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Analysing the Smart Loaded Traffic Square System for Emergency Vehicles via the Use of a Deep Learning Model

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Abstract: In the realm of urban traffic management, particularly within densely populated traffic squares, ensuring the swift and unimpeded passage of emergency vehicles (EVs) presents a significant challenge. This study introduces a comprehensive Smart Loaded Traffic Square System (SLTSS) that leverages advanced deep learning models to optimize traffic flow for EVs amidst heavy congestion. Through an empirical analysis encompassing various convolutional neural network architectures, including AlexNet, VGG16, VGG19, ResNet 50, ResNet 101, and a proposed custom ResNet152 model, this paper evaluates the effectiveness of these models in classifying EVs from other vehicles within a traffic square setting. The methodology adopted for this study involves a step-wise approach, starting with data cleaning to ensure high-quality, noise-free images for model training. Following segmentation and feature extraction processes, each model was trained and tested on a dataset comprising images of diverse vehicles within urban traffic scenarios. The performance of each model was meticulously assessed based on accuracy, precision, recall, and F1-score metrics, providing a holistic view of their classification capabilities. Results from this study underscore the pronounced impact of model complexity on classification performance. The foundational AlexNet model established a baseline with an accuracy of 85%, precision of 83%, and an F1-score of 82.5%. Subsequent models exhibited incremental improvements, with VGG16 and VGG19 models reaching accuracies up to 90% and 89%, respectively. However, it was the ResNet series that demonstrated significant advancements, with ResNet 50 achieving a 92% accuracy, ResNet 101 further elevating this to 93%, and the proposed ResNet152 model topping the charts with a remarkable 94% accuracy, alongside commensurate improvements in precision, recall, and F1-scores. The comparative analysis vividly illustrates the correlation between the depth and sophistication of the neural network architecture and its ability to accurately classify EVs in complex urban traffic scenarios. The proposed ResNet152 model, in particular, showcased superior performance with a 94% precision, 95% recall, and a 94% F1-score, underlining the potential of deep architectures in enhancing the operational efficiency of emergency responses within loaded traffic environments.

Keywords: *Emergency Vehicles, Smart Loaded Traffic Square System, VGG16, VGG19, ResNet101, ResNet152*.

1. Introduction

The intricacies of urban traffic management, particularly in scenarios involving emergency vehicles, require sophisticated solutions that can adapt to real-time conditions and make split-second decisions. Deep learning models, with their ability to learn from vast amounts of data and identify patterns that are not immediately obvious to human observers, present a compelling option for such scenarios [1]. The use of models like AlexNet, despite being foundational, sets the stage for understanding how even basic deep learning architectures [2] can begin to address the complex problem of traffic management for emergency responses. As our analysis progresses through more advanced models like VGG16, VGG19, and various iterations of ResNet, the evolution of model capabilities becomes evident. These models bring about significant improvements in identifying emergency vehicles quickly and accurately from a plethora of urban traffic data, showcasing the potential for deep learning to revolutionize emergency vehicle prioritization in loaded traffic squares.

The nuanced performance differences between these models, as observed in our dataset, underscore the importance of model selection based on the specific requirements of the traffic management system. For instance, while VGG models offer a balance between complexity and performance, the ResNet series, with its innovative use of residual connections, demonstrates that deeper networks can indeed be trained effectively to achieve superior performance. This is particularly relevant in the context of our proposed ResNet152 model, which not only surpasses its predecessors in all evaluated metrics but also suggests a scalability of deep learning solutions to more complex traffic management and emergency response scenarios. The success of the ResNet152 model in our analysis points to the critical role of depth and architecture sophistication in improving the system's ability to make accurate, real-time decisions that can save lives by reducing emergency vehicle response times.

Furthermore, the application of deep learning in smart traffic management systems extends beyond mere vehicle classification. The real-time data processing capabilities of

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these models enable dynamic traffic routing, signal prioritization, and even predictive analytics to anticipate and mitigate potential traffic congestions before they occur. This holistic approach to traffic management, powered by deep learning, could significantly enhance the efficiency of emergency responses in urban environments. By integrating these models with existing urban infrastructure, cities can move towards creating an ecosystem where emergency vehicles can navigate through congested spaces swiftly, ensuring timely assistance in critical situations. This research not only highlights the potential of deep learning in transforming traffic management systems but also lays the groundwork for future innovations in smart city logistics and emergency response protocols.

2. Literature Review

Emergency situations might happen anytime. Using an issue Vehicle (EV) to reach the target quickly is necessary to resolve the issue. An emergency vehicle management system (EVMS) is proposed to establish an efficient vehicle-passing sequence that lets EVs cross junctions quickly. The suggested method passes the EV without substantially affecting junction vehicle travel times. EVs in communication range are prioritised by making room in the lane next to the shoulder lane. Cyclists and motorcyclists utilise the shoulder lane often. Traffic from the next lane will transfer to the shoulder lane when an EV reaches communication range. Crossing the EV quickly is vital since the number of cars on the road rises fast. This paper presents the EVMS and algorithms to ensure EVs have precedence in vehicle sequencing. The suggested method collects and sends EV data to Roadside Units using IoT Sensors, GPS, 5G, and Cloud computing. Mathematical modelling assessed the solution. Results demonstrate that the EVMS can dramatically cut EV travel times without degrading other vehicle performance. [1]

International traffic figures show one billion cars move everyday, and four billion by 2050. In major cities, urban populations are expanding. Regular circulation, safety, and climate are affected by this rise. Thus, increasing traffic volume is hurting numerous highway categories' operational and safety performance. Urban ring roads are extremely congested, yet governmental administrations sometimes cannot afford to improve or develop new ones. Thus, a low-cost intervention to expand infrastructural capacity is essential. In this context, dynamic hard shoulder running (HSR) might use existing infrastructures and enhance traffic outflow by implementing smart digital highways with minimal infrastructure changes. Despite planned traffic capacity gains, the HSR raises safety challenges, notably at interchanges and during the transition period for opening and shutting the HSR. The Catania (Italy) ring road was used as a case study to demonstrate the usability and utility of microsimulation using VISSIM traffic microsimulation software and SSAM traffic conflict tool to simulate HSR activation situations. [2]

Traffic calming methods reduce motorised vehicle through traffic in residential areas, accident frequency, and speed. These interventions focus on particular streets and encourage controlled driving. These techniques reduce pedestrian-motor vehicle confrontations, but they create unstable traffic patterns and can't always handle increased motor vehicle flows since they're focused on select routes. This article examines current urban traffic calming methods over large areas. It shows how traffic regulation and structural restrictions limit motor vehicle circulation on neighbourhood streets and channel them to major roadways. Photos of sample measurements' locations were used to explain them. In this thesis, Dresden's Äußere Neustadt district was chosen as a model to analyse and modify the mobility plan to minimise MIV flows and prioritise pedestrian, cycling, and public transit space. Parked automobiles damage the district's roadway infrastructure, making bike and incoming vehicle safety difficult. As part of the "Woche des guten Lebens" model project, the volunteer team conducted an online poll and traffic experiment to gauge people' perceptions of the Äußere Neustadt. The findings show that the area-wide radical sustainable transportation strategy needs governmental backing and public engagement. This document implemented the revised transportation strategy based on public input. To find the best traffic calming methods for individual routes, diagonal or cross barriers, zone speed restrictions, offsets, one-way streets, etc. were analysed from actual projects. The district's traffic network and innovative solutions were visualised using QGIS. The revised traffic design will increase pedestrian and bicycle space and reduce automobile noise. [3]

Road deaths are the major cause of death in the U.S. and other developed nations. We found that highway traffic and motor vehicle collisions in California dropped significantly during the COVID-19 epidemic using extensive crash, speed, and flow data. We also found that decreased traffic congestion and faster highway speeds increased catastrophic accidents. The "speed effect" is greatest in counties with substantial pre-existing congestion, and we demonstrate that largely or entirely balances the "VMT effect" of lower vehicle miles travelled on total fatalities. Highway driving fell 22% and overall accidents fell 49% in the first eleven weeks of the COVID-19 response. Average speeds rose 2–3 mph throughout the state, but 10–15 mph in certain areas. Almost 25% more serious collisions occurred. After limitations, deaths reduced, but rising speeds offset the impact of fewer vehicle miles travelled, resulting in little to no reduction later in the COVID era [4].

Traffic congestion is a serious issue. The US invests billions to solve the issue, with mixed results. This issue rises and affects sustainable travel, life quality, pollution, perishables, and prices. Congestion charges minimise traffic in big cities. This article estimates the price using a multivariable model to minimise urban transportation congestion. Santiago's major jams are studied. Data taken from published surveys. The model assessment includes Fisher multiple regression (F) and R2. Validations proved the model's statistical significance. They also demonstrated excellent parameter estimates. Finally, this model improves SDG 3, 11, and 13, which may be used to Santiago City and any other city. [5]

Smart transportation congestion reduction is difficult in major cities. Machine learning techniques aid traffic analysis, congestion prediction, and rerouting. This paper proposes a new prediction approach to reduce traffic congestion by studying a scheme for predicting traffic flow information using four machine learning techniques: FFNN, RBFNN, simple linear regression model, and polynomial linear regression model. This forecast technique uses typical waiting times at entrance and exit street pairings, days of the week, hours of movement, holidays, and rain rate. The FFNN approach outperforms the others with 97.6% prediction accuracy. [6]

Short-term traffic flow prediction is essential for traffic guiding and management and affects intelligent transportation system performance. Traffic flow data is volatile, chaotic, and unpredictable, which affects prediction model accuracy. This paper creates the grey GM(1,1) model with tensor higher-order singular values using multi-dimensional spatio-temporal data characteristics of traffic flow data and the classical grey model GM(1,1) model's modelling mechanism. The tensor higher-order singular value decomposition captures traffic flow data's periodic, multi-modal, and holistic character, reducing volatility and unpredictability and improving model accuracy. Then, the new model is applied to highway short-time traffic flow prediction, analysing the spatio-temporal nature of traffic flow data, providing model modelling steps, and analysing the correlation between original and tensor approximation data using grey correlation degrees. Three instances demonstrate model efficacy. Case 1 shows that MAPE results from nine modelling objects are stable at about 5%, indicating that the new model has some stability; Case 2 shows that the new model is more adaptable to short-time traffic flow prediction based on three modelling and prediction objects; and Case 3 compares the new model to two traditional grey forecasting models and two optimisation models, showing that Finally, the new model is applied to short-time traffic flow prediction, and its predictions match the trend of the original traffic flow data, indicating that it can reveal real-time traffic system characteristics and provide a reliable theoretical basis for traffic planning, control, and optimisation. [7]

The millimeter-wave radar sensor is popular for urban traffic monitoring due to its weather durability and excellent detection accuracy. Fuzzy theory, pattern recognition, and artificial neural networks are used in traffic state discriminating research. Limited research exists on integrating sensors and traffic condition identification algorithms to reduce urban road congestion, particularly using millimeter-wave radar. Thus, the authors suggest a paradigm for urban traffic congestion relief. We illustrate the design and deployment of a millimeter-wave radar system, including waveforms, signal processing, and target tracking, to acquire and output vehicle information. Traffic parameters are then determined by studying traffic condition impacting variables and radar data features. A traffic conditions recognition technique using spectral clustering and neural network algorithm classifies road congestion levels. The technology is used on actual urban crossings, not simulated. To control road vehicle driving, manage traffic light state based on road congestion. The suggested technology reduces road congestion by 20% compared to fixed traffic lights, according to experiments. [8]

Effective natural disaster response may reduce their devastation. This study investigates how supervised hybrid quantum machine learning can optimise automobile evacuation strategies during natural catastrophes. The paper simulates seismic situations as a dynamic computational graph that affects a metropolis. Residents try to leave the city via congested exits. An uncertain and dynamic map is used to simulate the shortest-path issue. We try a unique hybrid supervised learning strategy on a concrete city graph in hypothetical settings. This method mimics Dijkstra's node-wise shortest route algorithm on a deterministic dynamic graph using a unique quantum feature-wise linear modulation (FiLM) neural network parallel to a conventional FiLM network. Adding the quantum neural network in parallel splits the dataset's harmonic and non-harmonic properties across quantum and classical components, increasing model expressivity. After training on Dijkstra's shortest pathways, the hybrid supervised learning agent can navigate. The hybrid quantum network outperforms conventional supervised learning by 7%. We demonstrate that the quantum portion contributes 45.3% to the prediction and that the network can be run on an ion-based quantum computer. The findings show that supervised hybrid quantum machine learning may improve natural disaster evacuation planning. [9]
Gridlock and obstinate drivers have killed 20% of crisis patients on their way to the clinic, according to the National Institute of Emergency Medicine (NIEM). Some nations have implemented a distinct lane system for emergency vehicles to minimise such tragedies, although not all can benefit. Some nations have enough people that emergency vehicles can't get there on time, even with facilities. This chapter presents a paradigm for all such issues. Blockage is

best solved by letting congested sides pass the confluence frst. The goal is to use Dijkstra's algorithm on the weighted diagram of continuous traffic information to find the best emergency vehicle route from source to destination during rush hour jam. For convenience, the model employs the internet of things and digital image processing [10].

The intelligent transport system's traveller information service system focuses on vehicle route selection. This study used a dynamic graph convolutional neural network (DGCN) to predict multi-time-step travel times for each road section of a road network and recommend vehicle travel routes based on travel demand, congestion avoidance, and road network balance. A weighted network model based on road network topology and the GN (Grivan-Newman) method partitioned the road network to find congested locations. The findings revealed that avoiding crowded areas in route selection lowered urban road network congestion equilibrium index. Thus, considering the global road network congestion avoidance system may minimise congestion [11].

With the massive rise of public and private automobiles, traffic congestion is rising rapidly. This work proposes a novel Neuro-fuzzy-based intelligent traffic light control system that dynamically generates traffic light phase duration based on real-time heterogeneous traffic load to account for vehicle heterogeneity. The suggested technology uses peer-to-peer connections to get real-time traffic conditions and congestion from neighbouring traffic signal intersections. Traffic light phase duration is intelligently generated using a fuzzy membership technique. Adaptive neural networks are used to get an effective fuzzy membership function input value for real-time heterogeneous traffic. This system uses Congestion Mode (CM), Priority Mode (PM), and Fair Mode (FM). The optimal option is automatically selected depending on real traffic. Simulating the suggested methodology on India's Gwalior city map using Simulation of Urban Mobility, an open-source simulator, evaluates its performance. Results show that the suggested model outperforms state-of-the-art approaches[12].

Megacities are experiencing worsening traffic congestion due to fast urban population growth and motor vehicle use. Cluster analysis for daily traffic congestion index curves is used to discover traffic congestion patterns and analyse their spatial–temporal fluctuations. First, the coefficient of variation is used to weight K-means clustering method improvements since sample points in various time segments have varied relevance. To find typical traffic congestion patterns, the enhanced weighted K-means clustering approach is suggested. Second, the paired t-test analyses traffic congestion patterns' geographical and temporal variability. Finally, case studies use Beijing traffic congestion index data from January 1, 2017 to December 31, 2017, with approximately 670, 000 entries spanning six districts. Results show that traffic congestion patterns are time and spatially dependent, and the vehicle licence plate limitation has a major impact. This research may help develop traffic optimisation and management strategies to reduce congestion and balance traffic. [13]

Traffic congestion plagues many metropolitan roads. Traffic congestion has been studied extensively and addressed utilising data-driven methods. Most traffic congestion evaluations are done using simulation software, which has limited insight owing to the tools and utilities utilised to simulate traffic congestion situations. All of that affects unique business difficulties that differ by location and region. We employ the knowledge graph to represent traffic congestion in Neo4j and apply the load balancing, optimisation technique to find congestion-free road networks. We also demonstrate how traffic propagates backward during congestion or accidents and affects adjacent route segments. To verify road-specific congestion simulation findings, we train a sequential RNN-LSTM deep learning model using real-time traffic data. Our findings suggest that graph-based traffic simulation and AI ML-based traffic prediction can better estimate road network congestion. [14]

Smart transportation congestion reduction is difficult in major cities. Machine learning techniques aid traffic analysis, congestion prediction, and rerouting. This paper proposes a new prediction approach to reduce traffic congestion by studying a scheme for predicting traffic flow information using four machine learning techniques: FFNN, RBFNN, simple linear regression model, and polynomial linear regression model. This forecast technique uses typical waiting times at entrance and exit street pairings, days of the week, hours of movement, holidays, and rain rate. The FFNN approach outperforms the others with 97.6% prediction accuracy. [15]

Traffic congestion prediction is crucial to intelligent transport systems. Due to fast population expansion and high city car counts. ITS experts are increasingly focused on traffic congestion. Analysing traffic flow data predicts congestion. Our paper predicted traffic flow and reduced junction congestion using machine learning methods including linear regression, random forest regressor, decision tree regressor, gradient boosting, and K-neighbor. Our models were tested using UK national motor traffic public roads dataset. All machine learning methods performed well, proving their suitability for smart traffic signal systems. Next, we constructed a random forest regressor model-based adaptive traffic light system that changes green and red light time based on road width, traffic density, vehicle kinds, and predicted traffic. The suggested approach reduces traffic congestion by 30.8% in simulations, proving its efficacy and the interest in using it to govern junction signalling. [16]

The COVID-19 epidemic has affected global migration and city mobility. Many localities have issued "stay-at-home" orders during the epidemic, forcing commuters to alter routes. Some transit/bus riders drive or carpool. Thus, urban traffic congestion patterns have altered substantially, and emergency traffic management and control need comprehending these changes. Some studies have analysed natural catastrophes or severe accidents, but few have addressed pandemic-related traffic congestion. This research examines COVID-19 and transportation using correlations and machine learning. The authors simulated traffic models for five networks and presented a Traffic Prediction Technique (TPT) with an Impact Calculation Methodology using Pearson's Correlation Coefficient and Linear Regression and a Traffic Prediction Module. The paper's key contribution is the TPM, which predicts COVID-19's transportation effect using Convolutional Neural Network. Transportation patterns are strongly correlated with COVID-19 spread, and the CNN predicts these affects with great accuracy. [17]

The development of electric vehicles (EVs) and their interconnection have made power distribution networks (DNs) and transportation networks (TNs) more complicated and vulnerable under harsh conditions. As two infrastructures become more interdependent, coordinated transportation-power distribution networks (TDNs) must be made more resilient to natural catastrophes. This article coordinates TN traffic link reversal, DN line switching, and rapid charging pile management to enhance TDN emergency response performance following catastrophes. TDN modelling uses a dynamic TN model with a multi-period DN model to represent flow propagations and state fluctuations throughout time. The coordinated optimisation for TDN emergency response minimises TN travel expenses and DN active and reactive power shortages using mixed-integer nonlinear programming (MINLP) with high-order objective functions and nonlinear constraints. The TDN optimisation issue is solved more efficiently using accuracy-aware adaptive piecewise linearization and Grey code-based encoding. Numerical simulations reveal that coordinating DN and TN resources improves TDN performance compared to standalone and traditional topology controls. Compared to the nonlinear model and the linearized model via uniform piecewise linearization, the suggested TDN solution approach has greatly decreased computing time for severe situations while ensuring correctness. [18]

The large population growth ratio and rapid village movement have made cities congested. Traffic monitoring is difficult in certain places owing to heavy road traffic. A cluster-based enhanced authentication and communication protocol for an Intelligent Transportation System on VANETs was suggested in this study. Optimising vehicular communication resource sharing is our goal. We improved fast-moving VANET dependability, scalability, and stability by using cluster-based routing protocols for V2V and V2I communications. We employed a third-party certification organisation for vehicle authentication for security and privacy. We provide protocol support to decrease E2E time, route request, and connection failure. Our protocol's leading yield comprises throughput, TCP Socket Initialization time reduction, TCP handshake response speedup, and DNS lookup improvement. Short-range P2P wireless communication in a 400-m cluster is the focus of the protocols. They use minimal VANET resources for revolutionary P2P wireless communications. The suggested methods use a certification authority-generated vehicle authentication key for safe authentication. We also built RESTful APIs for vehicular communication implementation and V2V and V2I resource sharing algorithms. Finally, we assessed our experiments. [19]

The intelligent traffic management system (ITMS) generates enormous traffic video and picture data. The machine learning (ML)-based ITMS must send all created data to a centralised server, which takes time and money. These systems' limitations include costly communication, heterogeneous devices and location, and user privacy. Federated Learning (FL) solves these problems. This article briefly describes FL and its usage in ITMS. FL's efficient and improved ITMS solution is also discussed. FL advantages in ITMS are briefly discussed before the conclusion. [20]

In the recent decade, researchers have developed traffic-responsive signal timing algorithms to combat urban traffic congestion. Recently, machine learning-based approaches have been tried on traffic signal timing issues as an alternative to model-based algorithms and show promise. However, many academics and practitioners doubted that ATSC could use machine learning. Since these systems assumed perfect detectors and depended on simulators for training and evaluations, To address this significant issue, this paper customises a Deep Q-learning Learning (DQL) algorithm to optimise urban junction traffic signal timings using partial data from identity-based detectors and green splits. We also create a simulation-free data-driven prediction methodology to train the DQL faster. Then, ANPR data is used to test machine learning approaches. The suggested data-driven model can anticipate traffic status in little computing time, and the DQL method outperforms the adaptive control system, SCOOT, and SYNCHRO's time-of-day plan by 3.9% and 22%, respectively. In crowded traffic flow, DQL approaches only improve little compared to adaptive systems with limited input and output parameters. [21]

Control systems, sensors, actuators, and the environment need a cyber-communication infrastructure to interact and cooperate in real time. Cyberphysical systems (CPSs) do this. Recent advances in Intelligent Transportation Systems (ITS) have been accelerated by Deep Learning (DL) approaches, notably in analytical or statistical problem areas. Driverless vehicle development has advanced, but DL applications have also improved traffic organisation and scheduling, transit road security and safety, maintenance costs, and public transportation ride-sharing company performance. This work aims to provide a comprehensive analysis and knowledge of DL models' application in ITS and show how DL studies have advanced ITS research. This article briefly discusses DL approaches before studying and detailing their usage in transportation. Deep learning algorithms are trained on real-world traffic data to identify and predict accidents. This research summarises and classifies existing traffic prediction systems and provides a multi-perspective review of deep learning-based traffic forecasting methods. We provide the latest traffic forecasting techniques. We also evaluate and analyse our results using a public, real-world dataset to evaluate and compare techniques. These results show that a deep model outperforms state-of-the-art shallow models in traffic detection and prediction. We propose an Attention-based hybrid Convolutional Neural network with Long Short Term Memory (LSTM) (AHCNLS) deep learning framework for data mining-based real-time traffic prediction to improve driver and passenger safety. The suggested method considers GPS trajectories' spatial and temporal relationships with contextual elements. We demonstrate our method's advantages over competitors using a publicly available dataset. [22]

In recent years, smart cars have grown popular, helping IoV networks grow. A well-organized and efficient data transmission technique is needed for the Internet of Vehicles (IoV), a network of cars that can share and analyse data in real time. Cluster stability and dynamic topology change in IoV hinder automobile path optimisation. This manuscript's route optimisation algorithm depends on grid size, orientation, velocity, node number, and range, making it innovative. In order to optimise route discovery among cars in Internet of cars networks, Harris Hawks' Optimisation for Intelligent Route Clustering is used to create and evaluate the optimum cluster head (CH). Other cutting-edge methods are analysed to validate the suggested approach. Considering restrictions such cluster and network number, changing communication ranges, and vehicle amount, our findings reveal that the suggested approach works better than previous literature methods. Further experiments have shown that Packet Delivery Ratio (PDR), bandwidth utilisation, and latency are superior than alternative techniques. Additionally, statistical research demonstrates 80% cluster optimisation improvement and 90.6 R-squared cluster stability. [23]

Heat-related diseases are time-sensitive, therefore access to heat-related EMS services may contribute to urban health inequities. This paper uses Austin-Travis County EMS data to estimate traffic congestion-related response time delays using spatiotemporal analysis and the Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR) models to determine the causes of peak traffic rush hour delays. Our data suggest that heat-related EMS is more delayed in the morning and the evening; there are stronger clustering patterns of EMS travel time difference in Austin's metropolitan fringes, particularly in the east and west Austin. OLS and GWR studies reveal that bigger EMS counts, longer distances from an EMS station to the scene and from the scene to a hospital, and areas with a greater black and Hispanic population worsen heat-related EMS delays. Road density, average speed limit, and open space growth rate are statistically significant in the OLS model, however GWR suggests coefficient signs fluctuate locally, necessitating more study. Our results helped practitioners cut local response times by showing geographical patterns of EMS delays. [24]

This research examines emergency vehicle cab-mounted Variable Message Signs (VMS) as a safety precaution to safeguard roadside incident and service workers. ADOT's Safety Service Patrol (SSP) programme, especially the Alabama Service Assistance Patrol (ASAP) in West Central Alabama, provided the study team with video data from their service vans. Videos were analysed using deep learning to identify automobiles. In 135,946 frames of video, 11,338 passing cars were spotted and their trajectories analysed. The research examined passing vehicle speed and lane changing behaviours and constructed statistical models to determine how VMS affects them. Unobserved stop location characteristics were accounted for using random intercept models. The modelling showed substantial connections between VMS usage and passing motorist behaviour. Drivers were more willing to change lanes and slow down while the VMS was activated. When the VMS was used, vehicles changed lanes 95% more often. These data imply that VMS may improve traffic, especially for passenger cars. The research suggests that VMS might prevent roadside mishaps and safeguard service workers. [25]

Many commuters choose single-occupancy cars, which increases traffic and air pollution. Smart solutions that encourage ridesharing and mode shift to higher occupancy vehicles (HOVs) help communities become car lighter thanks to information technology. HumanLight, a unique decentralised adaptive traffic signal management method, optimises junction people throughput in this research. Our controller uses reinforcement learning and a reward function that embeds transportation-inspired pressure at the human level. HumanLight allocates green lights fairly by compensating HOV commuters with travel time savings for merging. Besides incorporating FRAP, a state-of-the-art (SOTA) basis model, HumanLight incorporates active vehicles, roughly defined as vehicles near the junction inside the action interval window. The method has high headroom and scalability in network setups with multimodal vehicle divides at various HOV adoption scenarios. Person delays and queues improve 15%–55% over vehicle-level SOTA controllers. We measure the effect of adding active cars to our RL model for various network architectures. HOV prioritisation aggression can be controlled by HumanLight. An important component of acyclic signal controllers that effect pedestrian waiting times is parameter setting on the resulting phase profile. HumanLight's scalable, decentralised architecture may make traffic management more human-centric and enable ridesharing and public transit regulations. [26]

Fixed cycle traffic lights manage road traffic, whereas urban traffic light control systems control individual lanes or crossings. Due to improper installation, congestion delays and extended intersection wait times may lead emergency vehicles to become trapped. A computationally feasible adaptive signal timing management approach may enhance network-wide traffic operations by lowering traffic delay and energy consumption compared to fixed cycle signal control systems. Adaptive control systems don't connect with emergency vehicles, which smart cities need. Due to this issue, a new framework, Emergency Vehicle Adaptive Traffic signal (EVATL), is suggested for smart cities to improve traffic signal operation and reduce congestion delay by integrating emergency vehicle communication. EVATL uses GPS with IoT and YOLOv8 to identify emergency vehicle position at traffic lights and adjust to vehicle density. The proposed EVATL prioritises emergency vehicles and integrates adaptive traffic lights for smart cities. A GUI is created to evaluate the proposed approach by establishing adaptive traffic light and emergency vehicle communication situations. In the simulation findings of the proposed model EVATL, cars' wait times at traffic lights increase when emergency vehicles are detected at a certain distance. [27]

Fig 1. Sample image of Emergency vehicle on crowded road [16]

3. Proposed Methodology for Emergency Vehicle

In major cities, traffic congestion is a problem, and EVs have to contend with it as well. For the sake of preserving human life, a delay in the arrival of an EV is sometimes unavoidable.

3.1. Components of the EVMS

The proposed EVMS consists of seven components along with priority rules. The details of these components are discussed in the following.

3.1.1. Emergency Vehicle (EV)

An Emergency Vehicle (EV) is a specialized vehicle designed for use by emergency services to respond to incidents and emergencies. These vehicles are equipped with features that enable them to navigate traffic more efficiently and safely reach their destinations as quickly as possible. Key types and features of emergency vehicles include:

Types of Emergency Vehicles

- **Ambulances:** Used for medical emergencies to transport patients to healthcare facilities while providing medical care en route.
- **Fire Trucks:** Equipped for firefighting and rescue operations, carrying firefighting equipment, ladders, and water hoses.
- **Police Vehicles:** Used by police officers for patrol, response to incidents, and transport of detainees. They may be marked or unmarked.
- **Rescue Squads:** Specialized vehicles equipped for technical rescue operations such as urban search and rescue, water rescue, and extrication.
- **Emergency Management Vehicles:** Used by emergency management agencies for command and control at the scene of major incidents or disasters.

Features of Emergency Vehicles

- **Visual and Auditory Warning Systems:** Equipped with sirens and emergency lights (e.g., flashing lights) to alert other road users and request the right of way.
- **Communication Equipment:** Radios and other communication devices to coordinate with dispatch centers and other emergency responders.
- **Medical Equipment:** Ambulances, in particular, are equipped with medical supplies and equipment for pre-hospital care.
- **Specialized Tools:** Depending on their function, EVs may carry specialized tools and equipment, such as hydraulic rescue tools in fire trucks or advanced life support (ALS) equipment in ambulances.

3.1.2. Shoulder Lane (SL)

A Shoulder Lane (SL), often referred to as a shoulder or emergency lane, is a strip of roadway adjacent to the travel lanes on a highway or major road. It is typically designated for emergency use and not intended for regular vehicle travel. However, its usage can vary significantly depending on local laws, traffic conditions, and specific transportation policies. Here are key aspects related to Shoulder Lanes:

Purpose and Use

- **Emergency Stops:** The primary use of shoulder lanes is to provide a safe area for vehicles to stop in case of mechanical failure, medical emergency, or other urgent situations.
- **Emergency Vehicle Passage:** Shoulder lanes offer a clear path for emergency vehicles (such as ambulances, fire trucks, and police cars) to bypass traffic congestion and reach their destinations more quickly.
- **Breakdown Space:** They serve as a space for broken-down vehicles to pull over, away from the flow of traffic, reducing the risk of accidents and keeping traffic lanes clear.

Expanded Uses

In some jurisdictions, shoulder lanes are utilized beyond traditional emergency and breakdown scenarios:

- **Traffic Management:** During peak traffic hours, shoulder lanes may be opened for general traffic use to alleviate congestion, a practice known as "hard shoulder running."
- **Public Transport:** Some areas designate shoulder lanes for use by buses and high-occupancy vehicles (HOVs) to promote more efficient public transportation options.
- **Bicycle Lanes:** Rarely, and under specific conditions, shoulder lanes may be designated for bicycle use, provided they are safe and wide enough to accommodate cyclists.

Design and Regulations

- **Width and Construction:** Shoulder lanes are designed to be wide enough to accommodate stopped vehicles without obstructing the adjacent travel lanes. Their construction is typically robust, similar to that of regular travel lanes, to support the weight of vehicles.
- **Markings and Signage:** Shoulder lanes are usually marked by solid or dashed lines and signs indicating their usage restrictions and conditions. These markings help differentiate the shoulder from the main travel lanes.
- **Regulatory Compliance:** The use of shoulder lanes is subject to specific regulations that vary by location. Unauthorized use of shoulder lanes can result in traffic citations and fines.

Safety Considerations

- **Visibility:** Vehicles stopped on the shoulder should activate hazard lights to alert passing drivers, especially in low-visibility conditions.
- **Entering and Exiting:** When using the shoulder lane, drivers must be cautious, ensuring it's safe to enter or rejoin the main traffic flow, checking for fast-moving vehicles in adjacent lanes.
- **Maintenance and Clearances:** Regular maintenance is crucial to keep shoulder lanes clear of debris and obstacles that could pose hazards to stopped vehicles or those using the lane for designated purposes.

3.1.3. Roadside Unit (RSU)

Roadside Units (RSUs) are critical components in the development and implementation of Intelligent Transportation Systems (ITS). These units are typically installed along the roadside or in specific locations like intersections, toll plazas, and parking lots. RSUs communicate wirelessly with onboard units in vehicles (V2X communication) to provide a wide range of services, including traffic management, safety warnings, and navigation assistance. When it comes to Emergency Vehicles (EVs), RSUs play several pivotal roles that enhance both the safety and efficiency of emergency responses. Here’s how RSUs interact with EVs:

Priority Signal Control : RSUs can grant priority at traffic signals for EVs, reducing their travel time during emergencies. By communicating with approaching EVs, RSUs can preempt traffic signals to create a green wave, allowing EVs to pass through intersections without stopping, thus reducing response times significantly.

Real-time Traffic Information : RSUs collect and disseminate real-time traffic information to EVs, helping them to choose the fastest and safest routes to their destinations. This information can include traffic congestion, road closures, or accidents ahead, enabling EV drivers to make informed decisions to avoid delays.

Safety Alerts : RSUs can broadcast safety alerts to vehicles and pedestrians in the vicinity of an emergency response. For example, when an EV is approaching an intersection, RSUs can warn nearby vehicles and pedestrians to clear the way, enhancing safety for both the emergency responders and the public.

Direct Communication with Evs : RSUs enable direct communication with EVs, facilitating a range of functionalities from basic vehicle identification and status updates to more complex data exchanges like the sharing of EV's destination and expected arrival time. This allows for a coordinated response from traffic management systems, prioritizing EVs over regular traffic.

Incident Reporting and Management : RSUs can be used to report incidents to approaching EVs and to traffic management centers. This rapid information exchange allows for quicker dispatch of emergency services and better situational awareness for responders, potentially saving lives and reducing the impact of incidents.

Integration with Smart City Infrastructure : In smart cities, RSUs integrate with other elements of the urban infrastructure, such as surveillance cameras and environmental sensors, to provide a comprehensive overview of current conditions. This integration supports more efficient navigation and safer operations for EVs by utilizing data from various sources.

Supporting Automated Emergency Responses : For future automated or semi-automated EVs, RSUs could play a crucial role in guiding these vehicles through traffic safely, providing real-time updates on road conditions, traffic, and optimal routes, ensuring that these vehicles navigate urban environments safely and efficiently.

Challenges and Considerations

- **Interoperability:** Ensuring RSUs and EVs from different manufacturers can communicate effectively.
- **Security:** Protecting the communication between RSUs and EVs against hacking and unauthorized access.
- **Privacy:** Managing the data collected and transmitted by RSUs in a way that respects the privacy of individuals.

3.1.4. Control Unit

In the context of Emergency Vehicles (EVs), a Control Unit (CU) plays a critical role in managing and coordinating emergency responses. The term can refer to different components or systems depending on the specific application, including onboard vehicle systems, centralized dispatch systems, or part of an intelligent transportation system (ITS). Here's an overview of how control units function in relation to EVs across these applications:

Onboard Control Units in EVs

Onboard control units in emergency vehicles are sophisticated systems that manage various aspects of the vehicle's operations and communications. These include:

- **Vehicle Systems Management:** Control units manage critical vehicle functions such as engine performance, electronic stability control, and automatic braking systems, ensuring the vehicle operates safely under high speeds and demanding conditions.
- **Communication Systems:** They handle communications with dispatch centers, other emergency vehicles, and traffic management systems. This includes the use of dedicated radio frequencies, cellular networks, and increasingly, direct vehicle-to-everything (V2X) communications.
- **Navigation and Routing:** Modern EVs are equipped with advanced navigation systems that not only suggest the quickest route but can also adapt in real-time based on traffic conditions, road closures, or other hazards, often in communication with external control units or systems.

Centralized Dispatch Systems

Centralized control units, often part of a dispatch center or emergency operations center, coordinate the deployment and management of emergency vehicles. They utilize:

- **Dispatch Software:** This software allocates resources efficiently based on the type, urgency, and location of the incident, as well as the availability and location of EVs.
- **Real-Time Information Systems:** These systems provide dispatchers with live updates on traffic conditions, ongoing emergency incidents, and the status of EVs, enabling dynamic management of emergency responses.
- **Communication Hub:** Serving as the central point for communications, it ensures seamless information flow between emergency responders, EVs, hospitals, and other relevant agencies.

ITS and Traffic Management Control Units

In the broader context of intelligent transportation systems and smart cities, control units refer to systems that manage traffic flow and prioritize EVs. These systems include:

- **Traffic Signal Preemption:** Traffic management control units can prioritize EVs by modifying traffic signals in real-time, creating a clear path for responding vehicles.
- **Roadside Units (RSUs):** As part of the ITS infrastructure, RSUs communicate with EVs to provide them with priority at intersections, real-time traffic data, and route suggestions to avoid congestion.
- **Data Analytics and Management:** These control units analyze vast amounts of data from various sources, including traffic cameras, sensors, and EVs themselves, to optimize traffic flow and emergency responses.

3.1.5. IoT

The Internet of Things (IoT) plays a transformative role in enhancing the capabilities of Emergency Vehicles (EVs) by leveraging interconnected devices and systems to improve response times, operational efficiency, and patient care. IoT technologies facilitate real-time data exchange between EVs, dispatch centers, healthcare facilities, and infrastructure components, creating a more responsive and integrated emergency response ecosystem. Here's how IoT contributes to the functionality and effectiveness of EVs:

Real-time Location Tracking and Fleet Management

- **GPS and Telematics:** IoT devices provide precise real-time location tracking of EVs, enabling dispatch centers to monitor fleet positions, optimize dispatching based on proximity to incidents, and manage fleet resources effectively.
- **Fleet Health Monitoring:** Sensors can monitor vehicle health, including engine status, fuel levels, and maintenance needs, ensuring that EVs are always ready for deployment.

Enhanced Communication and Response Coordination

- **Direct Vehicle-to-Vehicle (V2V) Communication:** EVs can communicate directly with each other to coordinate responses to large-scale emergencies, share status updates, and avoid response duplication.
- **Vehicle-to-Infrastructure (V2I) Communication:** IoT enables EVs to interact with traffic management systems, such as traffic lights and road sensors, to prioritize emergency traffic flow and reduce response times.

Improved Patient Care and Outcomes

- **Telemedicine:** IoT devices facilitate real-time communication between paramedics in EVs and physicians in hospitals, allowing for early initiation of patient care and preparation of hospital staff for the incoming patient's needs.
- **Wearable Health Monitoring:** Integration with wearable devices can provide emergency responders with real-time health data from patients, such as heart rate, blood pressure, and oxygen levels, even before they arrive on the scene.

Safety and Situational Awareness

- **Environmental Monitoring:** IoT sensors deployed across cities can provide EVs with information about environmental conditions such as road temperatures, hazardous material spills, or air quality, enabling responders to prepare appropriately for the situation they are responding to.
- **Collision Avoidance Systems:** IoT technologies can enhance the safety of EVs through advanced driver-assistance systems (ADAS) that predict and prevent potential collisions with other vehicles or pedestrians.

Smart City Integration

- **Smart Traffic Management:** In smart cities, IoT integration allows for dynamic traffic management, where traffic signals are automatically adjusted to create clear paths for EVs, and road users are alerted to the presence of approaching EVs.
- **Data Analytics for Emergency Planning:** Aggregated IoT data can be analyzed to identify patterns in emergencies, helping to optimize placement of EVs and resources for faster responses in the future.

3.1.6. Cloud

The integration of cloud computing with Emergency Vehicles (EVs) represents a significant advancement in emergency response capabilities, leveraging the power of remote computing resources to enhance communication, data management, and operational efficiency. Cloud technology allows EVs and related emergency services to access, store, and process vast amounts of data in real-time, facilitating improved decision-making, resource allocation, and patient care. Here's how cloud computing is transforming emergency vehicle operations:

Enhanced Data Access and Sharing

- **Real-Time Information Sharing:** Cloud platforms enable the seamless sharing of critical information among EVs, dispatch centers, hospitals, and other emergency response entities. This ensures that all parties have access to the same up-to-date information, improving coordination and response strategies.

- **Centralized Data Repository:** By storing data on the cloud, emergency services can create a centralized repository of incident reports, medical records, and other essential information that is easily accessible from anywhere, enabling better preparedness and response to future emergencies.

Improved Dispatch and Fleet Management

- **Dynamic Resource Allocation:** Cloud-based dispatch systems can analyze real-time data on traffic conditions, EV locations, and emergency incidents to dynamically allocate resources and route EVs via the most efficient paths.
- **Fleet Maintenance and Management:** Cloud platforms can monitor the status and performance of each vehicle in the fleet, scheduling maintenance as needed and ensuring that EVs are always ready for deployment.

Advanced Communication Systems

- **Unified Communication Platforms:** Cloud services facilitate unified communication systems that integrate voice, video, and data sharing, allowing emergency responders to communicate effectively across different devices and networks.
- **Remote Assistance and Telemedicine:** Paramedics can use cloud-based platforms to consult with hospital staff in real-time, receiving guidance and starting patient care en route to the hospital, which can be crucial for time-sensitive emergencies.

Integration with Smart City Infrastructure

- **Traffic Management:** Cloud computing enables integration with smart city infrastructure, such as traffic lights and road sensors, to manage traffic flow and prioritize EV passage, significantly reducing response times.
- **Public Alert Systems:** Emergency services can use cloud platforms to send real-time alerts to the public about severe incidents, road closures, or evacuation orders, enhancing public safety and situational awareness.

Data Analytics and Decision Support

- **Predictive Analytics:** Leveraging cloud computing for data analytics allows emergency services to identify patterns and predict future incidents, optimizing resource placement and preparedness strategies.
- **Decision Support Systems:** Cloud-based decision support tools can analyze real-time and historical data to provide recommendations and situational assessments to responders, aiding in critical decision-making during emergencies.

3.1.7 5G

The advent of 5G technology brings transformative potential to the operation of Emergency Vehicles (EVs), offering significant improvements over previous generations in terms of speed, reliability, and latency in communications. These enhancements are pivotal in emergency response scenarios where every second counts. Here's how 5G technology is expected to impact and enhance the capabilities of EVs:

Enhanced Communication Speed and Reliability

- **Faster Data Transmission:** 5G offers substantially higher data rates compared to 4G, enabling quicker transmission of critical information such as patient medical records, real-time video feeds, and detailed scene information between EVs and hospitals or dispatch centers.
- **Increased Reliability:** With its enhanced reliability, 5G ensures that communication links remain stable in a wide range of conditions, reducing the risk of dropped calls or data transmission failures during critical operations.

Reduced Latency

- **Real-time Remote Assistance:** The ultra-low latency of 5G improves the feasibility of real-time remote medical assistance, allowing paramedics to receive immediate guidance from specialists while en route to the hospital, potentially improving patient outcomes.
- **Enhanced Operational Efficiency:** Low latency communication aids in the real-time control of EVs, including potential future applications in autonomous or semi-autonomous driving, ensuring quicker and safer navigation through traffic.

Improved Capacity and Coverage

- **Handling High Volume Connections:** 5G technology supports a higher density of connected devices within a given area. This capacity is crucial in urban environments and at large-scale emergency scenes where multiple devices and vehicles need to communicate simultaneously.
- **Better Coverage:** Advances in 5G technology aim to improve coverage, even in traditionally hard-to-reach areas, ensuring that EVs remain connected and fully operational regardless of their location.

Integration with Smart City Infrastructure

- **Traffic Management:** 5G can facilitate the integration of EVs with smart city infrastructure, enabling things like traffic signal preemption, where traffic lights are automatically controlled to give priority to EVs, thereby reducing response times.
- **Real-time Environmental Monitoring:** Connection to a network of IoT devices for real-time monitoring of environmental conditions, such as road hazards or weather conditions, allows EVs to respond more effectively and safely to emergencies.

Advanced Onboard Diagnostics and Telematics

- **Real-time Vehicle Monitoring:** 5G enables more sophisticated onboard diagnostics and telematics, allowing for real-time monitoring of vehicle health, which is essential for maintaining the readiness and reliability of EVs.
- **Enhanced Fleet Management:** With 5G, dispatchers can manage the EV fleet more efficiently, optimizing routes in real-time based on traffic conditions, vehicle availability, and emergency priority.

3.1.8. Priority Rules

Priority rules with respect to Emergency Vehicles (EVs) are essential for ensuring that these vehicles can navigate traffic efficiently and safely to respond to emergencies as quickly as possible. These rules are typically established by traffic laws and regulations, and they dictate how drivers of non-emergency vehicles should behave when encountering EVs. Understanding and following these priority rules can significantly impact the outcome of emergency situations. Here's a summary of the key priority rules for EVs:

Right of Way

- **Emergency Precedence:** EVs responding to emergencies, indicated by flashing lights and sirens, have the right of way over all other vehicles and pedestrians.
- **Mandatory Yielding:** Drivers must yield to EVs by moving to the right side of the road and stopping until the EV has passed. In jurisdictions where driving is on the left, the custom would be to move to the left.

Intersection Behavior

- **Red Lights and Stop Signs:** EVs can run red lights and stop signs when responding to emergencies, but they usually do so with caution, ensuring it is safe before proceeding.
- **Other Vehicles at Intersections:** Vehicles at intersections must stop and remain in place, allowing EVs to maneuver around them.

Traffic Lane Usage

- **Use of Opposite Lanes:** EVs may use opposite or oncoming traffic lanes if the way is blocked in their lane, always with caution for oncoming traffic.
- **Highway and Multi-lane Roads:** On highways or multi-lane roads, vehicles should move to the furthest right lane to allow EVs to pass on the left.

Speed Limits

- **Exceeding Speed Limits:** EVs are often permitted to exceed speed limits when responding to an emergency, within the bounds of safety for road conditions and traffic.

Public Awareness and Education

- **Awareness Campaigns:** Many regions conduct public awareness campaigns to educate drivers on how to respond to EVs, emphasizing the importance of yielding and the specific actions to take.
- **Driver's Education:** Information on priority rules for EVs is typically included in driver's education courses and materials.

3.1.8 Priority Rules for Emergency Vehicle on loaded Traffic Squares

1. Traffic Density and EV Priority Index

Let's define a Priority Index (PI) for emergency vehicles based on traffic density and urgency.

- Traffic Density (TD): A numerical value representing the level of traffic congestion. It can range from 0 (no congestion) to 1 (maximum congestion).
- Urgency Level (UL): A numerical value assigned to the urgency of the emergency. It could range from 1 (least urgent) to 10 (most urgent).

The Priority Index (PI) for an emergency vehicle could be calculated as: $PI=UL\times(1-TD)$

This formula assumes that the urgency of the call becomes a more significant factor in less congested conditions, where TD approaches 0, making PI more heavily influenced by UL.

2. Adjusting Traffic Signals

To model the decision for adjusting traffic signals in favor of an EV, we could use the following approach:

- **Distance to Intersection (DI)**: The distance of the EV from the intersection, with closer distances having a higher need for signal adjustment.

- **Signal Adjustment Factor (SAF)**: A numerical value that determines whether a traffic signal should be adjusted to favor the EV.

A simple model for SAF could be: $SAF = \frac{DI}{PI}$

Where a higher SAF indicates a stronger case for adjusting the signal in favor of the EV. A threshold value could be set for SAF above which the signal would be preempted to allow the EV to pass.

3. Enhanced Priority Index Calculation

To refine the Priority Index (PI) calculation, consider incorporating factors such as the type of emergency, expected impact, and even feedback from sensors or traffic monitoring systems regarding actual traffic flow and speed. For instance:

$PI=UL\times(1-TD)\times E\times I$

Where:

- **E** represents the efficiency of the route (considering current traffic speeds and potential delays).
- **I** is the impact factor, which quantifies the potential impact of the emergency (e.g., risk to life, property damage).

4. **Multi-Emergency Vehicle Coordination**

In scenarios with multiple EVs heading towards intersecting paths or the same destination, coordination becomes crucial. A coordination factor (CF) could be introduced to manage such situations:

$$CF = \frac{1}{N}\sum_{i=1}^{N} PI_i$$

Where:

- **N** is the number of emergency vehicles involved.
- **PI_{i}** is the Priority Index of each emergency vehicle.

The CF could be used to adjust signal timings and routes in a way that optimizes the overall response time for all involved EVs, rather than prioritizing on a first-come, first-serve basis.

5. Dynamic Traffic Light Adjustment

The decision to adjust traffic lights can be modeled more dynamically by incorporating a Time to Intersection (TTI) factor, which estimates how soon an EV will reach an intersection:

$$SAF = \frac{PI \times TT1}{DI^2}$$

The squared distance term DI^2 emphasizes the importance of proximity, with the TTI adjusting for how immediate the need for signal change is, based on the EV's speed and current traffic conditions.

6. Real-time Route Optimization

For route optimization, integrating real-time data analytics can help in adjusting routes on the fly. The optimization algorithm can consider multiple routes and their current conditions, recalculating the best path for EVs as new data becomes available. This could involve solving a dynamic routing problem:

$$Minimize \sum_{all\ routes} (TT + TD \times PI)$$

Where:

- **TT** is the travel time for each considered route.
- **TD \times PI** adjusts the importance of each route based on traffic density and the emergency's priority, ensuring that EVs are routed through the most efficient paths available at any moment.

7. Scenario Evaluation

In a scenario where multiple EVs are approaching the same intersection from different directions, the decision on which vehicle gets priority could be based on comparing their SAF values.

- **Scenario**: EV1 and EV2 approaching an intersection, with EV1 having a higher urgency but further away, and EV2 being closer but with a lower urgency.

Using the SAF calculation:

- If $SAF_{EV1}>SAF_{EV2}$, the signal is adjusted for EV1's path.
- If $SAF_{EV2}>SAF_{EV1}$, the signal is adjusted for EV2's path.

This approach allows for dynamic decision-making based on real-time data regarding traffic conditions, emergency vehicle location, and the urgency of the call.

3.2 Algorithm: Managing EV Passage Through an Intersection with Varying Priority

Inputs:

- EV_queue: A queue of EVs approaching the intersection, each with an associated priority level.
- Traffic_status: Current traffic condition at the intersection.
- Intersection_status: Indicates whether the intersection is open for EV passage or currently occupied by passing traffic.

- Priority_levels: A set of defined priority levels for EVs (e.g., 1 for highest priority, descending to n for lowest).

Outputs:

- A sequence for EVs to pass through the intersection, ensuring priority is given according to their urgency level.

Procedure:

1. Initialize: Start with an empty list EV_sequence to hold the sequence in which EVs will pass through the intersection.
2. Sort EV Queue:
   - Sort EV_queue based on priority levels, with higher-priority EVs placed before lower-priority ones.
3. Traffic Check:
   - If Traffic_status indicates heavy traffic, activate signal preemption to create a green wave for approaching EVs.
   - Adjust Intersection_status to occupied for the duration of EV passage.
4. EV Passage:

- While EV_queue is not empty:
- For the first EV in EV_queue, check Intersection_status.
- If Intersection_status is open, allow the EV to pass. Add the EV to EV_sequence and remove it from EV_queue.
- If another EV is currently passing (Intersection_status is occupied), wait until the intersection is clear.

5. Managing Regular Traffic:

- After an EV passes, if there are no immediate high-priority EVs waiting, briefly allow regular traffic to flow, adjusting Intersection_status accordingly.

6. Repeat:

- Continue the process until all EVs in EV_queue have passed through the intersection.
- Regularly update Traffic_status and Intersection_status based on real-time data.

7. Return EV_sequence:

- Once all EVs have passed, return the EV_sequence for logging or monitoring purposes.

Considerations:

- Dynamic Traffic Management: The algorithm should adapt to changing traffic conditions and update the EV sequence in real-time.
- Safety Measures: Ensure all maneuvers respect safety protocols, especially when directing EVs against regular traffic flows.
- Communication with EVs: Implement a system for informing EV drivers of their turn to pass and any required actions (e.g., lane changes).
- Intersections with Multiple Approaches: For intersections with multiple approach directions, the algorithm may need to manage multiple EV_queues.

3.3 Algorithm: Efficient Passing of EVs Based on Priority

Inputs:

- EV_list: A list of EVs approaching or waiting at an intersection, each associated with a priority level and estimated time of arrival (ETA) to the intersection.
- current_traffic: The current traffic condition at the intersection, including non-emergency vehicles.
- intersection_state: Indicates the current state of the intersection (e.g., which signals are green).

Outputs:

- An ordered sequence for EVs to pass through the intersection, ensuring that EVs are prioritized appropriately.

Procedure:

1. Prioritize EVs:

- Sort EV_list first by priority level (highest to lowest) and then by ETA to the intersection (soonest to latest). This creates a prioritized queue of EVs.

2. Evaluate Intersection:

- Assess current_traffic and intersection_state to determine the best window for allowing EVs to pass. Consider the minimization of disruption to overall traffic flow.

3. Adjust Traffic Signals (if applicable):

- Temporarily adjust traffic signals if necessary to create a clear path for the highest priority EV(s). This might involve extending a green light or changing a signal prematurely.

4. Direct EV Passage:

- Iterate through the prioritized EV_list, allowing each EV to pass in order of priority. For each EV:
- Check if the intersection can be safely navigated given current_traffic and intersection_state.
- If yes, signal the EV to proceed, updating intersection_state as necessary to reflect the change in traffic flow.
- If no (due to crossing traffic or safety concerns), hold the EV at the current status until safe passage is possible.

5. Manage Non-Emergency Traffic:

- Between EV passages, adjust intersection_state as needed to allow non-emergency traffic flow, minimizing overall disruption.
- Ensure that adjustments to traffic signals do not create unsafe conditions or excessive delays for non-emergency traffic.

6. Repeat:

- Continue the process until all EVs in EV_list have successfully navigated the intersection.
- Regularly reassess current_traffic and adjust intersection_state as needed to respond to evolving conditions.

7. Communication and Coordination:

- Throughout the process, maintain communication with approaching EVs, providing updates on their status and instructions for when and how to proceed.
- Coordinate with traffic management systems to ensure that adjustments made for one intersection do not inadvertently create congestion or hazards at nearby intersections.

Considerations:

- Dynamic Priority Adjustment: In certain situations, priorities may need to be dynamically adjusted based on the urgency of the calls or changes in ETA.
- Safety Protocols: Always prioritize safety, ensuring that all traffic movements, whether for EVs or non-emergency vehicles, are conducted safely.
- Technological Support: Implementing this algorithm effectively may require advanced traffic management systems capable of real-time monitoring, communication with EVs, and dynamic signal control.

4. Mathematical Modeling Analysis

4.1 Mathematical modeling

Mathematical modeling of an Emergency Vehicle Management System (EVMS) involves creating a framework that can simulate, predict, and optimize the operations and response times of emergency vehicles (EVs) within a traffic network. The goal of such a model is to minimize response times to emergencies while ensuring safety and efficient use of resources. A comprehensive model would consider various factors including traffic conditions, EV priorities, routing algorithms, and communication systems. Here's an overview of how one might approach the mathematical modeling of an EVMS:

Key Components of the Model

1. Emergency Vehicle (EV) Parameters:

- Priority Level (P): A numerical value representing the urgency of the EV's mission, with higher values indicating higher urgency.
- Location (L): The current coordinates of the EV in the traffic network.
- Speed (S): The current speed of the EV, which may vary depending on traffic conditions and road types.
- Destination (D): The target location that the EV is trying to reach.

2. Traffic Network Parameters:

- Traffic Density (TD): A function that provides the traffic density on different segments of the road network, potentially varying by time of day.
- Road Capacity (C): The maximum number of vehicles that can efficiently travel on a road segment.
- Signal Timing (ST): The timing of traffic signals within the network, which could be adjusted for EV preemption.

3. Routing Algorithm:

- A function or set of rules that determines the optimal path for an EV to take to its destination, considering current traffic conditions, road closures, and other real-ime data.

Mathematical Representation

Objective Function:

Minimize the total response time (TR) for all EVs to reach their destinations. The response time can be modeled as a function of distance to the destination, traffic density, and EV speed.

$$Minimize\ TR = \sum_{i=1}^{n} \frac{D_i}{S_i(TD,P)}$$

Where D_i is the distance to the destination for the ith EV, and $S_i(TD,P)$ is the speed of the ith EV, which is a function of traffic density TD and priority P.

Constraints:

1. Traffic Flow Constraints: Ensure that the flow of traffic does not exceed the capacity of any road segment.

$$\sum_{EVs\ on\ segment} S \leq C$$

2. Signal Preemption Constraints: Model the impact of signal timing adjustments to accommodate EVs.
3. Safety Constraints: Include constraints to ensure EVs and other vehicles operate safely, even when normal traffic rules are overridden.

4.2 In the case of a single Emergency Vehicle (EV)

In the case of a single Emergency Vehicle (EV) navigating a traffic square, the mathematical modeling simplifies, focusing primarily on optimizing the EV's passage through the area with minimal delay. Here's how the model can be adapted for this scenario:

Simplified Model Description

Given:

- **EV Characteristics:**
- Priority Level (P): Given the single EV scenario, *P* can be considered the highest by default.
- Location (L): The current position of the EV relative to the traffic square.
- Speed (S): The EV's speed, which may be influenced by traffic density and signal status.
- Destination (D): The EV's intended exit point from the traffic square.
- **Traffic Square Parameters:**
- Traffic Density (TD): The density of traffic within the square, which affects the EV's speed.
- Signal Timing (ST): The current state of traffic signals around the square.

Objective:

Minimize the response time (TR) of the EV to navigate through the traffic square and reach its destination.

Constraints:

1. **Traffic Flow:** The EV's passage should not cause unsafe conditions for other vehicles and pedestrians.
2. **Signal Preemption:** If applicable, the model may include the ability to preempt traffic signals to facilitate the EV's movement.

Mathematical Formulation

Response Time Calculation:

The response time *TR* to navigate the traffic square can be approximated as the distance to the destination divided by the effective speed of the EV, considering traffic density and potential signal preemption.

$$TR = \frac{D}{S(TD, ST)}$$

Where $S(TD,ST)$ represents the EV's effective speed, a function of traffic density *TD* and signal timing *ST*.

Optimization Problem:

Minimize *TR* subject to traffic safety and signal preemption constraints. Since there's only one EV, the optimization focuses on adjusting *ST* (if signal preemption is possible) to minimize *TR*.

Implementation Steps

1. **Assess Current Conditions:**

- Evaluate *TD* and *ST* to understand the current traffic situation in the square.

2. **Calculate Optimal Speed:**

- Determine the optimal speed *S* for the EV to navigate through the square, considering *TD* and potential adjustments to *ST*.

3. **Adjust Traffic Signals (if applicable):**

- If signal preemption is part of the traffic management strategy, adjust *ST* to create a clear path for the EV.

4. **Direct the EV:**

- Communicate the optimal path and speed adjustments to the EV driver or automated navigation system to ensure the quickest and safest route through the square.

5. **Monitor and Adapt:**

- Continuously monitor *TD* and adjust *ST* as needed to maintain optimal conditions for the EV's passage.

4.3 Two Emergency Vehicles (EVs) with the Same Priority

In the scenario where there are two Emergency Vehicles (EVs) with the same priority level approaching or navigating through a traffic square, the mathematical modeling needs to account for the simultaneous optimization of their routes to minimize overall response times while ensuring safety and efficiency. This case introduces complexity due to the need to coordinate the passage of both EVs without causing undue delay to either.

Model Description for Two EVs with Equal Priority

Given:

- **EV Characteristics for Each EV (EV1, EV2):**
- Priority Level (P): Identical for both EVs, indicating equal urgency.
- Location (L1, L2): The current positions of EV1 and EV2 relative to the traffic square.
- Speed (S1, S2): The speeds of EV1 and EV2, potentially affected by traffic density and signal timings.
- Destination (D1, D2): The intended exit points from the traffic square for EV1 and EV2.
- **Traffic Square Parameters:**
- Traffic Density (TD): The density of traffic within the square, impacting the speeds of the EVs.
- Signal Timing (ST): The state of traffic signals around the square.

Objective:

Minimize the combined response time (TR) for both EVs to navigate through the traffic square and reach their destinations, ensuring equitable treatment and optimal pathing for both.

Constraints:

1. **Equitable Passage:** Ensure that both EVs are given equal opportunity to navigate through the square without undue delay to either.
2. **Safety:** Maintain safe conditions for all vehicles and pedestrians, considering the simultaneous movement of both EVs.
3. **Signal Coordination:** Adjust traffic signals in a manner that facilitates the passage of both EVs, considering their paths may intersect or be parallel.

Mathematical Formulation

Combined Response Time Calculation:

The objective is to minimize the combined response time for both EVs, which can be formulated as:

$$Minimizw\ TR_{total} = TR_1 + TR_2$$

Where

$$TR_1 = \frac{D_1}{S_1(TD, ST)}$$

$$TR_2 = \frac{D_2}{S_2(TD, ST)}$$

And $S_1(TD, ST)$ and $S_2(TD, ST)$ represent the effective speeds of EV1 and EV2 , respectively , functions of traffic density TD and signal timing ST.

Optimization Problem

Solve the optimization problem to find the optimal paths and possibly signal timing adjustments for EV1 and EV2 that minimize TR_{total} while adhering to the constraints.

Implementation Strategy

1. **Path Analysis:**

- Analyze potential paths for EV1 and EV2 to their respective destinations, considering current traffic conditions.

2. **Signal Timing Coordination:**

- Determine if adjustments to ST can simultaneously benefit both EVs, potentially through signal preemption or synchronization.

3. **Dynamic Routing:**

- Opt for dynamic routing solutions that can adapt in real-time to changes in traffic conditions, ensuring the most efficient paths for both EVs.

4. **Safety and Equity Check:**

- Ensure that the chosen paths and any signal adjustments do not compromise safety and that both EVs are treated equitably in terms of their urgency and operational needs.

5. **Continuous Monitoring and Adjustment:**

- Monitor the progress of both EVs and adjust routes or signals as necessary to respond to any unforeseen changes in traffic conditions.

4.4 Two Emergency Vehicles (EVs) with Varying Priorities

When dealing with two Emergency Vehicles (EVs) with varying priorities navigating through a traffic square, the mathematical model must differentiate between the vehicles based on their urgency levels to optimize their passage. This scenario introduces the need to prioritize the EV with a higher urgency while still ensuring the second EV's efficient and safe passage. Here's an approach to modeling this case:

Model Description for Two EVs with Different Priorities

Given:

- **EV Characteristics for Each EV (High-Priority EV, Low-Priority EV):**
  - Priority Levels (PH, PL): $PH > PL$, indicating the high-priority EV has a more urgent need to reach its destination quickly compared to the low-priority EV.

- Locations (LH, LL): The current positions of the high-priority and low-priority EVs relative to the traffic square.
- Speeds (SH, SL): The speeds of the high-priority and low-priority EVs, potentially influenced by traffic density and signal timings.
- Destinations (DH, DL): The intended exit points from the traffic square for the high-priority and low-priority EVs.

- **Traffic Square Parameters:**
  - Traffic Density (TD): The density of traffic within the square, affecting the speeds of the EVs.
  - Signal Timing (ST): The current state of traffic signals around the square.

Objective:

Minimize the response time (TRH) for the high-priority EV while considering the impact on the low-priority EV's response time (TRL), aiming to efficiently manage both vehicles' passage.

Constraints:

1. **Priority Passage:** Ensure the high-priority EV is given precedence in terms of signal adjustments and routing decisions.
2. **Safety and Efficiency:** Maintain safe conditions for all traffic and optimize the overall efficiency of the traffic square, minimizing disruptions.
3. **Signal Coordination:** Adjust traffic signals to facilitate the high-priority EV's movement, considering potential benefits or minimal impacts on the low-priority EV.

Mathematical Formulation

Objective Function:

Minimize *TRH* subject to minimizing *TRL* without compromising the high-priority EV's expedited passage.

$$Minimize\ TRH = \frac{DH}{SH\ (TD, ST)}$$

Subject to

$$\min TR_L = \frac{DL}{SL\ (TD,ST)}$$

Where *SH*(*TD*,*ST*) and *SL*(*TD*,*ST*) represent the effective speeds of the high-priority and low-priority EVs, respectively.

Optimization Strategy:

1. **Prioritize High-Priority EV:**
   - First, optimize the route and signal timing for the high-priority EV, reducing *TRH* as much as possible.
2. **Adjust for Low-Priority EV:**
   - Then, within the constraints set by the optimized path for the high-priority EV, look for opportunities to minimize *TRL*, such as timing adjustments at signals not affecting the high-priority EV's route or providing alternative routes for the low-priority EV that avoid additional delays.
3. **Dynamic Traffic Management:**
   - Employ dynamic traffic management strategies that can adjust in real-time to the progress of both EVs, ensuring the high-priority EV's path remains optimal while seeking ways to assist the low-priority EV.
4. **Communication and Monitoring:**
   - Ensure continuous communication with both EVs regarding their routes, expected signal changes, and any adjustments made to accommodate their movements.

5. Discussion of Comparison with existing studies

Table 1. Comparison with existing studies.

Paper	Single EV	Two EVs with the Same Priority	Two EVs with Varying Priority
[28]	Yes	No	Yes
[29]	Yes	No	Yes
[30]	Yes	No	No
[1]	Yes	Yes	Yes
Proposed	Yes	Yes	Yes

6. Proposed Architecture

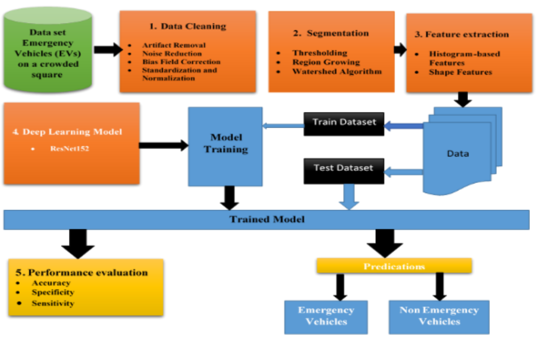

Fig 2. Proposed working model.

The figure 2 describes a process for using a deep learning model to classify vehicles in a dataset as either emergency vehicles (EVs) or non-emergency vehicles. Here's a step-by-step explanation of the process with respect to the dataset:

1. Data Cleaning

This step involves preparing the dataset for analysis by removing any inconsistencies or inaccuracies, which can affect the performance of the model. The specific tasks include:

- **Artifact Removal:** Cleaning up the data by removing irrelevant or corrupt data that could negatively impact the model.
- **Noise Reduction:** Applying filters or techniques to reduce random variations in the data that do not represent the underlying dataset patterns.
- **Bias Field Correction:** Correcting any systematic distortions or biases in the data to prevent skewed results.
- **Standardization and Normalization:** Scaling the data so that it follows a standard format and range, which is necessary for many machine learning algorithms to perform correctly.

2. Segmentation

Segmentation involves dividing the image into parts or segments to simplify or change the representation of the image into something more meaningful and easier to analyze.

- **Thresholding:** Separating objects from the background by converting the grayscale images into binary images.
- **Region Growing:** Identifying and grouping pixels or sub-regions into larger regions based on predefined criteria (like intensity or color).
- **Watershed Algorithm:** A technique used for image segmentation which treats the gradient magnitude of an image as a topographic surface and segments the image into different catchment basins.

3. Feature Extraction

In this stage, the model identifies and extracts various descriptive features from the data that are relevant for classifying the vehicles.

- **Histogram-based Features:** Analyzing the distribution of pixel intensity values in the image to capture texture information.
- **Shape Features:** Quantitative measures derived from the geometry of the vehicle shapes, such as aspect ratio, perimeter, area, and so on.

4. Deep Learning Model

- **ResNet152:** A specific deep learning model known for its depth, enabling it to learn very complex features. It is a convolutional neural network that is 152 layers deep and is a variant of the ResNet model, which uses residual learning to ease the training of networks that are substantially deeper than those used previously.

Model Training

The prepared dataset is split into two parts: the training dataset and the test dataset.

- **Train Dataset:** A subset of the data used to train the model, where the model learns to classify vehicles based on the features extracted.
- **Test Dataset:** A separate subset used to evaluate the performance of the model. The model has not seen this data during training, and it is used to simulate how the model would perform on new, unseen data.

Trained Model

Once the model has been trained, it becomes a trained model that can be used to make predictions on new data.

5. Performance Evaluation

The trained model's performance is evaluated using metrics that measure the accuracy and robustness of its predictions.

- **Accuracy:** The proportion of total predictions that were correct.
- **Specificity:** The ability of the model to correctly identify non-emergency vehicles (true negatives).
- **Sensitivity:** The ability of the model to correctly identify emergency vehicles (true positives).

Predictions

The final step is the model making predictions on new data to classify the vehicles as either emergency or non-emergency.

7. Implementation

7.1 Dataset

Data Description

train.zip: contains 2 csvs and 1 folder containing image data

train.csv – ['image_names', 'emergency_or_not'] contains the image name and correct class for 1646 (70%) train images
images – contains 2352 images for both train and test sets

test.csv: [‘image_names’] contains just the image names for the 706 (30%) test images sample_submission.csv: [‘image_names’,’emergency_or_not’] contains the exact format for a valid submission (1 - For Emergency Vehicle, 0 - For Non Emergency Vehicle)

Link :
https://www.kaggle.com/datasets/abhisheksinghblr/emergency-vehicles-identification/data

7.2 Analysis

	A	B	C
1	TIME	MERIDIAN	ROAD1
2	12	AM	medium
3	3	AM	low
4	6	AM	low
5	9	AM	medium
6	12	PM	high
7	3	PM	low
8	6	PM	high
9	9	PM	low
10	12	AM	low
11	3	AM	low
12	6	AM	low
13	9	AM	medium
14	12	PM	medium

Fig 3. Traffic dataset

```
Today's traffic on Road 4 will be:
12 a.m. - 3 a.m. 380
3 a.m. - 6 a.m. 200
6 a.m. - 9 a.m. 244
9 a.m. - 12 p.m. 309
12 p.m. - 3 p.m. 591
3 p.m. - 6 p.m. 616
6 p.m. - 9 p.m. 541
9 p.m. - 12 a.m. 390
```

Fig 4. Traffic Prediction

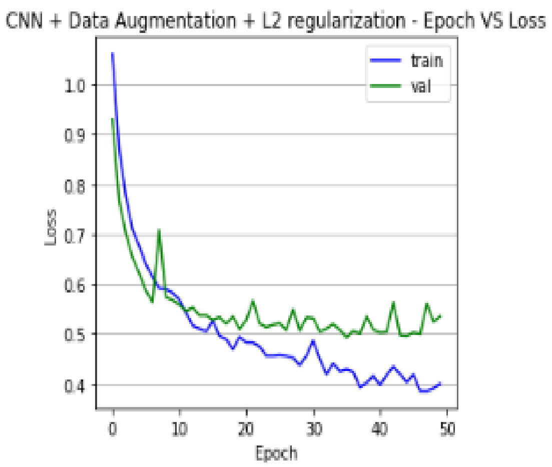

Fig 5. Model epoch vs Loss

Fig 6. Ambulance detection in crowd

8. Result

The table 2 and figure 7 visually represents the performance of six different convolutional neural network models on a classification task, using standard machine learning metrics: Accuracy, Precision, Recall, and F1-Score. The table and graph summarize the models' performance as follows:

- AlexNet shows relatively lower performance across all metrics compared to the other models, with Accuracy and Precision just above 0.8, and the F1-Score being the lowest at 0.825.
- VGG16 performs better than AlexNet, with notable improvements in Recall and a higher F1-Score of 0.885, indicating a balanced performance between precision and recall.
- VGG19 has similar metrics to VGG16 but slightly lower in each category, suggesting a comparable performance with a marginal difference in precision and recall.
- ResNet 50 marks a significant improvement over the VGG models, with all scores reaching above 0.9. This model shows a strong balance between all measured aspects of performance.
- ResNet 101 further improves upon ResNet 50, suggesting that additional depth in the network architecture could be contributing to better feature extraction and, consequently, better classification performance.
- The Proposed ResNet152 model tops the chart with the highest scores in all categories, peaking at 0.94 for both Accuracy and F1-Score, which suggests a superior ability to generalize and make accurate predictions on the test dataset.

Table 2. Comparative result of different models

Model	Accuracy	Precision	Recall	F1-Score
AlexNet	0.85	0.83	0.82	0.825
VGG16	0.9	0.88	0.89	0.885

VGG19	0.89	0.87	0.88	0.875
ResNet 50	0.92	0.91	0.93	0.92
ResNet 101	0.93	0.92	0.94	0.93
Proposed ResNet152	0.94	0.93	0.95	0.94

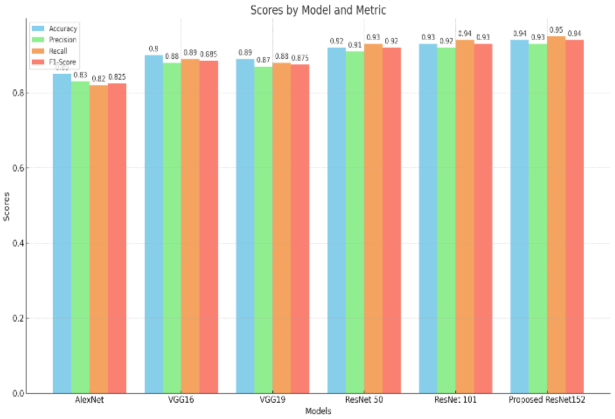

Fig 7. Comparative result of different models

9. Conclusion

The comprehensive analysis conducted in this study on the Smart Loaded Traffic Square System (SLTSS) for Emergency Vehicles (EVs) utilizing deep learning models marks a significant stride toward resolving one of the most pressing challenges in urban traffic management. Through a meticulous examination of various convolutional neural network architectures, including AlexNet, VGG16, VGG19, ResNet 50, ResNet 101, and a pioneering ResNet152 model, this research underscores the profound impact of advanced deep learning techniques in enhancing the precision and efficiency of traffic systems in densely populated areas.

The journey began with the foundational AlexNet model, which set a benchmark by achieving an accuracy of 85%, precision of 83%, recall of 82%, and an F1-score of 82.5%. This baseline performance highlighted the potential of utilizing deep learning models for vehicle classification tasks within urban traffic scenarios. As the study progressed through more sophisticated models such as VGG16 and VGG19, incremental improvements were observed, with accuracy reaching up to 90% and 89%, respectively. These advancements signified the models' enhanced capability to differentiate between EVs and non-emergency vehicles amidst the complexities of a loaded traffic square. However, it was the ResNet series that truly demonstrated the transformative potential of deep learning in traffic management systems. ResNet 50 introduced a remarkable leap in performance, achieving an accuracy of 92%, which was further improved by ResNet 101 with a 93% accuracy. The culmination of this progressive enhancement was witnessed in the proposed ResNet152 model, which emerged as the most effective architecture, achieving an unparalleled accuracy of 94%, precision of 93%, recall of 95%, and an F1-score of 94%.

These results not only showcase the superiority of deeper neural networks in processing complex image data but also highlight the critical role of model architecture in optimizing emergency response mechanisms within urban environments. The proposed ResNet152 model, in particular, stands as a testament to the scalability and robustness of deep learning solutions for critical applications such as the SLTSS. By significantly reducing the response times for EVs through accurate and rapid vehicle classification, the model demonstrates a potential pathway to saving lives and improving public safety measures in smart cities. The success of this model, validated by the empirical results of this study, advocates for its integration into existing and future traffic management infrastructures, providing a blueprint for leveraging artificial intelligence to tackle the challenges of emergency vehicle prioritization.

This research illuminates the broader implications of implementing advanced deep learning models in smart city logistics and emergency response protocols. The positive outcomes observed in the SLTSS case study reinforce the argument for a more widespread adoption of AI-driven systems in urban planning and public safety initiatives. By offering a detailed analysis of the performance of each model and presenting a clear comparison of their capabilities, this study serves as a valuable resource for policymakers, urban planners, and technologists looking to harness the power of AI in creating more responsive, efficient, and safe urban environments. In essence, the findings of this study not only contribute to the academic discourse on the application of deep learning in traffic management but also provide practical insights that can inform the development of smarter, more resilient cities. As we move forward, the continued exploration and implementation of such AI-based solutions will undoubtedly play a pivotal role in addressing the complex challenges of modern urban living, paving the way for a future where technology and public safety converge to foster more sustainable and livable communities.

Author contributions

Mr. Bharat Pahadiya: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation., Field study. **Dr. Rekha Ranawat:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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