Optimising Ambulance Response: A Data-Driven Approach in Wales

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A dissertation submitted in partial fulfilment of the requirements for **MSc in Data Science and Analytics** by taught programme, supervised by Professor **Paul Harper**

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EXECUTIVE SUMMARY

In a world where every second counts in medical emergencies, optimizing ambulance response times has become a critical priority. This dissertation examines the crucial matter of ambulance response times for the Welsh Ambulance Service Trust (WAST), concentrating on enhancing operational efficiency to achieve the government-imposed 8.5-minute target for life-threatening situations. This research utilises machine learning, time-series forecasting, and geospatial analysis to deliver data-driven insights that enhance ambulance deployment and minimise delays.

The XGBoost classification model was created to forecast whether ambulances would achieve the response time objective. XGBoost achieved an accuracy of 66.89% and a recall rate of 94%, identifying Overall_Traffic, HourOfDay, and IsCriticalIncident as significant determinants of reaction times (Choi et al., 2020). The Prophet model for time-series forecasting demonstrated significant efficacy in predicting ambulance demand during peak hours, achieving a Mean Absolute Error (MAE) of 4.50 and a Root Mean Squared Error (RMSE) of 5.85 (Taylor & Letham, 2018).

Geospatial research revealed substantial discrepancies between urban and rural regions. Rural areas like Powys and Ceredigion consistently failed to meet response time targets due to extended travel distances and a limited number of ambulances, while metropolitan centres such as Cardiff benefitted from superior ambulance coverage and infrastructure (Schmidt et al., 2020). These findings underscore the necessity for strategic resource distribution in underprivileged regions.

This study also recognised the potential of future technologies such as blockchain and LSTM networks to enhance response times and data-sharing security (Zheng et al., 2018). The study's recommendations provide actionable measures to optimize WAST's operations, enabling a greater number of ambulances to achieve essential response benchmarks, thereby boosting patient outcomes and preserving lives throughout Wales.

This initiative establishes a robust basis for forthcoming advancements in emergency medical services, allowing WAST to maintain a leading position in data-driven EMS optimisation.

ACKNOWLEDGMENTS

I am deeply appreciative of the significant contributions and assistance from various individuals who have been essential to completing this study endeavour

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I wish to express my sincere gratitude to **Dr. Giles Greene** for facilitating access to essential data via the **Digital Healthcare Wales (DHCW)** data warehouse, which significantly broadened the scope of my research. I am profoundly grateful for his support in providing the necessary resources for a thorough examination of ambulance response times in Wales.

I would like to convey my heartfelt appreciation to the **Welsh Ambulance Service Trust (WAST)** and the colleagues at **Public Health Wales**. Their contributions, especially in facilitating access to essential data and delivering technical support, have been crucial to the project's success.

I am profoundly grateful to my family and friends for their unwavering support and comprehension during this academic pursuit. Their steadfast support has consistently provided strength and encouragement.

This study effort exemplifies the generosity and commitment of these remarkable individuals, for whom I am deeply grateful for their support and contributions.

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ABSTRACT

This dissertation examines the enhancement of ambulance response times for the Welsh Ambulance Service Trust (WAST), aiming to achieve the government-imposed 8.5-minute response target for critical situations. The project seeks to improve the operational efficiency of WAST and minimise reaction time discrepancies between urban and rural locations through the integration of machine learning models, time-series forecasting, and geospatial analysis.

The study used XGBoost as the primary classification model to forecast the likelihood that an ambulance would meet the response objective. XGBoost attained an accuracy of 66.89% and a recall rate of 94%, successfully identifying significant variables affecting reaction times, including Overall_Traffic, HourOfDay, and IsCriticalIncident (Choi et al., 2020). The Prophet model exhibited proficiency in time-series forecasting of ambulance demand, achieving a Mean Absolute Error (MAE) of 4.50 and a Root Mean Squared Error (RMSE) of 5.85. This enabled Prophet to effectively predict high-demand intervals, including weekends and public events (Taylor & Letham, 2018).

Geospatial study indicated substantial urban-rural discrepancies in response times. Rural regions, such Powys and Ceredigion, consistently encountered prolonged delays due to logistical difficulties, while larger centres like Cardiff benefitted from superior ambulance coverage and infrastructure (Schmidt et al., 2020). These findings highlight the necessity for targeted measures to enhance response times in underprivileged regions.

This study emphasises the promise of emerging technologies, including blockchain for safe real-time data sharing and LSTM networks for sequential forecasting, to improve the efficiency of ambulance services (Zheng et al., 2018). The study provides actionable recommendations for WAST to enhance resource allocation, improve patient outcomes, and more effectively address emergency response requirements throughout Wales.

1 INTRODUCTION

1.1 Research Background

Ambulance response times are pivotal in influencing patient outcomes during emergency medical incidents. The prompt arrival of an ambulance at the site within a crucial timeframe might determine the outcome between life and death, especially in cases of cardiac arrest or serious injuries. The Welsh Ambulance Service Trust (WAST) in Wales is responsible for achieving the government-imposed aim of an 8.5-minute response time for critical situations. Nonetheless, other issues like traffic congestion, geographical limitations in rural regions, and inclement weather frequently hinder WAST from reliably achieving this objective.

Prior studies have emphasised that the spatial allocation of ambulance services and the incorporation of real-time data are essential for enhancing response times (Schmidt et al., 2020). Geographic Information Systems (GIS) and fundamental predictive models have been employed to enhance ambulance positioning and deployment techniques; nevertheless, these methods frequently neglect to consider dynamic variables such as traffic and weather conditions. Recent improvements in machine learning models such as XGBoost and time-series forecasting tools like Prophet have demonstrated potential in predicting ambulance demand and enhancing resource allocation (Choi et al., 2020; Villani et al., 2017). Even so, there is still not enough written about how to combine real-time traffic data with the possibilities of new technologies like blockchain for safe data sharing among many parties (Zheng et al., 2018).

This study utilizes machine learning techniques and geographical analysis to improve the accuracy of ambulance response time predictions and forecast future demand, building upon prior research. The project seeks to enhance WAST by incorporating real-time traffic and meteorological data into predictive models, thereby offering more efficient and scalable solutions for difficulties in urban and rural settings. This study examines the utility of geospatial heatmaps to pinpoint areas with recurrent delays, thereby aiding in the strategic positioning of ambulances. The novel application of blockchain technology for safe data sharing will be examined, establishing a foundation for more transparent and responsible EMS operations.

1.2 Research Issue

Despite numerous improvements, WAST still faces difficulties achieving the 8.5-minute response time objective, particularly in rural and densely populated metropolitan regions. External factors, including erratic traffic patterns, inclement weather conditions, and the geographical allocation of ambulances, significantly affect WAST's capacity to respond swiftly to crises. Current systems, although useful in some circumstances, frequently lack the thorough integration of real-time data and predictive analytics essential for adapting to these dynamic elements (Ong et al., 2010).

In rural regions such as Powys, the availability of ambulances is constrained by extensive travel distances, resulting in frequent failures to meet response targets. In metropolitan areas like Cardiff, severe traffic congestion can result in considerable delays, especially during peak hours (Schmidt et al., 2020). Although GIS-based solutions have enhanced ambulance deployment (Peters & Hall, 1999), they are insufficient for real-time modifications due to their dependence on static data. The absence of safe data sharing across many stakeholders in the emergency medical services (EMS) ecosystem intensifies the issue, resulting in inefficiencies in ambulance dispatch systems (Zheng et al., 2018).

This study tackles these difficulties by creating a real-time, data-driven system that uses machine learning models and incorporates real-time traffic and weather data to improve resource allocation. The project investigates the application of blockchain technology to facilitate secure, transparent, and efficient data sharing, hence enabling effective collaboration among numerous stakeholders in EMS.

1.3 Objective and Purpose of the Research

The principal objective of this project is to enhance ambulance response times for WAST through the application of machine learning models, geospatial analysis, and real-time data integration. The research aims to improve resource allocation and operational efficiency by predicting ambulance demand and pinpointing areas with persistent delays. The subsequent aims are followed to accomplish this.

1. Construct and evaluate prediction models, such as XGBoost and Prophet, to anticipate ambulance response times and future demand.
2. Incorporate real-time traffic and meteorological data into these models to enhance predictive accuracy.
3. Perform a geographic heatmap analysis to pinpoint areas with recurrent ambulance delays, allowing for more strategic ambulance deployment.

Investigate the viability of employing blockchain technology for secure data exchange and dynamic dispatch systems in Emergency Medical Services (EMS).

1.4 Investigative Enquiries

1. How may machine learning models, such as XGBoost, and time-series forecasting tools, like Prophet, be utilised to enhance ambulance response times for WAST?
2. What effect can real-time variables, such as road congestion and inclement weather, exert on projections of ambulance response times?
3. How can geospatial analysis tools, such as heatmaps, uncover regions with recurrent delays, and what are the consequences of these findings for resource allocation?
4. What are the prospective advantages of blockchain technology for facilitating secure, real-time data exchange among players in the EMS ecosystem, and in what ways could it enhance ambulance dispatch systems?

1.5 Justification for Research

This research is motivated by the increasing demand for more efficient and adaptive emergency response systems, especially since WAST struggles to achieve its response time objectives (Villani & Palazzi, 2020). This project utilises real-time data from traffic and meteorological sources, together with sophisticated machine learning models, to enhance the dynamism and responsiveness of ambulance dispatch and resource management. Blockchain technology, albeit nascent in Emergency Medical Services (EMS), offers a viable alternative for enhancing data security, transparency, and trust among stakeholders (Zheng et al., 2018). This integration of real-time data, predictive modelling, and safe data sharing mitigates significant deficiencies in existing EMS operations.

This study goes beyond traditional forecasting models by combining diverse data sources and employing sophisticated algorithms capable of discerning dynamic trends in traffic and meteorological data. This endeavour seeks to address a notable deficiency in the research and offer practical recommendations for WAST to enhance its response methods (Choi et al., 2020).

1.6 Importance of Research

This study's findings could substantially enhance WAST's operational efficiency, ensuring a greater number of ambulances achieve the crucial 8.5-minute response objective (Schmidt et al., 2020). Enhanced response times can result in superior patient outcomes, especially in critical situations. The incorporation of real-time data and predictive models provides a scalable system that can be tailored to EMS services worldwide, especially in resource-constrained environments. This research investigates the potential of blockchain technology for secure data sharing, hence fostering a more transparent and responsible EMS ecosystem, which guarantees that key decisions are informed by accurate and reliable data (Zheng et al., 2018).

2 LITERATURE REVIEW

2.1 The Importance of Ambulance Response Times and Advancements in EMS Technology

The response time of ambulances is a crucial performance parameter in emergency medical services (EMS), especially in life-threatening scenarios like cardiac arrests and severe trauma incidents. Achieving the Welsh Ambulance Service Trust (WAST) response time objective of 8.5 minutes is crucial for patient survival, although it is frequently impeded by variables including geographical constraints, traffic congestion, and environmental conditions. The amalgamation of machine learning, real-time data analysis, and geospatial information systems has surfaced as a potential strategy to address these difficulties. Further investigation into emerging technologies, such as blockchain and hybrid forecasting models, presents more opportunities for improving ambulance services. Blockchain technology could be utilised to securely disseminate real-time data among diverse stakeholders, including traffic management and healthcare institutions. LSTM networks provide a sophisticated deep learning approach for forecasting future ambulance demand, particularly in contexts where time-series data is essential (Hochreiter & Schmidhuber, 1997; Zheng et al., 2018). This literature review examines data-driven solutions and evaluates their significance in optimising ambulance response times.

2.2 Mitigating Geographic Obstacles to Prompt Ambulance Response

The spatial allocation of ambulances significantly influences response times, especially in rural and sparsely populated regions. Rural areas frequently experience insufficient ambulance coverage, resulting in extended response times and diminished patient outcomes. Schmidt et al. (2020) emphasised the urban-rural disparity, observing that response times are more rapid in metropolitan regions owing to the greater availability of ambulances. Brown et al. (2020) observed that population density greatly influences the survival rates of out-of-hospital cardiac arrest patients, as response times are reduced in densely populated areas.

Researchers have utilised geospatial analysis methods, including Geographic Information Systems (GIS), to tackle these geographical difficulties. Peters and Hall (1999) illustrated how GIS-based models can pinpoint underperforming areas by visualising ambulance response efficacy across diverse geographical locations. Although GIS enhances operational efficiency in urban environments, its efficacy diminishes in rural regions due to suboptimal road conditions and extended distances, which constrain prediction accuracy. Peters and Hall (1999) analysed EMS services, illustrating how geographical disparities result in differing response times between urban and rural regions. Their use of GIS models resulted in better ambulance allocation in densely populated urban areas. Nonetheless, rural regions such as Powys exhibited prolonged response times attributable to inadequate infrastructure. This disparity underscores the necessity for real-time data integration within resource allocation algorithms. This signifies a necessity for more dynamic deployment tactics that account for both urban and rural intricacies, akin to the hybrid geospatial models employed in emergency services planning.

2.3 Addressing Traffic and Temporal Obstacles in Ambulance Services

Traffic congestion and the time of day significantly affect ambulance response times. Ong et al. (2010) highlighted that peak traffic periods considerably impede ambulance response times in urban settings, resulting in the inability to achieve designated response time objectives. Furthermore, Hedges et al. (2008) discovered that response times were prolonged at peak hours and in heavily congested regions. This is essential for EMS services, which frequently encounter difficulties in forecasting the impact of traffic congestion on real-time ambulance deployment.

The application of machine learning algorithms, such as XGBoost, to classify the likelihood of ambulances meeting the 8.5-minute objective has demonstrated potential in tackling these temporal variables. Choi et al. (2020) illustrated the efficacy of machine learning in categorising time-sensitive variables, including traffic congestion and time of day. Although machine learning techniques such as XGBoost enhance predictive accuracy, they are frequently constrained by the quality and recency of traffic data. Incorporating real-time traffic data from IoT devices can improve these models, as evidenced by Alkinani et al. (2021), who utilised a 5G-enabled IoT system to forecast and observe traffic conditions in real time. A study conducted by Ong et al. (2010) examined the substantial reduction of delays in urban centres through real-time traffic monitoring. The incorporation of IoT-enabled 5G systems, as demonstrated by Alkinani et al. (2021), facilitated real-time traffic updates, enhancing the capacity to redirect ambulances in congested regions. These developments, in conjunction with blockchain technology for secure data sharing, signify the next phase in EMS optimisation. Besides IoT devices, blockchain technology may be utilised to securely disseminate real-time traffic data across various stakeholders, safeguarding data privacy and security while preserving the timeliness and accuracy essential for effective EMS implementation (Zheng et al., 2018).

Blockchain technology may be utilised to facilitate the secure sharing of real-time traffic data among many stakeholders, safeguarding data privacy and security while preserving the speed and accuracy essential for effective EMS deployment. This methodology would enhance data reliability and guarantee the scalability of real-time data applications in EMS.

2.4 Alleviating the Effects of Meteorological Conditions on Ambulance Response Durations

The impact of meteorological conditions on ambulance response times is significant. Villani and Palazzi (2020) established a notable association between high temperature fluctuations and heightened EMS dispatch volumes. Inclement weather, including substantial precipitation or snowfall, results in prolonged response times, especially in remote areas where road accessibility may be compromised. Ong et al. (2010) noted that adverse weather conditions intensify delays in ambulance transportation, particularly in rural regions.

To tackle environmental issues, predictive models may integrate weather forecasts with additional temporal and traffic data. The Prophet model employed in forecasting ambulance demand for this project integrates meteorological data to predict heightened EMS demand during inclement weather conditions. Tandberg and Garrison (1998) emphasised that seasonal fluctuations and severe weather might considerably impact EMS demand.

Notwithstanding these advancements, the application of meteorological data in EMS optimisation continues to encounter problems concerning forecast precision and promptness. Adverse weather conditions, as indicated by Villani and Palazzi (2020), resulted in extended ambulance response times. Their research examined the forecasting potential of time series models, including ARIMA and LSTM networks, to incorporate meteorological data, leading to enhanced resource allocation during severe weather occurrences. Hybrid models that include ARIMA for long-term seasonal forecasts and LSTM networks for short-term environmental predictions may yield more precise forecasts in extremely dynamic weather circumstances. Bettencourt and Howlett (2021) investigated the efficacy of deep learning models, including LSTM, in precisely forecasting environmental changes and their effects on EMS demand.

2.5 Enhancing Ambulance Deployment with Machine Learning

The use of machine learning to improve EMS operations has shown significant promise in mitigating response time issues. Choi et al. (2020) utilised XGBoost to forecast ambulance response times, including variables such as traffic conditions and geographical characteristics. XGBoost, despite its outstanding accuracy, is predominantly reactive, depending on historical data for its predictions. LSTM networks, which specialise in sequential data and can adjust to evolving patterns, may improve the predictive powers of EMS systems. LSTM networks are exceptionally proficient in analysing and forecasting time-series data, rendering them appropriate for ambulance demand prediction applications. LSTM's capacity to learn sequential patterns renders it especially appropriate for dynamic scenarios characterised by rapid fluctuations in ambulance demand (Hochreiter & Schmidhuber, 1997).

Also, Villani et al. (2017) used SARIMA models to guess how many EMS calls would be needed for diabetic emergencies. This shows how important time series forecasting is for planning how to best use EMS resources. SARIMA models are constrained by their incapacity to accommodate unexpected occurrences or disturbances in data patterns. Integrating SARIMA with more adaptable models, such as LSTM, may increase robustness and precision in forecasting ambulance demand.

The amalgamation of hybrid models, which merge conventional forecasting techniques with machine learning methodologies, may enhance the precision of demand estimates. Beckett and Lyons (2020) investigated the integration of ARIMA and Prophet models, enabling the identification of both seasonal patterns and anomalies in ambulance demand.

2.6 Using IoT and Blockchain to Optimize Real-Time Energy Management Systems

The implementation of IoT technology in EMS optimisation has markedly enhanced the capacity to monitor real-time traffic, road conditions, and ambulance positions. Alkinani et al. (2021) showed that 5G and IoT-based systems can deliver immediate data on accidents and real-time traffic information, hence minimising delays in ambulance response times. Nevertheless, IoT by itself cannot address all data-related concerns. Concerns of data security, privacy, and interoperability necessitate consideration.

Blockchain technology presents a viable answer to these difficulties by facilitating safe and transparent data sharing across emergency services, hospitals, and traffic management agencies. In the realm of emergency services, blockchain can guarantee that the real-time data exchanged among diverse stakeholders is reliable and impervious to tampering. Moreover, blockchain-enabled smart contracts can automate procedures like ambulance dispatching by using real-time traffic and environmental data, thus enhancing reaction times and decision-making precision (Zheng et al., 2018). Through the use of blockchain, EMS agencies can disseminate real-time data across several platforms while upholding data privacy requirements. Blockchain technology provides viable alternatives for secure, instantaneous data sharing, as indicated by Bettencourt and Howlett (2021). Blockchain guarantees data integrity and scalability by establishing a decentralised, transparent data-sharing network among EMS agencies, hospitals, and traffic authorities. The incorporation of 5G-enabled IoT systems, as articulated by Alkinani et al. (2021), augments the precision of real-time traffic monitoring, thereby enhancing ambulance routing and response times. Moreover, blockchain-based smart contracts can automate decisions utilising real-time data, such as adaptive ambulance routes influenced by traffic and weather conditions, ensuring expedited and precise responses.

2.7 Optimizing Workforce Distribution for Emergency Medical Services

Staffing and labour management are critical for ensuring the EMS's efficiency. Asghar et al. (2021) employed SARIMA models to forecast employee absences and enhance personnel distribution during peak EMS demand periods. By forecasting personnel shortages, EMS organisations can more effectively deploy resources and guarantee that there are no significant deficiencies in coverage during periods of peak demand.

The use of machine learning to forecast personnel requirements based on historical trends and real-time data indicates a promising approach to workforce management. By amalgamating staff absence data with ambulance demand forecasts, EMS agencies may make astute judgements regarding resource distribution, guaranteeing sufficient personnel to address demand, particularly during peak times or significant incidents.

2.8 Future innovations to improve ambulance service efficiency

The incorporation of emerging technologies, including deep learning, blockchain, and hybrid forecasting models, has the capacity to transform EMS operations. Blockchain technology could enable secure, real-time sharing of essential data among stakeholders in the EMS ecosystem, including hospitals, traffic control systems, and ambulance providers. Blockchain can significantly contribute to real-time decision-making by guaranteeing data integrity and privacy, especially in contexts that demand elevated data security.

Furthermore, deep learning algorithms, including LSTM networks, can enhance the precision of predictions concerning ambulance demand and response durations. LSTM networks are engineered to process sequential data, rendering them adept at predicting time-sensitive variables such as demand surges during emergencies or swift alterations in traffic circumstances. Blockchain technology may enable secure, real-time exchange of essential data among stakeholders, such as hospitals, traffic control systems, and ambulance services. Utilising blockchain, EMS providers can automate decision-making via smart contracts, guaranteeing more precise and prompt responses in emergencies (Zheng et al., 2018).

Bettencourt and Howlett's research from 2021 showed how useful LSTM models are for improving EMS by using them for "what-if" scenario analysis to guess how different actions would affect demand. Integrating blockchain technology with IoT systems could facilitate comprehensive data transparency, enabling all stakeholders in an emergency response to trust the information they receive and respond swiftly and decisively.

2.9 Principal Insights and Prospective Consequences

The enhancement of ambulance response times by data-driven methodologies has progressed markedly with the introduction of machine learning, time series forecasting, IoT, and innovative technologies such as blockchain. The literature endorses the application of predictive analytics, including XGBoost and Prophet models, to improve EMS operations by delivering real-time insights regarding ambulance demand and response efficacy. Furthermore, incorporating real-time traffic data, meteorological forecasts, and geospatial information guarantees that ambulance deployment techniques remain both adaptive and sensitive to fluctuating conditions.

This assessment aligns with current research while incorporating revolutionary aspects like IoT integration and the possibility of blockchain-based data exchange. Investigating additional applications of LSTM networks and hybrid forecasting models places the Welsh Ambulance Service Trust (WAST) in the vanguard of EMS innovation. By remaining at the forefront of these advancements, EMS providers can more effectively address the increasing need for swift emergency response, thereby improving patient outcomes and decreasing fatality rates in critical scenarios.

3 METHODOLOGY

3.1 Data Acquisition and Preparation

Data collection constitutes the foundation of our investigation. The research sought to compile a comprehensive dataset for analysing ambulance response times by integrating various data sources, including ambulance records, meteorological information, and traffic data.

3.1.1 Data Sources

The dataset comprises comprehensive records from multiple platforms:

- Welsh Ambulance Service Trust (WAST): The principal dataset included timestamps for emergency call responses, dispatch information, incident severity, and details of ambulance journeys. It also incorporated geographical data to evaluate urban and rural response times (Villani et al., 2020).
- Traffic and Weather Data: External variables such as traffic congestion and meteorological conditions were obtained from public APIs and aligned with ambulance data. The external datasets included measures such as precipitation, fog, and traffic congestion, all of which are critical for understanding their influence on ambulance delays. Traffic congestion at peak hours markedly prolongs reaction times, especially in urban regions (Schmidt et al., 2020; Choi et al., 2020).
- Population Data: Census data included population density metrics, which facilitated the examination of disparities in ambulance response times between urban and rural regions. Rural areas often have extended response times owing to limited resources and increased distances between ambulance stations (Schmidt et al., 2020).

3.1.2 Data Cleaning and Preparation

The preliminary dataset was refined and standardised to guarantee precision and uniformity among various sources. This step was essential for preparing the data for subsequent analysis and modelling.

- Addressing Incomplete Data: Traffic and meteorological data frequently exhibited absent values, especially in rural regions. Missing data was imputed utilising the mean or median for numerical variables and the mode for categorical variables. This facilitated a more comprehensive dataset without undermining the integrity of the analysis (Beckett & Lyons, 2020).
- Outlier Detection and Elimination: Outliers, including response times above several hours or negative values, were eliminated. The Interquartile Range (IQR) approach was utilised to detect and eliminate these outliers to avoid distorting the analysis.
- Standardisation of Timestamps: Given that data originated from diverse sources with differing timestamp formats (e.g., local time versus UTC), a standardisation procedure was implemented to guarantee precise alignment of all datasets, particularly in correlating ambulance journeys with traffic and weather data (Taylor & Letham, 2018).
- Data Granularity Alignment: Ambulance data was documented with a high level of granularity (second-by-second), but traffic and weather data were frequently accessible at extended intervals (e.g., hourly). To address this issue, the ambulance data was consolidated, and the external data was restructured, guaranteeing that all datasets functioned at the same level of granularity for precise model development.

3.1.3 Feature Selection and Dimensionality Reduction

After the dataset was sanitised, pertinent features were chosen to enhance the efficacy of the predictive models.

- Feature Selection: Multiple variables from the WAST dataset were preserved, notably MPDSPriorityType (emergency level) and TimeToDispatch, which directly influence response times. Extraneous variables, including unique identifiers, were eliminated to diminish noise in the dataset (Villani et al., 2020).
- One-Hot Encoding of Categorical Variables: Categorical variables, including incident priority and region, were converted into binary features by one-hot encoding. This phase enabled the models to manage categorical data efficiently and discern the impact of event types on response times (Choi et al., 2020).

3.2 Exploratory Data Analysis (EDA)

An Exploratory Data Analysis (EDA) was performed to elucidate the determinants affecting ambulance response times and to discern patterns and correlations among the dataset's numerous attributes.

3.2.1 Temporal Patterns of Response

Response times were categorised into essential time metrics, including TimeToPickup, TimeToLocationConfirmed, TimeToDispatch, and TimeToArrivalAtScene. The analysis was conducted across areas and at different times of day to comprehend the impact of numerous factors on ambulance service delivery.

- Descriptive statistics were produced for essential temporal metrics. The average Time to Arrival at Scene was 17.25 minutes, with a standard variation of 9.51 minutes, surpassing the government-mandated aim of 8.5 minutes. The significant variety in response times indicated difficulties, especially in rural regions, in achieving the response targets (Schmidt et al., 2020).

	TimeToLocationConfirmed	TimeToDispatch	TimeToPickup	TimeToArrivalAtScene
count	44409.0	44409.0	44409.0	44409.0
mean	0.74	1.47	0.14	17.25
std	0.67	0.83	0.44	9.51
min	0.08	0.13	0.0	0.08
25%	0.38	0.98	0.03	9.95
50%	0.55	1.27	0.03	15.22
75%	0.83	1.7	0.05	22.78
max	15.77	17.0	9.97	50.0

Figure 1: Summary table of Descriptive Statistics

- Histograms were created to illustrate the dispersion of the Initial TimeToPickup the call till TimeToArrivalAtScene, with a vertical red line denoting the 8.5-minute response target. The histograms indicated a skewed distribution, with a significant proportion of instances surpassing the objective, particularly for TimeToArrivalAtScene. The extended tail in the histogram signifies that numerous rural regions experience considerable delays. The analysis confirmed that the clock for measuring response times begins from the **initial Call Connected Time**, rather than the dispatch time.

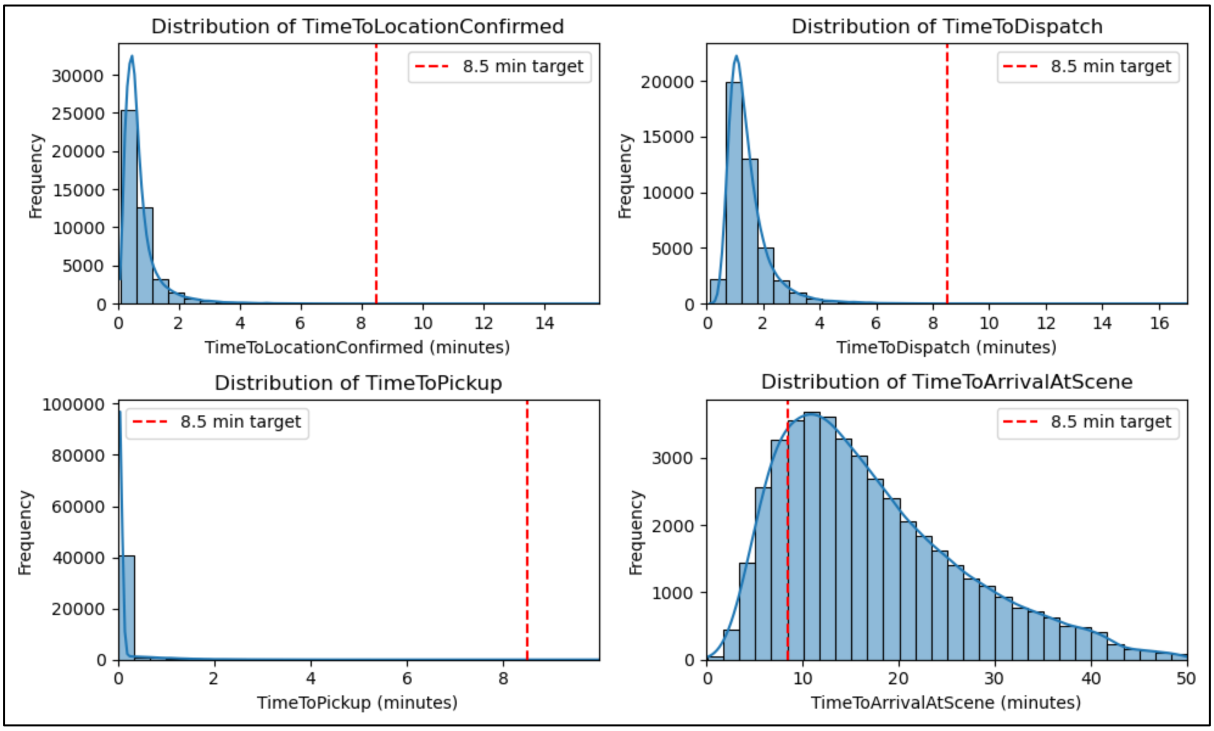

Figure 2 : Time Distribution

- Box Plot of Response Times Categorised by Location:

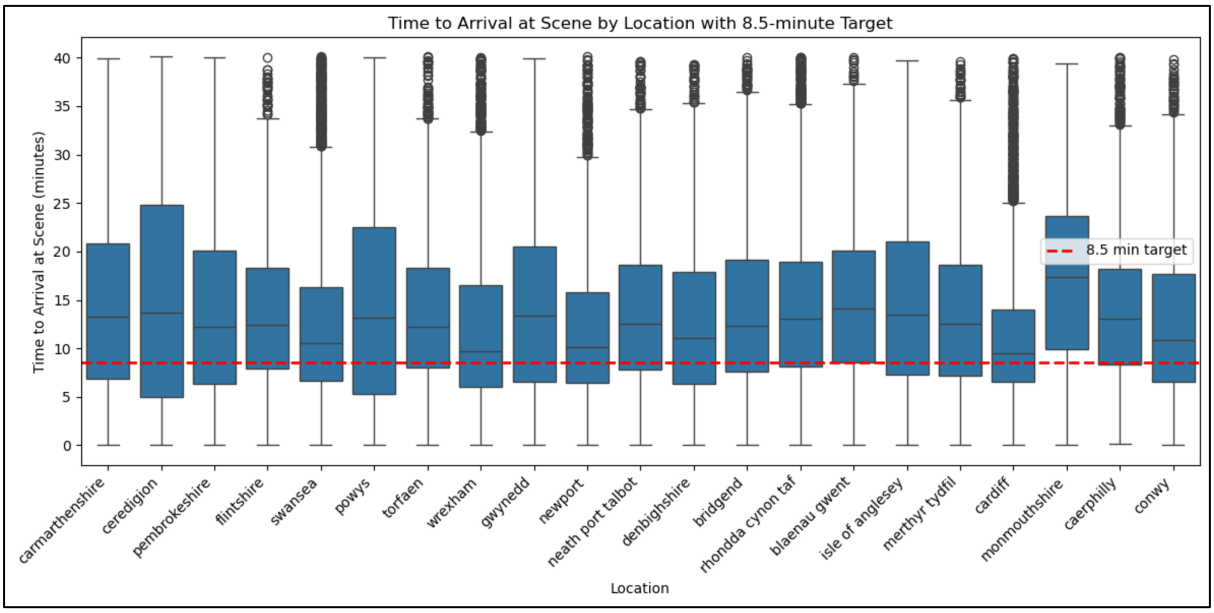

Figure 3 : Response Times Categorised by Location

A box plot was generated to compare response times among various regions. Urban locations, such as Cardiff and Newport, demonstrated more uniform response times that aligned more closely with the aim. Conversely, rural areas like Powys and Ceredigion exhibited considerably more variability and notably extended response times, reflecting logistical difficulties associated with travel distances and ambulance accessibility (Schmidt et al., 2020).

- Crosstabulation and Heatmap (Dispatch Duration vs. Response Duration):

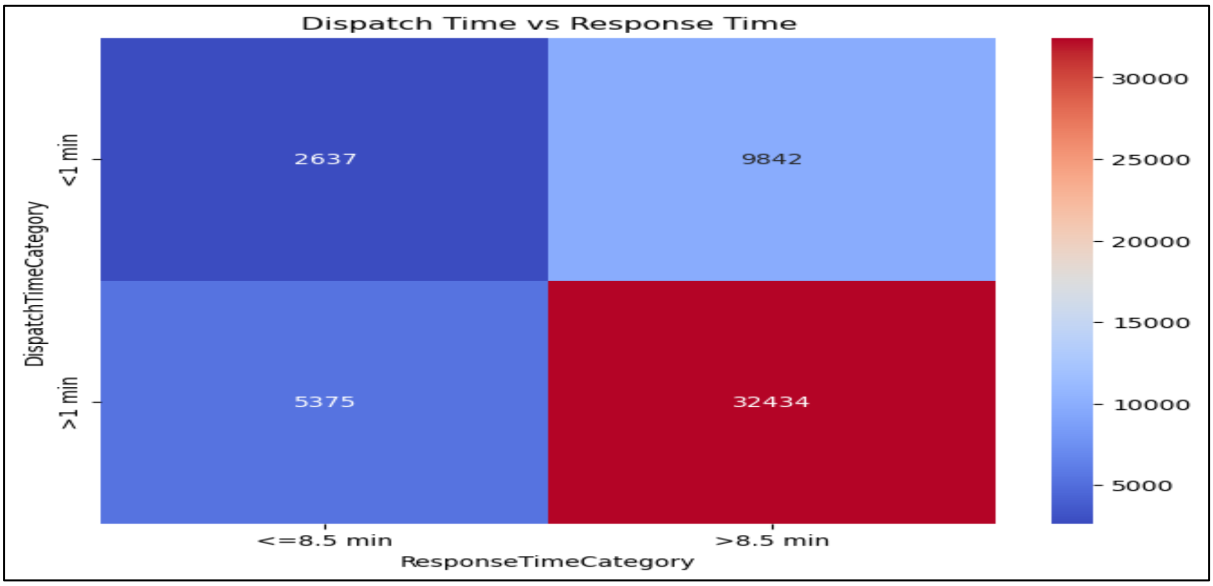

Figure 4 : Dispatch Duration vs Response Duration

A crosstabulation and heatmap were created to examine the correlation between dispatch time and overall response time. The findings indicated that situations with dispatch delays over 1 minute were less certain to achieve the 8.5-minute objective. Despite dispatch being completed in under a minute, circumstances like highway congestion or rural location frequently resulted in delays.

3.2.2 Influence of Traffic and Meteorological Conditions

The influence of external elements, including traffic congestion and weather conditions, was evaluated to comprehend their effect on ambulance response times, especially during peak demand or adverse environmental conditions (Villani et al., 2020).

- Violin Plots (Rush Hour versus Non-Rush Hour):

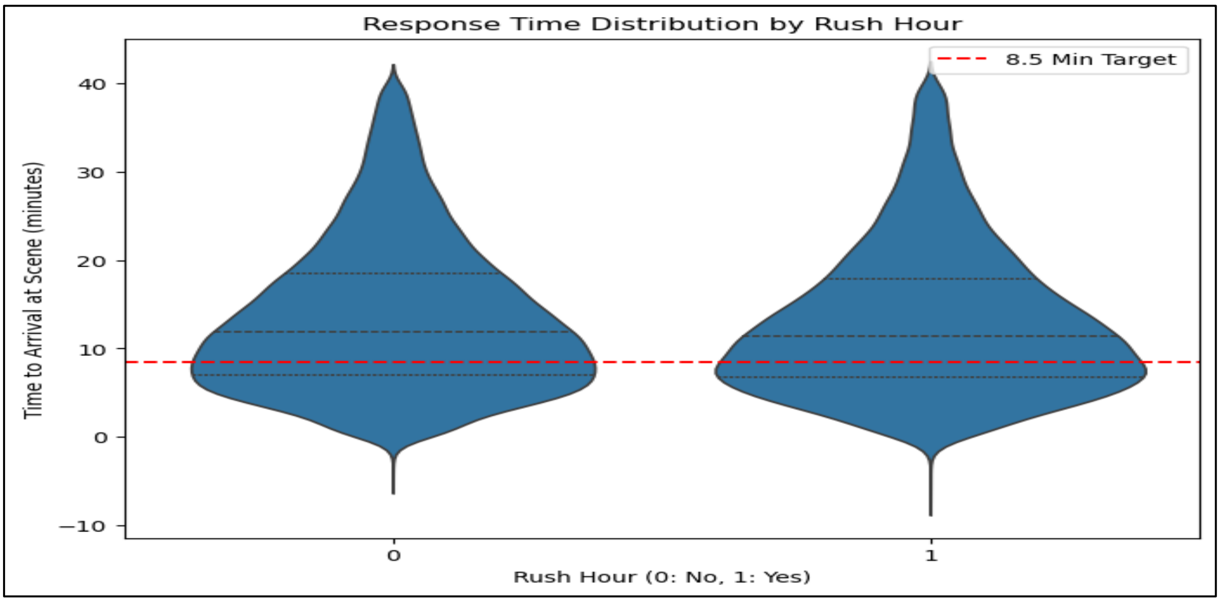

Figure 5 : Response Time Distribution by Rush Hour

A violin plot was employed to examine the distribution of response times during peak hours (8–10 AM and 5–7 PM) with those during non-peak hours. The broader distribution and elevated median during peak hours validated the substantial impact of traffic congestion on ambulance response times. In rural areas, where traffic is minimal, variables such as road conditions may lead to extended reaction times (Choi et al., 2020).

- Stacked Bar Graph (Influence of Traffic and Precipitation):

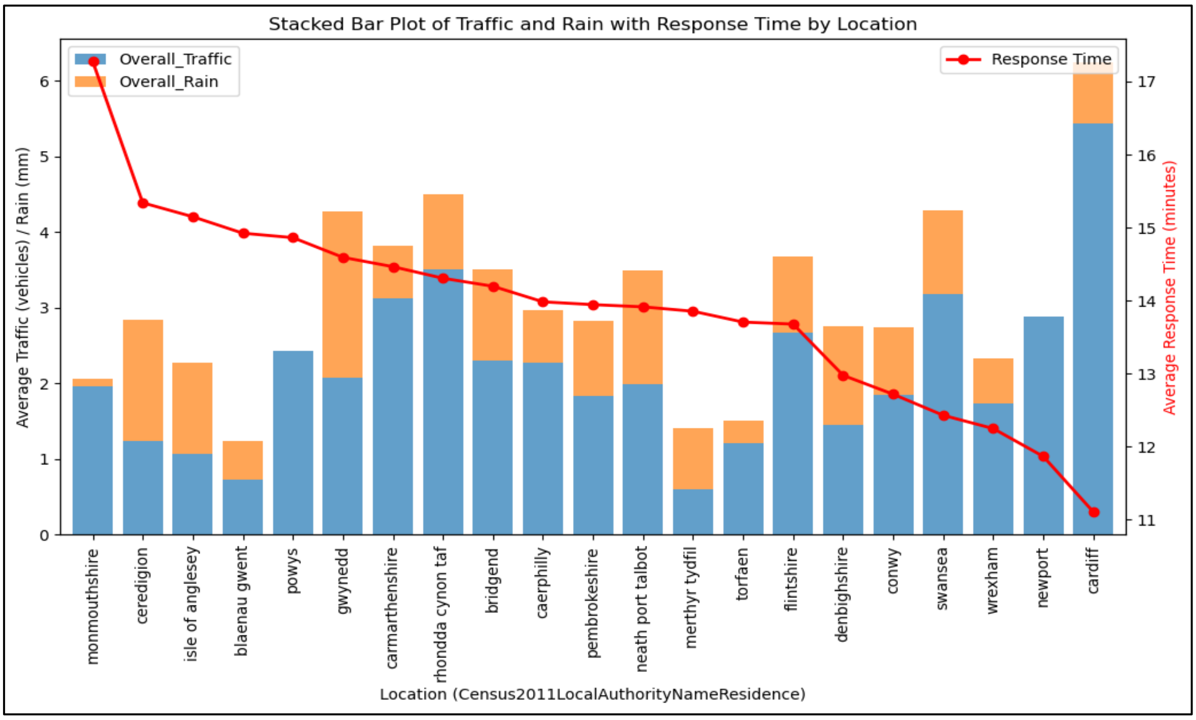

Figure 6 : Influence of Traffic and Precipitation

A stacked bar graph illustrated the cumulative impact of traffic and precipitation on response times in different regions. The graph demonstrated that urban areas, despite being significantly affected by traffic, achieved shorter response times owing to superior infrastructure and ambulance accessibility. In rural regions, precipitation had a more adverse effect, substantially prolonging journey durations on inadequately maintained roadways.

- Ambulance Demand against Vehicle Availability:

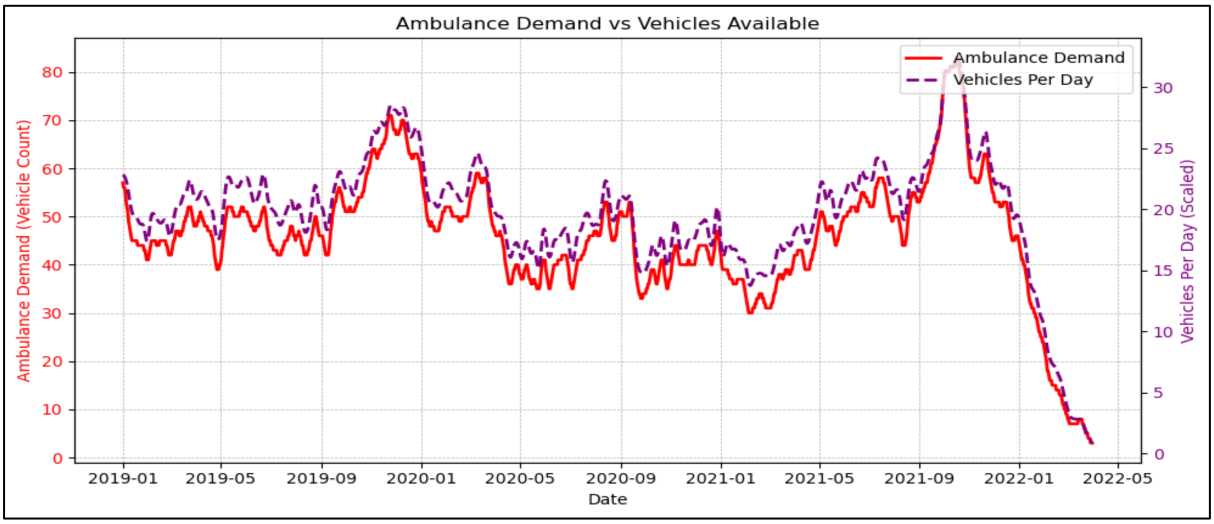

Figure 7 : Ambulance Demand vs Vehicle Availability

A line graph illustrating ambulance demand in relation to vehicle availability revealed a significant disparity during peak demand periods. The graph highlighted the necessity for improved forecasting models to align vehicle availability with projected demand (Schmidt et al., 2020).

3.2.3 Geospatial and Demographic Analysis

Multiple geospatial visualisations were developed to acquire a spatial comprehension of ambulance response times. These visualisations emphasised regional differences and the practical difficulties of delivering equitable ambulance services across various geographical regions.

- Geospatial Heatmap Illustrating Response Times by Location:

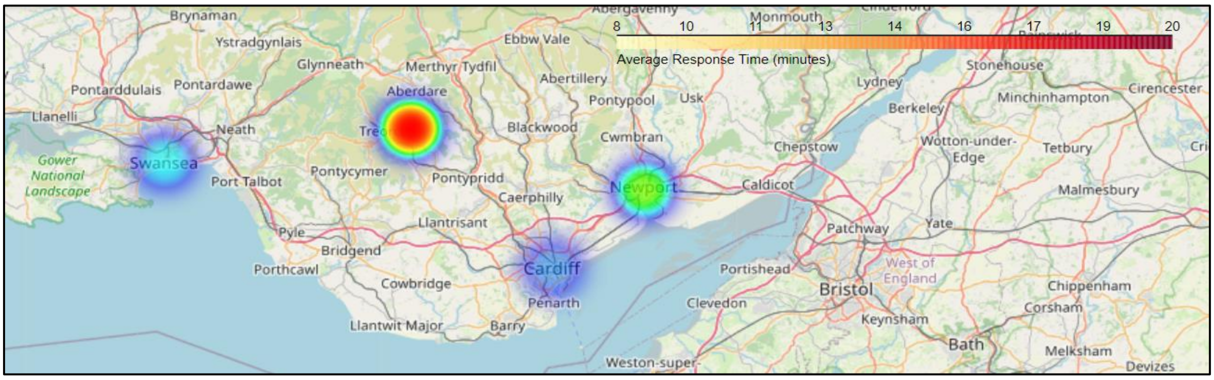

Figure 8 : Response Time by Location

A geographical heatmap was created to illustrate reaction times in various places. Darker hues signified extended response durations, which were more common in rural regions like Powys and Ceredigion. Urban regions such as Cardiff frequently show reduced response times, indicating superior ambulance availability and road infrastructure (Villani & Palazzi, 2020).

- Comparison of Population and Response Time:

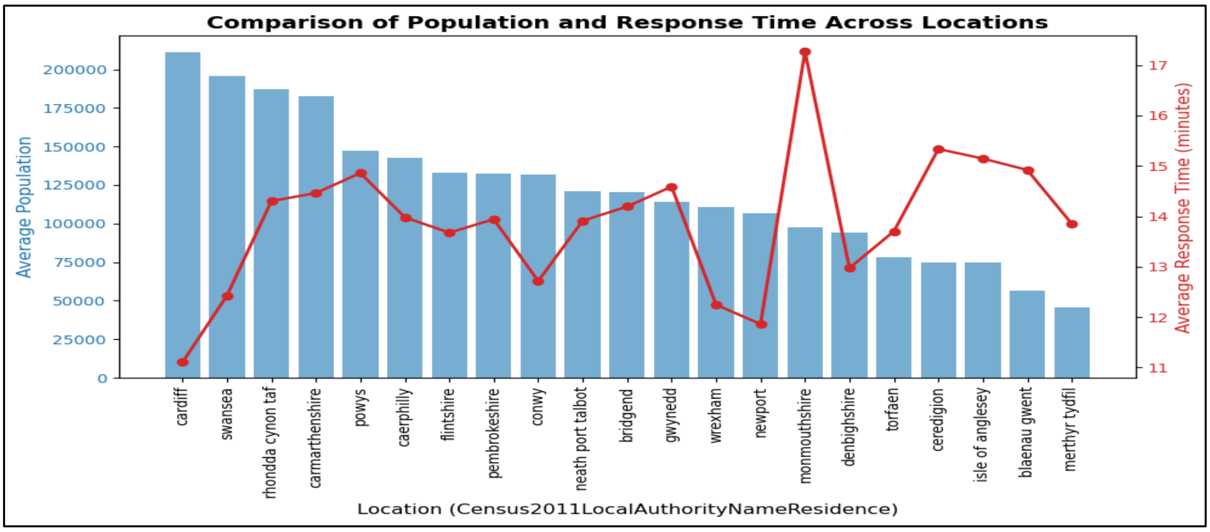

Figure 9 : Population and Response Time across Location

This comparison chart illustrated the correlation between population density and reaction times. In metropolitan regions, elevated population density and increased ambulance availability facilitated reduced response times. In poorly populated rural regions, a limited number of ambulances and extended travel durations resulted in considerable delays (Beckett & Lyons, 2020).

- Response Duration by Area Classification:

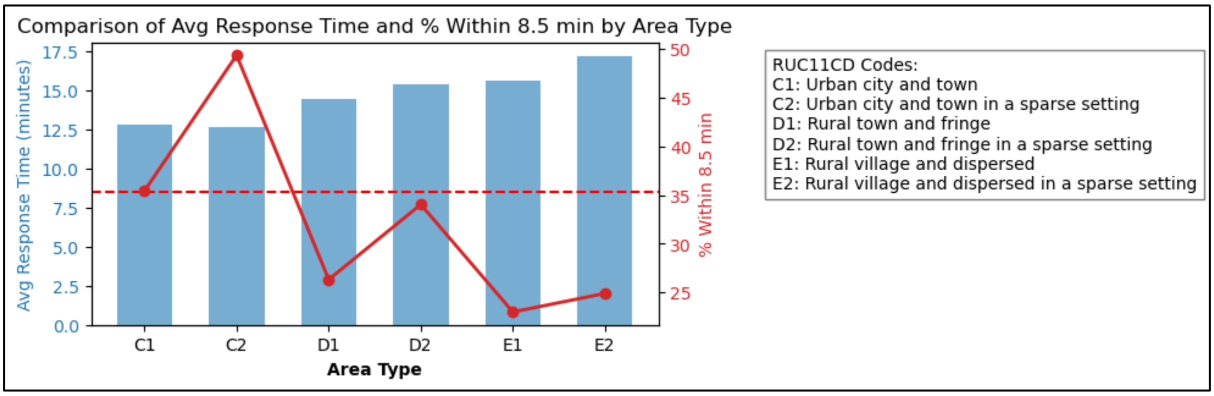

Figure 10 : Response Duration by Area Classification

Response times were studied across different area types via a bar graph. Urban regions (C1, C2) had shorter average response times and higher percentages of responses within 8.5 minutes. Conversely, rural regions (E1, E2) demonstrated extended response times and failed to achieve the 8.5-minute benchmark, reflecting logistical difficulties associated with travel distances and ambulance accessibility (Schmidt et al., 2020).

3.2.4 Temporal Trends in Reaction Time

Alongside the analysis of regional and external factors, temporal patterns were assessed to comprehend the influence of the time of day, day of the week, and the nature of occurrences on response times.

- Heatmap depicting Incident Frequency by Day of the Week and Hour of the Day:

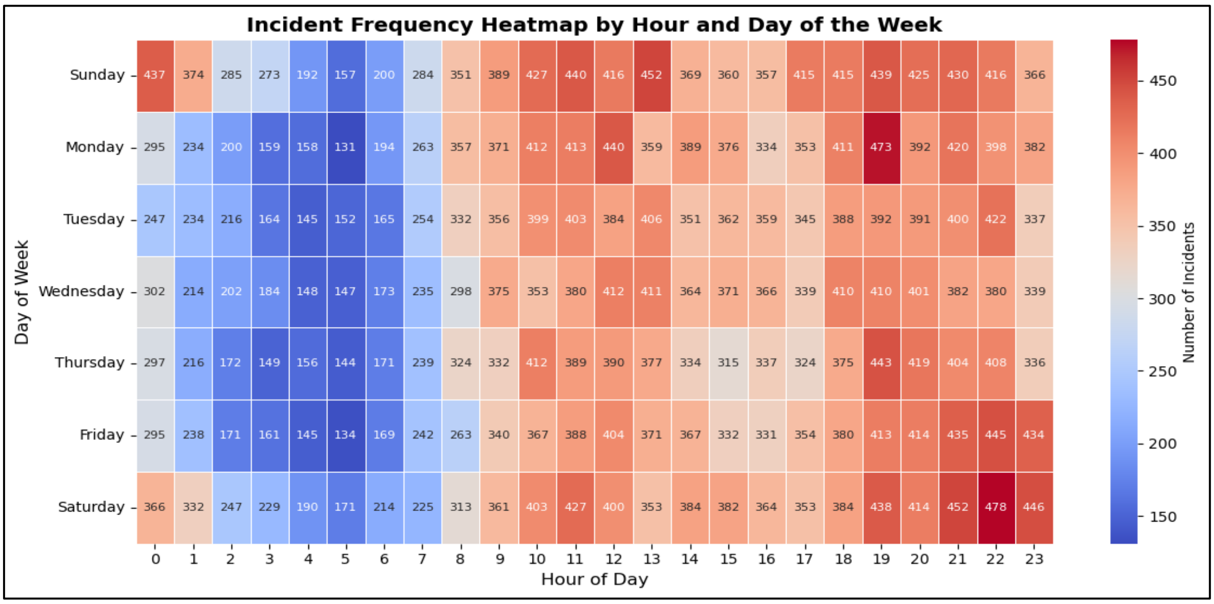

Figure 11 : Incident Frequency by Hour and Day of the Week

A heatmap depicted the incidence frequency across various hours of the day and days of the week. Peak incident periods transpired in the late afternoon and early evening, especially on weekends, when public activities or elevated social engagement led to heightened call numbers. This research offered insights on optimising shift scheduling and ambulance availability to accommodate increased demand during peak periods.

- Response Time for Critical versus Non-Critical Incidents:

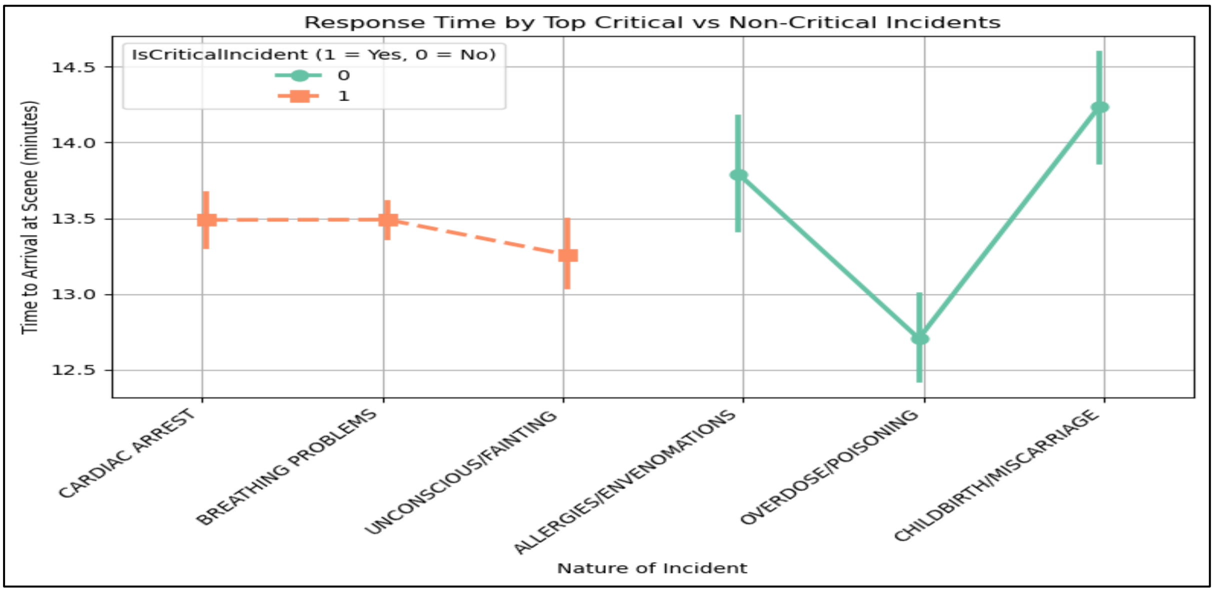

Figure 12 : Response Time by Top Critical vs Non-Critical Incidents

A line graph illustrated the response times for critical (life-threatening) and non-critical incidents. The statistics indicated that response times for important incidents were typically reduced as ambulances prioritised these emergencies. Nonetheless, major incidents in rural regions periodically surpassed the target due to logistical difficulties (Choi et al., 2020).

- Correlation Matrix of Principal Features:

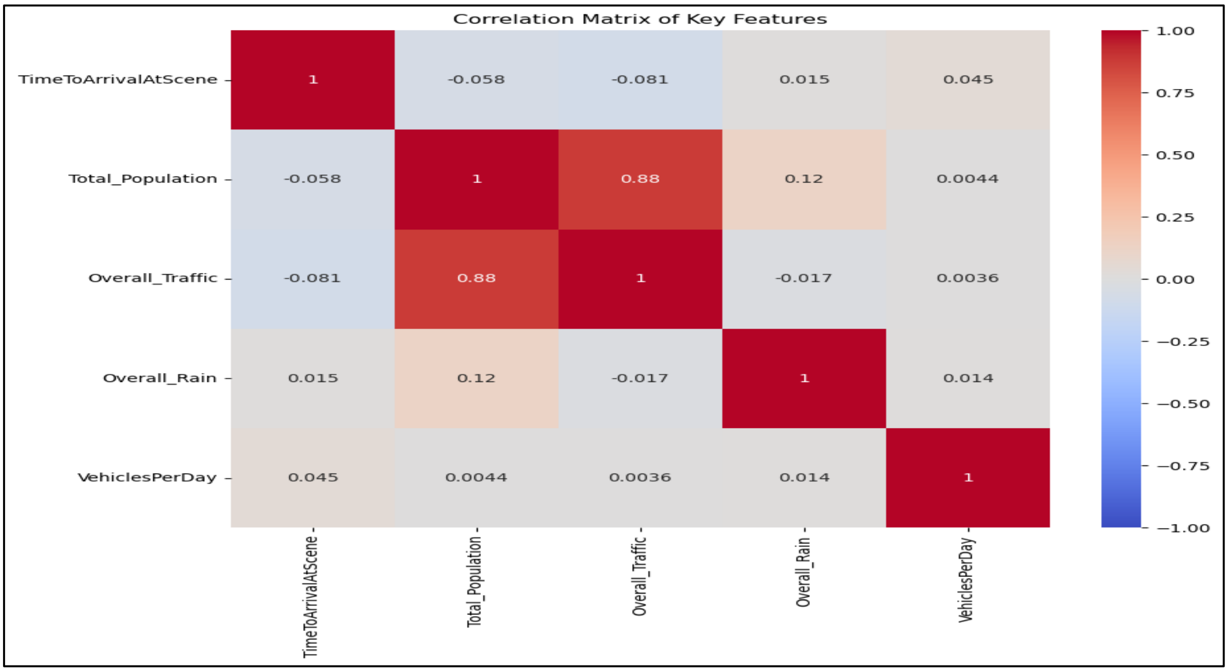

Figure 13 : Correlation Matrix of Key Features

A correlation matrix was employed to analyse the correlations among variables, including population, traffic, and response times. A robust positive connection (0.88) exists between total population and overall traffic, suggesting that regions with high population density typically experience increased traffic levels. Nevertheless, response times exhibited poor relationships with other variables, suggesting negligible direct influence (Villani & Palazzi, 2020).

3.3 Feature Engineering

Feature engineering is essential for augmenting machine learning models' prediction capabilities by converting raw data into significant features. Insights derived from Exploratory Data Analysis (EDA) guided the development of features that encapsulate temporal, environmental, and operational variables influencing ambulance response times. The developed features substantially enhanced the model's predicted accuracy.

3.3.1 Temporal Characteristics

Temporal characteristics were crucial for capturing time-dependent fluctuations in ambulance demand. These properties enabled the program to identify daily and weekly trends that fluctuate, modifying forecasts according to traffic and peak hours.

- HourOfDay: This attribute denotes the exact hour an incident occurred, allowing the model to account for peak traffic periods, especially during rush hour. It is essential in influencing ambulance response times, particularly during peak congestion periods in metropolitan environments (Choi et al., 2020).
- DayOfWeek: Ambulance demand generally adheres to weekly trends, with increased call volumes on weekends, especially in rural areas. This feature enabled the model to modify estimates according to the day of the week, facilitating more precise forecasts of peak demand periods such as Saturdays.
- RushHour: While less significant than other temporal variables, RushHour was incorporated to denote whether the incident transpired during high traffic periods (e.g., 8-10 AM, 5-7 PM). Its contribution was significant, especially when integrated with other traffic-related attributes.

3.3.2 Ecological Characteristics

Environmental factors, including road congestion and inclement weather, substantially affect ambulance response times, especially in urban and rural areas. These attributes enabled the model to consider dynamic, real-world factors that affect travel velocity and delays (Villani et al., 2020).

- Overall_Traffic: Traffic congestion significantly impacted ambulance response times, especially in urban regions. This component measured the degree of road congestion at the time of occurrence, allowing the model to modify forecasts according to expected travel speed at peak traffic times.
- Overall_Rain: Meteorological conditions, especially precipitation, frequently impede ambulance transit in rural areas with little infrastructure. This component considered rainfall levels during each occurrence, enabling the model to modify forecasts depending on anticipated delays due to unfavourable driving conditions (Villani et al., 2020).

3.3.3 Operational and Demographic Characteristics

Operational and demographic characteristics were developed to address the logistical difficulties related to ambulance services. These characteristics indicate the infrastructure, population density, and event severity, all of which significantly influence response times.

- VehiclesPerDay: This attribute measures the traffic density on the roads during the event. It indicates the quantity of cars present, serving as a surrogate for traffic congestion and its impact on ambulance mobility. The total volume of vehicles on the road substantially affects the response time of ambulances (Choi et al., 2020).
- Total_Population: Population density was used to account for variations in response times between urban and rural regions. Urban regions typically possess superior ambulance service and infrastructure, while rural areas frequently experience extended trip distances. This element enabled the model to address discrepancies between population density and ambulance availability (Schmidt et al., 2020).
- IsCriticalIncident: This binary attribute indicates whether the occurrence poses a life-threatening risk. Critical incidents are prioritised for expedited dispatch and response times; thus, incorporating this feature enabled the model to distinguish cases necessitating swifter reactions (Villani et al., 2020).
- Urban_Rural: This feature differentiates between urban and rural environments, highlighting variations in ambulance accessibility, infrastructure, and road conditions. It facilitated the analysis of discrepancies in travel velocity and response durations across various regions (Schmidt et al., 2020).

3.4 Model Formulation

This research utilised two model types to accomplish its goals: classification models to determine if an ambulance would fulfil the 8.5-minute threshold and time-series models to project future ambulance demand. The development process emphasized improving model performance through hyperparameter optimization and rectifying data inconsistencies to ensure precise forecasts. The outcomes from feature significance analysis and cross-validation influenced the model selection process.

3.4.1 Classification Models

Various machine learning models were assessed, and their efficacy was measured by their capacity to manage intricate interactions among features such as traffic, weather, and time of day. These models were developed to forecast whether an ambulance will achieve the 8.5-minute response time objective.

- Logistic Regression: Logistic regression served as the foundational model. Although it is straightforward to interpret and rapid to implement, it inadequately predicted ambulance response times in more intricate situations, especially those characterised by heavy traffic or severe weather conditions. The assumption of linearity in logistic regression between input attributes and outcomes made it less able to find interactions in the data that were not linear. This led to a 63.5% model accuracy. Also, the fact that logistic regression didn't remember many of the times ambulances didn't reach the goal showed that it wasn't good at handling the uneven dataset, since most of the times it did reach the response target (Schmidt et al., 2020).

- Random Forest: The Random Forest ensemble learning method was evaluated to address the shortcomings of logistic regression. This approach effectively captured non-linear interactions by generating numerous decision trees and averaging their predictions. Nonetheless, Random Forest encountered difficulties with data imbalance, as the majority of instances satisfied the response time target, resulting in skewed forecasts. Notwithstanding hyperparameter optimisation (e.g., modifying the number of trees and the maximum depth), the model attained merely 65.3% accuracy. It outperformed logistic regression but was still constrained in forecasting the minority class, specifically instances where ambulances failed to fulfil the 8.5-minute objective (Schmidt et al., 2020).
- XGBoost (Extreme Gradient Boosting) was the most effective model in the classification challenge, owing to its proficiency in managing skewed data and its capacity to capture intricate feature relationships. XGBoost uses gradient boosting, in which each subsequent tree rectifies the mistakes of its predecessor, thereby iteratively minimizing prediction inaccuracies. The combined regularisation methods (L1 and L2) also prevent overfitting, which makes it suitable for this dataset with complicated and uneven features (Choi et al., 2020). Following comprehensive hyperparameter optimisation (learning rate, tree depth, boosting iterations, etc.), XGBoost attained a maximum accuracy of 66.89%. The recall rate of 94% demonstrated the model's efficacy in identifying instances where ambulances met the 8.5-minute target. The feature importance plot indicated that variables such as VehiclesPerDay, HourOfDay, and Overall_Traffic were the most significant predictors of ambulance response times, underscoring the influence of traffic and peak hours on emergency service efficacy.

3.4.2 Temporal Sequence Prediction Models

Various time-series models were utilised to predict future ambulance demand by analysing seasonal patterns, demand spikes, and external influences such as traffic and weather conditions. These models facilitated the prediction of demand surges, especially during public events and weekends, which are essential for resource distribution.

- ARIMA (AutoRegressive Integrated Moving Average): ARIMA was selected for its capacity to represent time-series data. Nevertheless, it faced challenges due to the seasonal and cyclical fluctuations inherent in ambulance demand, particularly during peak periods such as weekends. Because ARIMA couldn't consider outside factors like traffic and weather, it had high error rates (an MAE of 7.63), which meant it wasn't good for short-term forecasting during demand spikes (Villani & Palazzi, 2020).
- SARIMAX (Seasonal ARIMA with Exogenous Variables): SARIMAX was employed to augment ARIMA by integrating external variables, such as traffic and weather, to enhance predictive accuracy. SARIMAX more effectively captures the cyclical nature of ambulance demand compared to ARIMA by incorporating seasonality and the influence of external variables. Nevertheless, it necessitated comprehensive hyperparameter optimisation and continued to face challenges with swift demand

variations. SARIMAX enhanced ARIMA's performance, attaining an MAE of 6.08, although it exhibited less flexibility relative to more contemporary models.

- Prophet: Developed by Facebook, Prophet surpassed both ARIMA and SARIMAX by adeptly managing numerous seasonalities (daily, weekly, yearly) and external event-driven elements (e.g., public holidays, social events). The Prophet's capacity to integrate these variables allowed for a more precise prediction of ambulance demand, particularly during weekends and public events when demand surges are most prevalent. Prophet attained a Mean Absolute Error (MAE) of 4.50 and a Root Mean Square Error (RMSE) of 5.85, establishing it as the superior model for forecasting high-demand intervals. Its adaptability in addressing absent data, as well as its ability to mimic intricate seasonal patterns with minimal adjustment, further enhanced its exceptional performance (Taylor & Letham, 2018).

3.5 Assessment and Verification of Models

3.5.1 Cross-Validation

XGBoost was validated by 10-fold cross-validation, which affirmed the model's robustness and generalisability over various dataset folds. XGBoost attained an average accuracy of 66.89% and a commendable recall rate of 94%, illustrating its efficacy in detecting successful ambulance responses in various contexts (Villani et al., 2020).

3.5.2 Assessment Criteria

A variety of criteria were utilised to assess both the classification and time-series models:

3.5.2.1 Classification Metrics:

- Accuracy: Assesses the total ratio of correct forecasts. XGBoost attained the best accuracy at 66.89%.
- Precision: Represents the ratio of true positive predictions to the total expected positives, crucial for minimising false positives.
- Recall is essential for assessing the model's effectiveness in identifying instances where ambulances met the 8.5-minute threshold. The recall rate of 94% for XGBoost was a significant measure of its dependability (Choi et al., 2020).
- The F1-Score is the harmonic mean of precision and recall, providing a balanced assessment of both criteria. XGBoost's elevated F1-Score demonstrated its ability to balance these elements.

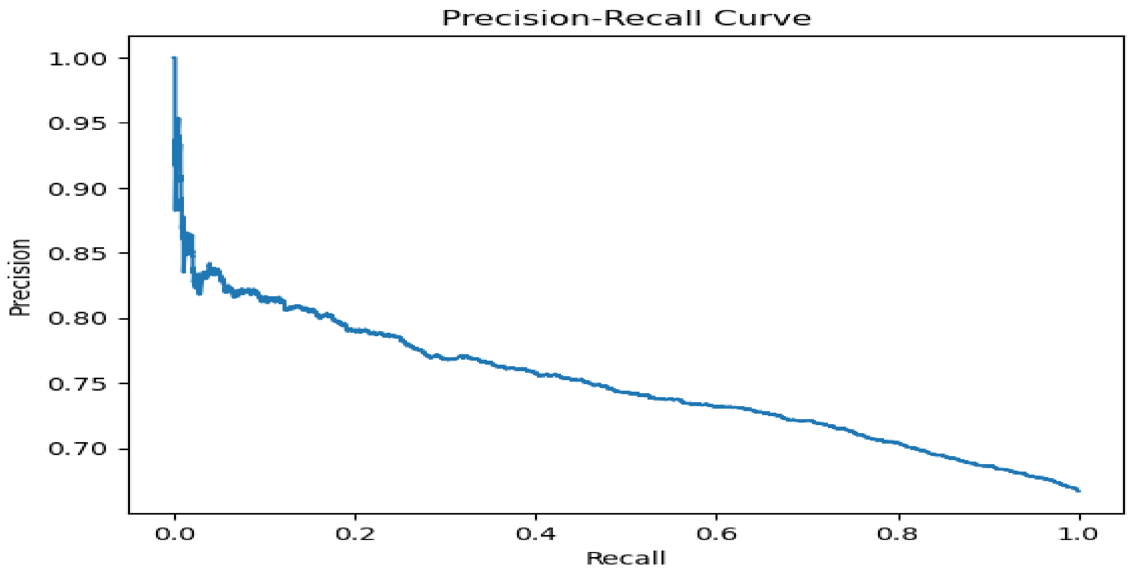

Figure 14 : Precision – Recall Curve

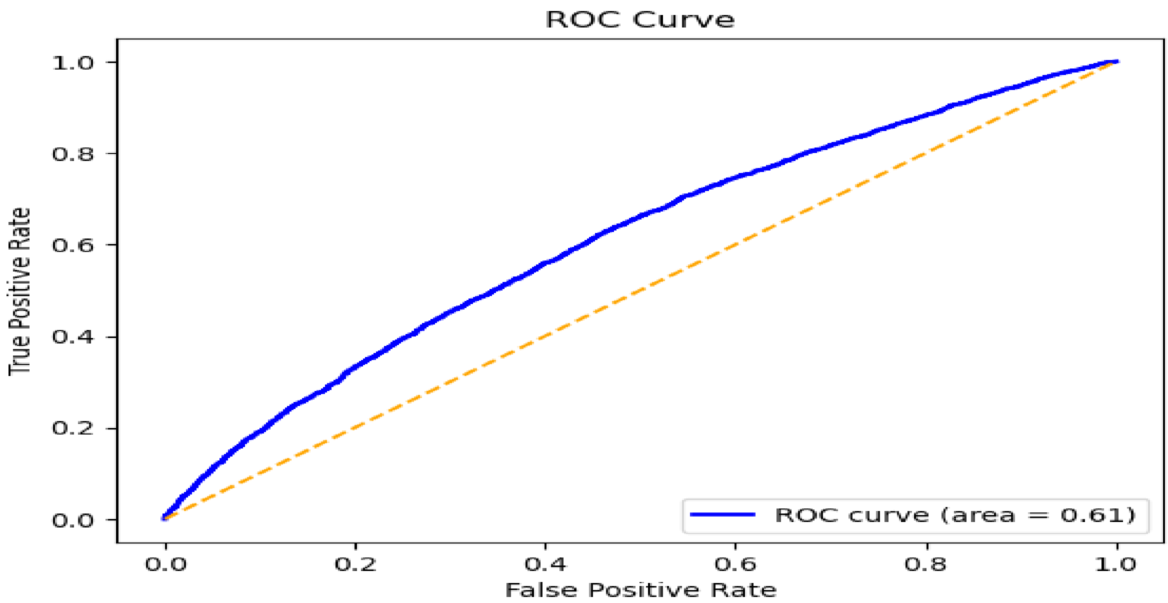

Figure 15 : ROC Curve

3.5.2.2 Temporal Metrics:

Mean Absolute Error (MAE): Assesses the average size of prediction inaccuracies. The Prophet model's Mean Absolute Error (MAE) of 4.50 established it as the most precise model for forecasting ambulance demand (Taylor & Letham, 2018).

Root Mean Squared Error (RMSE): Highlights significant prediction errors. The Prophet model's RMSE of 5.85 demonstrated superior management of substantial demand fluctuations compared to ARIMA and SARIMAX.

3.5.3 SHAP (SHapley Additive exPlanations) for Model Interpretation

SHAP was employed to elucidate the contribution of each feature to the predictions of the XGBoost model, hence enhancing its interpretability.

- Global Interpretability: SHAP indicated that factors such as Overall_Traffic, HourOfDay, and VehiclesPerDay were the most significant in forecasting whether an ambulance would achieve the 8.5-minute threshold. These observations underscore the significance of traffic congestion and peak hours in influencing response times (Villani et al., 2020).
- Local Interpretability: SHAP facilitated the elucidation of individual predictions, enabling WAST to ascertain the reasons behind some ambulances failing to meet their targets in certain areas or at designated times. This research yielded practical insights for resource distribution and strategic planning.

3.6 Constraints of the Model and Analytical Evaluation

Although the models exhibited robust performance, many limitations were recognised:

The models depended on past traffic and weather data, restricting their capacity to include real-time events such as road closures or inclement weather conditions. Integrating real-time data streams will markedly improve the forecast accuracy of the models, especially in metropolitan environments where traffic patterns vary swiftly (Choi et al., 2020).

The models exhibited superior performance in metropolitan areas due to the consistency and predictability of the data, in contrast to rural regions. In remote areas like Powys and Ceredigion, limited data and extended travel distances diminished model precision. This discrepancy indicates the necessity for more customised models that consider geographical differences (Schmidt et al., 2020).

While XGBoost effectively addresses unbalanced data, models such as Logistic Regression and Random Forest have difficulties. To resolve this issue, methodologies like SMOTE (Synthetic Minority Over-sampling Technique) may be utilised to enhance the models' capacity to predict instances where ambulances do not achieve the target.

4 RESULTS AND DISCUSSIONS

This section delineates the results derived from the models constructed and assessed during the research. The text examines critical insights derived from the analysis of ambulance response times, the influence of external factors like traffic and weather, and the ramifications for the Welsh Ambulance Service Trust (WAST). The findings are situated within the framework of meeting the government-imposed 8.5-minute response time objective for life-threatening crises while simultaneously tackling discrepancies between urban and rural regions.

4.1 Model Efficacy and Predictive Precision

The efficacy of the classification models—Logistic Regression, Random Forest, and XGBoost—was assessed to see if an ambulance would achieve the 8.5-minute response objective. Furthermore, time-series models (ARIMA, SARIMAX, and Prophet) were employed to predict ambulance demand.

4.1.1 Classification Models

Logistic Regression, serving as the baseline model, had the least effective performance, with an accuracy of 63.5% and a ROC AUC of 0.58. Its restricted ability to manage non-linear interactions resulted in inaccurate predictions, especially in scenarios of significant traffic congestion or inclement weather conditions. Logistic Regression failed to encapsulate the intricate relationships between variables such as traffic intensity and time of day.

Random Forest: The Random Forest model surpassed the baseline with an accuracy of 65.3% and a ROC AUC of 0.60. Although it outperformed Logistic Regression, Random Forest had difficulties due to the dataset's imbalanced nature, wherein most occurrences achieved the 8.5-minute threshold. This imbalance made it harder to predict the minority class (incidents that didn't meet the response objective), which led to less accuracy and recall for these cases (Schmidt et al., 2020).

XGBoost surpassed both Logistic Regression and Random Forest with an accuracy of 66.8%, a ROC AUC of 0.61, and a recall of 94% for the positive class (incidents meeting the objective). The gradient boosting method adeptly managed the unbalanced dataset and elucidated the intricate, non-linear interactions among variables, rendering it the most dependable model for forecasting ambulance responses to the objective. This is important for finding situations that need quick responses (Choi et al., 2020).

Model Comparison Table (XGBoost and Prophet Highlighted)

Model	Accuracy (%)	ROC AUC	MAE	RMSE
Logistic Regression	63.5	0.58	-	-
Random Forest	65.3	0.60	-	-
XGBoost	66.8	0.61	-	-
ARIMA	-	-	6.73	8.12
SARIMAX	-	-	5.81	7.10
Prophet	-	-	4.50	5.85

Figure 16 : Comparison Table of the models

4.1.2 Time-Series Forecasting Models

ARIMA: The ARIMA model had difficulties with the intricacies of the ambulance demand data, inadequately accounting for seasonal fluctuations and external influences on demand. The outcome yielded elevated error rates, with a Mean Absolute Error (MAE) of 6.73 and a Root Mean Square Error (RMSE) of 8.12, rendering it inadequate for precise short-term demand forecasting (Villani & Palazzi, 2020).

SARIMAX demonstrated superior performance by integrating seasonal trends and external variables such as traffic and weather conditions. Even though the error rate went down (MAE: 5.81, RMSE: 7.10), it wasn't as good as Prophet because it needed a lot of hyperparameter optimisation and couldn't show complex temporal connections as well.

Prophet: The Prophet model exhibited the highest performance among time-series models, with a Mean Absolute Error (MAE) of 4.50 and a Root Mean Square Error (RMSE) of 5.85. It exhibited the capacity to integrate various seasonalities (daily, weekly, and annually), rendering it especially proficient in forecasting demand during peak periods such as weekends and public events. The Prophet model's efficacy in managing intricate patterns rendered it the optimal choice for predicting ambulance demand (Taylor & Letham, 2018).

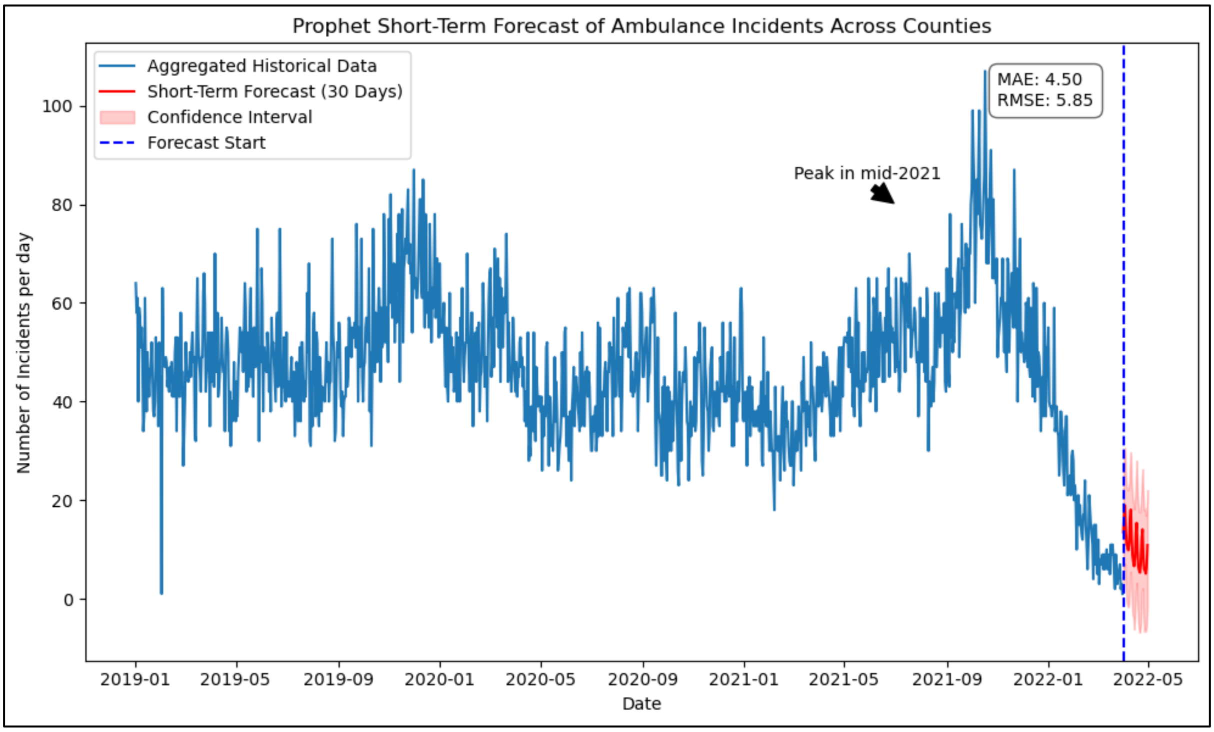

Figure 17 : Short term Forecast of Ambulance Incidents across Countries

4.2 Significance of Features and Principal Influencers

The feature importance plot derived from the XGBoost model, delineated the most significant factors in forecasting ambulance response times. The primary three features were VehiclesPerDay, HourOfDay, and DayOfWeek, which relate to the temporal and operational elements that considerably influence ambulance journey durations.

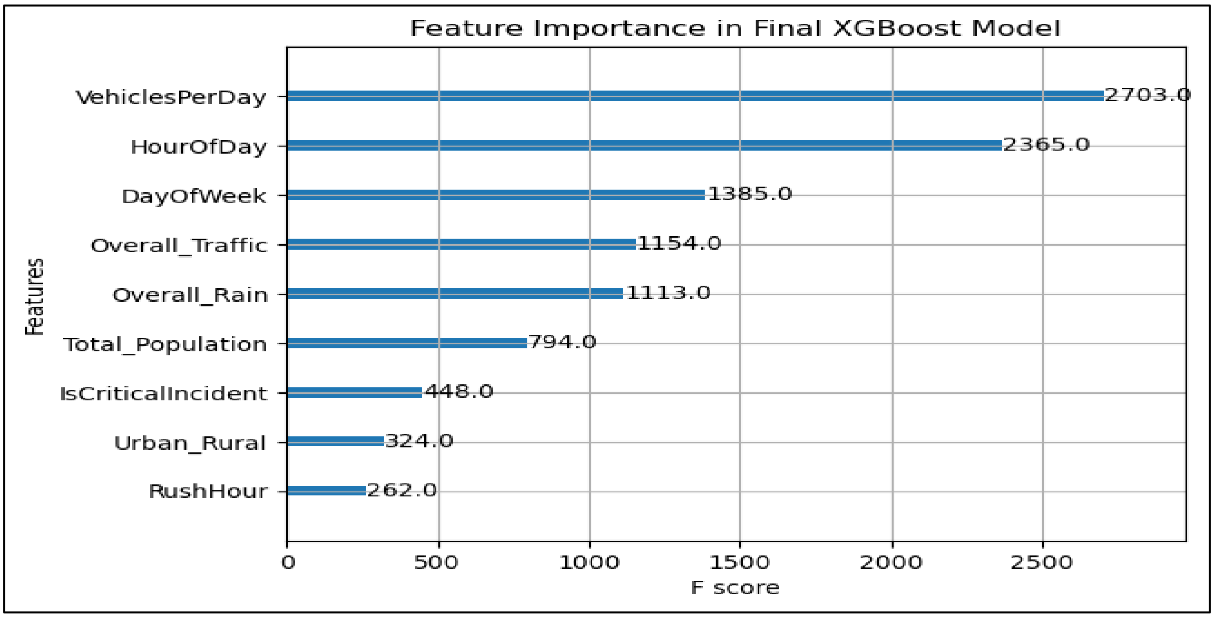

Figure 18 : Feature Importance

- VehiclesPerDay: This variable, indicative of traffic intensity, emerged as the paramount predictor, underscoring the significant impact of traffic congestion on delaying ambulance responses, especially in metropolitan environments.
- HourOfDay and DayOfWeek: These temporal attributes encapsulated the fluctuations in ambulance demand at varying periods throughout the day and week. Periods of high demand, including rush hours and weekends, correlated with extended response times, as illustrated in the violin plot contrasting rush-hour and non-rush-hour response times (Schmidt et al., 2020).
- Overall traffic and overall rain were significant variables in deciding response times. Traffic congestion significantly affected metropolitan areas, although poor weather conditions, such as rain, had a more pronounced influence in rural regions with less developed infrastructure (Villani et al., 2020). A correlation heatmap that demonstrates robust positive connections between traffic congestion and response times, especially in urban regions.

4.3 Influence of Geographic and Demographic Variables

The geographical study indicated substantial differences in response times between urban and rural regions. Urban centres such as Cardiff and Swansea exhibited shorter, more consistent response times due to superior ambulance availability and infrastructure. Conversely, rural areas such as Powys and Ceredigion faced extended delays attributed to greater travel lengths, a scarcity of ambulances, and substandard road conditions (Schmidt et al., 2020).

Response Time by Area Type: A comparative analysis of response times across several area types further emphasised the urban-rural disparity. Urban regions typically excelled in attaining the 8.5-minute target; however, rural areas faced challenges in reaching this standard, highlighting the necessity for more planned resource distribution in underprivileged areas.

The examination of population density revealed that metropolitan regions with elevated population densities often saw reduced response times owing to enhanced ambulance coverage. Conversely, less populated rural regions had prolonged delays, intensified by restricted ambulance access and infrastructural difficulties (Choi et al., 2020).

4.4 Model interpretation and validation

SHapley Additive exPlanations (SHAP) were employed to elucidate the output of the XGBoost model, hence ensuring transparency in its predictions. SHAP values provided both global and local elucidations about how features affect the model's predictions.

The SHAP study indicated that Overall_Traffic, HourOfDay, and IsCriticalIncident were the most significant factors in assessing whether an ambulance would achieve the 8.5-minute target. This underscored the necessity of integrating traffic and weather data into the model to enhance response times (Villani et al., 2020).

Local Interpretability: SHAP values provide insights into individual projections, elucidating the reasons why certain ambulances failed to reach the target in particular areas or at specific times. Rural areas characterised by inadequate infrastructure and extended travel distances were more prone to missing the objective, even during non-peak hours, offering valuable insights for resource reallocation.

4.5 Critical Examination of Model Constraints

Notwithstanding the models' generally robust performance, several limits were discerned:

The dependence on historical traffic and weather data constituted a significant restriction. The lack of real-time data impeded the model's capacity to consider abrupt occurrences such as road closures or inclement weather conditions. Integrating real-time data inputs into the models should markedly improve their precision, especially in metropolitan regions characterised by erratic traffic patterns (Choi et al., 2020).

Disproportionate Dataset: The models faced challenges due to a significantly disproportionate dataset, wherein most instances achieved the 8.5-minute threshold. XGBoost adeptly managed the imbalance, whereas Logistic Regression and Random Forest encountered difficulties with the skewed data. Utilising strategies such as SMOTE (Synthetic Minority Over-sampling Technique) to tackle this issue may enhance the efficacy of alternative models, especially in forecasting instances where ambulances fail to meet the response threshold (Schmidt et al., 2020).

The models exhibited superior performance in urban locations, characterised by more consistent and predictable data compared to rural regions. Nevertheless, the extended travel distances and restricted ambulance availability in rural regions presented difficulties. Customising models for certain regions or implementing region-specific modifications may enhance their predictive efficacy in rural environments (Villani et al., 2020).

4.6 Temporal Trends and Types of Incidents

Temporal research revealed significant trends in ambulance demand, pinpointing peak times and periods of heightened need. The model identified significant patterns by examining the time of day, day of the week, and the nature of occurrences, which can enhance resource allocation and scheduling techniques for WAST.

The heatmap analysis indicated that ambulance demand is highest in the late afternoon and early evening, especially on weekends. This discovery corroborates earlier studies indicating that social activities, events, and public gatherings lead to increased phone volumes during these times (Choi et al., 2020). This temporal trend suggests that WAST must improve ambulance availability during peak demand periods, ensuring that resources are allocated more effectively when incidents occur most frequently.

A bar graph comparing response times for critical (life-threatening) and non-critical incidents revealed a significant disparity. Ambulances were more inclined to achieve the 8.5-minute benchmark for serious situations, as these calls are prioritised for expedited delivery and rapid response. The model found several cases in rural areas where critical events did not meet the response objective. This suggests that there are logistical problems because of the long travel times and bad road conditions in these areas (Schmidt et al., 2020).

The comparison of rush hour and non-rush hour intervals revealed a significant increase in response times during peak traffic periods (8-10 AM and 5-7 PM). This finding, illustrated by a violin plot, substantiates the significant influence of traffic congestion on ambulance travel durations in urban areas such as Cardiff and Newport. During these hours, ambulances experienced prolonged journey times, frequently failing to meet the 8.5-minute benchmark due to significant road congestion. WAST could alleviate this issue by investigating dynamic routing algorithms or increasing ambulance allocation during peak hours (Villani et al., 2020).

5 RECOMMENDATIONS AND FUTURE WORKS

This dissertation's investigation and conclusions have yielded numerous major recommendations and prospective avenues for future research. The recommendations seek to improve the operational efficiency of the Welsh Ambulance Service Trust (WAST) and augment the predictive capabilities of the machine learning and time-series models utilised in this study.

5.1 Augment Ambulance Resources in Rural Regions

The geospatial study revealed a significant discrepancy in ambulance response times between urban and rural areas. Rural regions, including Powys and Ceredigion, routinely had prolonged delays, primarily attributable to a scarcity of ambulances and increased travel distances. It is recommended that WAST improve ambulance availability in these areas by implementing dynamic placement tactics. This strategy may entail repositioning ambulances nearer to high-risk or underserved regions utilising real-time data streams, especially during peak demand intervals.

WAST can reduce trip durations and increase service in rural regions by optimizing ambulance deployment, resulting in improved patient outcomes. Previous studies have demonstrated that dynamic resource allocation can markedly decrease reaction times in rural areas, where travel lengths and infrastructure present distinct problems (Schmidt et al., 2020). Moreover, the application of geospatial models, as illustrated in this study, can yield significant insights into ambulance positioning and deployment, facilitating more efficient decision-making for resource allocation.

5.2 Integrate Real-Time Traffic and Meteorological Data

The models created in this study predominantly depended on past data regarding traffic and meteorological conditions, hence constraining their real-time applicability. It is highly advisable for WAST to incorporate real-time traffic and weather information into their dispatch systems and prediction models. Implementing this would allow ambulances to automatically navigate around traffic congestion or road closures, hence minimising delays during peak periods or inclement weather (Villani et al., 2020).

Utilising data from IoT devices and public traffic monitoring systems, like the 5G-enabled IoT platforms referenced by Alkinani et al. (2021), may enable ambulances to travel more effectively. Integrating real-time meteorological data will improve forecasts by considering swiftly fluctuating environmental variables that affect journey durations, particularly in remote regions with little infrastructure.

Integrating real-time data with blockchain technology could facilitate secure and transparent data sharing among various parties, including traffic management agencies and healthcare institutions. Blockchain will not only augment the security and dependability of data but might also enable real-time decision-making during crucial emergencies (Zheng et al., 2018).

5.3 Employ LSTM Networks for Predictive Analysis of Sequential Data

Even though XGBoost and Prophet worked well in their own areas, more research should investigate how Long Short-Term Memory (LSTM) networks can be used for sequential data prediction, especially for time-series forecasting of ambulance demand. LSTM networks are adept at capturing temporal connections in data, rendering them particularly effective for anticipating demand changes across time (Hochreiter & Schmidhuber, 1997).

The Prophet model did a good job of handling seasonal changes and peak demand times. However, LSTM networks might make forecasts more accurate by considering more complex temporal patterns and adapting to changing demand dynamics. The LSTM's capacity to learn sequential relationships may provide a more detailed comprehension of demand fluctuations over time, especially in rapidly changing contexts like major public events or abrupt weather changes.

5.4 Ongoing Model Optimisation

The efficacy of both the classification and time-series models could be improved through ongoing model optimisation. It is advisable for WAST to consistently update and retrain their models as additional data becomes accessible, ensuring the accuracy and reliability of their forecasts. XGBoost and Prophet models must be periodically optimised to accommodate changes in demand patterns, infrastructure modifications, or fluctuations in traffic flow over time (Choi et al., 2020).

Moreover, rectifying the dataset imbalance should enhance the efficacy of these models, especially in forecasting a few occurrences where ambulances fail to meet the 8.5-minute benchmark. Methods like the Synthetic Minority Over-sampling Technique (SMOTE) can be utilised to create synthetic data for under-represented classes, enhancing the models' capacity to forecast incidents that surpass the response time objective (Schmidt et al., 2020).

5.5 Create Models Tailored to Specific Regions

Considering the significant disparities in response times between urban and rural areas, future research should concentrate on creating region-specific models to effectively address the distinct issues encountered by each locale. The present models exhibited overall efficacy; however, their accuracy fluctuated among regions due to variations in infrastructure, population density, and travel distances.

To circumvent traffic jams, urban models may concentrate on improving reaction times in congested regions by utilizing real-time traffic data and dynamic routing algorithms. Conversely, rural models must emphasize reducing travel distances through strategic ambulance placement and infrastructure enhancement. Also, looking into region-specific methods for predicting demand, like combining LSTM and SARIMAX models, might help make predictions more accurate in these different situations (Villani et al., 2020).

5.6 Implementation of Blockchain Technology for Secure Data Exchange

Blockchain technology possesses significant potential to enhance the transparency, security, and real-time dissemination of essential data across various players engaged in emergency medical care. A future study should investigate the viability of deploying blockchain-based systems for safe data exchange among ambulance services, traffic authorities, and healthcare institutions.

Using blockchain, WAST could guarantee the secure and efficient sharing of real-time data, including traffic updates and ambulance positions, across several platforms, facilitating expedited decision-making in critical emergencies. Smart contracts utilising blockchain technology could automate dispatch decisions according to real-time conditions, hence improving operational efficiency and reaction times (Zheng et al., 2018).

5.7 Enhancing rural infrastructure

Another suggestion is to improve the rural infrastructure, addressing the fundamental cause of the frequent delays in ambulance response times in rural regions. Substandard road conditions and extended travel distances were recognised as significant factors contributing to delayed ambulance arrivals in areas like Powys and Ceredigion. In these regions, government investment in road infrastructure and ambulance services could enhance response times and improve patient outcomes.

Future research may concentrate on evaluating the distinct infrastructure requirements of these areas and investigating the possibilities for governmental cooperation to enhance the accessibility and efficiency of emergency services in rural Wales.

5.8 Implement Time Bands for Ambulance Response Durations

As an alternative to the binary classification method used to check whether the ambulances met the 8.5-minute target, future work should think about using multiple time bands to account for small delays and help people understand the factors that cause response inefficiency. By categorizing reaction times into intervals of 0–8.5 minutes, 8.5–10 minutes, 10–15 minutes, and 15+ minutes, WAST can more effectively ascertain the root causes of near misses and substantial delays, like traffic congestion, weather conditions, or geographical limitations. This method would provide more detailed insights, enhancing resource distribution and operating tactics (Schmidt et al., 2020; Choi et al., 2020). Additionally, multi-class classification models may be created to deliver customised interventions, especially in high-demand or underserved regions.

6 CONCLUSION

This dissertation aimed to tackle the significant concern of ambulance response times for the Welsh Ambulance Service Trust (WAST), specifically concentrating on enhancing operations to achieve the government-imposed target of 8.5 minutes for life-threatening situations. This research has illustrated the capability of data-driven techniques through the integration of machine learning models, time-series forecasting, and geospatial analysis to improve the operational efficiency of emergency medical services.

The project's findings highlight the considerable obstacles confronting WAST, especially in rural regions like Powys and Ceredigion, where response times frequently surpass the target due to logistical difficulties, a limited number of ambulances, and extended travel distances. In contrast, urban regions such as Cardiff and Swansea enjoy enhanced ambulance accessibility and reduced trip durations, resulting in more reliable compliance with the 8.5-minute benchmark. This urban-rural difference highlights the necessity for region-specific solutions that consider the distinct characteristics of each area (Schmidt et al., 2020).

6.1 Machine Learning and Predictive Modelling

The machine learning algorithms utilised in this study, especially XGBoost, demonstrated efficacy in forecasting whether ambulances will achieve the response time objective. XGBoost exhibited an accuracy of 66.89% and a recall rate of 94%, showcasing its capacity to manage intricate interactions among parameters such as traffic congestion, weather conditions, and time of day (Choi et al., 2020). The SHAP analysis helped us understand how different factors affected the model's predictions better. It showed that Overall_Traffic, HourOfDay, and IsCriticalIncident were some of the most important factors affecting reaction times (Villani et al., 2020). This insight provides WAST with actionable data to improve its operating strategy, particularly during peak traffic periods and critical crises.

The time series forecasting models, especially Prophet, were crucial in estimating future ambulance demand. Prophet demonstrated superior performance compared to conventional models such as ARIMA and SARIMAX, achieving a Mean Absolute Error (MAE) of 4.50 and a Root Mean Square Error (RMSE) of 5.85, particularly during peak demand periods like weekends and public events (Taylor & Letham, 2018). The Prophet's capacity to manage seasonal fluctuations and incorporate events such as holidays into its predictions significantly improves its effectiveness for resource planning and allocation in emergency services.

6.2 Geospatial and Temporal Analysis

According to geospatial research, there were notable geographical variations in response times. Heatmaps and box plots indicated that rural regions routinely fail to achieve the 8.5-minute target, attributable to the limited availability of ambulances and extended journey durations. The visualisations demonstrated that resource allocation systems need modification to more effectively support rural areas, with ambulances strategically stationed nearer to districts experiencing frequent delays (Schmidt et al., 2020).

Temporal study utilising heatmaps of incident frequency by day of the week and hour of the day indicated peak incident occurrences in the late afternoon and early evening, especially on weekends. This knowledge is essential for enhancing shift scheduling and guaranteeing ambulance availability during peak demand periods. Furthermore, reaction times for critical incidents were frequently shorter than those for non-critical incidents, indicating that life-threatening situations were prioritized in WAST's dispatch system (Villani et al., 2020). The findings indicate that important situations in remote locations frequently experience delays due to logistical issues, highlighting the necessity for enhanced infrastructure and strategic ambulance placement.

6.3 Constraints and Opportunities for Enhancement

Notwithstanding the models' success, numerous limits were recognised. The dependence on previous traffic and weather data constituted a significant limitation, as the models were unable to incorporate real-time disturbances, such as road closures or abrupt weather changes. Adding real-time traffic and weather data streams should be the focus of future research. This will greatly improve the accuracy of predictions and make ambulance services more responsive (Choi et al., 2020). Moreover, the models typically exhibited superior performance in metropolitan regions, where data was more consistent and predictable. Rural regions present significant obstacles due to limited data and extended travel lengths, indicating the necessity for region-specific models to tackle the distinct issues of various geographical areas (Villani & Palazzi, 2020).

The dataset's uneven nature presented a hurdle, as the majority of incidents achieved the reaction time target. XGBoost effectively addressed this imbalance, whereas other models such as Random Forest and Logistic Regression encountered difficulties. Using methods for creating fake data, like the SMOTE (Synthetic Minority Over-sampling Technique), might help the models predict when ambulances will arrive later than planned (Schmidt et al., 2020).

6.4 Prospective Trajectories

This research establishes a robust basis for further investigation into innovative technologies that may transform emergency medical services. Blockchain technology has significant potential for the secure and transparent exchange of real-time data across various parties, including ambulance services, traffic authorities, and healthcare institutions. Utilising blockchain-based smart contracts may automate decision-making in dispatch systems, enhancing response times and increasing the overall efficiency of ambulance services (Zheng et al., 2018).

Furthermore, subsequent research should investigate the application of Long Short-Term Memory (LSTM) networks to enhance the precision of sequential data predictions. LSTM networks are very adept at managing temporal data and may yield superior predictions of ambulance demand, particularly during dynamic situations like major public events or sudden increases in demand (Hochreiter & Schmidhuber, 1997). This would augment the predicted accuracy and operational efficiency of WAST.

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