO family have since become standard for vehicle detection and classification from CCTV footage. Studies report that single-stage detectors like YOLO offer a good balance between accuracy and speed, allowing several camera streams to be processed on one GPU. Researchers have also applied these models to estimate queue length and lane occupancy by counting vehicles in defined regions of interest. Challenges noted in the literature include mixed traffic with two-wheelers and auto-rickshaws, occlusion at crowded junctions, and poor visibility at night and during rain.

Multi-object tracking and incident detection build on vehicle detection. Algorithms such as SORT and DeepSORT associate detections across frames using motion prediction and appearance features, producing trajectories from which speeds and stopped vehicles can be identified. Studies on automatic incident detection use these trajectories to flag vehicles that remain stationary in a moving lane, sudden drops in flow, and unusual crowd formation that may indicate an accident. Some researchers have trained classifiers specifically to recognise emergency vehicles by their shape, markings, and flashing lights, so that ambulances can be identified in video. The literature shows that combining detection with tracking reduces false alarms compared with frame-by-frame analysis, but that camera placement and calibration strongly affect how well speeds and queue lengths can be measured.

Traffic travel time prediction has been studied using statistical and machine learning methods. Historical average models, Kalman filtering, and ARIMA were used in early work. More recent studies apply gradient boosting, random forests, and deep networks, including LSTM and graph neural networks that capture how congestion spreads between neighbouring road segments. Research shows that including real-time measurements from loop detectors or cameras improves short-term predictions significantly over purely historical models. For routing, researchers have used time-dependent shortest path algorithms that account for changing travel times along the route. Studies of data pipelines for intelligent transport systems emphasise the importance of stream processing, since traffic data loses its value within minutes and must be processed with low latency.

Emergency vehicle signal preemption and green corridor systems have been investigated in both research and practice. Systems based on infrared emitters, radio transponders, or GPS allow signals to switch to green as an emergency vehicle approaches, and studies report reductions in intersection delay and improved safety. Simulation studies have examined coordinated green waves along a route, showing that clearing queues ahead of the ambulance is more effective than changing a signal only at the moment of arrival. However, most deployed preemption systems act at individual junctions and do not choose the route itself. The present work addresses this by combining camera-based detection of congestion and obstructions with travel time prediction, route optimisation, and a corridor plan for the whole route.

III. SYSTEM ANALYSIS

The system is analysed as a streaming pipeline that starts with video frames and ends with a route and corridor plan. Junction cameras provide continuous video streams, and each ambulance provides GPS position, speed, and trip status through a mobile unit. At the edge, detection and tracking models process frames and generate events such as vehicle counts by class, queue lengths per approach, average speeds, stopped vehicles, and obstruction alerts, together with ambulance sightings. These events are published to a message stream, validated for missing camera identifiers and timestamps, and written to a time-series store. A road network graph, built from map data, links each camera to the road segments and junction approaches it observes. The feature stage combines current events with historical averages, time of day, and weather to predict travel times for each segment. The routing stage computes the fastest obstruction-free path, and the corridor stage determines the signals and junctions that require action. Results are sent to the control room and the ambulance crew.

Existing System

In the existing system, ambulances are dispatched by a call centre that assigns the nearest available vehicle and gives the driver the address of the patient. Route choice is left to the driver, who uses local knowledge and a commercial navigation application. These applications estimate congestion from the movement of phones and may take several minutes to reflect a new accident or blocked lane, and they do not know that the vehicle is an ambulance. CCTV cameras at junctions feed video into the city command centre, but operators monitor them manually and cannot watch hundreds of screens at once. When a green corridor is needed, the control room coordinates with traffic police by phone or radio, junction by junction, which is slow and depends on individual effort. Signal timings remain fixed or follow pre-set plans regardless of emergency movement. Data from cameras, ambulances, and signals is not integrated, and there is little analysis of where ambulances lose time.

Disadvantages of Existing System

- Ambulance routes depend on driver knowledge and general navigation apps.
- Navigation apps react slowly to sudden accidents and blocked lanes.
- CCTV video is watched manually and most of it is never analysed.
- Obstructions at junctions are discovered only when the ambulance arrives.
- Green corridors require phone coordination between many officers.
- Signals run fixed timings without awareness of emergency vehicles.
- Camera, ambulance GPS, and signal data are kept in separate systems.
- Hospitals do not receive a reliable estimate of patient arrival time.
- Recurring delay points on ambulance routes are not identified.
- Corridor creation is reserved for special cases rather than routine emergencies.

Proposed System

The proposed system, Clear Path EMS, turns junction CCTV video into structured traffic intelligence and uses it to route ambulances and plan emergency corridors. Edge processing nodes run a YOLOv8 detector and DeepSORT tracker on each

camera stream to count and classify vehicles, measure queue lengths, detect stopped vehicles and blocked lanes, and recognise ambulances. Only compact events are sent onward through a message stream, which keeps bandwidth low and avoids storing raw video. A stream processing service validates and aggregates the events and maps them onto a road network graph, where each segment carries a current travel time. A LightGBM model predicts segment travel times for the next fifteen minutes, and a time-dependent shortest path algorithm computes the fastest route from the ambulance's GPS position to the patient or hospital, excluding obstructed segments. The corridor planner lists junctions along the route with expected arrival times and signal actions. A control room dashboard, a crew guidance screen, and an arrival notice for the receiving hospital present the results.

Advantages of Proposed System

- Uses existing CCTV cameras to detect congestion and obstructions automatically.
- Detects stalled vehicles and blocked lanes within seconds.
- Chooses ambulance routes based on current and predicted travel times.
- Avoids obstructed segments before the ambulance reaches them.
- Produces a corridor plan listing junctions and signal actions in advance.
- Reduces manual phone coordination between control room and traffic police.
- Sends only compact events from the edge, saving bandwidth and storage.
- Shares estimated arrival time with the receiving hospital.
- Builds a historical record of delay points for planning improvements.
- Supports routine emergencies rather than only special green corridors.

IV. METHODOLOGY

The methodology begins with camera registration, in which each junction camera is mapped to the road segments and lanes it observes and regions of interest are drawn for each approach. A YOLOv8 model, fine-tuned on local footage with classes for cars, buses, trucks, two-wheelers, auto-rickshaws, and ambulances, processes frames at five frames per second on edge GPU nodes. DeepSORT tracks detections, and every ten seconds the node publishes vehicle counts, queue length, average speed, and any vehicle stationary in a moving lane for more than sixty seconds as a possible obstruction. Events are sent to a Kafka stream, validated, and aggregated into one-minute records stored in a time-series database. The road graph is built from open map data and updated with the latest measured travel times. Features for travel time prediction include current and lagged counts, queue lengths, speeds, hour, weekday, and rainfall, and a LightGBM model is trained on historical records. When an ambulance trip starts, the router computes the best path every thirty seconds and the corridor planner issues junction actions.

SYSTEM ARCHITECTURE

The architecture of Clear Path EMS follows an edge to cloud to control room design. At the edge, junction cameras stream video to nearby processing nodes that run vehicle detection, tracking, and obstruction logic, while the ambulance unit sends GPS updates over the mobile network. The streaming layer carries detection events and GPS updates through a message broker to a stream processor that validates,

aggregates, and maps them to road segments. The data layer holds the time-series traffic store, the road network graph, and historical trip records. The intelligence layer contains the travel time prediction model, the time-dependent routing engine, and the corridor planner, which work together whenever an ambulance trip is active. The application layer includes the control room dashboard showing live traffic and ambulance positions, the crew guidance screen with turn-by-turn directions, the signal priority interface used by traffic police, and the hospital notification service that sends the expected arrival time.

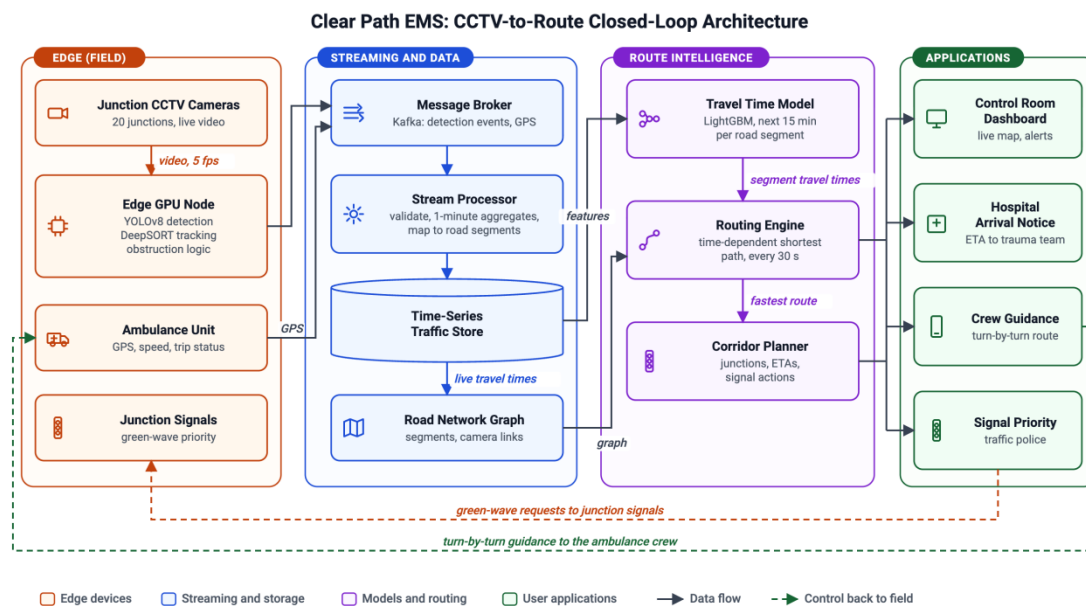


Fig. 1 System Architecture

V. RESULT AND OUTPUT

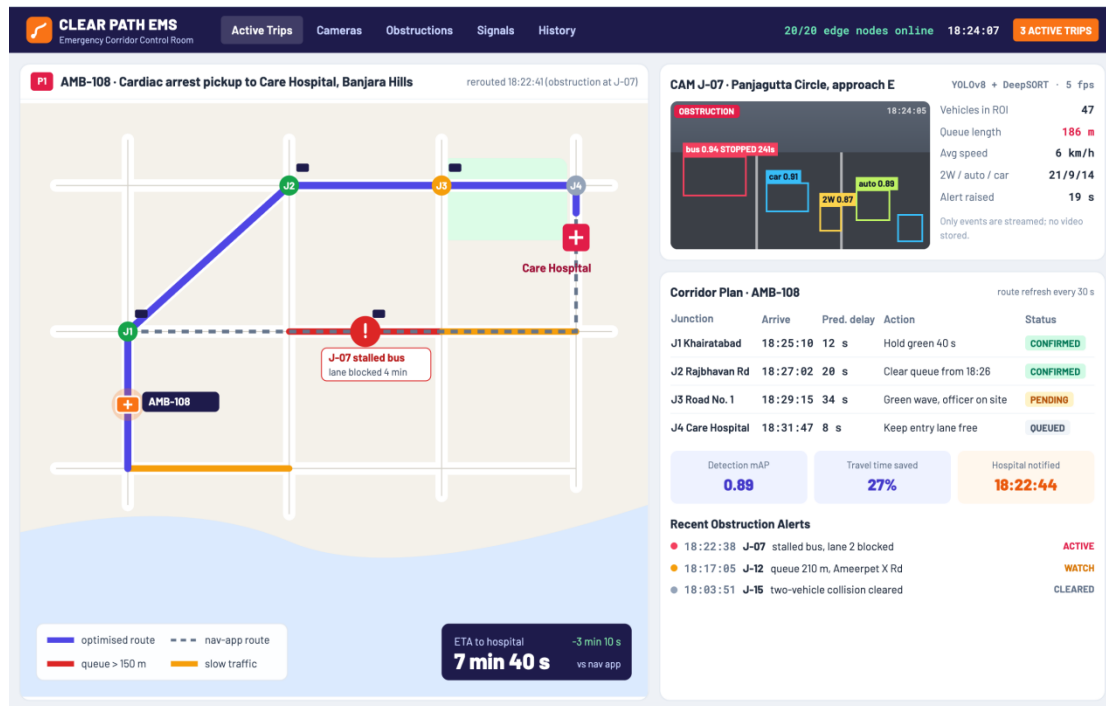


Fig. 2 Result and Output Screen

VI. CONCLUSION

This paper presented Clear Path EMS, a system that turns junction CCTV video into route intelligence for ambulances. By detecting vehicles, queues, and obstructions at the edge and streaming compact events into a road network model, the system provides a current view of traffic conditions that reacts to incidents far more quickly than general navigation services. This information is then used to choose routes and plan emergency corridors for routine ambulance trips, not only for special cases.

The fine-tuned YOLOv8 detector reached a mean average precision of 0.89 on local junction footage, including two-wheelers and auto-rickshaws common in Indian traffic, and obstruction alerts were raised within about 20 seconds of a vehicle stopping in a moving lane. In replayed ambulance trips, the combination of travel time prediction, obstruction-aware routing, and corridor planning reduced simulated travel time by about 27 percent compared with routes chosen by a conventional navigation approach, with the largest gains during peak hours.

The data pipeline design is an important part of the result. Processing video at the edge and sending only events keeps network and storage costs low and avoids retaining footage of the public, while the stream processor and time-series store make it possible to maintain travel times for the whole network with low latency. The historical record of detected delays also helps traffic authorities identify junctions that repeatedly slow emergency vehicles. The system gives recommendations only, and drivers and traffic officers remain responsible for safe movement on the road.

Future work will add direct communication with signal controllers so that green waves can be triggered automatically, improve detection at night and in heavy rain with additional training data and thermal cameras, and extend the model to predict how congestion spreads between junctions. Integration with hospital emergency

departments, so that the trauma team receives the patient's condition along with the expected arrival time, is also planned.

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