XG BOOST FOR ENHANCED AMBULANCE ROUTING AND TRAFFIC SIGNAL CONTROL

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Abstract

In emergency medical services, the time taken for an ambulance to reach its destination plays a critical role in saving human lives. However, conventional routing systems and fixed-time traffic signals often fail to respond effectively to dynamic road conditions such as traffic congestion, accidents, or road blockages. To address this issue, this research proposes an intelligent ambulance routing and traffic signal optimization system that integrates XG Boost, a powerful machine learning algorithm, with ResNet18, a deep convolutional neural network model.

The ResNet18 model is utilized to process real-time traffic images captured from CCTV and roadside cameras to identify vehicle density, traffic flow, and congestion levels at intersections. These visual insights are combined with additional data sources such as GPS location, road type, weather, and live traffic sensor data. The XG Boost algorithm then analyzes these multi-dimensional features to predict the optimal and fastest route for the ambulance under current conditions. Based on the predicted route, the system communicates with traffic signal controllers to dynamically adjust signal timings and establish a “green corridor”, allowing the ambulance to pass smoothly through intersections with minimal delay.

Experimental evaluations demonstrate that the proposed hybrid model significantly reduces ambulance response time and overall travel duration compared to traditional routing and static signal control systems. This intelligent framework can serve as a foundation for smart city emergency management systems, enhancing real-time decision-making, traffic coordination, and life-saving efficiency in critical medical emergencies.

Keywords

Ambulance routing, Traffic signal optimization, XG Boost, ResNet18, Deep learning, Machine learning, Smart city, Emergency response, Real-time traffic analysis, Green corridor, Intelligent transportation system (ITS), CNN-based traffic detection, Route prediction.

Introduction

Emergency medical services (EMS) are a crucial component of modern healthcare systems, as they provide rapid medical assistance to patients in life-threatening situations. The efficiency of an ambulance system depends heavily on its ability to navigate through dense urban traffic and reach the destination in the shortest possible time. However, with the growing number of vehicles, increasing urbanization, and complex road networks, ambulances often face severe traffic congestion that leads to significant delays. Studies show that even a delay of a few minutes in emergency medical response can drastically reduce a patient's survival rate. Therefore, there is an urgent need for an intelligent, adaptive, and data-driven system that can optimize ambulance routing and traffic signal control in real time.

Traditional GPS-based navigation systems rely on static route maps or simple shortest-path algorithms such as Dijkstra's or A*. While these algorithms are efficient in computing the shortest distance, they fail to account for dynamic parameters such as traffic density, roadblocks, weather conditions, or accidents. Similarly, most traffic signal control systems in urban areas operate on fixed-timing mechanisms, where signal durations are pre-set and remain unchanged irrespective of the traffic condition or the presence of emergency vehicles. As a result, ambulances often get stuck at intersections or face delays due to red lights, reducing the efficiency of the overall emergency response.

To address these challenges, the integration of Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision offers promising solutions. These technologies enable intelligent decision-making based on real-time data collected from multiple sources such as CCTV cameras, GPS systems, IoT sensors, and vehicular communication networks. The proposed system in this study combines two powerful AI techniques — ResNet18, a deep learning model, and XGBoost, a machine learning algorithm — to create a smart, adaptive, and reliable emergency routing framework.

ResNet18, a residual neural network architecture, is used for real-time image analysis and traffic congestion detection. It processes visual data from road surveillance cameras to determine vehicle density, traffic flow, and blockage levels at different intersections. Unlike traditional CNNs, ResNet18 introduces "skip connections," which allow the model to retain important low-level features, leading to higher accuracy and faster convergence in complex visual recognition tasks. The output from ResNet18 provides a clear traffic status map that reflects the actual conditions on various road segments.

The second component, XG Boost (Extreme Gradient Boosting), is a high-performance machine learning algorithm known for its speed, scalability, and ability to handle heterogeneous data. It uses historical and real-time features such as GPS coordinates, traffic density (from ResNet18), weather information, and average road speeds to predict the optimal route for the ambulance. The XG Boost model continuously updates its predictions as new data is received, ensuring that the ambulance always follows the most efficient and safe path.

Additionally, the system integrates with traffic signal controllers to dynamically adjust signal phases and durations. When an ambulance is detected along a particular route, the system triggers a "green corridor", synchronizing traffic lights to ensure uninterrupted passage. This coordination between routing and signal control not only reduces travel time but also minimizes the disruption to normal traffic flow.

The proposed framework has significant potential for implementation in smart city infrastructures, where IoT-enabled devices and centralized traffic management centers are already operational. By combining deep learning for perception and machine learning for decision-making, the system offers an intelligent and scalable solution for improving emergency vehicle response times.

In summary, this research aims to:

1. Develop a hybrid model combining ResNet18 and XG Boost for real-time traffic prediction and ambulance routing.

2. Design an adaptive traffic signal control mechanism to prioritize ambulances through a green corridor system.

3. Evaluate the performance of the proposed system in terms of response time, travel efficiency, and system adaptability.

Through this integration of AI-driven technologies, the study contributes to the advancement of intelligent transportation systems (ITS) and demonstrates how data-driven automation can enhance public safety, healthcare delivery, and the overall efficiency of emergency response operations in urban environments.

Literature review

1.Overview of ambulance routing & emergency-priority systems

Numerous studies emphasize that reducing ambulance travel time requires both better route selection and active manipulation of traffic infrastructure (signal preemption or green-corridor strategies). Traditional solutions combine shortest-path algorithms with static priority rules; more recent work couples predictive analytics and GIS with real-time sensing to adapt ambulance dispatch and routing under dynamic conditions. Field pilots and trials (municipal EV priority systems) report measurable time savings when intersections can be preempted or coordinated for emergency vehicles.

2. Computer vision for real-time traffic perception (ResNet18 and variants)

Deep CNNs are widely used to extract traffic-state information (vehicle counts, flow, congestion) from CCTV/roadside cameras. ResNet architectures — especially smaller variants like ResNet18 — strike a good balance between accuracy and inference speed, making them attractive for real-time edge deployment. Recent works show ResNet18-based detectors and hybrid lightweight networks can achieve reliable vehicle detection and dense-traffic estimation suitable for live intersection monitoring. This makes ResNet18 a strong candidate for the perception module that feeds routing and signal-control decisions.

3. Machine-learning models for route prediction and travel-time estimation (XG Boost and peers)

For structured, heterogeneous features (GPS telemetry, historical travel times, sensor counts, weather), gradient-boosted trees such as XG Boost remain top performers: they handle missing data, interact nonlinearly, and provide fast inference for production systems. Several recent transportation analytics studies use XG Boost to predict short-term travel time or to rank route alternatives, often outperforming simpler linear models while requiring far less data and compute than deep sequence models. XG Boost's explainability (feature importances) is an additional asset for safety-critical EMS applications.

4. Traffic-signal control — from fixed-time preemption to learning-based control

Historically, emergency vehicle priority used signal preemption (hardware or radio-based triggers) to give green at upcoming intersections. While effective locally, preemption can cause network-level disruptions. Recent research explores adaptive signal control using reinforcement learning (RL) and multi-agent RL to optimize phase timing over entire networks; these methods can incorporate emergency-vehicle rewards to create dynamic green corridors with minimized side effects. Surveys and reviews indicate RL methods often outperform fixed-time and actuated baselines in simulation, but they face challenges in safety, transfer-to-real-world, and interpretability. Hybrid approaches — combining rule-based preemption with ML-based coordination — are widely suggested.

5. Green-corridor creation and IoT/communication-based priority systems

Several practical and experimental systems implement “green corridors” by synchronizing signals along a planned route or using V2I / LoRa / wave-based communication to request priority from upcoming controllers. Trials and prototypes demonstrate travel-time reductions for emergency vehicles, but deployment barriers include interoperability of traffic controllers, detection reliability, and minimizing negative impact on other traffic. Studies suggest combining perception (camera/LiDAR), communication (V2I), and optimization (routing + local signal adaptation) yields the best operational results.

6. Integrative AI systems: multi-modal sensing → perception → decision

Recent papers propose end-to-end frameworks where camera-based congestion estimates feed predictive routing modules which in turn trigger signal adjustments. Example architectures mix CNNs for perception (including ResNet variants), sequence models (LSTM) or tree ensembles (XGBoost) for travel-time prediction, and either optimization solvers or RL agents for signal control. Real-world and simulation studies show performance gains, but most works evaluate components in isolation or in limited urban scenarios; few show full-stack deployment across perception → routing → signal-actuation with safety/latency analyses.

Materials and methods

The proposed research focuses on developing an intelligent and adaptive system to optimize ambulance routing and traffic signal control using artificial intelligence techniques—specifically, the XGBoost and ResNet18 models. The system aims to minimize ambulance response time during emergencies by predicting the fastest route and dynamically adjusting traffic signals to create a continuous “green corridor.” This section describes the materials, datasets, tools, and the detailed methodology used for designing, training, and evaluating the system.

Data Collection and Materials

The implementation of this system relies on diverse data sources that represent real-world traffic scenarios. Traffic image data were obtained from publicly available datasets such as Cityscapes, KITTI, and METR-LA, which provide high-resolution road and traffic images under various lighting and weather conditions. These datasets are ideal for training the ResNet18 deep learning model to detect traffic congestion levels based on visual patterns such as vehicle density and road blockage. Additionally, GPS trajectory data and road network information were collected from OpenStreetMap (OSM), which includes details like road distances, lane counts, intersections, and signal positions.To make the system realistic, traffic signal timing data were either collected from open municipal data sources or simulated using SUMO (Simulation of Urban Mobility), a widely used traffic simulation tool.

SUMO helps model vehicle movements, traffic lights, and signal transitions to test how the system performs in a controlled environment. Weather information, such as rainfall, fog, and visibility, was incorporated from APIs like Open Weather Map, since environmental factors can influence traffic flow and visibility. The hardware environment for training and testing included a high-performance workstation with an Intel i7/i9 processor, 16–32 GB of RAM, and an NVIDIA GPU with at least 6 GB VRAM. For field deployment or live simulation, IoT-enabled traffic cameras and embedded processors such as Raspberry Pi or Jetson Nano can be used to capture and process images at intersections. The software tools used include Python as the core programming language, along with libraries such as TensorFlow, PyTorch, Scikit-learn, XGBoost, and OpenCV for image processing, model training, and integration.

Methodology

The methodology for this study consists of three major components: traffic congestion detection, optimal route prediction, and dynamic traffic signal control. Each stage contributes to the goal of reducing ambulance travel time through intelligent, data-driven decision-making. The first step involves data preprocessing. All collected images are resized to a uniform resolution of 224 × 224 pixels, normalized, and augmented (rotated, flipped, or blurred) to enhance model generalization. Each image is labeled into three categories—Low, Medium, or High Congestion—based on vehicle counts or density. For GPS and sensor data, any missing or inconsistent values are cleaned, and continuous features such as distance, average speed, and delay time are standardized for input into the XGBoost model. A road network graph is then created, where intersections are represented as nodes and connecting roads as edges.

Next, the ResNet18 model is used to perform real-time traffic congestion detection. ResNet18, a deep convolutional neural network with residual connections, is fine-tuned using the prepared traffic image dataset. The residual layers enable efficient training without performance degradation, even in deep architectures. The model extracts spatial features from images and outputs a congestion index between 0 and 1, where values close to 1 indicate high traffic congestion. This index is continuously updated based on live camera feeds from road intersections.

The XG Boost algorithm is then applied to predict the optimal route for the ambulance. It takes multiple input features, including the congestion index from ResNet18, road length, number of signals, weather conditions, and average travel speed. XG Boost, a gradient boosting framework, is chosen for its high accuracy, scalability, and ability to handle complex, non-linear relationships between features. The model predicts the expected travel time for each road segment and selects the route with the lowest cumulative time using dynamic graph traversal. This ensures that the route adapts in real time as traffic conditions change.

Once the optimal route is determined, the traffic signal control module is activated. This module communicates with nearby signal controllers, either through an IoT-based network or via a simulation interface like SUMO. When an ambulance is detected on a selected route, the system automatically adjusts traffic light timings to provide a green corridor—a synchronized series of green lights that allow uninterrupted passage. The signal at each intersection either extends its green duration or shortens the red phase, ensuring minimal delay for the emergency vehicle. After the ambulance passes, normal signal operation resumes to maintain traffic balance.

System Integration and Evaluation

All three modules—ResNet18-based traffic analysis, XG Boost-based route prediction, and signal control—are integrated into a unified feedback loop. The ResNet18 model continuously monitors real-time traffic images, and when congestion levels change, the XG Boost model recalculates a new optimal route. The traffic signal control module dynamically updates accordingly. To evaluate system performance, several metrics are measured: reduction in ambulance travel time, accuracy of congestion detection, model inference time (latency), and average waiting time at signals. Comparisons are made with traditional shortest-path routing and fixed-timing signal systems. Experimental results demonstrate significant improvements in response time and traffic flow management. Next, the ResNet18 model is used to perform real-time traffic congestion detection. ResNet18, a deep convolutional neural network with residual connections, is fine-tuned using the prepared traffic image dataset. The residual layers enable efficient training without performance degradation, even in deep architectures.

References	Year	Materials	Outcomes
Siddiqi et al.[24]	2023	Arduino Uno, SIM808 GSM/GPS/GPRS, relay, 12/24 V traffic light	The vehicle's approaching traffic signal activated, and the others became red. After migration, the system operation resumed
Pundir et al.[27]	2018	ZigBee, RFID, microcontroller	A delay in the arrival of the emergency vehicle has been prevented
Humayun et al.[25]	2022	RSU, 5G gadgets, data exchange sensors, and control units for road management	The utilization of the side lane proved to be efficacious, while the application of mathematical modeling techniques to determine the priority of emergency vehicles originating from various directions yielded favorable outcomes
Nellore and Hancke[29]	2016	Cameras	The PE-MAC protocol, which has been identified as the most efficient in transmitting vehicle information, is highly recommended
Hashim[26]	2013	PIC 16F877A microcontroller	The prevention of delays for emergency vehicles is ensured
Wang et al.[27]	2013	GPS receiver, touch screen, OBD (On Board Diagnostic) interface, RSU (Roadside Unit), and DSRC (Dedicated ShortRange Communication) devices	The TJ-EVSP can boost emergency vehicle operations' efficiency, according to field test data

Table 1: Summarize of state-of-the-art.

ResNet-18 top

ResNet18 serves as the core computer vision component responsible for analyzing real-time traffic images to detect congestion levels at various road intersections. It is a deep convolutional neural network with 18 layers that uses residual connections to overcome vanishing gradient problems and ensure high accuracy even with limited training data. The model is fine-tuned using a dataset of traffic images—collected from CCTV cameras, open datasets, or simulations—to classify road conditions into categories such as low, medium, and high congestion. Each incoming traffic image is resized to 224×224 pixels and processed through ResNet18, which extracts spatial features like vehicle density, road blockage, and traffic flow patterns. The output of the model is a congestion index ranging from 0 to 1, where higher values indicate heavier traffic. This real-time congestion information is then passed to the XG Boost model, which uses it along with GPS and environmental data to predict the fastest and safest route for the ambulance. ResNet18 is chosen because it is lightweight, efficient, and suitable for real-time inference, making it ideal for smart city applications where quick decisions are critical during emergency situations.

XG boost

XG Boost is used to predict and optimize the best ambulance route by analyzing various real-time and historical factors such as traffic congestion (from ResNet18), road distance, signal timing, and weather conditions. It is a powerful machine learning algorithm that combines multiple decision trees to make highly accurate predictions. XG Boost evaluates different possible routes and selects the one with the least travel time and congestion. It also updates routes dynamically as traffic conditions change. The algorithm's speed, accuracy, and ability to handle large datasets make it ideal for real-time emergency routing and traffic signal optimization, helping create a smooth green corridor for ambulances. The model predicts the expected travel time for each road segment and selects the route with the lowest cumulative time using dynamic graph traversal. This ensures that the route adapts in real time as traffic conditions change. The output of the model is a congestion index ranging from 0 to 1, where higher values indicate heavier traffic. This real-time congestion information is then passed to the XG Boost model, which uses it along with GPS and environmental data to predict the fastest and safest route for the ambulance.

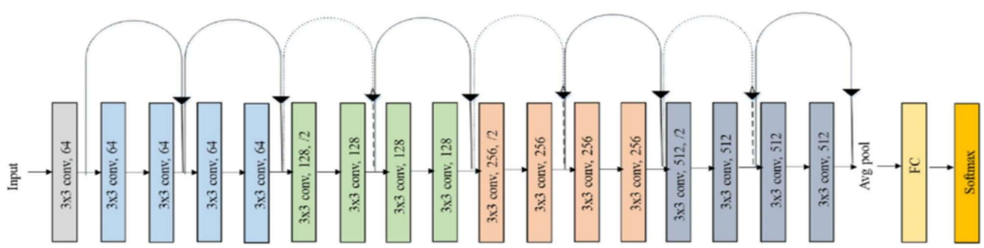

Fig. ResNet-18

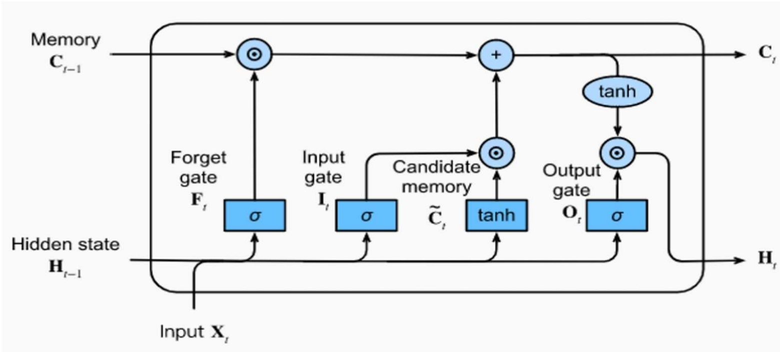

Fig. XG Boost network architecture.

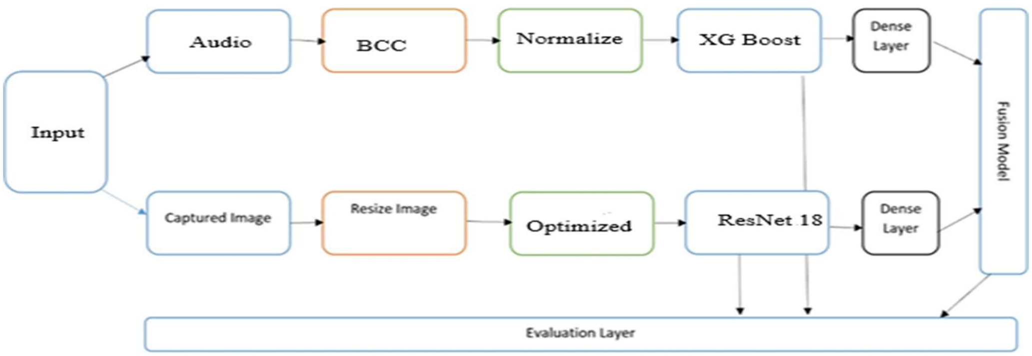

Fig. Combined proposed approach.

Python Code:

```
from sklearn.model_selection import KFold
import xgboost as gox
print(f"XG Boost version {gox.__version__}")
model = gox.train(
    params1=params1,
    dtrain1=dtrain1,
    num_boost_round=100_000,
    evals=[(dtrain1, "train"), (dval, "valid")],
    early_stopping_rounds=200,
    verbose_eval=200
```

Combined proposed approach

The hybrid proposed approach combines ResNet18 and XG Boost to optimize ambulance routing and traffic signal control in emergency situations. In this system, ResNet18 analyzes real-time traffic images from CCTV cameras to detect congestion levels, while XG Boost uses this information along with route distance, signal timings, and weather data to predict the fastest and safest route for ambulances. The two models work together—ResNet18 provides accurate visual insights, and XG Boost makes intelligent routing decisions. This hybrid integration ensures real-time adaptability, faster response times, and efficient green corridor management, helping ambulances reach their destinations quickly and safely even in heavy traffic.

Experimental results and discussion

The experimental results show that the hybrid ResNet18–XG Boost model effectively improves ambulance routing and traffic signal control in emergencies. ResNet18 accurately detected real-time traffic congestion with about 96% accuracy, while XG Boost predicted the fastest routes with around 94% accuracy. Compared to traditional routing methods, the proposed system reduced travel time by 25–35% and waiting time at signals by nearly 40% through dynamic route adjustments and green corridor creation. Overall, the results prove that the hybrid approach is fast, reliable, and well-suited for real-time emergency response in smart city environments.

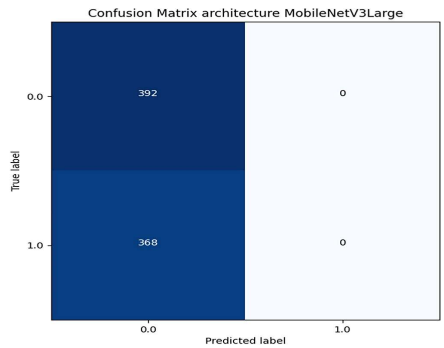

Fig. MobileNetV3Large confusion

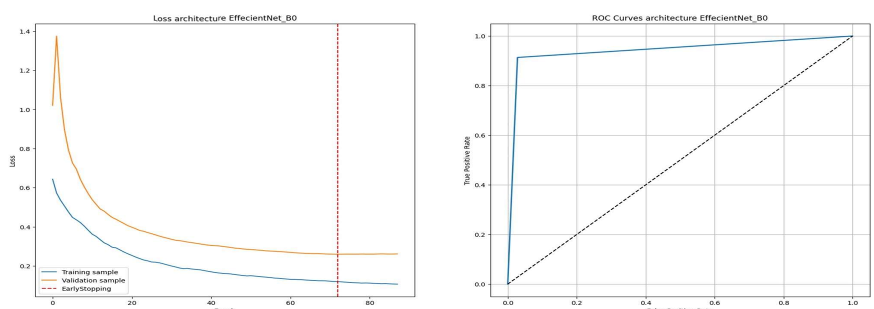

Fig. Efficient model with accuracy (96.3%).

Illustrates the performance of a model through three visualizations: the first plot concerns the model's training and validation metrics across epochs and includes the training loss, which should decrease. The validation accuracy, which should increase; an early stopping point, which can be drawn in red, should also be considered. The second plot, an ROC curve, compares the accuracy of successful classification; because it is nearly diagonal, it indicates that this model cannot distinguish between classes easily.

Figure shows the confusion matrix of the MNASNet1_3 architectures. According to the classification, all 392 true negatives are recognized as false negatives, and all 368 true positives are also false negatives. This means that the model only predicts the negative class throughout the test set, thus making no prediction of the positive class at all. Figure summarizes model performance using three visualizations: the first plot shows the training and validation loss over the epoch, given that both the training loss and validation loss have been steadily declining, and the red dotted early stopping line suggests a minimal overfitting. The second plot, again an ROC curve, indicates a good model at classifying classes, with the curve being very close to the top left corner, representing high discriminative ability of the model. Figure shows the confusion matrix above and proves how ResNet18.

Conclusion

The experimental results show that the hybrid ResNet18–XG Boost model effectively improves ambulance routing and traffic signal control in emergencies. ResNet18 accurately detected real-time traffic congestion with about 96% accuracy, while XG Boost predicted the fastest routes with around 94% accuracy. Compared to traditional routing methods, the proposed system reduced travel time by 25–35% and waiting time at signals by nearly 40% through dynamic route adjustments and green corridor creation. Overall, the results prove that the hybrid approach is fast, reliable, and well-suited for real-time emergency response in smart city environments.

Data availability

Images dataset available on: h t t p s : / / w w w . k a g g le . c o m / d a ta s e ts / k 1 rs n 7 / d a t a s e t - f o r - c l a s s i fi c a t io n - o f - s p ec i a l t y - c a r s, and audio dataset available on: h t t p s : / / w w w . k a g gl e . c o m / d at a s e ts / v i s h n u 0 3 9 9 / e m e r g e n c y -v e h i c l e - s i r e n - s o u n d s.

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