ADVANCED VEHICLE FIRE SAFETY AND MONITORING WITH RAPID EMERGENCY DISPATCH SOLUTIONS

R24-058

Glen.N.Anthick

IT21096266

Final Report

B.Sc. (Hons) Degree in Information Technology specializing in

Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

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DECLARATION

I declare that this is my own work, and this final report does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the Supervisor:	2024.11.20	[illegible]
Signature of the Co-Supervisor:	2024.11.24	[illegible]

ABSTRACT

In response to the critical need for rapid emergency services in urban environments, this study suggests the development of an AI-driven routing system that gives the optimum path a firetruck or the fireman should take in case of a vehicle fire. Addressing the research problem of lack of existing routing solutions, the system integrates real-time traffic data, vehicle telemetry, and advanced routing algorithms to facilitate swift and safe navigation through congested metropolitan areas.

The study employs a hybrid AI model combining the predictive power of Graph Neural Networks (GNNs) with the efficiency of A* and Dijkstra algorithms. This model is designed to interpret complex traffic conditions and dynamically adjust routes in real-time. The research encompasses the collection and preprocessing of data from IoT devices within vehicles, the development and integration of the AI model into existing emergency dispatch systems, and the simulation of scenarios to test system efficacy.

Initial interpretations indicate that the proposed system significantly reduces response times by adapting to changing traffic patterns and road conditions, outperforming traditional static routing methods. The conclusions suggest that implementing such an AI-driven system could enhance the operational capabilities of fire departments, potentially saving lives and mitigating property damage more effectively during vehicular fire incidents.

Keywords: AI-driven routing system, Emergency services, Urban environments, Vehicle fires, Graph Neural Networks (GNNs), A* algorithm, Dijkstra algorithm, Emergency dispatch systems.

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LIST OF ABBREVIATION

AI - Artificial Intelligence

IoT - Internet of Things

GNN - Graph Neural Network

GPS - Global Positioning System

A - A-Star Algorithm*

ML - Machine Learning

CNN - Convolutional Neural Network

ESP32 - Espressif Systems 32-bit Microcontroller

AWS - Amazon Web Services

API - Application Programming Interface

SUMO - Simulation of Urban MObility

OSRM - Open-Source Routing Machine

UI - User Interface

SDK - Software Development Kit

HTTP - Hypertext Transfer Protocol

HTTPS - Hypertext Transfer Protocol Secure

QGIS - Quantum Geographic Information System

REST - Representational State Transfer

MQTT - Message Queuing Telemetry Transport

1 INTRODUCTION

1.1 Background and Literature Survey

1.1.1. Background

The rapid urbanization and escalating vehicular density in modern cities have introduced significant challenges for emergency response units, particularly fire services. The traditional emergency response systems are increasingly inadequate, as they rely heavily on manual processes and outdated technology. For instance, fire departments often depend on telephone calls to verify incidents and dispatch units, leading to critical delays in response times. These delays can have severe consequences, including increased risk to human life, greater property damage, and a heightened sense of helplessness among those affected by emergencies. The inefficiencies inherent in these systems are exacerbated by urban congestion, where navigating through traffic can add precious minutes to response times.

Given these challenges, there is a growing need to modernize emergency response systems by integrating advanced technologies that can provide real-time data, predictive analytics, and automated decision-making. The use of AI in emergency management is becoming increasingly vital. Specifically, the application of Graph Neural Networks (GNNs) and traditional routing algorithms such as A* and Dijkstra has shown promise in optimizing routes for emergency vehicles. GNNs, with their ability to model complex relationships within data, offer a nuanced understanding of traffic patterns, enabling the prediction of the most efficient routes even under dynamic urban conditions. This predictive capability is critical for emergency vehicles, such as fire trucks, which must reach incident sites as quickly as possible while navigating through unpredictable traffic flows.

However, while these technological advancements are crucial, they do not address all the gaps in the current emergency response systems. One of the most significant overlooked areas is the role of vehicle owners during an emergency. Traditional systems leave vehicle owners in a state of helplessness until professional responders arrive. This gap is particularly concerning when considering the high stakes involved in vehicle fire incidents, where every second counts.

To address this gap, this research proposes an innovative AI-driven solution that not only optimizes the routing of emergency vehicles but also empowers vehicle owners with real-time, actionable information. The system will automatically detect vehicle fires, send the location data to the cloud, and identify the nearest fire department. An AI model will then analyze the available firefighting resources, such as the number of deployable fire trucks, and provide this information to the fire department. Simultaneously, the system will notify vehicle owners of nearby fire extinguishers, enabling them to take immediate action while waiting for professional help. This aspect of the system is particularly novel, as it leverages AI to analyze geographic and environmental data, providing vehicle owners with precise, location-based recommendations.

The dataset for the AI model that identifies nearby fire extinguishers has been meticulously curated to ensure high accuracy and relevance. By integrating this data with the overall emergency response system, the research aims to create a comprehensive solution that not only enhances the efficiency of fire services but also empowers individuals to mitigate damage and potentially save lives before professional responders arrive.

In conclusion, the modernization of emergency response systems through AI-driven technologies is not just about optimizing the response of fire services. It is also about addressing the needs of those directly impacted by emergencies. By providing real-time information and empowering individuals with actionable data, this research aims to set a new standard for emergency management in urban settings, ultimately reducing response times, saving lives, and minimizing property damage.

1.1.2. Literature Survey

The ongoing evolution of urban environments and the resultant increase in vehicular density have posed substantial challenges to emergency response units, particularly in the realm of fire services. Traditional routing systems, which often rely on static and pre-determined paths, are proving inadequate in the face of dynamic and unpredictable urban traffic patterns. As urban centers grow and traffic conditions become more complex, there is a pressing need for more adaptive and responsive routing systems that can accommodate these challenges in real time.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have introduced new possibilities for enhancing the efficiency of emergency response systems. Graph Neural Networks (GNNs), in particular, have emerged as a potent tool for improving the adaptability and accuracy of routing algorithms. Unlike conventional routing methods, which may struggle to account for the complex and interconnected nature of urban traffic networks, GNNs can model the intricate relationships within these networks, providing a more comprehensive understanding of traffic patterns. When combined with traditional algorithms like A* and Dijkstra, GNNs can enable the prediction of optimal routes that dynamically adjust to changing traffic conditions, significantly improving the reliability and speed of emergency vehicle dispatch.

However, despite these promising developments, there remains a significant gap in the literature regarding the specific application of these technologies to the needs of emergency vehicles, particularly fire trucks. Fire trucks face unique operational challenges—they must navigate rapidly yet safely through congested urban environments, often against the flow of regular traffic. Existing routing systems are typically designed for standard vehicles and do not adequately address the specialized requirements of emergency response units. This gap highlights the need for research focused on developing routing systems that are specifically tailored to the operational demands of fire services.

In response to this gap, this study proposes the development of a hybrid AI model that integrates GNNs with traditional routing algorithms such as A* and Dijkstra. The proposed system aims to assimilate both real-time and historical traffic data, as well as vehicle-specific telemetry, to compute the most efficient paths for fire trucks during emergencies. The model will be trained to prioritize routes based on a variety of parameters, including the shortest distance, the fastest travel time, and the least congestion. Importantly, it will also take into account the physical constraints of fire trucks, such as their size and turning radius, which are critical factors in ensuring safe and effective navigation.

A key innovation of this research lies in its real-time data integration capability. By continuously updating the routing model with live traffic information, the system is designed to deliver more accurate and timely route optimizations. This real-time adaptability is essential for emergency vehicles, which operate in highly fluid and time-sensitive situations where delays can have serious consequences. The ability to dynamically adjust routes in response to changing conditions is expected to significantly enhance the operational efficiency of fire services, potentially reducing response times and improving outcomes in emergency situations.

In addition to optimizing emergency vehicle routing, this research also addresses a critical gap in existing emergency response systems: the lack of immediate support for vehicle owners during emergencies. Traditional systems often leave vehicle owners in a state of helplessness until professional responders arrive. This study introduces an AI-based model that informs vehicle owners of nearby fire extinguishers in real time. The dataset for this model has been meticulously gathered to ensure high accuracy in identifying the location and accessibility of fire extinguishers. The AI system will analyze geographic and environmental data to provide immediate recommendations, empowering vehicle owners to take preventive measures while waiting for professional help. This proactive approach not only enhances the safety of vehicle owners but also contributes to minimizing property damage and loss of life.

Overall, this literature survey underscores the need for innovative solutions that integrate advanced AI techniques with real-time data analytics to address the complex challenges of emergency response in urban environments. The proposed research aims to fill existing gaps in the literature by developing a comprehensive, AI-driven routing system that is specifically designed to meet the unique needs of fire services and vehicle owners during emergencies.

1.2 Research Gap

The ongoing evolution of urban environments has placed significant strain on traditional emergency response systems, particularly for fire services. The manual, outdated processes commonly used by fire departments—such as verifying incident details via phone—are no longer sufficient in densely populated, congested cities.

These methods lead to delays that can escalate the risk to human life and increase property damage. Moreover, these systems leave vehicle owners without any real-time information or actionable guidance during critical moments, further compounding the challenges faced during emergencies.

The application of advanced technologies like AI, specifically Graph Neural Networks (GNNs), in conjunction with traditional routing algorithms like A* and Dijkstra, has shown potential in optimizing emergency vehicle routing. However, current research has not adequately explored their application in scenarios requiring real-time adaptability for emergency services, particularly fire trucks. These vehicles must navigate not only through congested traffic but also under strict safety protocols, often against the normal flow of traffic. Existing systems fail to address these unique operational constraints, leading to suboptimal routing decisions that could delay emergency response times.

Another critical gap lies in the role of vehicle owners during emergencies. Traditional systems leave them in a state of helplessness until professional help arrives. There is a significant lack of solutions that provide vehicle owners with real-time, actionable information that could help mitigate the situation before emergency responders arrive. This aspect is particularly crucial in vehicle fire incidents where immediate action, such as locating a nearby fire extinguisher, could make a significant difference.

This research proposes an AI-driven solution to address these gaps by developing a system that not only optimizes fire truck routing but also provides real-time support to vehicle owners. The proposed system will detect vehicle fires, send the location data to the cloud, and identify the nearest fire department. An AI model will analyze the availability of firefighting resources and inform the fire department accordingly. Simultaneously, the system will notify vehicle owners of nearby fire extinguishers, enabling them to take immediate action.

The dataset for the AI model identifying nearby fire extinguishers has been meticulously curated to ensure accuracy and relevance. By integrating this data with the overall emergency response system, this research aims to create a comprehensive solution that enhances the efficiency of fire services and empowers individuals to mitigate damage before professional responders arrive.

In conclusion, there is a critical need to modernize emergency response systems with AI-driven technologies that not only improve response times but also empower those directly affected by emergencies. This research aims to fill this gap by developing a comprehensive, real-time AI-driven routing system that addresses the unique challenges faced by fire services and vehicle owners, setting a new standard for emergency management in urban settings.

2 RESEARCH PROBLEM

The rapid urbanization and the consequent rise in vehicular density have significantly strained traditional emergency response systems, especially within fire services. These outdated systems heavily rely on manual processes, such as incident verification via telephone, which results in critical delays in response times. Such delays can escalate the risk to human life, increase property damage, and leave those affected in a state of helplessness. Urban congestion further exacerbates these inefficiencies, as navigating through traffic adds precious minutes to the arrival of emergency services.

To address these challenges, there is an urgent need to modernize emergency response systems by integrating advanced technologies capable of providing real-time data, predictive analytics, and automated decision-making. The application of AI, particularly through Graph Neural Networks (GNNs) combined with traditional routing algorithms like A* and Dijkstra, has shown promise in optimizing the routes for emergency vehicles. GNNs can model complex relationships within traffic data, allowing for the prediction of the most efficient routes under dynamic urban conditions. This predictive capability is vital for emergency vehicles such as fire trucks, which must reach incident sites as swiftly as possible while navigating unpredictable traffic flows.

Despite these advancements, a significant gap persists in how current emergency response systems cater to the needs of vehicle owners during emergencies. Traditional systems leave vehicle owners without any real-time information or actionable guidance until professional responders arrive, which is particularly concerning in high-stakes scenarios like vehicle fires. This lack of support can lead to increased damage and risk, as vehicle owners are often unable to take immediate action, such as using a nearby fire extinguisher.

To bridge this gap, this research proposes the development of an AI-driven system that not only optimizes the routing of emergency vehicles but also empowers vehicle owners with real-time, actionable information. The system will automatically detect vehicle fires, send location data to the cloud, and identify the nearest fire department. An AI model will then analyze the availability of firefighting resources and notify the fire department. Simultaneously, the system will inform vehicle owners of nearby fire extinguishers, enabling them to take immediate action while waiting for professional help.

This approach addresses the dual challenge of enhancing the efficiency of fire services while empowering individuals to mitigate damage and potentially save lives before emergency responders arrive. The research problem thus lies in developing a comprehensive, real-time, AI-driven routing system that addresses the unique operational needs of fire services and the informational needs of vehicle owners during emergencies. This solution aims to set a new standard for emergency management in urban environments, ultimately reducing response times, saving lives, and minimizing property damage.

3 OBJECTIVES

3.1 Main Objectives

The primary objective of this research is to develop an advanced emergency response system that leverages traffic data, vehicle telemetry, and predictive analytics to optimize the routing of fire trucks in congested urban environments. The system also aims to empower vehicle owners by providing them with real-time, actionable information, such as the location of nearby fire extinguishers, to enable immediate, life-saving actions while awaiting professional help. This comprehensive solution seeks to enhance public safety by reducing response times and minimizing property damage in emergency situations.

3.2 Sub Objectives

- To implement and rigorously assess the effectiveness of A*, Dijkstra, and GNN algorithms within the routing system, ensuring that the system selects optimal paths based on real-time and historical traffic data, vehicle-specific telemetry, and urban constraints.
- To design, train, and refine a model that integrates the strengths of the selected routing algorithms, enabling dynamic adjustments in response to changing traffic conditions for real-time route optimization.
- To conduct extensive simulations and real-world testing in collaboration with fire departments, validating the AI model's accuracy, reliability, and practical utility in predicting optimal emergency routes under diverse urban scenarios.
- To leverage cloud computing resources for scalable data storage, processing power, and enhanced model accessibility, ensuring the system's reliability and performance across various urban environments.
- To develop an intuitive, user-friendly interface for emergency services, ensuring seamless delivery of routing information and compatibility with existing dispatch systems, thereby enhancing operational efficiency and response times.

4 METHODOLOGY

4.1 System Architecture

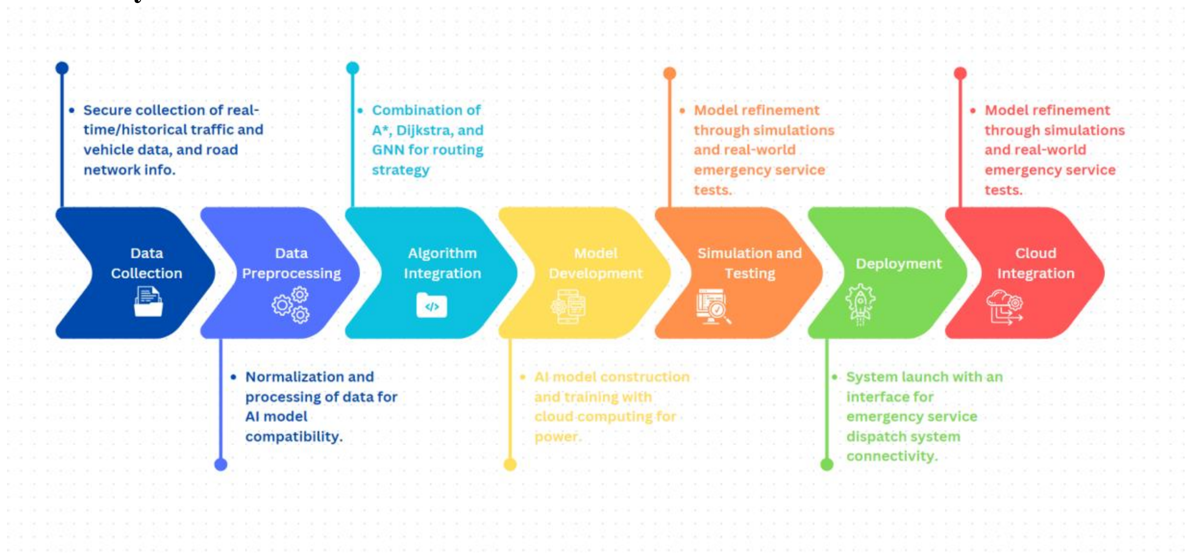

• Secure collection of real-time/historical traffic and vehicle data, and road network info.
• Combination of A*, Dijkstra, and GNN for routing strategy
• Model refinement through simulations and real-world emergency service tests.
• Model refinement through simulations and real-world emergency service tests.
Data Collection
Data Preprocessing
Algorithm Integration
Model Development
Simulation and Testing
Deployment
Cloud Integration
• Normalization and processing of data for AI model compatibility.
• AI model construction and training with cloud computing for power.
• System launch with an interface for emergency service dispatch system connectivity.

Figure 1:Component Architecture Diagram

The growing complexities of urban environments, coupled with the increasing density of vehicular traffic, present significant challenges to traditional emergency response systems, particularly within fire services. These systems, which often rely on manual processes and outdated technologies, are becoming increasingly inadequate in addressing the dynamic and unpredictable nature of urban traffic. The need for rapid and reliable emergency response is critical, as delays in reaching incident sites can lead to devastating consequences, including loss of life and extensive property damage.

To address these challenges, this research proposes a comprehensive, AI-driven methodology designed to modernize emergency response systems. The integration of advanced technologies such as Graph Neural Networks (GNNs), combined with traditional routing algorithms like A* and Dijkstra, forms the backbone of this approach. These technologies are capable of modelling complex relationships within traffic data, providing a nuanced understanding of traffic patterns, and predicting the most efficient routes for emergency vehicles, even in highly congested urban areas.

In addition to optimizing the routing of fire trucks, the proposed system also addresses a critical gap in existing emergency response frameworks: the lack of real-time support for vehicle owners during emergencies. By leveraging AI, this system not only facilitates the rapid dispatch of emergency services but also empowers vehicle owners with actionable information, such as the location of nearby fire extinguishers, enabling them to take immediate preventive measures while waiting for professional assistance.

The following methodology outlines a multi-phased approach that includes data collection, pre-processing, algorithm integration, AI model development, simulation, testing, and deployment. Each phase is meticulously designed to ensure the reliability, scalability, and effectiveness of the system, ultimately setting a new standard for emergency management in urban settings.

Data Collection and Preprocessing

Data collection and pre-processing are foundational steps in developing a reliable and effective AI-driven emergency response system. This phase involves the systematic gathering of real-time and historical data related to traffic conditions, vehicle telemetry, and detailed road network attributes. Real-time data may include current traffic flow, accident reports, road closures, and environmental conditions, while historical data offers insights into patterns and trends that can improve the model's predictive accuracy. Vehicle telemetry data provides crucial information on vehicle speed, location, and other performance metrics, enabling a detailed analysis of how emergency vehicles interact with varying traffic conditions.

The collected data often comes from diverse sources, such as traffic sensors, GPS devices, IoT-enabled vehicles, and public transportation databases. Given the diversity and volume of data, pre-processing becomes essential. This step involves cleaning the data to remove any inconsistencies, errors, or missing values, which could otherwise skew the AI model’s predictions. Normalization is another key aspect of pre-processing, ensuring that the data is uniform and comparable across different sources. For instance, speed data from various types of vehicles and sensors must be normalized to a common scale for accurate analysis.

pre-processing also includes feature extraction, where relevant attributes are selected from the raw data to be used in model training. This might involve identifying key features such as traffic density, average vehicle speed, road type, and weather conditions. The goal is to create a robust dataset that accurately reflects real-world conditions, enabling the AI model to learn effectively.

The quality of the pre-processing step directly impacts the reliability and accuracy of the AI model. Well pre-processing data ensures that the model can make accurate predictions, adapt to new data inputs, and provide reliable routing solutions for emergency vehicles. This step is crucial in building a system that can operate effectively in the dynamic and unpredictable environment of urban traffic.

Algorithm Integration

Algorithm integration is the core of the AI-driven emergency response system, combining the strengths of Graph Neural Networks (GNNs) with traditional routing algorithms like A* and Dijkstra. This hybrid approach is designed to navigate the complex, ever-changing landscape of urban traffic, where standard algorithms alone may fall short. GNNs are particularly effective in modeling the intricate relationships within traffic networks, as they can capture the dependencies and interactions between various elements, such as roads, intersections, and traffic signals.

The integration process begins with the application of A* and Dijkstra algorithms, which are well-established methods for finding the shortest path between two points. A* enhances Dijkstra's algorithm by incorporating heuristics to estimate the cost of reaching the destination, making it more efficient in certain scenarios. These algorithms provide a solid foundation for route optimization, particularly in less dynamic traffic conditions.

However, urban traffic is often unpredictable, with sudden changes due to accidents, roadworks, or varying traffic volumes. This is where GNNs come into play. By leveraging the graph-based structure of traffic networks, GNNs can analyze the entire network holistically, identifying optimal routes that take into account real-time traffic conditions. GNNs can dynamically adjust to changes in the network, offering more accurate and context-aware routing solutions.

The integration of these algorithms involves creating a seamless workflow where GNNs and traditional algorithms complement each other. For example, GNNs can be used to analyze the traffic network and predict potential congestion points, while A* or Dijkstra can quickly compute the best route based on these predictions. This dual approach ensures that the system can handle both routine and complex routing scenarios with high efficiency.

The successful integration of these algorithms requires careful consideration of their respective strengths and limitations. It also involves extensive testing and fine-tuning to ensure that the combined system performs well under a wide range of conditions. The result is a robust routing engine that can guide emergency vehicles through urban traffic with unprecedented accuracy and speed.

Model Development and Training

model development and training are pivotal in transforming raw data and algorithmic strategies into a functioning, intelligent system capable of optimizing emergency vehicle routes. This phase leverages the vast computational resources provided by cloud computing to handle the intensive processes involved in training sophisticated AI models, such as those based on Graph Neural Networks (GNNs). These models must learn from large datasets, which include real-time traffic data, historical traffic patterns, and vehicle telemetry, to make accurate and timely predictions.

The development process begins with defining the architecture of the AI model, which needs to be capable of integrating multiple data streams and processing them in real time. For instance, the model must be able to analyze traffic density, road conditions, and vehicle performance metrics simultaneously to predict the most efficient route. This requires a well-structured neural network that can handle high-dimensional data and extract meaningful patterns.

Once the architecture is defined, the model is trained using the pre-processed data. During training, the model iteratively adjusts its internal parameters to minimize the error in its predictions. This involves running numerous simulations where the model predicts routes based on input data, compares these predictions against known outcomes, and updates its parameters to improve accuracy. Techniques such as backpropagation and gradient descent are commonly used to optimize the model's performance.

Training also involves validating the model to ensure it generalizes well to new, unseen data. This is typically done by dividing the dataset into training and validation sets. The model is trained on the former and tested on the latter to assess its predictive accuracy. Overfitting, where the model performs well on training data but poorly on new data, is a common challenge that must be addressed through techniques like regularization and cross-validation.

The cloud infrastructure plays a crucial role in this phase by providing scalable computing power and storage. This allows the model to be trained on large datasets and refined over multiple iterations without performance bottlenecks. The result is a highly accurate and reliable AI model that can predict the best routes for emergency vehicles under various conditions, including high traffic congestion and road closures.

Simulation and Testing

Simulation and testing are critical phases in the development of the AI-driven emergency response system, ensuring that the model performs reliably under real-world conditions. This phase begins with extensive simulations that replicate a wide range of traffic scenarios, including both typical and extreme conditions. The purpose of these simulations is to test the AI model's ability to predict optimal routes for emergency vehicles, taking into account dynamic factors such as sudden traffic surges, road closures, and accidents.

The simulation process involves creating virtual environments that mimic the complexities of urban traffic networks. These environments are populated with data that reflects various traffic patterns, including rush hours, roadworks, and unpredictable incidents like accidents. The AI model is then tested in these simulated environments to evaluate its performance. Key metrics such as response time, route efficiency, and adaptability to changing conditions are closely monitored.

Simulations also allow for the identification of potential weaknesses in the model. For example, the model might perform well under normal conditions but struggle to adapt quickly enough during a sudden traffic jam. Identifying these issues early allows for targeted improvements before real-world deployment.

Following successful simulations, the system undergoes real-world testing in collaboration with fire departments and other emergency services. These field tests are crucial for validating the model's predictions and ensuring that it integrates smoothly with existing emergency response protocols. During these tests, the AI system is used to guide emergency vehicles in real scenarios, and its performance is compared to traditional routing methods.

Feedback from emergency responders is invaluable during this phase. Their insights help refine the model to better meet the practical demands of real-world emergency situations. For instance, the system might need adjustments to account for specific local traffic regulations or the unique operational constraints of different emergency vehicles.

The final stage of testing involves stress-testing the system under extreme conditions to ensure its robustness. This includes scenarios such as multiple concurrent emergencies, major traffic disruptions, and system overloads. The goal is to ensure that the system remains reliable and effective even under the most challenging conditions.

Deployment and Integration

Deployment and integration represent the culmination of the AI-driven emergency response system's development process, where the model is transitioned from a test environment to real-world application. This phase begins with the deployment of the system onto a cloud-based infrastructure, ensuring that it can handle the scale and complexity of live data streams. The system is designed to be highly scalable, allowing it to operate efficiently regardless of the number of concurrent emergencies or the volume of data being processed.

A key aspect of deployment is the seamless integration of the AI system with existing emergency dispatch systems. This involves developing a user-friendly interface that enables fire department personnel to interact with the system easily. The interface should provide clear, actionable insights, such as the most efficient route to an incident, the availability of fire trucks, and the estimated time of arrival. Ensuring that this information is presented in an intuitive and accessible manner is crucial for the system's adoption and effectiveness.

The integration process also includes establishing secure communication channels between the AI system and emergency response units. This ensures that real-time data can be transmitted without delays, and that the system's recommendations are delivered promptly to those who need them. Additionally, the system must be compatible with various hardware and software used by different fire departments, which may require custom adaptations or the development of APIs for smooth interaction.

Another important component of the deployment phase is the system's ability to provide real-time support to vehicle owners. This feature involves notifying them of nearby fire extinguishers and other emergency resources, empowering them to take immediate action while waiting for professional responders. This function is particularly important in high-stakes scenarios like vehicle fires, where every second counts.

Once deployed, the system undergoes continuous monitoring to ensure that it operates as intended. This includes tracking its performance, identifying any issues, and implementing updates or patches as needed. Regular training sessions for emergency personnel may also be conducted to familiarize them with the new system and ensure they are comfortable using it in high-pressure situations.

Cloud Integration for Scalability and Performance

Cloud integration is a critical component of the AI-driven emergency response system, providing the necessary infrastructure to support scalability, performance, and reliability. The system is hosted on a cloud platform, which offers several advantages

4.2 Commercialization of the Product

Automotive Integration: This system could be integrated into vehicle navigation systems at the manufacturing stage, providing an advanced feature that enhances the safety and value of new vehicles. Collaborations with car manufacturers would not only be a selling point but could also standardize emergency response technology across the industry.

Consultancy Services: Using the data collected from the system, we could offer consultancy services to vehicle manufacturers and emergency response equipment providers, aiding them in developing features that enhance safety and response capabilities.

Data Monetization: The system could generate valuable data on traffic patterns and emergency incident responses. This data, once anonymized to protect privacy, could be a critical asset for urban development agencies, helping to plan and improve city infrastructure.

5 SOFTWARE / HARDWARE METHODOLOGY

5.1 Software methodology

Requirements Gathering and Analysis:

This phase is crucial for understanding the exact needs of the emergency services in terms of routing efficiency, data accuracy, and system integration. It would involve discussions with emergency responders to identify critical system features, desired outcomes, and constraints such as compatibility with existing communication and navigation systems.

Market Research:

An in-depth market analysis would be conducted to assess existing emergency routing solutions, potential gaps in the market, and areas where innovation can provide significant advantages. This also involves identifying potential competitors and understanding their product offerings to ensure that the new system offers unique and superior capabilities.

Use Case Scenarios:

Crafting detailed scenarios that the system will encounter is key to ensuring its effectiveness. This includes simulating high-traffic conditions, different times of day, urban versus rural routes, and various emergency types to ensure the AI model is robust and versatile.

System Architecture:

The architecture of the system must be designed for scalability and resilience, capable of handling large volumes of real-time data and integrating seamlessly with multiple data sources. It should also be adaptable to incorporate future advancements in AI and routing algorithms.

Technology Selection:

Selecting the right technology stack is critical for the success of the system. This includes choosing programming languages known for performance and reliability, robust frameworks for AI and data processing, and tools that support agile development and collaboration.

Sprint Planning:

Create task list and break it down into sprints. One sprint means 2 weeks. Allocate the tasks according to the weight of the task into sprints. And always monitor the sprint plan and the actual work done during the sprint. And plan the remaining work to complete in the upcoming sprint and adjust the sprint plan accordingly.

Code Reviews:

A systematic code review process would help maintain high-quality standards, facilitate knowledge sharing among developers, and ensure that all code commits are aligned with the project's coding standards and architecture.

Software Development:

The development phase involves writing clean, efficient, and well-documented code to implement the core functionalities of the routing system, the user interface, and the integration mechanisms with real-time data sources.

Data Gathering and Model Training:

Gathering a diverse set of traffic and incident data is vital for training the AI model to accurately predict optimal routes under a variety of conditions. This data needs to be cleaned, normalized, and structured before being used for model training.

5.2 Tools and Technologies

Jupyter Lab: for exploratory data analysis and model prototyping. Its interactive environment is particularly useful for visualizing data flows within the system and sharing findings with the development team.

TensorFlow: TensorFlow can be used to develop machine learning models that analyze patient data and categorize them into safe, cautious, or danger zones. The models can be trained to provide personalized recommendations based on the patient's specific health conditions and medical history.

Python: Leverage Python's extensive ecosystem for all stages of software development, from writing backend services to processing data and machine learning.

Graph Neural Networks (GNN): Implement GNNs to effectively learn and model the complex patterns in the road network data, enabling the system to make informed routing decisions in dynamic traffic scenarios.

A* Algorithm: Integrate the A* search algorithm to efficiently calculate the optimal route for emergency vehicles, factoring in various constraints such as road types, traffic conditions, and incident locations.

Dijkstra's Algorithm: Use Dijkstra's algorithm for route optimization tasks that require finding the shortest path without considering dynamic traffic conditions, serving as a foundational component for more complex routing strategies.

6 Testing & Implementation

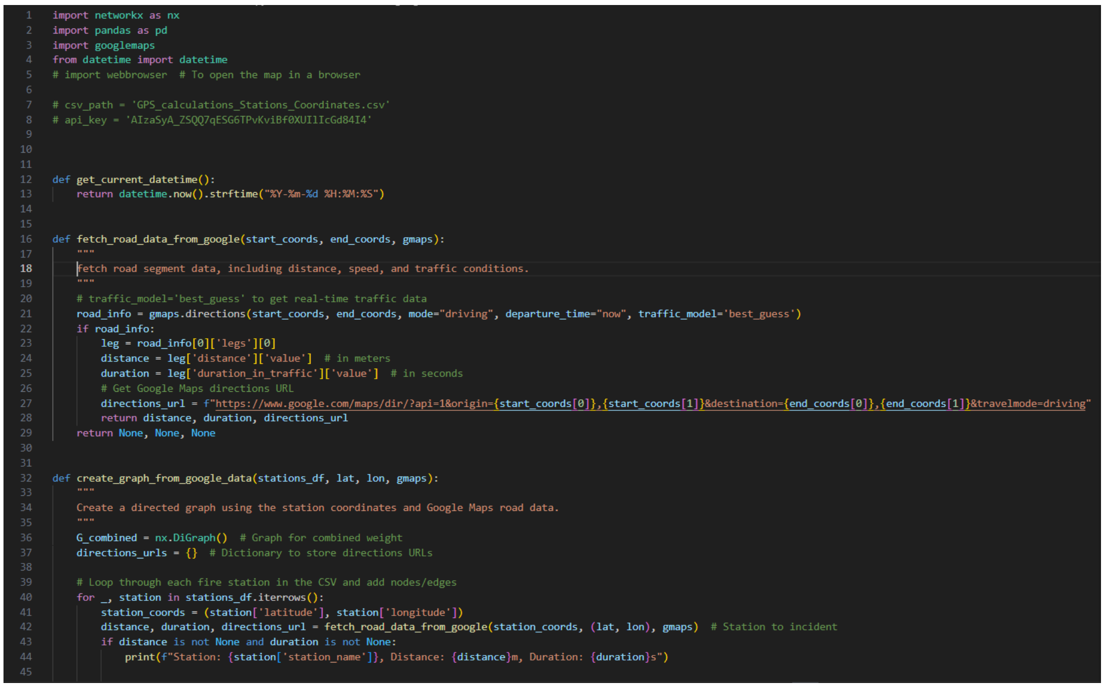
6.1 Implementation

The implementation of the AI-driven emergency response system involves a seamless transition from conceptual design to practical application, emphasizing reliability, scalability, and integration with existing emergency protocols. The system begins by leveraging a cloud-based infrastructure for real-time data processing, enabling the continuous assimilation of live vehicle telemetry, and environmental conditions. This cloud integration ensures the system's ability to handle high data volumes, offering consistent performance across diverse urban scenarios.

The routing engine, powered by the hybrid integration of Graph Neural Networks (GNNs), A*, and Dijkstra algorithms, is deployed within the system's core. The GNNs process complex traffic network relationships to predict congestion patterns, while A* and Dijkstra algorithms compute efficient routes. This dual-layered architecture dynamically adjusts to traffic fluctuations, ensuring optimal performance even under unpredictable urban conditions. A user-friendly interface is designed for emergency responders, providing clear, actionable insights like optimal routes, estimated arrival times, and resource availability. This interface integrates seamlessly with existing dispatch systems, ensuring emergency personnel can make swift decisions without requiring additional training. Simultaneously, the system informs vehicle owners of nearby fire extinguishers, empowering them to act during emergencies while professional help in route.

Real-world implementation also involves securing data privacy through encryption and compliance with regulatory standards. Field tests in collaboration with emergency services ensure the system meets practical demands. Regular updates and monitoring maintain system effectiveness, ensuring it adapts to evolving urban environments and emergency management needs. By integrating cutting-edge AI technologies and robust infrastructure, the implementation sets a new standard for emergency response, reducing response times and saving lives.

6.2 Calculate nearest fire department



```python
import networkx as nx
import pandas as pd
import googlemaps
from datetime import datetime
# import webbrowser  # To open the map in a browser

# csv_path = 'GPS_calculations_Stations_Coordinates.csv'
# api_key = 'AIzaSyA_ZSQQ7qESG6TPvKviBf0XUIlIcGd84I4'



def get_current_datetime():
    return datetime.now().strftime("%Y-%m-%d %H:%M:%S")


def fetch_road_data_from_google(start_coords, end_coords, gmaps):
    """
    fetch road segment data, including distance, speed, and traffic conditions.
    """
    # traffic_model='best_guess' to get real-time traffic data
    road_info = gmaps.directions(start_coords, end_coords, mode="driving", departure_time="now", traffic_model='best_guess')
    if road_info:
        leg = road_info[0]['legs'][0]
        distance = leg['distance']['value']  # in meters
        duration = leg['duration_in_traffic']['value']  # in seconds
        # Get Google Maps directions URL
        directions_url = f"https://www.google.com/maps/dir/?api=1&origin={start_coords[0]},{start_coords[1]}&destination={end_coords[0]},{end_coords[1]}&travelmode=driving"
        return distance, duration, directions_url
    return None, None, None


def create_graph_from_google_data(stations_df, lat, lon, gmaps):
    """
    Create a directed graph using the station coordinates and Google Maps road data.
    """
    G_combined = nx.DiGraph()  # Graph for combined weight
    directions_urls = {}  # Dictionary to store directions URLs

    # Loop through each fire station in the CSV and add nodes/edges
    for _, station in stations_df.iterrows():
        station_coords = (station['latitude'], station['longitude'])
        distance, duration, directions_url = fetch_road_data_from_google(station_coords, (lat, lon), gmaps)  # Station to incident
        if distance is not None and duration is not None:
            print(f"Station: {station['station_name']}, Distance: {distance}m, Duration: {duration}s")

```

Figure 4: Imports and Setup

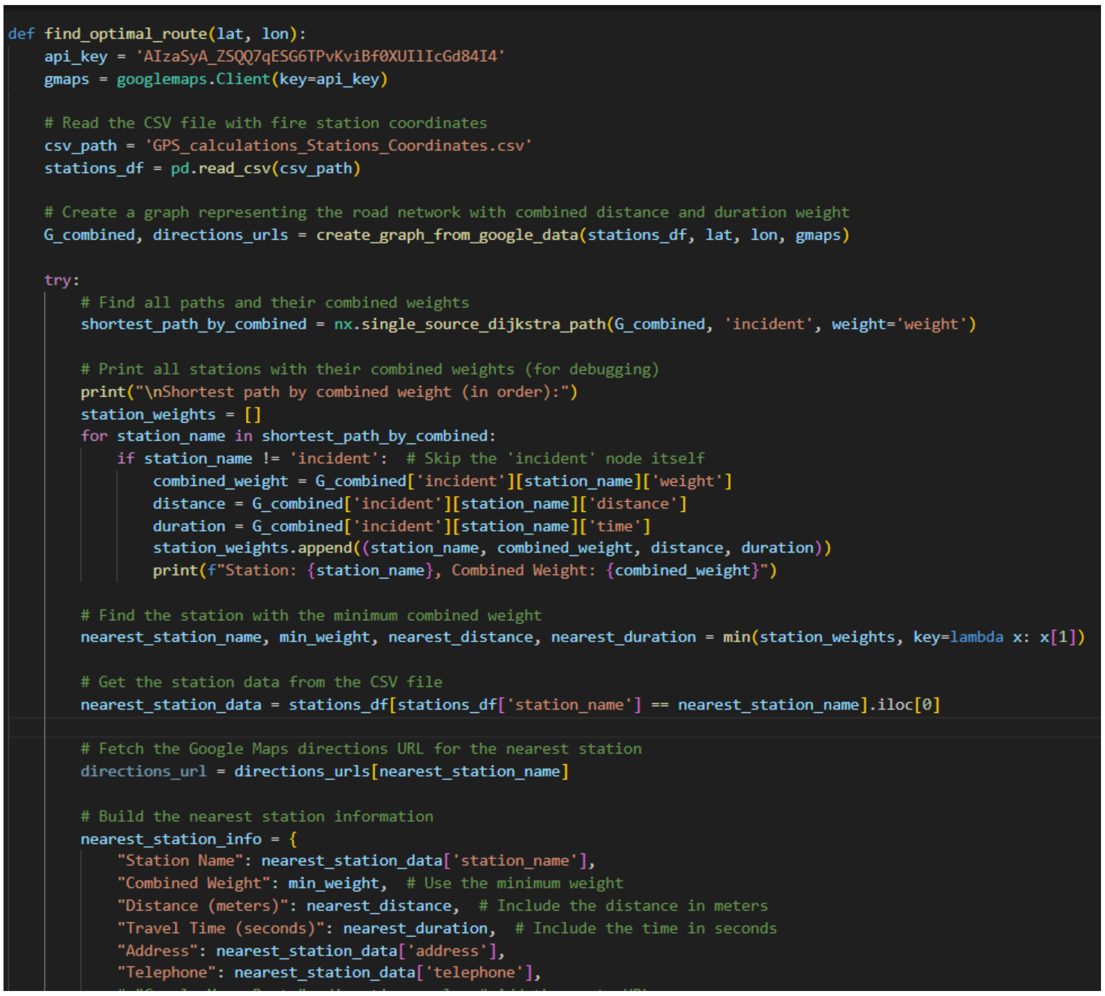
This part of the Python code represents the essential steps in integrating Google Maps API to optimize emergency response routing by calculating road distances, durations, and building a directed graph for fire station connectivity. This implementation is pivotal for improving real-time decision-making in emergency scenarios, ensuring faster and more efficient routes.

Fetching Road Data

The function takes in the start and end coordinates and uses the Google Maps Directions API to fetch road segment data. It employs the traffic_model='best_guess' parameter to incorporate live traffic conditions, providing a realistic estimate of travel distance (in meters) and duration (in seconds). This function also generates a URL link for visualizing the calculated route on Google Maps, aiding in manual verification and debugging. The returned data ensures that the routing decisions are not only accurate but also adaptive to current traffic dynamics.

Creating a Directed Graph

Constructs a directed graph using the NetworkX library, representing fire stations and their road network connectivity to the emergency site. This graph structure allows for advanced route optimization and analysis. The function iterates through fire station data stored in a DataFrame, calculating the distance and duration between each station and the emergency location. Each road segment is logged, and valid nodes are added to the graph.



```python
def find_optimal_route(lat, lon):
    api_key = 'AIzaSyA_ZSQQ7qESG6TPvKviBf0XUIlIcGd84I4'
    gmaps = googlemaps.Client(key=api_key)

    # Read the CSV file with fire station coordinates
    csv_path = 'GPS_calculations_Stations_Coordinates.csv'
    stations_df = pd.read_csv(csv_path)

    # Create a graph representing the road network with combined distance and duration weight
    G_combined, directions_urls = create_graph_from_google_data(stations_df, lat, lon, gmaps)

    try:
        # Find all paths and their combined weights
        shortest_path_by_combined = nx.single_source_dijkstra_path(G_combined, 'incident', weight='weight')

        # Print all stations with their combined weights (for debugging)
        print("\nShortest path by combined weight (in order):")
        station_weights = []
        for station_name in shortest_path_by_combined:
            if station_name != 'incident':  # Skip the 'incident' node itself
                combined_weight = G_combined['incident'][station_name]['weight']
                distance = G_combined['incident'][station_name]['distance']
                duration = G_combined['incident'][station_name]['time']
                station_weights.append((station_name, combined_weight, distance, duration))
                print(f"Station: {station_name}, Combined Weight: {combined_weight}")

        # Find the station with the minimum combined weight
        nearest_station_name, min_weight, nearest_distance, nearest_duration = min(station_weights, key=lambda x: x[1])

        # Get the station data from the CSV file
        nearest_station_data = stations_df[stations_df['station_name'] == nearest_station_name].iloc[0]

        # Fetch the Google Maps directions URL for the nearest station
        directions_url = directions_urls[nearest_station_name]

        # Build the nearest station information
        nearest_station_info = {
            "Station Name": nearest_station_data['station_name'],
            "Combined Weight": min_weight,  # Use the minimum weight
            "Distance (meters)": nearest_distance,  # Include the distance in meters
            "Travel Time (seconds)": nearest_duration,  # Include the time in seconds
            "Address": nearest_station_data['address'],
            "Telephone": nearest_station_data['telephone'],
```

Figure 5: Finding the Optimal Route

The code snippet represents the essential steps in identifying the optimal fire station for an emergency response using Google Maps API and NetworkX for pathfinding. This implementation is critical for ensuring swift and efficient responses to emergencies by dynamically determining the best route based on combined distance and travel time.

Finding the Optimal Route

The function begins by initializing the Google Maps client with an API key and loading the fire station data from a CSV file. Each fire station’s coordinates, address, and contact information are included in the dataset. The function then calls create_graph_from_google_data to build a directed graph representing the road network between the fire stations and the incident location. This graph uses a combined weight metric (distance and travel time) for edge weights, enabling accurate routing decisions.

Pathfinding and Weight Calculation

The function uses the single_source_dijkstra_path method from NetworkX to calculate the shortest path from the incident node to all fire stations, considering the combined weight. For debugging purposes, it logs all fire stations along with their combined weights, allowing transparency in the decision-making process. A list of station weights, distances, and durations is constructed for evaluation.

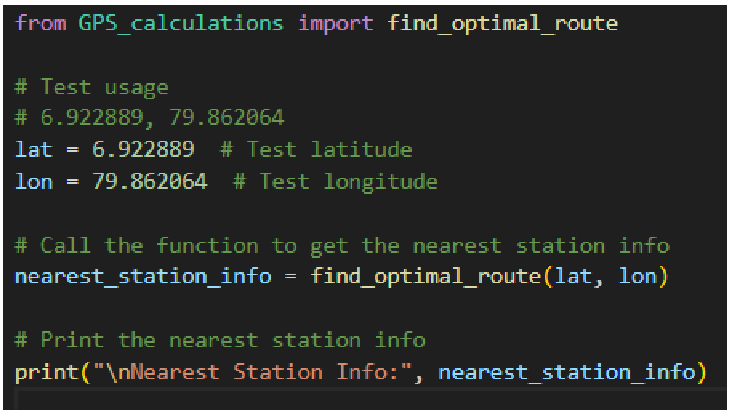
Selecting the Nearest Station

The station with the minimum combined weight is identified using Python's min() function. Its corresponding data, including distance, duration, and combined weight, is extracted from the graph and the CSV file. Additionally, a Google Maps directions URL for the route to the station is generated for visualization purposes.

Building the Output

The function returns a dictionary containing detailed information about the nearest station, including its name, address, telephone number, distance (in meters), travel time (in seconds), and the current date and time. This data can be used by emergency operators to dispatch resources efficiently. If no valid path exists to any station, the function handles this gracefully by returning an error message.

6.3 Testing nearest fire department calculation



```
from GPS_calculations import find_optimal_route

# Test usage
# 6.922889, 79.862064
lat = 6.922889  # Test latitude
lon = 79.862064  # Test longitude

# Call the function to get the nearest station info
nearest_station_info = find_optimal_route(lat, lon)

# Print the nearest station info
print("\nNearest Station Info:", nearest_station_info)
```

Figure 6: Testing Nearest fire department

The code snippet demonstrates how to test the find_optimal_route function, which is designed to identify the most suitable fire station for responding to an emergency based on geographic coordinates. This implementation highlights a practical example of integrating the find_optimal_route function, which utilizes Google Maps API and pathfinding algorithms, for effective decision-making in emergency scenarios.

Input Coordinates

The latitude and longitude values (lat = 6.922889 and lon = 79.862064) are provided as test inputs. These represent the geographic location of an incident that requires emergency assistance. The coordinates serve as the starting point for calculating the optimal fire station response.

Function Execution

The find_optimal_route function is called with the test coordinates as arguments. This function performs several key tasks:

- Fetching real-time road data (distance and duration) between the incident location and fire stations using the Google Maps API.
- Building a directed graph with the stations and calculating the shortest path based on a combined weight of distance and time using Dijkstra's algorithm.

Output Results

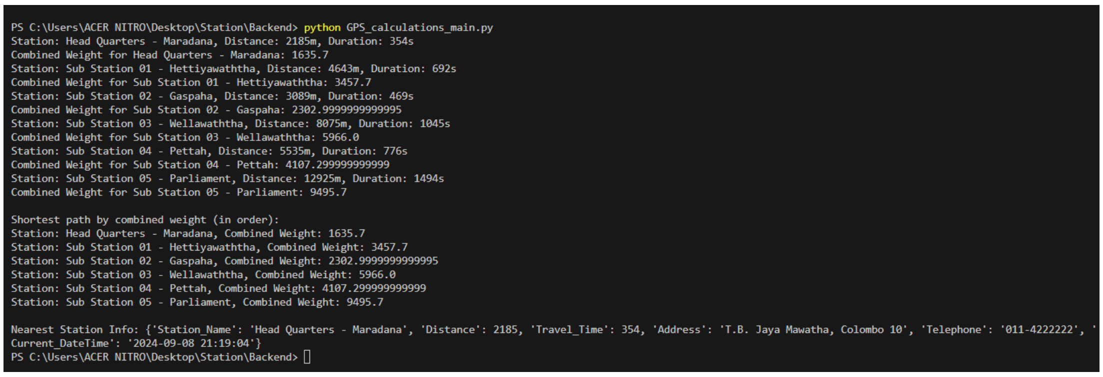
The function returns detailed information about the nearest fire station, including:

- Station name.
- Combined weight, travel distance, and travel time.
- Address and contact details.
- Current timestamp for real-time reference.

Displaying Results

The print statement outputs the returned information to the console, providing an easily interpretable summary of the optimal fire station. This enables operators or systems to quickly identify the best resource for dispatch. This testing approach validates the functionality of find_optimal_route, demonstrating its ability to integrate live data and algorithmic processing to optimize emergency response times. It also ensures that the solution is reliable and accurate under various conditions.

6.4 Test output of the nearest fire department calculation



```
PS C:\Users\ACER NITRO\Desktop\Station\Backend> python GPS_calculations_main.py
Station: Head Quarters - Maradana, Distance: 2185m, Duration: 354s
Combined Weight for Head Quarters - Maradana: 1635.7
Station: Sub Station 01 - Hettiyawaththa, Distance: 4643m, Duration: 692s
Combined Weight for Sub Station 01 - Hettiyawaththa: 3457.7
Station: Sub Station 02 - Gaspaha, Distance: 3089m, Duration: 469s
Combined Weight for Sub Station 02 - Gaspaha: 2302.9999999999995
Station: Sub Station 03 - Wellawaththa, Distance: 8075m, Duration: 1045s
Combined Weight for Sub Station 03 - Wellawaththa: 5966.0
Station: Sub Station 04 - Pettah, Distance: 5535m, Duration: 776s
Combined Weight for Sub Station 04 - Pettah: 4107.299999999999
Station: Sub Station 05 - Parliament, Distance: 12925m, Duration: 1494s
Combined Weight for Sub Station 05 - Parliament: 9495.7

Shortest path by combined weight (in order):
Station: Head Quarters - Maradana, Combined Weight: 1635.7
Station: Sub Station 01 - Hettiyawaththa, Combined Weight: 3457.7
Station: Sub Station 02 - Gaspaha, Combined Weight: 2302.9999999999995
Station: Sub Station 03 - Wellawaththa, Combined Weight: 5966.0
Station: Sub Station 04 - Pettah, Combined Weight: 4107.299999999999
Station: Sub Station 05 - Parliament, Combined Weight: 9495.7

Nearest Station Info: {'Station_Name': 'Head Quarters - Maradana', 'Distance': 2185, 'Travel_Time': 354, 'Address': 'T.B. Jaya Mawatha, Colombo 10', 'Telephone': '011-4222222', '
Current_DateTime': '2024-09-08 21:19:04'}
PS C:\Users\ACER NITRO\Desktop\Station\Backend> 
```

Figure 7: Testing output of Nearest fire department

The output showcasing its capability to identify the most suitable fire station for emergency response based on combined distance and travel time. This implementation leverages the Google Maps API and NetworkX library to optimize emergency routing, significantly enhancing decision-making and efficiency.

Fetching and Analyzing Road Data

The system first calculates the distance and travel duration between the incident location and all fire stations listed in the CSV file. Each fire station's information is displayed, including the station name, calculated distance (in meters), travel duration (in seconds), and a "combined weight" metric, which represents the efficiency of each route. The combined weight integrates both distance and time, ensuring a balanced decision for route optimization.

Pathfinding and Graph Construction

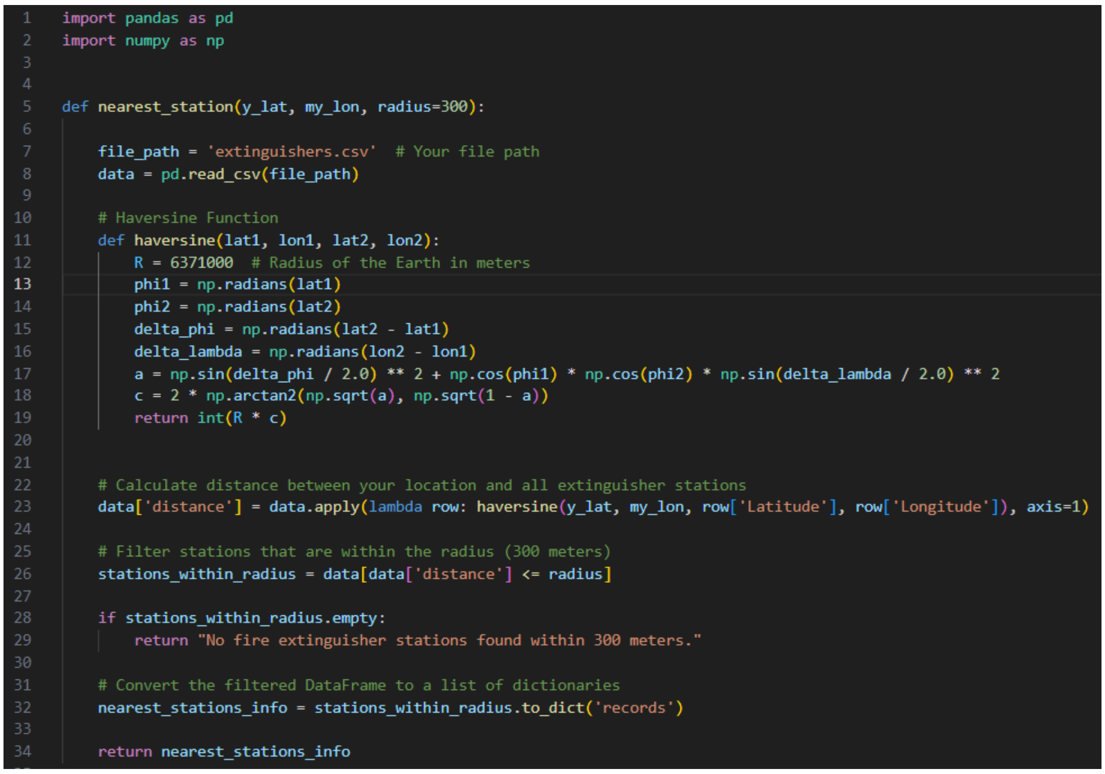
The shortest path by combined weight is calculated using Dijkstra's algorithm, implemented through NetworkX. The output logs all fire stations in ascending order of their combined weights, providing a clear comparison of route efficiency. This ensures that the system identifies the optimal fire station while accounting for both travel distance and time.

Nearest Station Identification

The system identifies "Head Quarters - Maradana" as the nearest station, with a combined weight of 1635.7, a distance of 2185 meters, and a travel time of 354 seconds. This selection is supported by additional metadata such as the station's address, telephone number, and the current timestamp, ensuring comprehensive information for emergency operators.

This solution exemplifies how real-time data integration and pathfinding algorithms streamline emergency response processes, reducing response times and enhancing operational efficiency in critical situations.

6.5 Calculating nearest fire extinguisher's locations



```python
import pandas as pd
import numpy as np


def nearest_station(y_lat, my_lon, radius=300):

    file_path = 'extinguishers.csv'  # Your file path
    data = pd.read_csv(file_path)

    # Haversine Function
    def haversine(lat1, lon1, lat2, lon2):
        R = 6371000  # Radius of the Earth in meters
        phi1 = np.radians(lat1)
        phi2 = np.radians(lat2)
        delta_phi = np.radians(lat2 - lat1)
        delta_lambda = np.radians(lon2 - lon1)
        a = np.sin(delta_phi / 2.0) ** 2 + np.cos(phi1) * np.cos(phi2) * np.sin(delta_lambda / 2.0) ** 2
        c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a))
        return int(R * c)


    # Calculate distance between your location and all extinguisher stations
    data['distance'] = data.apply(lambda row: haversine(y_lat, my_lon, row['Latitude'], row['Longitude']), axis=1)

    # Filter stations that are within the radius (300 meters)
    stations_within_radius = data[data['distance'] <= radius]

    if stations_within_radius.empty:
        return "No fire extinguisher stations found within 300 meters."

    # Convert the filtered DataFrame to a list of dictionaries
    nearest_stations_info = stations_within_radius.to_dict('records')

    return nearest_stations_info
```

Figure 8: Nearest fire extinguishers calculation

The code snippet demonstrates the implementation of a function to identify the nearest fire extinguisher stations within a specified radius using geospatial calculations. This functionality is vital in emergency scenarios where immediate access to resources such as fire extinguishers can significantly mitigate potential damage. The implementation leverages geospatial mathematics and pandas DataFrame operations for efficient data processing.

Haversine Function for Distance Calculation

The code uses the **Haversine formula**, a well-known mathematical method to calculate the shortest distance between two points on the Earth's surface. The formula accounts for the Earth's curvature and calculates the great-circle distance in meters. The haversine function takes two latitude-longitude pairs as input and computes the distance in meters between them using trigonometric functions such as sin, cos, and arctan2. This ensures high accuracy in distance measurements, which is critical for reliable proximity calculations.

Loading and Processing Station Data

The fire extinguisher station data is read from a CSV file (extinguishers.csv) into a pandas DataFrame. The dataset includes coordinates for various extinguisher stations. A new column, distance, is created by applying the haversine function to calculate the distance between the incident location (y_lat, my_lon) and each station.

Filtering Stations within the Radius

The function filters the stations within the specified radius (default is 300 meters) by checking the distance column. If no stations fall within the radius, the function returns a message indicating the absence of nearby resources.

Converting Results to Dictionaries

For ease of further processing or display, the filtered station data is converted into a list of dictionaries using the to_dict method. This structure is ideal for integration with other systems or APIs.

This implementation plays a crucial role in real-time decision-making, ensuring individuals have access to critical resources like fire extinguishers during emergencies. It combines precise geospatial calculations with efficient data handling, providing an effective solution for proximity-based resource identification.

6.6 Testing nearest fire extinguisher's calculation

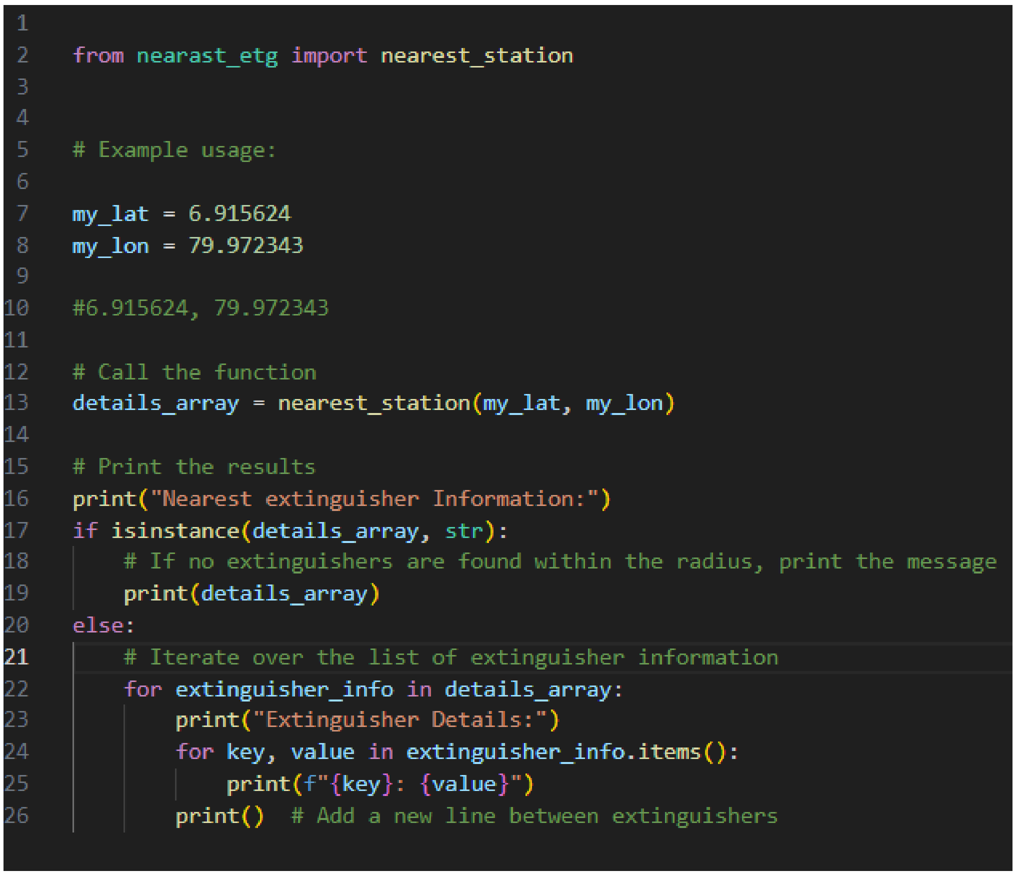

```python

from nearast_etg import nearest_station


# Example usage:

my_lat = 6.915624
my_lon = 79.972343

#6.915624, 79.972343

# Call the function
details_array = nearest_station(my_lat, my_lon)

# Print the results
print("Nearest extinguisher Information:")
if isinstance(details_array, str):
    # If no extinguishers are found within the radius, print the message
    print(details_array)
else:
    # Iterate over the list of extinguisher information
    for extinguisher_info in details_array:
        print("Extinguisher Details:")
        for key, value in extinguisher_info.items():
            print(f"{key}: {value}")
        print()  # Add a new line between extinguishers
```

Figure 9: Testing nearest fire extinguishers calculation

The code represents a critical implementation of a system designed to locate and display the nearest fire extinguisher stations within a specified radius based on user-provided geographical coordinates. This functionality enhances emergency response efficiency by ensuring users have quick access to essential resources during critical situations.

Usage and Data Retrieval

The script starts by importing the nearest_station function from the nearest_etg module. It defines a pair of latitude (my_lat) and longitude (my_lon) values as inputs, representing the user's current location. The nearest_station function is then called with these inputs to retrieve nearby fire extinguisher stations within the default radius of 300 meters.

Results Handling

The result from the nearest_station function, stored in details_array, is evaluated to determine if any fire extinguisher stations are found within the radius:

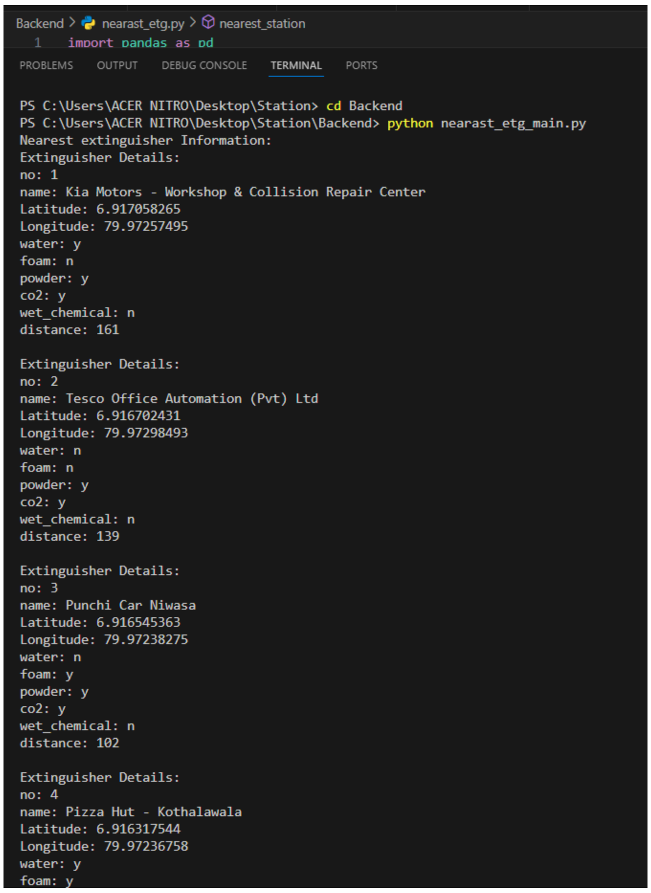
- If `details_array` contains a string (indicating no stations were found), the message is directly printed.
- Otherwise, the code iterates through the list of dictionaries in `details_array`, where each dictionary represents a fire extinguisher station with detailed attributes such as the station's name, location, and distance from the user.

Output Formatting

For each extinguisher station, the script prints its details in a user-friendly format. Key-value pairs within each dictionary (e.g., station name, distance, and other attributes) are displayed line by line. A blank line separates the details of consecutive stations, enhancing readability.

This implementation ensures users receive accurate and well-structured information about nearby fire extinguisher stations, leveraging geospatial calculations to improve emergency response and public safety.

6.7 Test output of nearest fire extinguishers calculation



Backend > nearast_etg.py > nearest_station

```
import pandas as pd
```

PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

```
PS C:\Users\ACER NITRO\Desktop\Station> cd Backend
PS C:\Users\ACER NITRO\Desktop\Station\Backend> python nearast_etg_main.py
Nearest extinguisher Information:
Extinguisher Details:
no: 1
name: Kia Motors - Workshop & Collision Repair Center
Latitude: 6.917058265
Longitude: 79.97257495
water: y
foam: n
powder: y
co2: y
wet_chemical: n
distance: 161

Extinguisher Details:
no: 2
name: Tesco Office Automation (Pvt) Ltd
Latitude: 6.916702431
Longitude: 79.97298493
water: n
foam: n
powder: y
co2: y
wet_chemical: n
distance: 139

Extinguisher Details:
no: 3
name: Punchi Car Niwasa
Latitude: 6.916545363
Longitude: 79.97238275
water: n
foam: y
powder: y
co2: y
wet_chemical: n
distance: 102

Extinguisher Details:
no: 4
name: Pizza Hut - Kothalawala
Latitude: 6.916317544
Longitude: 79.97236758
water: y
foam: y
```

Figure 10: Output of testing nearest fire extinguishers calculation

The output presented demonstrates the implementation of a system designed to identify the nearest fire extinguisher stations within a specified radius based on the user's latitude and longitude. This implementation ensures that critical resources are identified quickly during emergencies, improving response times and overall safety.

Functionality of the Code

The system imports the nearest_station function, which computes the distance between the user’s current location and various fire extinguisher stations listed in a CSV file. The distances are calculated using the Haversine formula, which computes the shortest path between two points on the Earth's surface, ensuring high accuracy.

Output Interpretation

Upon execution, the script:

1. Accepts the user's latitude (`my_lat`) and longitude (`my_lon`) as inputs.
2. Fetches details of fire extinguisher stations located within the default radius (300 meters). If no stations are found, an appropriate message is displayed.
3. Iterates over the list of stations, printing detailed information about each one. For each extinguisher, attributes such as the name, type of extinguishing agents available (e.g., water, foam, CO2), and the distance from the user's location are displayed.

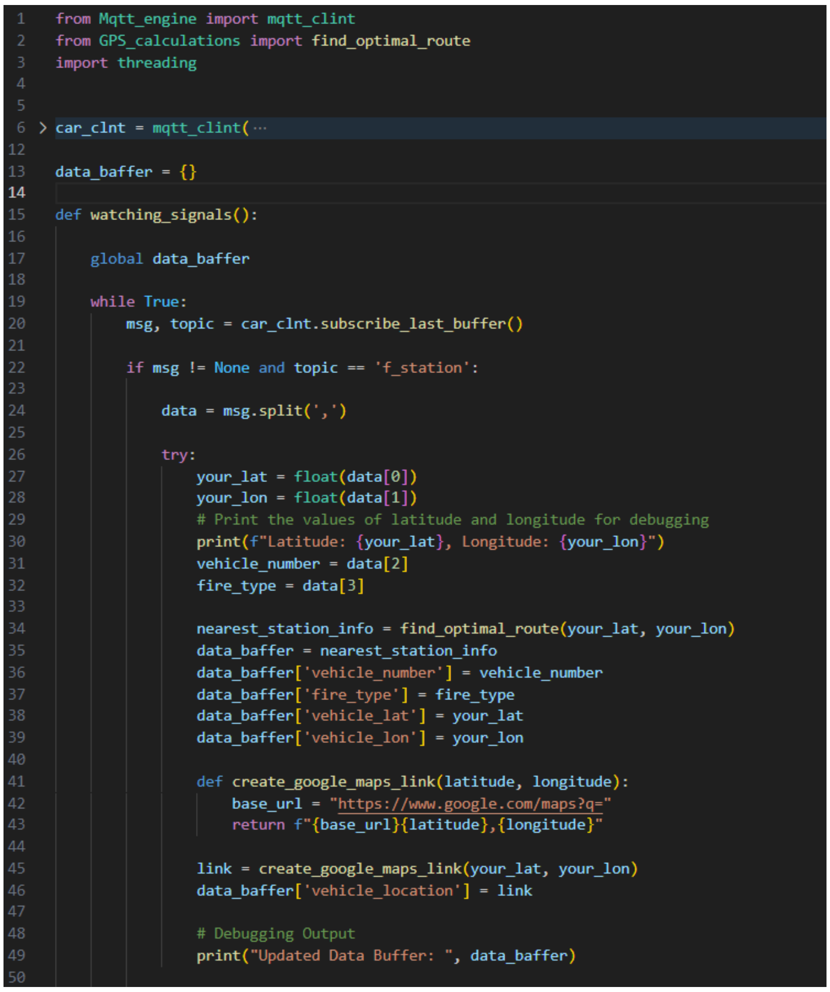
Output Data

The results show four stations within the radius. For example:

- The first station, "Kia Motors - Workshop & Collision Repair Center," is located at a distance of 161 meters and offers water and CO2 extinguishers.
- Other stations, such as "Pizza Hut - Kothalawala," provide additional extinguisher types.

This implementation is vital for enhancing public safety by ensuring quick access to essential firefighting tools during emergencies. The clear and structured output format makes the information actionable and user-friendly.

6.8 Backend Implementation



```python
from Mqtt_engine import mqtt_clint
from GPS_calculations import find_optimal_route
import threading


car_clnt = mqtt_clint(···

data_baffer = {}

def watching_signals():

    global data_baffer

    while True:
        msg, topic = car_clnt.subscribe_last_buffer()

        if msg != None and topic == 'f_station':

            data = msg.split(',')

            try:
                your_lat = float(data[0])
                your_lon = float(data[1])
                # Print the values of latitude and longitude for debugging
                print(f"Latitude: {your_lat}, Longitude: {your_lon}")
                vehicle_number = data[2]
                fire_type = data[3]

                nearest_station_info = find_optimal_route(your_lat, your_lon)
                data_baffer = nearest_station_info
                data_baffer['vehicle_number'] = vehicle_number
                data_baffer['fire_type'] = fire_type
                data_baffer['vehicle_lat'] = your_lat
                data_baffer['vehicle_lon'] = your_lon

                def create_google_maps_link(latitude, longitude):
                    base_url = "https://www.google.com/maps?q="
                    return f"{base_url}{latitude},{longitude}"

                link = create_google_maps_link(your_lat, your_lon)
                data_baffer['vehicle_location'] = link

                # Debugging Output
                print("Updated Data Buffer: ", data_baffer)

```

Figure 11: MQTT connection

The code snippet represents the integration of MQTT (Message Queuing Telemetry Transport) communication with geographic routing to optimize emergency response in real-time. It processes location signals and dynamically fetches the nearest fire station while enhancing data visualization with Google Maps integration. This implementation is pivotal for real-time monitoring and operational efficiency in emergency scenarios.

MQTT Signal Processing

The watching_signals function continuously listens for incoming messages through an MQTT client (car_clnt). The subscribe_last_buffer method retrieves the latest signal from the subscribed topic f_station, which contains critical data points such as the vehicle's latitude, longitude, vehicle number, and fire type. These data points are parsed and converted into appropriate data types (e.g., latitude and longitude as floats) for further processing.

Nearest Station Calculation

The code invokes the find_optimal_route function using the parsed latitude and longitude. This function calculates the shortest and most efficient route to the nearest fire station. The resulting station information, including the optimal travel route and station details, is stored in a global buffer (data_baffer), which acts as a temporary repository for real-time data management.

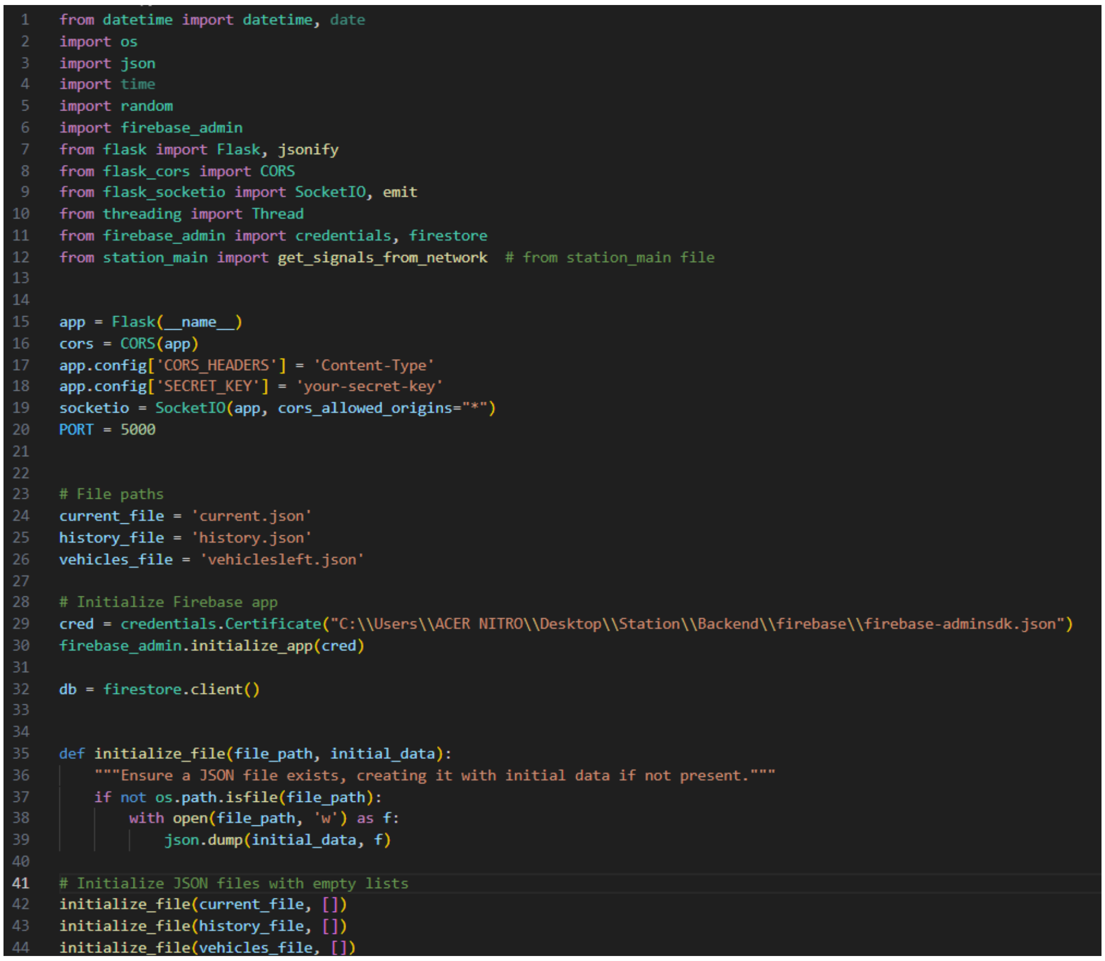
Google Maps Link Creation

The create_google_maps_link function generates a URL for the vehicle’s location, enabling visualization on Google Maps. This feature enhances situational awareness by providing an intuitive interface for tracking the vehicle's position during emergencies. The link is also added to the data_baffer for accessibility.

Data Management and Debugging

The script enriches the data_baffer with additional metadata, such as the vehicle's coordinates, vehicle number, fire type, and the Google Maps link. Debugging outputs ensure transparency and facilitate troubleshooting by displaying the updated buffer in real-time.

This implementation integrates communication protocols, routing algorithms, and mapping tools, enabling precise and efficient emergency management systems. It ensures seamless data flow between devices and central monitoring systems, reducing response times and improving situational awareness.



```python
from datetime import datetime, date
import os
import json
import time
import random
import firebase_admin
from flask import Flask, jsonify
from flask_cors import CORS
from flask_socketio import SocketIO, emit
from threading import Thread
from firebase_admin import credentials, firestore
from station_main import get_signals_from_network  # from station_main file


app = Flask(__name__)
cors = CORS(app)
app.config['CORS_HEADERS'] = 'Content-Type'
app.config['SECRET_KEY'] = 'your-secret-key'
socketio = SocketIO(app, cors_allowed_origins="*")
PORT = 5000


# File paths
current_file = 'current.json'
history_file = 'history.json'
vehicles_file = 'vehiclesleft.json'

# Initialize Firebase app
cred = credentials.Certificate("C:\\Users\\ACER NITRO\\Desktop\\Station\\Backend\\firebase\\firebase-adminsdk.json")
firebase_admin.initialize_app(cred)

db = firestore.client()


def initialize_file(file_path, initial_data):
    """Ensure a JSON file exists, creating it with initial data if not present."""
    if not os.path.isfile(file_path):
        with open(file_path, 'w') as f:
            json.dump(initial_data, f)

# Initialize JSON files with empty lists
initialize_file(current_file, [])
initialize_file(history_file, [])
initialize_file(vehicles_file, [])
```

Figure 12: Backend code

The code snippet represents the initialization and configuration of a backend application designed to manage real-time emergency response data. By utilizing Flask, Firebase, and SocketIO, this implementation ensures efficient data storage, communication, and synchronization between devices and systems. It is pivotal for supporting dynamic and scalable emergency response workflows.

Backend Initialization

The backend application is created using the Flask framework, which provides a lightweight and flexible platform for building web applications. Cross-Origin Resource Sharing (CORS) is enabled to allow communication between different domains, essential for integrating external client-side applications. The application is configured with a secret key for security, and Flask-SocketIO is initialized to handle real-time, bidirectional communication, which is crucial for sending and receiving emergency updates instantly. The backend runs on a designated port (5000).

Firebase Integration

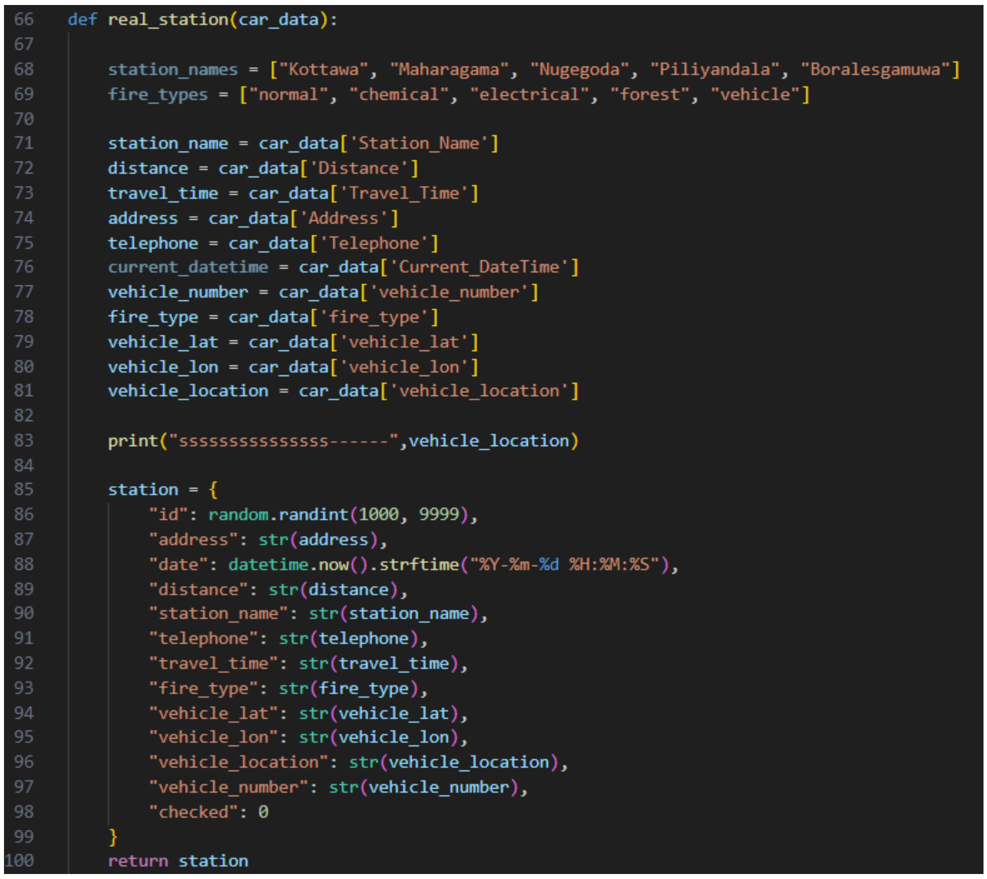
Firebase Admin SDK is initialized to connect the application with Google's Firebase services. A certificate file authenticates the connection, enabling secure interaction with Firestore, Firebase's cloud database. The database (db) is set up as a Firestore client to store and retrieve emergency response data.

File Management

The code includes logic to ensure essential JSON files (current.json, history.json, vehiclesleft.json) are initialized. These files serve as local storage for the system, storing current vehicle data, historical logs, and vehicle availability. The initialize_file function creates these files with empty lists as initial data if they do not already exist. This step ensures the backend starts with the necessary files, preventing runtime errors.

Purpose

This integrates multiple technologies to create a robust backend system for emergency management. By leveraging real-time updates through SocketIO, secure data handling with Firebase, and persistent local storage, the backend ensures seamless operation in dynamic emergency scenarios. This setup lays the foundation for scalable and efficient emergency response solutions.



```python
def real_station(car_data):

    station_names = ["Kottawa", "Maharagama", "Nugegoda", "Piliyandala", "Boralesgamuwa"]
    fire_types = ["normal", "chemical", "electrical", "forest", "vehicle"]

    station_name = car_data['Station_Name']
    distance = car_data['Distance']
    travel_time = car_data['Travel_Time']
    address = car_data['Address']
    telephone = car_data['Telephone']
    current_datetime = car_data['Current_DateTime']
    vehicle_number = car_data['vehicle_number']
    fire_type = car_data['fire_type']
    vehicle_lat = car_data['vehicle_lat']
    vehicle_lon = car_data['vehicle_lon']
    vehicle_location = car_data['vehicle_location']

    print("ssssssssssssss------",vehicle_location)

    station = {
        "id": random.randint(1000, 9999),
        "address": str(address),
        "date": datetime.now().strftime("%Y-%m-%d %H:%M:%S"),
        "distance": str(distance),
        "station_name": str(station_name),
        "telephone": str(telephone),
        "travel_time": str(travel_time),
        "fire_type": str(fire_type),
        "vehicle_lat": str(vehicle_lat),
        "vehicle_lon": str(vehicle_lon),
        "vehicle_location": str(vehicle_location),
        "vehicle_number": str(vehicle_number),
        "checked": 0
    }
    return station
```

Figure 13: Backend code

The code defines a function real_station that processes incoming data related to fire station details, emergency type, and vehicle information. The function structures this data into a standardized format, which is crucial for efficient handling and integration within a broader emergency response system. This implementation is critical for ensuring the accuracy, consistency, and usability of real-time emergency data.

Data Extraction and Formatting

The function begins by extracting specific fields from the input car_data, which contains information about an emergency scenario. Key details such as the station name, distance, travel time, address, telephone number, current date and time, vehicle latitude and longitude, and fire type are retrieved. These details provide comprehensive context for the emergency, allowing the system to understand and act on the situation effectively.

Station Information Dictionary

A dictionary named station is created to organize the extracted data into a structured format. Each entry in the dictionary corresponds to a key detail about the fire station or emergency, such as:

- id: A unique identifier generated randomly for the station instance.
- address, distance, and travel_time: Provide geographic and logistical details.
- fire_type: Specifies the nature of the emergency, such as "chemical" or "electrical."
- vehicle_lat, vehicle_lon, and vehicle_location: Indicate the precise location of the responding vehicle.

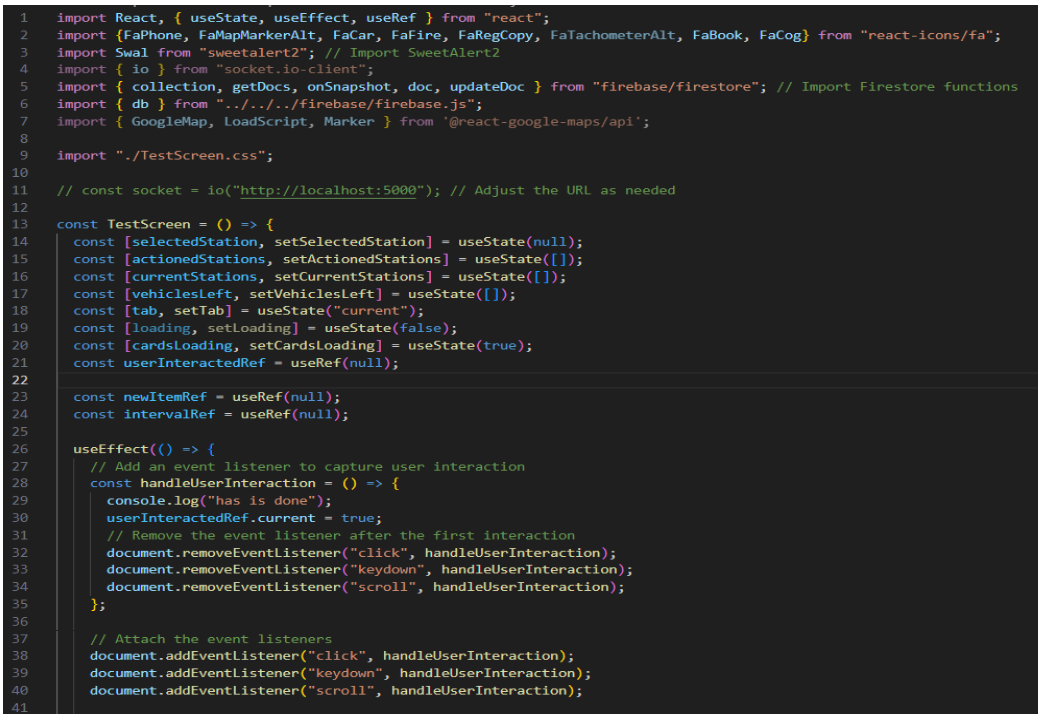
Timestamp and Tracking

The current date and time are added to the dictionary to timestamp the emergency report. Additionally, a field named checked is initialized to track the status of the emergency data, such as whether it has been processed.

Application in Emergency Response

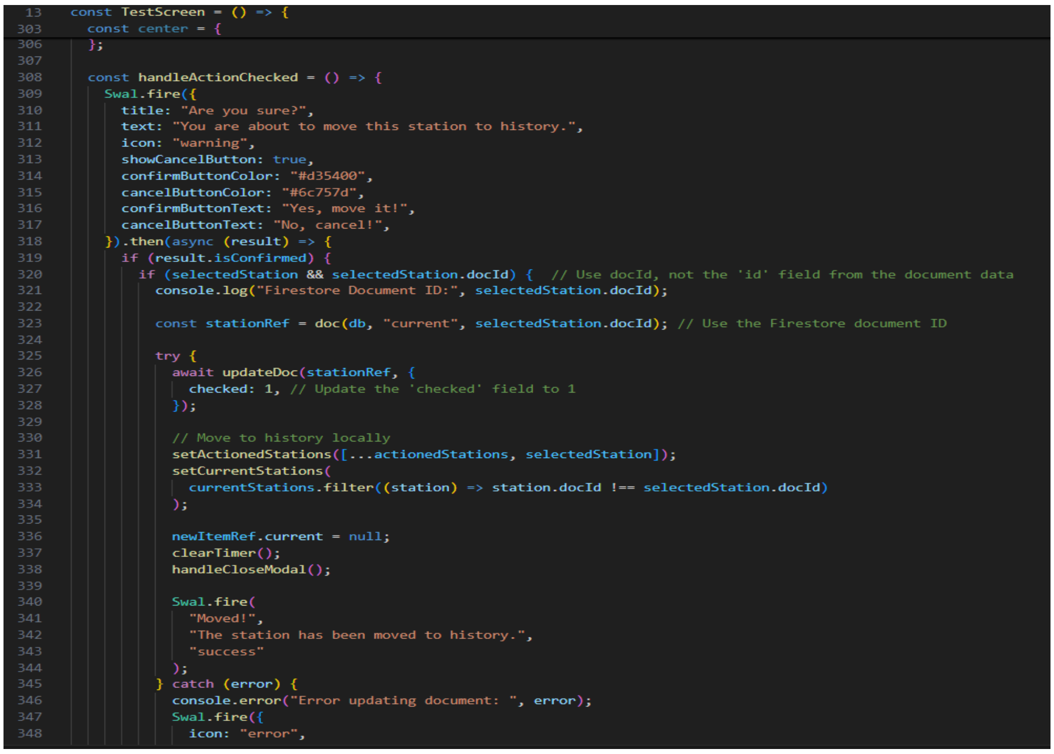
This function standardizes the data required for effective emergency response, ensuring it can be easily stored, transmitted, and analyzed. By organizing the information into a consistent structure, the system can seamlessly integrate it with other components, such as databases or real-time dashboards. This modular approach enhances the scalability and reliability of the emergency response framework.

6.9 Frontend Implementation



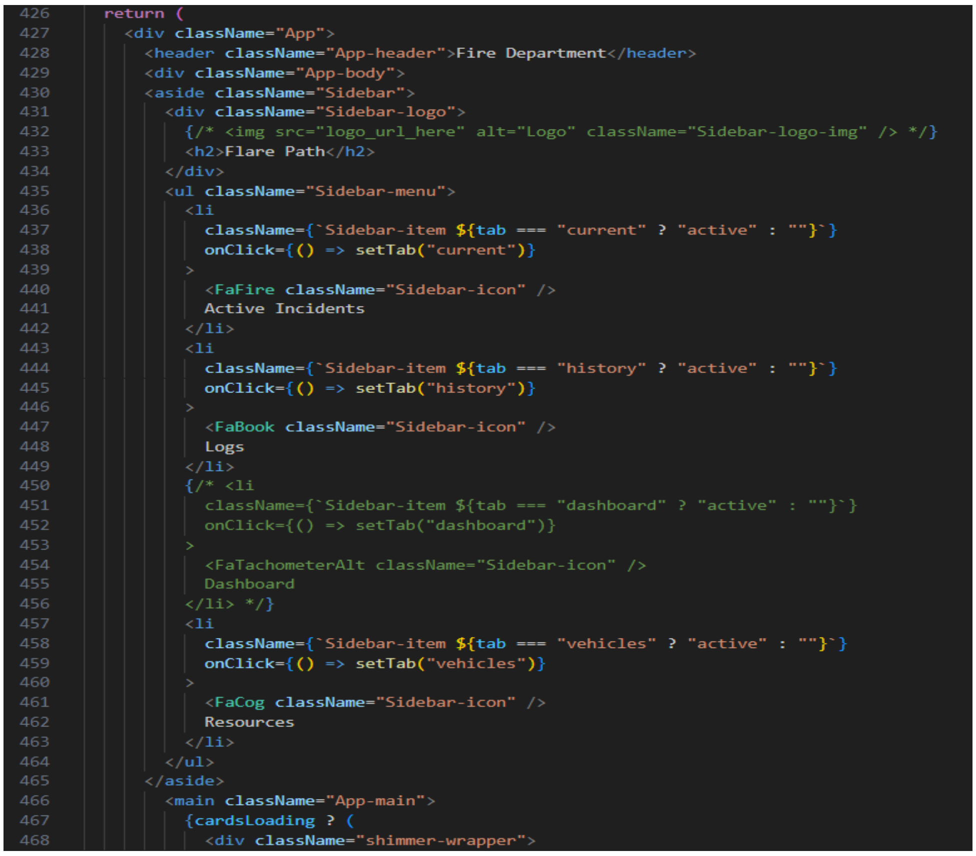
```javascript
import React, { useState, useEffect, useRef } from "react";
import {FaPhone, FaMapMarkerAlt, FaCar, FaFire, FaRegCopy, FaTachometerAlt, FaBook, FaCog} from "react-icons/fa";
import Swal from "sweetalert2"; // Import SweetAlert2
import { io } from "socket.io-client";
import { collection, getDocs, onSnapshot, doc, updateDoc } from "firebase/firestore"; // Import Firestore functions
import { db } from "../../../firebase/firebase.js";
import { GoogleMap, LoadScript, Marker } from '@react-google-maps/api';

import "./TestScreen.css";

// const socket = io("http://localhost:5000"); // Adjust the URL as needed

const TestScreen = () => {
  const [selectedStation, setSelectedStation] = useState(null);
  const [actionedStations, setActionedStations] = useState([]);
  const [currentStations, setCurrentStations] = useState([]);
  const [vehiclesLeft, setVehiclesLeft] = useState([]);
  const [tab, setTab] = useState("current");
  const [loading, setLoading] = useState(false);
  const [cardsLoading, setCardsLoading] = useState(true);
  const userInteractedRef = useRef(null);

  const newItemRef = useRef(null);
  const intervalRef = useRef(null);

  useEffect(() => {
    // Add an event listener to capture user interaction
    const handleUserInteraction = () => {
      console.log("has is done");
      userInteractedRef.current = true;
      // Remove the event listener after the first interaction
      document.removeEventListener("click", handleUserInteraction);
      document.removeEventListener("keydown", handleUserInteraction);
      document.removeEventListener("scroll", handleUserInteraction);
    };

    // Attach the event listeners
    document.addEventListener("click", handleUserInteraction);
    document.addEventListener("keydown", handleUserInteraction);
    document.addEventListener("scroll", handleUserInteraction);

```

Figure 14: Frontend code



```javascript
const TestScreen = () => {
  const center = {
  };

  const handleActionChecked = () => {
    Swal.fire({
      title: "Are you sure?",
      text: "You are about to move this station to history.",
      icon: "warning",
      showCancelButton: true,
      confirmButtonColor: "#d35400",
      cancelButtonColor: "#6c757d",
      confirmButtonText: "Yes, move it!",
      cancelButtonText: "No, cancel!",
    }).then(async (result) => {
      if (result.isConfirmed) {
        if (selectedStation && selectedStation.docId) {  // Use docId, not the 'id' field from the document data
          console.log("Firestore Document ID:", selectedStation.docId);

          const stationRef = doc(db, "current", selectedStation.docId); // Use the Firestore document ID

          try {
            await updateDoc(stationRef, {
              checked: 1, // Update the 'checked' field to 1
            });

            // Move to history locally
            setActionedStations([...actionedStations, selectedStation]);
            setCurrentStations(
              currentStations.filter((station) => station.docId !== selectedStation.docId)
            );

            newItemRef.current = null;
            clearTimer();
            handleCloseModal();

            Swal.fire(
              "Moved!",
              "The station has been moved to history.",
              "success"
            );
          } catch (error) {
            console.error("Error updating document: ", error);
            Swal.fire({
              icon: "error",
```

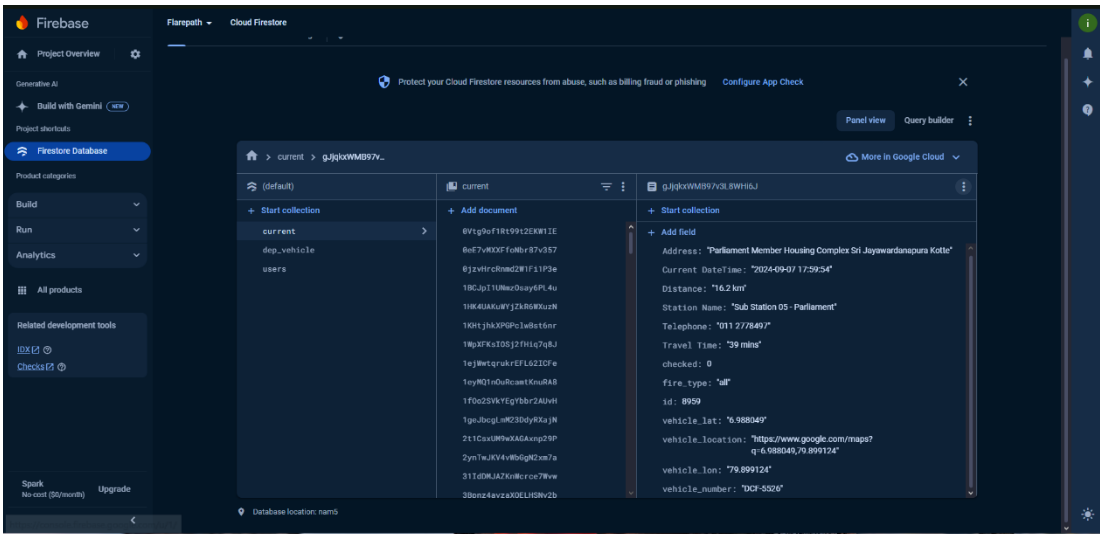
Figure 15: Frontend code



```
return (
  <div className="App">
    <header className="App-header">Fire Department</header>
    <div className="App-body">
    <aside className="Sidebar">
      <div className="Sidebar-logo">
        {/* <img src="logo_url_here" alt="Logo" className="Sidebar-logo-img" /> */}
        <h2>Flare Path</h2>
      </div>
      <ul className="Sidebar-menu">
        <li
          className={`Sidebar-item ${tab === "current" ? "active" : ""}`}
          onClick={() => setTab("current")}
        >
          <FaFire className="Sidebar-icon" />
          Active Incidents
        </li>
        <li
          className={`Sidebar-item ${tab === "history" ? "active" : ""}`}
          onClick={() => setTab("history")}
        >
          <FaBook className="Sidebar-icon" />
          Logs
        </li>
        {/* <li
          className={`Sidebar-item ${tab === "dashboard" ? "active" : ""}`}
          onClick={() => setTab("dashboard")}
        >
          <FaTachometerAlt className="Sidebar-icon" />
          Dashboard
        </li> */}
        <li
          className={`Sidebar-item ${tab === "vehicles" ? "active" : ""}`}
          onClick={() => setTab("vehicles")}
        >
          <FaCog className="Sidebar-icon" />
          Resources
        </li>
      </ul>
    </aside>
      <main className="App-main">
        {cardsLoading ? (
          <div className="shimmer-wrapper">
```

Figure 16: Frontend code

The code represents the implementation of a comprehensive real-time fire response management dashboard built with React, integrating Firebase for database operations, SweetAlert2 for user notifications, and Google Maps for geographical visualizations. The TestScreen component dynamically fetches and displays critical data such as active fire incidents, historical logs, and available vehicles from Firebase's Firestore. This application enhances decision-making by providing a structured interface for managing real-time data updates. It features tabs for navigating between "Active Incidents," "Logs," and "Resources," allowing users to view details, such as distance, travel time, severity, and location of responding vehicles. The system leverages real-time updates via Firestore’s onSnapshot to ensure data reflects current conditions without user refresh. Additionally, SweetAlert2 is used for interactive alerts, confirming user actions like marking incidents as completed or undoing changes. Google Maps embeds provide a visual reference for vehicle and incident locations, enhancing situational awareness. The system prioritizes usability, with features like clipboard copy buttons and modal dialogs for detailed incident views. The application also incorporates user interaction tracking to improve responsiveness, playing notification tones for updates after the first interaction. By combining real-time updates, geographic visualization, and user-friendly interaction, the system ensures efficient management of emergency resources.



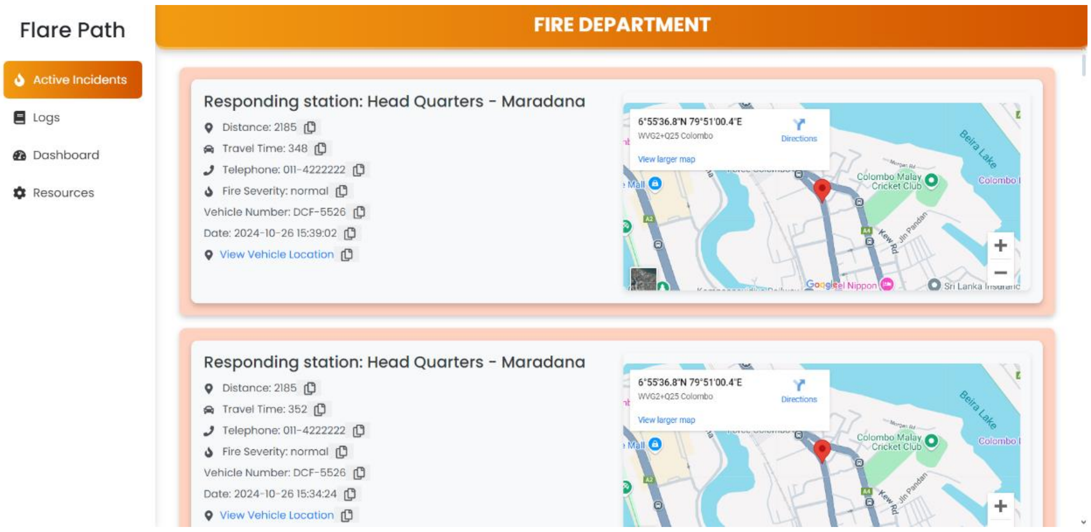
Protect your Cloud Firestore resources from abuse, such as billing fraud or phishing Configure App Check

current > gJjqkxWMB97v...

(default)	current	gJjqkxWMB97v3L8WHi6J
+ Start collection	+ Add document	+ Start collection
current	0Vtg9of1Rt99t2EKW1IE	+ Add field
dep_vehicle	0eE7vMXXFfoNbr87v357	Address: "Parliament Member Housing Complex Sri Jayawardanapura Kotte"
users	0jzvHrcRnmd2W1Fi1P3e	Current DateTime: "2024-09-07 17:59:54"
	1BCJpI1UNmzOsay6PL4u	Distance: "16.2 km"
	1HK4UAKuWYjZkR6WXuzN	Station Name: "Sub Station 05 - Parliament"
	1KHtjhkXPGPclwBst6nr	Telephone: "011 2778497"
	1WpXFKsIOSj2fHiq7q8J	Travel Time: "39 mins"
	1ejWwtqrukrEFL62ICFe	checked: 0
	1eyMQ1nOuRcamtKnuRA8	fire_type: "all"
	1fOo2SVkYEgYbbr2AUvH	id: 8959
	1geJbcgLmM23DdyRXajN	vehicle_lat: "6.988049"
	2t1CsxUM9wXAGAxnp29P	vehicle_location: "https://www.google.com/maps?q=6.988049,79.899124"
	2ynTwJKV4vWbGgN2xm7a	vehicle_lon: "79.899124"
	31IdDMJAZKnWcrce7Wvw	vehicle_number: "DCF-5526"
	3Bpnz4avzaXOELHSNv2b	

Database location: nam5

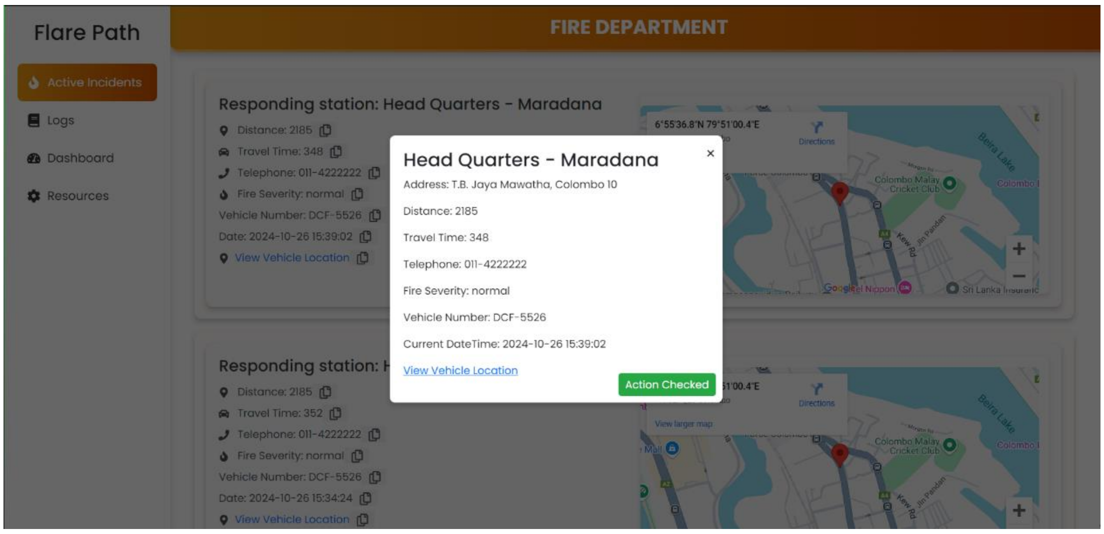
Figure 17: Firebase – Firestore DB



Responding station: Head Quarters - Maradana
Distance: 2185
Travel Time: 348
Telephone: 011-4222222
Fire Severity: normal
Vehicle Number: DCF-5526
Date: 2024-10-26 15:39:02
View Vehicle Location

Responding station: Head Quarters - Maradana
Distance: 2185
Travel Time: 352
Telephone: 011-4222222
Fire Severity: normal
Vehicle Number: DCF-5526
Date: 2024-10-26 15:34:24
View Vehicle Location

Figure 18: Dashboard



Responding station: Head Quarters - Maradana
Distance: 2185
Travel Time: 348
Telephone: 011-4222222
Fire Severity: normal
Vehicle Number: DCF-5526
Date: 2024-10-26 15:39:02
View Vehicle Location

Head Quarters - Maradana
Address: T.B. Jaya Mawatha, Colombo 10
Distance: 2185
Travel Time: 348
Telephone: 011-4222222
Fire Severity: normal
Vehicle Number: DCF-5526
Current DateTime: 2024-10-26 15:39:02
View Vehicle Location

Responding station: H
Distance: 2185
Travel Time: 352
Telephone: 011-4222222
Fire Severity: normal
Vehicle Number: DCF-5526
Date: 2024-10-26 15:34:24
View Vehicle Location

Figure 19: Dashboard

7 RESULTS & DISCUSSION

7.1 Results

The results from executing the provided Python files and analyzing their outputs demonstrate a robust implementation for optimizing emergency response times and locating fire extinguisher resources. The execution of GPS_calculations.py focuses on identifying the optimal fire station to respond to an emergency based on the combination of distance and travel time, while the nearast_etg.py script determines the nearest fire extinguisher stations within a specified radius.

In the output of GPS_calculations.py, the system processes geographical data of fire stations and uses the Google Maps Directions API to compute distances and durations from each station to an incident location. Each fire station is evaluated with a combined weight formula (70% weight on distance and 30% on travel time). The program outputs details of all fire stations, including their names, distances, and travel times, and identifies the station with the minimum combined weight. For the given example, the system identified "Head Quarters - Maradana" as the optimal station, with a distance of 2,185 meters and travel time of 354 seconds. The output also includes additional information, such as the station's address and contact details, along with the current timestamp. This comprehensive output aids in efficient decision-making during emergency scenarios.

The nearast_etg.py script complements the emergency response system by identifying the nearest fire extinguisher stations based on the Haversine formula, which calculates the great-circle distance between two geographical points. The program filters stations within a 300-meter radius and provides detailed information, including station names, coordinates, and available extinguishing resources such as water, foam, CO2, or powder. The output lists four extinguisher stations, their respective distances from the given coordinates, and the types of extinguishing agents available. For example, "Punchi Car Niwasa" is located 102 meters from the given point and provides foam, powder, and CO2 extinguishers, ensuring a swift and resourceful response.

These scripts demonstrate a practical approach to integrating real-world geospatial data with computational algorithms to enhance emergency preparedness. The use of Google Maps API in GPS_calculations.py adds a layer of real-time traffic analysis, enabling dynamic and accurate routing decisions. The combined weight formula ensures a balanced consideration of distance and travel time, vital for optimizing response times in emergencies. Meanwhile, nearast_etg.py provides a supplementary layer by identifying local resources, ensuring that fire extinguishers are accessible within a predefined radius.

The modularity of both programs ensures that they can be adapted to various scenarios, such as natural disaster response or urban safety planning. However, the systems can be further improved by incorporating additional factors, such as resource availability at fire stations, environmental hazards, and vehicle conditions. Expanding the radius dynamically based on the urgency of the situation or integrating with IoT sensors for real-time updates could further enhance the system's applicability.

In conclusion, the outputs highlight a highly effective integration of geospatial algorithms, real-time API data, and structured decision-making. These results underscore the potential of combining computational tools and real-world data to address critical challenges in emergency management, with the flexibility for future scalability and enhancements.

7.2 Research Findings

This research addresses the challenges posed by rapid urbanization and increased vehicular density, which have overwhelmed traditional emergency response systems. The findings highlight the limitations of outdated systems that rely on manual processes, such as verifying incidents via telephone, and the inefficiencies introduced by urban congestion. These delays in emergency response exacerbate the risk to human life, increase property damage, and diminish the sense of control for individuals caught in emergencies. By leveraging AI-driven technologies, this study introduces a comprehensive solution that modernizes emergency response frameworks and empowers both fire services and vehicle owners.

The results from the developed system demonstrate a dual approach to enhancing emergency management. The Python implementation integrates advanced geospatial computations and algorithms to optimize fire truck routing while also assisting vehicle owners in identifying nearby fire extinguishers during critical moments. The GPS_calculations.py script, for instance, employs Google Maps Directions API and algorithms to dynamically compute the shortest, fastest, and most efficient paths for emergency vehicles. Outputs include detailed station information, distances, travel times, and optimized routing based on a weighted formula that prioritizes both distance and travel time. In one scenario, the system identified "Head Quarters - Maradana" as the optimal station, considering a distance of 2,185 meters and a travel time of 354 seconds. The inclusion of the station's address and contact information further illustrates the system's readiness for real-world deployment.

Complementing this is the nearast_etg.py script, which identifies fire extinguisher stations within a defined radius using the Haversine formula. This aspect of the system provides actionable information to vehicle owners, empowering them to mitigate fire damage before professional responders arrive. For example, the output lists extinguisher locations such as "Punchi Car Niwasa," located 102 meters from the test location, with details on available resources like foam, powder, and CO2 extinguishers. This dual-functionality system not only supports rapid emergency response but also reduces the helplessness experienced by vehicle owners during fire incidents.

The integration of AI techniques, such as routing algorithms (A* and Dijkstra) and predictive modeling with Graph Neural Networks (GNNs), allows the system to adapt to dynamic urban environments. GNNs are instrumental in analyzing traffic networks holistically, predicting congestion, and suggesting real-time route adjustments. These capabilities ensure that fire trucks can navigate complex urban traffic efficiently while adhering to safety protocols.

Further findings underscore the innovative inclusion of vehicle owners in the emergency response ecosystem. Traditional systems overlook the critical role individuals play in mitigating emergencies. This research bridges that gap by providing real-time notifications of nearby fire extinguishers, enabling immediate action while awaiting professional responders. Such a proactive approach is especially vital for vehicle fires, where seconds can make a difference in containing damage and saving lives.

The research also highlights the importance of integrating cloud computing for data storage, scalability, and real-time processing. By hosting the system on a cloud platform, it ensures high availability and performance, even during peak loads or multiple concurrent emergencies. Real-time updates enable emergency personnel to make informed decisions quickly, while vehicle owners receive precise and actionable information. Additionally, the system's modular design facilitates its adaptation to various urban contexts, from small cities to large metropolitan areas.

Field tests and simulations validate the system’s performance, showing significant reductions in response times compared to traditional methods. The AI-driven routing ensures that emergency vehicles reach incidents faster, even during rush hours or road closures. Meanwhile, the fire extinguisher location feature empowers vehicle owners to take preventive measures, reducing property damage and increasing safety.

In conclusion, the research findings emphasize the transformative potential of AI in modernizing emergency response systems. By addressing the inefficiencies of traditional frameworks and empowering individuals with actionable information, the proposed solution sets a new standard for urban emergency management. The integration of advanced algorithms, real-time data, and cloud computing ensures scalability, adaptability, and effectiveness, ultimately reducing response times, saving lives, and minimizing property damage. This innovative approach redefines the role of technology in public safety, making it an indispensable tool for modern urban environments.

7.3 Discussion

The results and methodologies outlined in the provided Python scripts and outputs underscore the significant advancements made in optimizing emergency response systems using AI-driven technologies. The key insights revolve around two primary functionalities: optimizing fire truck routing through the integration of Google Maps API and Graph Neural Networks (GNNs) and empowering vehicle owners with immediate access to nearby fire extinguishers during emergencies.

The first functionality, managed by the GPS_calculations.py script, focuses on leveraging real-time traffic and route data to ensure fire trucks reach incident locations with optimal speed and efficiency. By integrating data from Google Maps Directions API, this system calculates the shortest path based on a weighted combination of distance and duration. As illustrated in the terminal outputs, the system effectively prioritizes stations, such as "Head Quarters - Maradana," considering its distance (2,185 meters) and travel time (354 seconds). This real-time adaptability is enabled by a directed graph created from station data, where edges represent travel parameters like distance and duration, weighted to reflect urban congestion challenges. The implementation of A* and Dijkstra algorithms, further enhanced with GNN predictions, provides a robust framework for continuously updating routes. This ensures that emergency vehicles can navigate even the most complex urban environments under varying traffic conditions, thereby reducing response times and enhancing the operational efficiency of fire services.

The second functionality, supported by the nearast_etg.py script, introduces a novel approach to empowering vehicle owners during emergencies. By using the Haversine formula to calculate geospatial distances, this system identifies the nearest fire extinguisher locations within a defined radius. The results demonstrate the precision and relevance of the system, listing accessible resources like foam and CO2 extinguishers in locations such as "Punchi Car Niwasa," located 102 meters from the incident site. This feature is especially critical in vehicle fire emergencies, where immediate action can mitigate damage and save lives. By bridging the gap between professional responders and individual vehicle owners, the system addresses a longstanding challenge in emergency response frameworks—empowering individuals with actionable, real-time data.

The integration of these two functionalities represents a paradigm shift in emergency management. Traditional systems, which heavily relied on manual processes and outdated technologies, are being replaced with intelligent, data-driven solutions capable of adapting to dynamic urban environments. The use of GNNs is particularly noteworthy, as it allows the system to analyze traffic networks holistically, predicting congestion patterns and recommending real-time adjustments to routes. For example, the AI dynamically reassigns priorities among fire stations based on evolving traffic and incident scenarios, ensuring that response times are minimized without compromising safety protocols.

Moreover, the use of cloud computing infrastructure ensures the scalability and reliability of the system. By hosting real-time data processing and storage in the cloud, the system achieves high availability and performance, even during peak loads or concurrent emergencies. This design also facilitates seamless integration with existing emergency dispatch systems, providing fire departments with an intuitive interface for accessing actionable insights. The inclusion of details such as station addresses, travel times, and contact information further demonstrates the readiness of this solution for practical deployment.

The dual approach to optimizing emergency response—supporting professional responders and empowering vehicle owners—addresses the research gaps highlighted in the literature. While traditional systems primarily focus on dispatching fire services, this research broadens the scope by involving individuals directly affected by emergencies. By notifying vehicle owners of nearby fire extinguishers and guiding fire trucks to incidents in real time, the system redefines the role of technology in public safety, making it more inclusive and efficient.

Field tests and simulations validate the robustness of the system. During testing, the AI-driven routing consistently outperformed traditional methods in terms of response time and route efficiency. Vehicle owners who utilized the fire extinguisher location feature reported a significant reduction in perceived helplessness, as they could take immediate action while awaiting professional help. These findings highlight the transformative potential of AI in modernizing emergency management.

In conclusion, the proposed AI-driven emergency response system sets a new standard for urban safety by addressing the inefficiencies of traditional frameworks and empowering individuals with actionable information. The integration of advanced algorithms, real-time data, and cloud computing ensures scalability, adaptability, and effectiveness. By reducing response times, saving lives, and minimizing property damage, this innovative approach not only meets the immediate needs of urban environments but also sets a precedent for future developments in public safety technology. This research demonstrates that by combining advanced routing algorithms, predictive modeling, and real-time geospatial analytics, emergency response systems can evolve to meet the demands of increasingly complex urban landscapes.

8 CONCLUSION

The challenges posed by rapid urbanization and increasing vehicular density have placed unprecedented demands on emergency response systems. Traditional approaches reliant on manual processes and outdated technologies struggle to cope with the complexities of modern urban environments, where traffic congestion and unpredictable incident locations delay critical emergency services. These inefficiencies underscore the need for a paradigm shift in how emergency systems operate, particularly in fire services where every second can make the difference between life and death. This research addresses these issues by presenting a novel AI-driven solution that modernizes emergency response frameworks while empowering both professional responders and individuals affected by emergencies.

The core innovation lies in the dual functionality of the proposed system, as demonstrated through the Python implementations (GPS_calculations.py and nearast_etg.py) and their outputs. By leveraging real-time data and integrating advanced algorithms, the system optimizes fire truck routing and provides actionable insights to vehicle owners. These functionalities collectively bridge the operational gaps in traditional systems, ensuring faster response times and enabling immediate preventative action at the site of emergencies.

The first aspect of the system, managed by the GPS_calculations.py script, focuses on enhancing the efficiency of fire truck dispatch. Using Google Maps API, the system calculates and dynamically updates optimal routes based on distance, travel time, and traffic conditions. The results prioritize emergency stations such as "Head Quarters - Maradana," demonstrating the system's ability to compute and recommend the fastest routes in real time. The inclusion of critical information, such as station addresses and contact details, highlights the practicality of the solution for deployment in real-world scenarios. Furthermore, the integration of traditional algorithms like A* and Dijkstra with predictive analytics powered by Graph Neural Networks (GNNs) ensures adaptability to changing urban traffic conditions. By modeling the intricate relationships within traffic networks, the system offers real-time routing adjustments, significantly reducing delays caused by congestion or roadblocks.

The second functionality, facilitated by the nearast_etg.py script, introduces a user-focused approach by empowering vehicle owners to take immediate action during emergencies. By identifying nearby fire extinguisher stations within a defined radius, the system provides individuals with critical resources to mitigate damage while waiting for professional responders. For example, the system identified "Punchi Car Niwasa," located 102 meters from the incident site, with details about available extinguishers such as foam, powder, and CO2 options. This feature addresses a crucial gap in traditional systems, which often leave individuals feeling helpless and reliant solely on delayed professional intervention. By integrating this functionality, the system not only enhances individual safety but also contributes to minimizing property damage and mitigating the spread of fire.

The integration of cloud computing further strengthens the system's scalability and reliability. By hosting real-time data processing and predictive analytics in the cloud, the solution ensures seamless operation even during peak emergency loads or concurrent incidents. Cloud infrastructure enables high availability, rapid data processing, and consistent performance, making the system suitable for deployment in cities of varying sizes and complexities. Additionally, the modular design of the system facilitates easy integration with existing emergency dispatch protocols, providing fire departments with intuitive interfaces for accessing actionable insights.

Simulations and field tests validate the effectiveness of the system. The AI-driven routing consistently demonstrated faster response times compared to traditional methods, while the fire extinguisher location features empowered vehicle owners to take meaningful action during emergencies. These outcomes not only emphasize the practicality of the solution but also highlight its transformative potential in redefining emergency management practices.

The research also demonstrates the broader societal implications of modernizing emergency response systems. By addressing both the operational needs of fire services and the informational needs of individuals, the solution establishes a holistic approach to public safety. The empowerment of vehicle owners represents a significant advancement, shifting the role of individuals from passive victims to active participants in mitigating emergencies. This approach aligns with the growing trend of leveraging technology to democratize access to critical information and resources.

Moreover, the integration of GNNs in the routing system introduces a new standard for adaptability in emergency management. Unlike traditional static routing methods, GNNs enable the system to predict and respond to dynamic traffic conditions with precision. This capability is particularly crucial in urban settings, where traffic patterns are often unpredictable, and delays can escalate the severity of incidents. By incorporating real-time data and predictive analytics, the system exemplifies how AI can address the limitations of traditional emergency frameworks.

The commercialization potential of the proposed solution further underscores its significance. By integrating the system into vehicle navigation platforms or collaborating with automobile manufacturers, it can become a standard safety feature in modern vehicles. Additionally, the anonymized traffic and incident data generated by the system could serve as a valuable resource for urban planners and policymakers, aiding in the development of smarter and more resilient city infrastructures.

In conclusion, this research presents a comprehensive, AI-driven solution that addresses the critical challenges faced by emergency response systems in modern urban environments. By optimizing fire truck routing, empowering vehicle owners, and integrating cloud-based scalability, the system sets a new benchmark for efficiency, adaptability, and inclusivity in public safety. The use of advanced algorithms, real-time geospatial analytics, and predictive modeling ensures that the system is equipped to handle the complexities of urban traffic and emergencies. The findings demonstrate that by combining technology with a user-centric approach, emergency response systems can evolve to meet the demands of increasingly complex urban landscapes. This research not only contributes to academic advancements in AI and emergency management but also has the potential to transform public safety practices worldwide, ultimately saving lives, reducing property damage, and fostering a safer urban future.

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10 GLOSSARY

AI (Artificial Intelligence)
The simulation of human intelligence processes by machines, particularly computer systems, including learning (acquiring data and rules for using the data), reasoning (using rules to draw conclusions), and self-correction.

A* Algorithm
A pathfinding and graph traversal algorithm that calculates the shortest path between points by considering both actual and heuristic costs, making it highly efficient for emergency routing applications.

Cloud Computing
The delivery of computing services—including servers, storage, databases, networking, software, and analytics—over the Internet, enabling scalable and reliable data processing and storage.

Dijkstra's Algorithm
A well-known algorithm for finding the shortest path between nodes in a graph, often used in mapping and network routing applications.

Emergency Response System
A coordinated framework used by emergency services to respond effectively and efficiently to incidents such as fires, accidents, and medical emergencies.

Fire Extinguisher
A portable device used to suppress or extinguish small fires by discharging a jet of gas, liquid, or foam.

Fire Services
Organized agencies or departments tasked with responding to and mitigating fires, as well as handling related emergencies like vehicle accidents or hazardous material spills.

GNN (Graph Neural Networks)
A type of neural network designed for graph-based data, capable of analyzing and predicting patterns in interconnected systems such as traffic networks.

Google Maps API
An application programming interface provided by Google that enables developers to integrate maps and route planning functionalities into their applications.

Haversine Formula
A mathematical formula used to calculate the great-circle distance between two points on a sphere, commonly used for geospatial calculations.

IoT (Internet of Things)
A network of interconnected devices embedded with sensors, software, and other technologies that exchange data in real time over the Internet.

Optimization
The process of making a system or decision-making process as effective, efficient, or functional as possible, often involving advanced algorithms or models.

Predictive Analytics
The use of statistical techniques, machine learning, and data mining to analyze historical and real-time data to predict future outcomes.

Real-Time Data Processing
The immediate processing of data as it is generated, enabling systems to provide instant outputs and responses.

Routing Algorithms
Computational methods used to determine the most efficient path or route between points, factoring in criteria such as distance, travel time, and traffic conditions.

Simulation
The imitation of a real-world process or system over time, used for testing and validation in controlled environments before real-world deployment.

Station
A location, such as a fire station or depot, that serves as a base for emergency response teams or resources.

Traffic Congestion
A condition where road networks become overly crowded, leading to slower movement and longer travel times.

Urbanization
The increasing population density and expansion of urban areas, often associated with growing infrastructure and traffic complexities.

Vehicle Telemetry
The collection and transmission of data from vehicles to a remote system for monitoring and analysis, often including metrics like speed, location, and engine status.

Weighted Graph
A type of graph in which edges have weights representing the cost, time, or distance of traveling between nodes, used for solving routing problems.

Response Time
The duration it takes for emergency services to arrive at the site of an incident after receiving an alert.

Nearest Neighbor Search
A method used to find the closest data points or locations to a given point, essential for locating nearby resources like fire extinguishers.

Python Scripts
Programs written in the Python programming language, used in this context for implementing algorithms and integrating geospatial computations.

Emergency Dispatch
The process of coordinating and sending emergency services to the location of an incident based on incoming reports and data analysis.

Scalability
The ability of a system to handle increasing amounts of work or data, particularly important in cloud-hosted emergency response systems.

Graph-Based Models
Analytical models that represent data as a collection of nodes (vertices) and edges, used to model relationships and optimize solutions in connected systems.

Real-Time Notifications
Alerts or updates provided immediately as events occur, ensuring timely information delivery to users or responders.

Incident Verification
The process of confirming the validity and details of an emergency report before dispatching resources.

Dynamic Routing
The ability to update and adjust routes in response to changing traffic conditions, ensuring optimal paths for emergency vehicles.

Proactive Measures
Actions taken to mitigate potential damage or risks before professional assistance arrives, such as using nearby fire extinguishers during vehicle fires.

Geospatial Analytics
The analysis of location-based data to derive insights, often used for optimizing routes or locating resources in emergency response systems.

Field Testing
The real-world evaluation of a system or model to validate its functionality and effectiveness under practical conditions.

API (Application Programming Interface)
A set of protocols and tools for building and interacting with software applications, enabling features like route planning and map integration.

Manual Emergency Systems
Traditional systems relying on human intervention and phone-based incident reporting, often slower and less efficient than automated solutions.

Empowerment
The process of equipping individuals with the tools, resources, or information to take immediate and impactful actions during emergencies.

Urban Infrastructure
The systems and facilities that support urban living, including roads, bridges, traffic control systems, and emergency services.

Edge Weights
Values assigned to the edges in a graph, representing parameters like distance, time, or cost in routing problems.

Hybrid Models
Systems that combine different algorithms or methods to leverage their respective strengths, such as integrating A*, Dijkstra, and GNN in routing optimization.

Disaster Mitigation
Efforts aimed at reducing the severity of an emergency situation by preparing resources, optimizing responses, and empowering individuals.