A Survey on Traffic Management and Control System for Emergency Vehicles

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Abstract

Emergency response plays a pivotal role in ensuring public safety and the well-being of individuals in critical situations. Timely and efficient deployment of emergency vehicle is essential to minimize response times and mitigate potential threats to human lives and property. This survey paper comprehensively reviews the various approaches, strategies and technologies employed in optimizing traffic flow for emergency vehicles. The paper first outlines the significance of swift emergency vehicle response, emphasizing the critical role it plays in medical emergencies and law enforcement. It then examines the existing traffic management methods and challenges that affect the timely movement of emergency vehicles, including congestion, infrastructure limitations and communication issues. This survey also highlights case studies and real-world implementation, displaying the effectiveness and challenges of different traffic flow optimization strategies. Additionally, it discusses the ethical implications, privacy concerns, and societal impacts of prioritizing emergency vehicles.

Keywords - Machine learning, object detection, traffic optimization.

1. Introduction

In today's world of transportation and emergency response systems, the integration of machine learning is causing a major transformation. Machine learning is a powerful tool that's changing the game by using clever computer programs and data analysis to make emergency situations on our roads much better. This is important because it means we can manage traffic in a smarter way when ambulances, fire trucks, or police cars need to rush to help people in critical situations. Machine learning is like the hero in this story. It helps emergency services work faster and safer, which means they can do their job better and save more lives. As our cities get bigger and traffic jams become a common problem, using machine learning is like having a brilliant idea to solve the unique challenges that emergency responders face. It's like giving them a superpower to make sure they can get to emergencies quickly, navigate through traffic easily, and do their job in the best way possible, ultimately making our communities safer. Efficient traffic management and control systems have become indispensable for maintaining the orderly flow of traffic. Beyond facilitating the daily compute, these systems are of paramount importance during emergencies, when every second counts. Emergency vehicles, such as ambulances, firs trucks, and law enforcement vehicles, are entrusted with the critical task of responding rapidly to life-threatening incidents. However, navigating through congested roadways during emergencies can be challenging, and even minor delays can have dire consequences for those in need.

To address these challenges and enhance the safety and effectiveness of emergency response operations, the development of a robust Traffic Management and Control System for Emergency Vehicles has gained increasing importance. This innovative system seamlessly blends advanced technology and real-time data integration with Machine Learning Algorithms to prioritize and expedite the movement of emergency vehicles while ensuring the safety of all road users. By equipping emergency vehicles with the capability to preemptively alter traffic signals, and receive live traffic updates, this system empowers them to reach their destinations swiftly and safely, potentially saving lives in the process.

In this context, we will delve into the key components, benefits, and the transformative impact of such a system on emergency services and public safety, emphasizing the vital role it plays in mitigating the challenges posed by urban congestion during critical situations. The Traffic Management and Control System for Emergency Vehicles is not just a technological innovation; it's a lifeline that ensures timely assistance when it's needed most.

2. Literature Survey

The proposed navigation solution consists of vehicle-based traffic and road network data. Vehicle-based traffic data enables the identification of priority vehicles such as ambulances and fire trucks. Road network data contains road attributes for priority vehicles. The proposed system combines the learned vehicle type behaviors with traffic data and road attributes to make privileged emergency routing according to the vehicle type. Machine learning methods are utilized to classify vehicle behavior inference and classification using vehicle tracking data to distinguish vehicle types. The data of each vehicle is recorded from the vehicle tracking system as source ID, data date, GPS data (altitude, latitude, longitude), speed, and angular direction. Then, a matrix is created based on acceleration behaviors to distinguish vehicle types. The model is trained using convolutional neural networks (CNN) with vehicle tracking data generated according to classified vehicle types by acceleration behaviors, and vehicle-based traffic data is generated. [1].

The approach in the paper proposes use of the GPS integrated in the smartphones of the driving candidates which will help the traffic control systems to determine the density of the people on roads and accordingly can check the path of the emergency vehicle which they will receive from every emergency vehicle to reach the desired hospital and thereby make the route clear by making the timers of the corresponding signals green for 10 minutes prior to the emergency vehicle reaches the signal. They have proposed the advanced system which makes use of the integrated GPS module from smartphones to get the density near the signals having the specific radius of the latitude and longitude for every signal. [2]

The paper has presented an approach to schedule emergency vehicles in traffic. The approach combines the measurement of distance between the emergency vehicle and intersections using visual sensing methods, vehicle counting and time sensitive alert transmission within the sensor network. The distance between the emergency vehicle and the intersection is calculated from visual data using Euclidean distance, Manhattan distance and Canberra distance techniques for comparison. A complete description of the use of visual sensing techniques in vehicle detection and counting is also presented. The measured information like vehicle count, distance and speed are very useful for a traffic management center to manage emergency traffic efficiently. They have proposed a PE-MAC protocol, which is a new back off selection and contention window adjustment scheme to achieve low broadcast delay for emergency messages. [3].

An algorithm is proposed for classification of the emergency vehicles by following the method of capturing videos by the camera sensor, converting into the images and these images are processed by various algorithms and finally the program give the output whether the vehicle detected is an ambulance or not. Our approach can be integrated with CCTV to monitor emergency vehicles and provide them precedence in traffic so they may pass. Establishing emergency service skills for the nighttime and inclement weather is difficult but equally important to react inclement weather.[4].

The paper aims to review the current state of-the-art technologies in smart traffic management for ambulances and explore future directions for research and development in this field by using cameras of the signal and Arduino uno for emergency vehicle detection and sending the information to the traffic signal control and accordingly change the traffic lights. Emergency vehicle stuck in a traffic condition is detected with detection algorithm and then the traffic signal gets an alert by which it changes the signal to green from red. For the video part we use the already setup CCTV which is used by the traffic department for traffic violations. This live stream is broken into image frames and then the algorithm is run which searches with the dataset images and then alerts if a match is found from the image frames. [5].

The proposed intelligent traffic management technique, based on YOLO and Ale Net offers a comprehensive approach to efficiently manage high traffic. The approach includes data collection, YOLO implementation, feature extraction, traffic flow analysis, traffic sign identification, prediction and alert system and performance evaluation. Data collection employs the YOLO algorithm, which also preprocesses traffic video footage. The algorithm locates and tracks vehicles, labels them with details about the cars, traffic flow, and traffic signs, and then generates a set of bounding boxes around the cars. Feature extraction involves using Alex Net to extract high-level characteristics of observed cars from the YOLO output. These extracted features may include vehicle size, color, and type. Traffic flow analysis then utilizes YOLO data to examine vehicle movement and speed, identifying busy regions and forecasting traffic conditions [6].

The paper presents a method in which the vehicles are sensed and processed through imaging techniques. This avoids the need of electronic sensors. A web camera is placed with the traffic light to capture image frames. The purpose of the proposed system is to reduce the congestion and to reduce the time taken for the system in the absence of vehicles on road. It takes more consideration for the vehicle estimation by predicting the metal content of each vehicle. To automate traffic signal system based on density estimation and emergency vehicle detection such as ambulance. The benefits of this new method include non-use of sensors or RFID tags which reduces the stress of traffic sergeants. MATLAB simulation reduces the production costs and helps to achieve high speed and accuracy. Further with improvements, this work can be extended to detect road accidents and to identify violations that occurs in the spiral car movements. (see Fig. 1)[7].

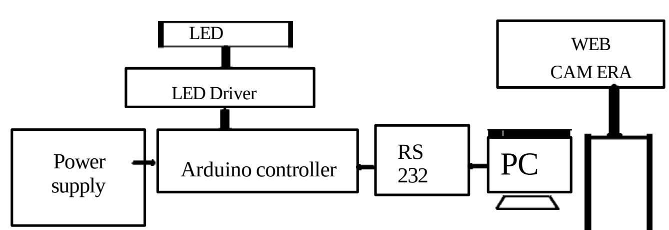

Fig. 1 Working system [7]

The article refers to the use of Vehicle-to-Infrastructure technology to enhance Emergency Vehicle Traffic Signal Management systems. V2I technology allows for communication between vehicles and infrastructure such as traffic signals and can provide real time data on traffic conditions, signal timing, and the location and status of emergency vehicles. By utilizing this data, the system can prioritize emergency vehicles and adjust signal timing to provide green lights as needed, allowing emergency vehicles to navigate through traffic more quickly and safely. V2I technology also enables the communication between vehicles, allowing emergency vehicles to coordinate with other vehicles and avoid collisions. It can create predictive models of traffic patterns, enabling the system to anticipate the movement of emergency vehicles and adjust signal timing accordingly. Overall, the use of V2I technology in the system can improve emergency response capabilities, reduce response times, and enhance safety for both emergency responders and other road users [8].

The ultrasonic sensor sense the obstacle i.e. vehicle in front of emergency vehicle it send a signal to the controller. The controller turns on the head light and sends information through lifi systems to the indicator of the next vehicle. Photo detector at the indicator receives the data and pass to the controller of that vehicle. The controller turn on the buzzer, that is present at the dashboard and turn on the headlight to transfer the information to the next vehicle through lifi. It continues until information reaches the first vehicle and transmits to the traffic signal system to turn on the green light and clear the path for emergency vehicles. The information like break apply, speed of the vehicle or any failure, damage in the vehicle etc can share through a lifi system. The patient information can be shared to the hospital through lifi communication. Traffic signal timer can be controlled dependent on number of vehicle present in front of the ambulance. [9].

The paper proposes to use the Enhanced particle Swarm optimization for the traffic signal control. The optimisation algorithm considers factors such as current queue length, recorded traffic flow, delay at each phase, and average waiting time in each direction for output determination, which is to suggest the traffic right-of-way assignment for each traffic phase. The final goal for the simulation is to investigate the traffic flow response towards different traffic signal applied. The control algorithm applied in the intersections will be investigated by simulating the traffic inflow and outflow information. The simulation is performed in small scale with simple control mechanism, which the intersections correlated to each other but the flows between the intersections. The traffic network is simulated under fixed time signal control and algorithm, and enhanced particle swarm optimisation algorithm respectively. Under the case of non-congested traffic, fixed time control can have better performance over particle swarm optimization algorithm as the latter is relatively unstable while unnecessary over-computation should be avoided. The proposed algorithms do not run under a fully congested condition where all directions are being congested. A fully congested network is abnormal condition where an expansion of infrastructure might be a better solution.

From the results, particle swarm optimisation algorithms are more efficient in, dealing with high traffic flow as it reduces the queue length of the congested direction significantly, compared to that of fixed control. At the same time, it means more traffic can be handled and congestion can be relieved faster. All entries (four directions) at the junction with enhanced particle swarm optimisation algorithm received more balanced allocation of average waiting times, which are maintained under 500 seconds eventually. [10].

The article implements the genetic algorithm for traffic flow control. Genetic algorithms' characteristic to evolve through generations of chromosomes and solution to choose the fittest optimum chromosomes that let it has the ability to self- optimizing from generation to generations. In this paper, the genetic algorithm is used in the traffic flow control to optimize the traffic flow within the intersection. The genetic algorithm is shown to be effective and capable to do the optimization of the traffic flow. The simulation is run for 600 seconds and the only difference is the incoming traffic flow is involved in the organization algorithm with the genetic algorithm in this simulation. The effects of various traffic characteristics are also being studied in this paper. As for queue length, which is also the total number of vehicles waiting at the intersection to be given the permission to be passed through, it is known as the performance indicator. Besides that, queue length also may bring some effects toward the traffic flow control, as the queue length may be too long and was unable to be released by the traffic flow control fast enough to ensure the smoothness of the traffic flow within the intersection. [11].

This paper proposes a method in which Each vehicle can be installed with a RFID tag. This RFID tag would store all the information regarding the vehicle such as the vehicle number, etc. RFID tags can be used in identifying each vehicle uniquely and also help the driver to receive some traffic messages. The existing signaling system can be coupled with the RFID controller. Thus when a vehicle passes by a signal, the signal can automatically keep the count of the vehicles passing by it, and help in detection of traffic congestion. Each signal should be stored with a threshold value for which it should be red and green. Now depending upon the frequency of the vehicles passing by the signal per second, the timer can be dynamically controlled. Each controller of the signal should be stored with a value of minimum frequency of the vehicles passing by the signal. As soon as this minimum frequency is reached, the controller should send a command to the signal to turn red. Thus the signal is controlled dynamically. [12].

The first and primary element of this system is the wireless sensor nodes consisting of sensors. The sensors interact with the physical environment means vehicles presence or absence while the local server sends the sensors data to the central microcontroller. This system involves the 4*2 array of sensor nodes in each way. This signifies 4 levels of Traffic and 2 lanes in each way. The sensors are ultrasonic sensors which transmits status based on presence of vehicle near it. The sensor nodes transmit at specified time intervals to the central microcontroller placed at every intersection.

The Microcontroller receives the signal and computes which road and which lane has to be chosen based on the density of Traffic. The computed data from Microcontroller is then transmitted to the local server through Wi-Fi connectivity. The controller makes use of the collected data to perform the Intelligent Traffic routing. In this system, the primary aim is to gather the information of moving vehicles based on WSN to provide them a clear path till their destinations and traffic signals should switch automatically to give a clear way for these vehicles [13]. The paper presents the proposed architecture for an ITMS inspired by the fused concepts of VANET and IoT that prioritizes the emergency vehicles on roads. The system firstly measures the gap between an intersection and the emergency vehicle, then dispatched EV from that particular intersection with the consideration that either the traffic signals are hacked or non-hacked, the type of incident and emergency car type. Every emergency vehicle has a unique identity that distinguishes it from the rest of the vehicles on the road. Once the information of emergency vehicles is obtained from sensors, it estimates the distance of emergency vehicles from an intersection and delivers access to the emergency vehicle on that particular road segment immediately. The RSU of the current intersection (RSU-A) informs the RSU of neighboring intersections (RSU-B) with the details of velocity of emergency car and number of vehicles which is moving towards the same intersection-B. On receipt of information from RSU-A, RSU-B will estimate its arrival time at the intersection-B. RSU-B will then regulate both the green light sequence and duration on the basis of expected time of arrival of the same and the received vehicle details from RSU-A. [14].

The research proposes dynamic determination of green light duration at traffic intersections, continuous monitoring of emergency vehicle arrival at different lanes, and addressing deadlock and starvation conditions due to repeated emergency vehicle arrivals. The proposed algorithm operates in two stages. In the first stage, emergency vehicles are categorized based on standard policies, assigning priority values to each type of vehicle. The algorithm also considers the security level of emergency vehicles during dispatching, as verified by authorities. In the second stage, the algorithm considers the distance of each emergency vehicle from the intersection point. Additionally, the system collaborates with a Code Messaging Service (CMS) and GPS-enabled mobile devices to further optimize emergency vehicle management. The methodology involves traffic volume detection, emergency vehicle presence check, and traffic phase selection based on the presence and priority of emergency vehicles. The algorithm also considers the direction and lane of emergency vehicle presence, as well as the maximum queue length of each phase at the intersection.[15]. The approach involves the integration of computational modeling and numerical models to assess the impact of the proposed system on time factors and the overall on-road traffic scenario. Utilizing radiofrequency identification, the system could effectively identify and prioritize emergency vehicles in real-time. The methodology explore incident management systems, employing intelligent traffic control to mitigate delays and enhance the efficiency of emergency vehicle response.

The study incorporates microscopy to analyze the micro-level interactions and behaviors within the traffic flow. Validation involves comprehensive simulations or practical implementations to evaluate the effectiveness of the Smart Priority-Based Traffic Control System, emphasizing its impact on emergency vehicle prioritization and its implications for other on-road traffics.[16]. This study outlines a methodology for the Detection and Prioritization of Emergency Vehicles within an Intelligent Traffic Management System (ITMS). The approach involves the deployment of real-time monitoring systems, utilizing sensors or cameras, for the identification of emergency vehicles in the traffic flow. Detection algorithms, which could include heuristic and prediction algorithms, are employed to enhance accuracy. Once identified, the methodology incorporates scheduling algorithms to prioritize the movement of emergency vehicles through junctions efficiently. The role of Roadside Units (RSUs) is employed in facilitating communication and coordination between the ITMS and emergency vehicles. The study delves into the impact of varying traffic densities on the effectiveness of the proposed system. Validation involves simulations or practical implementations to assess the efficiency of the Detection and Prioritization mechanism within the ITMS in improving emergency response times. [17].

The paper proposes a system in which whenever ambulance reaches to the accident spot, first the ambulance driver will feed the patient's information in the android application. This information will be sent to the hospital's server for further processes. On the way whenever ambulance halts at the traffic signal, the ambulance driver will send emergency command along with direction from the android application to the server. Also the current GPS coordinates of ambulance is also sent to the server. At the server, depending upon the co-ordinates of the ambulance, the nearest signal is detected and the emergency command along with the direction is sent to that particular signal. Depending on the direction received from the server that particular signal is made green. The system is divided into two modules. First module is a software module which consists of android application. Second module is the hardware module of traffic signal implementation. [18].

This paper uses a narrative literature review approach to compare and summarize on the existing techniques of traffic control system in the literature. The narrative literature review approach aims to discuss the state of a specific topic or theme from a theoretical and contextual point of view. This paper analysed the selected studies based on the following criteria: a) Techniques used to control traffic routing decisions. b) Traffic data collection methods to manage the routing decisions. c) Number and types of variables use to support the routing and signal decisions. The design for this system is divided in three systems. Firstly, is fitted in an emergency vehicle and known as an Emergency Vehicles System (EVS). Secondly, is fitted at traffic light junction and known as Traffic Junction System (TJS). Lastly, known as Base Station System (BSS). [19].

This study proposes a Traffic Control System catering to emergency vehicles, integrating RFID and sensor technologies. It involves deploying RFID tags on emergency vehicles, enabling seamless identification and communication with the traffic control system. Ultrasonic sensors contribute to real-time data collection, assessing the dynamic road environment and detecting the proximity of emergency vehicles. The system utilizes acoustics and object recognition techniques for enhanced accuracy. The approach aims to facilitate efficient traffic management by prioritizing emergency vehicles through automated responses triggered by RFID and sensor inputs.[20]. The study proposes an algorithm for traffic management, prioritizing emergency vehicles, particularly in the context of smart cities. This involves a cloud-based control center leveraging Internet of Things (IoT) technologies. Tracking and navigation systems are integrated, utilizing real-time data collection. Image processing aids in recognizing emergency vehicles and assessing dynamic road conditions. The algorithm dynamically adjusts traffic flow, granting priority to emergency vehicles for swift navigation.[21]. The solution centers on employing a Convolutional Neural Network (CNN) for intelligent traffic management during emergency scenarios. Initial stages involve defining the problem, collecting relevant datasets, and preprocessing data for CNN training. The designed CNN architecture is then trained using labeled examples, validated for generalization, and tested for performance metrics. Integration with a Traffic Management Center (TMC) allows real-time communication to influence traffic components. Implementation involves IoT Raspberry-Pi devices. Performance evaluation assesses the system's impact on response time, emergency vehicle efficiency, and traffic delays. [22].

This research employs an optimization-centric methodology for enhancing emergency response in smart cities. Initial steps involve modeling an Emergency Management System (EMS) considering real-time factors and resource constraints. The study integrates IoT technology to facilitate communication and coordination among emergency vehicles and traffic lights. An optimization algorithm is proposed for dispatching emergency vehicles efficiently and dynamically adjusting traffic lights to expedite their movement. The model is validated through simulations, considering diverse emergency scenarios. The approach aims to minimize response delays by strategically managing resources, highlighting a systematic optimization framework for improved emergency management in the context of smart cities.[23]. This solution focuses on a comprehensive approach, encompassing the development of V2V and V2I communication protocols with robust security controls, aiming to prevent emergency service misuse. Configurability is a key consideration, allowing adaptation to diverse emergency levels. Utilizing the iTETRIS simulation platform integrates ns-3 and SUMO for evaluating architecture effectiveness. This includes assessing dissemination delay and scalability via SUMO's mobility scenarios. Alternative data sources like faulty sensors prompt exploration of a mobile sensing approach for opportunistic data collection. Investigating sociotechnical adaptation scenarios involves aligning system and driver actions for maximum benefit.

Additionally, this study explores optimization techniques and AI search algorithms for an effective decision-making mechanism, considering real-time factors and security constraints.[24]. The paper presents an idea for traffic signal control in which a special camera was used to monitor the intersection in real-time. The camera output was a stream of video frames with a frame rate of 30 frames per second. The length of the road within the camera view was 15 metres. Video frames were binarized by using a background model with a threshold to detect and track all objects (vehicles). Region growing segmentation was used to segment the images and thus to count the vehicles and their bounding boxes. Variance and slab algorithms were used to process the data in order to calculate the time of the green signal. Computing the length of a cycle requires understanding the intervals of that cycle. [25].

The study introduces a solution for mitigating traffic congestion through an adaptive traffic signal control system designed for resource-constrained environments. The study formulates a cost function, considering factors such as real- time conditions, law enforcement requirements, and urban characteristics. Emphasis is placed on responsiveness to emergency vehicles, aiming to minimize delays during critical situations. The proposed system integrates green technologies and optimizes resource allocation, aligning with environmental considerations.[26]. This model presents a novel intelligent traffic recovery model tailored for emergency vehicles, employing a context-aware reinforcement learning approach. The methodology involves the formulation and implementation of an algorithm that utilizes reinforcement learning techniques and adapts to contextual information in real-time. The model is designed to dynamically learn and optimize traffic recovery strategies based on the unique context of emergency situations. Key steps in the methodology include defining the context-aware reinforcement learning model, training the system through interactions with its environment, and assessing its performance in recovering traffic conditions for emergency vehicles. Validation encompasses simulations or practical implementations to evaluate the model's adaptability and effectiveness, emphasizing its potential to provide intelligent and context- aware traffic recovery solutions for emergency services [27].

The study considers the optimization of the road structure to create virtual lanes for emergency vehicles, allowing them to travel at faster speeds and with special privileges such as overtaking from the opposite side. Additionally, the study focuses on optimizing signal lights to create a visible green corridor where traffic is not heavy at the point from which the emergency vehicle is moving. The research involves simulation using SUMO (Simulation of Urban MObility) to test the effectiveness of the proposed solution. The simulation consists of three parts: map (grid of roads), routes (several vehicles with different random routes), and traffic lights. The simulation involves the random selection of 500 vehicles for a period of 1500 time units with random trips, and the time taken to complete these trips is measured.

The study includes simulations to test the effect of traffic on vehicles when there are no special priority privileges, as well as simulations to compare the performance of emergency vehicles with and without route optimization and special access privileges. The results of the simulations are used to evaluate the effectiveness of the proposed solution in reducing time loss for emergency vehicles and its impact on the overall traffic flow. [28]. This paper aims to detect and track vehicles on a video stream and count those vehicles going across a predefined line. By using the count of vehicles on each side of the traffic light, we have optimized the traffic lights by assigning them time according to the traffic behavior in real-time. If we have less traffic or there is more traffic than usual, our model will optimize the light by increasing or decreasing the duration of the light. We have used YOLO and SORT algorithms on the live video feed to get the vehicle count in real-time. The capacity to anticipate traffic scenarios is significant for ideal management. For instance, if it is known that we would realize that some street will wind up clogged after some time, this data could be transmitted to street clients that can go around this street, consequently enabling the entire framework to diminish from blockage. Even for single intersections, there may be no optimum ideal arrangement.

With various intersections, the issue turns out to be significantly increasingly mind-boggling, as the condition of one light impacts the progression of traffic towards numerous different lights. [29]. The paper discusses the establishment of a traffic light regulation system on Sultan Agung street and surrounding areas where the traffic lights are connected to each other using fuzzy logic controller. Determine the system input and output, and the universe of each variable. In this study three input variables were used, namely the number of cars, number of motorcycles and queue length (m), while the output variable was the duration of the green light on (seconds). Determine the number of fuzzy sets in each input and output and membership functions. Each input variable will be defined as 3 fuzzy sets, while output variables are 5 fuzzy sets with trapezoid and triangle membership functions. Establish rules or fuzzy rules and determine the composition of the system rules (system inference). The system inference used is Max Min. The defuzzification process using the centroid method. The decision of the duration of the green light is the result of defuzzification. After the green light is on, there is a clear time for 5 seconds before the red light is on. The clear time is the time interval given to wait for a clean intersection of the vehicle. [30].

3. Related Work

Identify the specific region or city where the project will be implemented. Define the problem statement, including key challenges in traffic flow for emergency vehicles. Set clear objectives and goals for the project, such as reducing response times and improving public safety. Gather historical traffic data, including congestion patterns, traffic signal timings, and emergency vehicle response data. Analyze traffic data to identify areas with frequent congestion and delay in emergency vehicle movements. Survey and assess existing traffic management systems, signal preemption systems, and routing algorithms used in the selected region.

Evaluate their effectiveness in prioritizing emergency vehicles. Assess available technologies and tools for traffic flow optimization, such as traffic signal preemption systems, GPS-based navigation, and vehicle-to-infrastructure communication. Select appropriate technologies based on cost, compatibility, and effectiveness. Develop or customize software and hardware solutions as required. Conduct extensive testing and simulations to ensure the effectiveness of the chosen technologies and algorithms.

Algorithms used:

A. For object detection:

1) ***Region-based Convolutional Neural Networks (R- CNN)*****:** Region-based convolutional neural networks improve object detection by extracting essential features using selective search algorithms. This can be used for image analysis of vehicle detection. Ross Girshick in 2013 proposed an architecture called R-CNN to deal with the current challenge of object detection. This R-CNN architecture uses the selective search algorithm that generates approximately 2000 region proposals. These region proposals are then provided to CNN architecture that computes CNN features. These features are then passed in an SVM model to classify the object present in the region proposal. An extra step is to perform a bounding box regressor to localize the objects present in the image more precisely. Region proposals are simply the smaller regions of the image that possibly contains the objects we are searching for in the input image. To reduce the region proposals in the R- CNN uses a greedy algorithm called selective search.

Selective search is a greedy algorithm that combines smaller generated regions to generate region proposals.This algorithm takes an image as input and output generates region proposals on it. This algorithm has the advantage over random proposal generation in that it limits the number of proposals to approximately 2000 and these have a high recall.

2) ***Faster R-CNN:*** The R-CNN model, while effective for object detection, faced issues with speed. Fast R-CNN was introduced to address these issues, passing the entire image through a pre-trained Convolutional Neural Network. This method uses region of interest pooling to create a fully connected layer with an output. This improvement is discussed in the Faster R-CNN network. The main performance bottleneck of an RCNN lies in the independent CNN forward propagation for each region proposal, without sharing computation. Since these regions usually have overlaps, independent feature extractions lead to much repeated computation. One of the major improvements of the fast RCNN from the R-CNN is that the CNN forward propagation is only performed on the entire image. Compared with the R-CNN, in the fast R-CNN the input of the CNN for feature extraction is the entire image, rather than individual region proposals. Moreover, this CNN is trainable. Given an input image, let the shape of the CNN output be

1 * c * h1 * w1

Suppose that selective search generates n region proposals. These mark regions of interest on the CNN output. Then these regions of interest further extract features of the same shape in order to be easily concatenated. To achieve this, the fast R- CNN introduces the region of interest pooling layer: the CNN output and region proposals are input into this layer, outputting concatenated features of shape **n * c * h2 * w2** that are further extracted for all the region proposals. Using a fully connected layer, transform the concatenated features into an output of shape **n * d** where d depends on the model design. Predict the class and bounding box for each of the n region proposals. More concretely, in class and bounding box prediction, transform the fully connected layer output into an output of shape **n * q** (q is the number of classes) and an output of shape **n * 4**, respectively. The class prediction uses soft max regression.

3) ***YOLO (You only look once)*** - It is a popular object detection model architecture, often found on Google searches. It uses a top-notch neural network archetype for high accuracy and processing speed, making it a popular choice for object detection. The architecture takes an image as input and resizes it to 448*448 by keeping the aspect ratio same and performing padding. This image is then passed in the CNN network. This model has 24 convolution layers, 4 max-pooling layers followed by 2 fully connected layers. For the reduction of the number of layers, we use 1*1 convolution that is followed by 3* 3 convolution. Notice that the last layer of YOLOv1 predicts a cuboidal output. The loss function defined in YOLO is given as:

$$
\begin{aligned}
&\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
&+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2 \right] \\
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2
\end{aligned}
$$

Fig. 2 Loss function for You Only Look Once Algorithm [31]

The first two parts of the above loss equation represent localization mean-squared error, but the other three parts represent classification error. In the localization error, the first term calculates the deviation from the ground truth bounding box. The second term calculates the square root of the difference between height and width of the bounding box. In the second term, we take the square root of width and height because our loss function should be able to consider the deviation in terms of the size of the bounding box.

For small bounding boxes, the little deviation should be more important as compared to large bounding boxes. There are three terms in classification loss, the first term calculates the sum-squared error between the predicted confidence score that whether the object present or not and the ground truth for each bounding box in each cell. Similarly, The second term calculates the mean-squared sum of cells that do not contain any bounding box, and a regularization parameter is used to make this loss small. The third term calculates the sum-squared error of the classes belongs to these grid cells.

B. Classification:

This is used to distinguish emergency vehicles. **The Particle Swarm Optimization (PSO)** algorithm is a powerful meta-heuristic optimization algorithm and computational technique inspired by the collective behavior of natural organisms, such as birds or fish, that move together to achieve a common goal. In PSO, a group of particles (representing potential solutions) navigates through a problem's solution space to find the best possible solution. Each particle adjusts its position based on its own best-known solution (personal best) and the best solution discovered by the entire group (global best). This collaborative movement enables particles to converge toward optimal solutions over iterations. PSO is widely used for optimization problems in various fields, leveraging the power of collective intelligence to explore complex solution spaces and find optimal outcomes efficiently.

4. Methodology

The propose work involves real time object detection from the on-going traffic using the in built camera system of the traffic signals through video capturing and then image processing. After an emergency vehicle is detected, priority will be given to minimize the waiting time of emergency vehicles by traffic flow optimization algorithms. Subsequently coordinate with the adjacent traffic signals. In absence of an emergency vehicle e dynamic traffic signal duration will take place for minimum congestion at traffic signals. Below is the analysis of various algorithms that might be useful and for object detection.

4. 1. Implementation Details

You Only Look Once (YOLO) is a state-of-the-art object detection algorithm renowned for its efficiency and accuracy. YOLO approaches object detection as a single regression problem, directly predicting bounding boxes and class probabilities from full images in one evaluation. The architecture of YOLO consists of convolutional layers followed by fully connected layers, allowing it to make predictions across multiple spatial scales simultaneously.

A bounding box is a rectangular frame that encloses the detected object within an image. In YOLO, each bounding box prediction consists of four parameters: (1) the coordinates of the bounding box's top-left corner (x, y), (2) the width (w), and (3) the height (h). Additionally, each bounding box prediction is associated with a confidence score, representing the model's confidence in the detection, as well as class probabilities indicating the likelihood of each class present within the bounding box. The screenshots provided below showcase the bounding box outputs generated by the trained YOLO model during inference. Each screenshot depicts an input image overlaid with bounding boxes drawn around detected emergency vehicles, along with their associated confidence scores. These visual representations serve to illustrate the effectiveness of the YOLO algorithm in accurately identifying emergency vehicles within complex scenes.

Fig. 3 Bounding box used in YOLOv5

The graphs you sent me show the results of training a YOLOv5 object detection model to detect emergency vehicles. The graphs show various metrics and losses over the course of the training process.

- **train/box, train/cls, train/dfl:** These graphs show the training loss for different parts of the model. They are likely the bounding box loss, classification loss, and DFL loss, though the specific details may depend on the implementation.
- **metrics/precision(B), metrics/recall(B):** These graphs show the precision and recall for the model on the training set. Precision is the ratio of true positives to the total number of positive predictions, while recall is the ratio of true positives to the total number of actual positives.
- **val/box_loss, val/cls_loss, val/dfl_loss:** These graphs show the validation loss for the different parts of the model, similar to the training loss graphs above.
- **metrics/mAP50(B), metrics/mAP50-95(B):** These graphs show the mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds. These are common metrics used to evaluate object detection models.

The horizontal axis of each graph represents the training steps, while the vertical axis represents the value of the metric or loss.

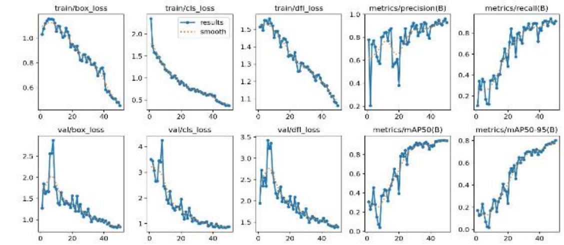

Fig. 4 Results of model training

5. Results

Confusion Matrix, which is a table that shows the performance of an algorithm at classifying data points. In this case, the rows represent the actual classes (ambulance, fire truck, background), and the columns represent the predicted classes. Each cell of the matrix shows the number of data points that were predicted to belong to a certain class, but actually belonged to another class.

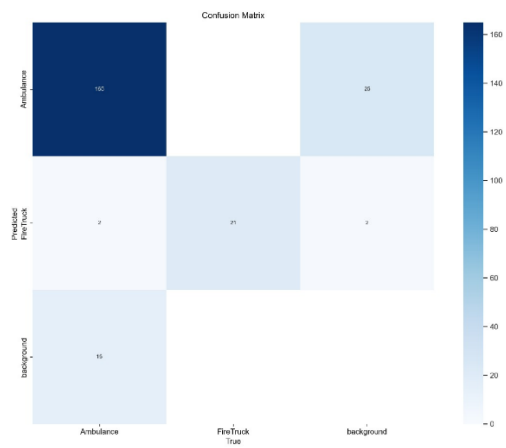

Fig. 5 Confusion Matrix produced as a result

YOLOv5 is used to identify emergency vehicles from images captured in CCTV camera at traffic signals. Our tweaked model has achieved an accuracy of more than 90% in identifying emergency vehicles.

Fig. 6 Prediction using YOLOv5

6. Conclusion

In conclusion, the incorporation of machine learning into traffic optimization for emergency vehicles represents a significant leap forward in our ability to respond effectively to critical situations. Through the utilization of real time data and sophisticated algorithms, machine learning has demonstrated its capacity to streamline emergency response processes, reduce response times, and ultimately enhance public safety. By providing intelligent traffic management solutions, it enables emergency vehicles to navigate congested roadways more efficiently ensuring that they reach their destination promptly. Furthermore, the potential to predict and preempt traffic during emergencies can save invaluable minutes, making the difference between life and death. As we continue to expand upon these technologies it is clear that machine learning holds immense promise in reshaping the landscape of emergency services, making our cities safer and more resilient in the face of unforeseen challenges.

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