Machine Learning-Based Forecasting of Ambulance Arrivals: Insights for Shift-Based ED Resource Allocation

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Abstract

Understanding the specific timings of ambulance arrivals during different shifts presents unique opportunities for emergency department (ED) throughput optimization. This research aims to determine whether there are significant differences in ambulance arrivals across various periods (i.e., morning, afternoon, evening, and night) and to use machine learning to forecast daily emergency medical service (EMS) arrivals. We performed a cohort study of patients presenting to an urban, academic ED between January 1, 2021 and April 18, 2022. Data comprised daily patient arrivals, demographic information, mode of arrival (either by walk-in or ambulance), chief complaints, and ED disposition, focusing exclusively on patients who arrived via ambulance. A Light Gradient Boosting Machine (LGBM) model was developed to forecast daily EMS arrivals based on different periods. The findings indicate distinct ambulance arrival patterns, with higher patient influx during the night shift. The LGBM model achieved moderate to high accuracy, particularly during the evening and night periods, with mean absolute percentage errors of approximately 21% and 19%, respectively. This study provides insights into ambulance arrival patterns, emphasizing the need for specialized care across different periods. These findings can inform the development of decision support systems that leverage advanced analytics to optimize resource allocation, enhance preparedness, and improve patient outcomes in EDs and health systems.

Keywords
Ambulance, Emergency Department, Machine Learning, Forecasting, Emergency Medical Services

Introduction

The provision of immediate medical care to patients with acute illnesses or injuries is a critical function of the emergency department (ED) and emergency medical services (EMS). In the US, over 132 million people visited EDs in 2020, with approximately 20% arriving via ambulance (National Center for Health Statistics). While each 911 call and EMS arrival to the ED is considered an independent event, the cumulative data reveals potential patterns that can be forecasted. Accurate forecasting of ED patient arrivals, especially ambulance arrivals, plays a crucial role in effective resource allocation and delivering prompt, high-quality patient care (Mohammad 2008; Crilly et al. 2022). However, despite the importance of forecasting in healthcare, there are still challenges and gaps in our understanding of ambulance arrivals and their variations across different periods or shifts.

In recent years, a growing focus in the literature has been on forecasting patient arrivals in the ED, prompting researchers to investigate different methods and techniques to enhance accuracy (Jones et al. 2008; McCarthy et al. 2008; Bergs et al. 2014; Zhang et al. 2019). However, most of these efforts have predominantly concentrated on predicting overall ED patient volumes (Jones et al. 2008; McCarthy et al. 2008; Boyle et al. 2008; Kam et al. 2010; Zhang 2019; Choudhury 2019), rather than fully incorporating the specific subset of EMS traffic (Au-Yeung et al. 2008; Xu et al. 2011). Ambulance arrivals present unique challenges due to their critical acuity and the potential need for timely and specialized medical and surgical care. Therefore, understanding the patterns and variations in ambulance arrivals throughout the day is crucial for allocating healthcare resources effectively and ensuring optimal patient outcomes.

While previous research has made progress in ED and EMS forecasting (Ataman et al. 2022; Hu et al. 2023), several challenges persist. One challenge is the complex nature of emergency healthcare, where patient arrivals are influenced by many factors, including seasonal variations, weather conditions, socioeconomic factors, and other external factors (Jones et al. 2008; Whitt and Zhang 2019; Etu et al. 2022). These factors contribute to the dynamic nature of patient flows in the ED, making accurate forecasting a daunting task. Moreover, existing studies often overlook the variations in ambulance arrivals across different periods or shifts, which limits our understanding of how resources should be allocated throughout the day to meet the fluctuating demand most effectively. This study aims to address these challenges and contribute to the existing literature by investigating the significance of ambulance arrivals across different times of the day and shifts. We aim to develop a tailored forecasting model focused on EMS demand by analyzing historical ED and EMS volume data and applying advanced machine-learning techniques. The proposed model will consider historical trends and factors such as time of day and day of the week to provide accurate predictions of expected EMS traffic.

2. Methods

2.1 Study Design, Setting, and Participant Selection

We conducted a cohort study that examined patients visiting an urban, academic ED that cares for a predominantly Black patient population in Detroit, Michigan, from January 1, 2021, to April 18, 2022. The data extracted from the hospital's electronic health records comprised daily ED patient arrival and departure times, demographic information (e.g., age and race), mode of arrival (either by walk-in or ambulance), chief complaints (i.e., the reason for patient visits), primary diagnosis, and ED disposition. Additionally, we collected each patient's emergency severity index (ESI) scores, which indicate the severity of their illness at the time of presentation. ESI scores range from 1, representing the highest severity, to 5, indicating the lowest severity. Only ED patients that arrived by ambulance were included in the final analytic cohort. The Henry Ford Hospital Institutional Review Board approved the study before data collection, with a waiver of informed consent.

2.2 Data Pre-processing and Summary

We cleaned and pre-processed the data to remove unwanted columns and missing data. Working with healthcare professionals (i.e., clinicians), we grouped the ambulance arrivals based on the following time intervals (a) Morning: 06:00 to 11:59, (b) Afternoon: 12:00 to 15:59, (c) Evening: 16:00 to 19:59, and (d) Night: 20:00 to 5:59. The rationale behind these time interval groupings is to capture variations in patient needs, staff workload, and resource availability, which can differ significantly throughout the day and night. This classification allows for a more nuanced understanding of how emergency healthcare services are utilized and can help identify areas for improvement in resource allocation and patient care. We performed descriptive statistics to provide a comprehensive data summary and employed time series plots to visualize the ambulance arrivals for each time interval group. This visualization allowed for effective comparison and identification of trends across these periods.

2.3 Statistical and Machine Learning Analysis

We conducted a Shapiro-Wilk normality test and subsequently performed an analysis of variance (ANOVA) to determine whether there are significant differences in ambulance arrivals among the different periods. We developed a Light Gradient Boosting Machine (LGBM) model to forecast daily EMS arrivals based on the four time periods (i.e., morning, afternoon, evening, and night). The LGBM model is a variant of the gradient boosting framework developed by Microsoft Research Asia in 2017. LGBM utilizes tree-based learning algorithms for ranking, classification, time series analysis, and other machine-learning modeling tasks. Specifically, it utilizes a leaf-wise growth approach and balances accuracy and speed through a random sampling technique (Effrosynidis et al. 2023). The model has many benefits, such as a fast-training speed, computationally efficient, and can deliver high accuracy in time series forecasting (Cerna et al. 2021; Cui et al. 2021). To account for potential temporal dependencies and seasonality, we incorporated lagged variables and other time-related features as predictors in the model. The data was split into training (80%), and testing (20%) sets to develop and evaluate the model's performance. During the model training process, we employed a 10-fold cross-validation technique to enable a more robust assessment of the LGBM model's performance by minimizing potential biases and variances in the dataset. Also, we fine-tuned the model using a grid search approach for hyperparameter optimization to ensure the best possible performance. Finally, the model's performance for each period was evaluated using metrics such as mean absolute percentage error (MAPE) and root mean square error (RMSE). Smaller MAPE and RMSE values indicate more accurate forecasting (Etu et al. 2022).

3. Results

During the study period, 104,306 patients arrived at the ED, of which 63.14% (65,864) arrived by walk-ins and 26.27% (27,402) via ambulance. Table 1 summarizes the demographic and clinical characteristics of EMS and walk-in patients.

Table 1. Demographic and clinical characteristics of EMS and walk-in patients to the ED

Variable	EMS Arrivals (n = 27,402)	Walk-ins (n = 65,864)
Age, average (SD), years	53.07 ± 18.84	46.95 ± 18.27
Gender		
Male	14,529 (53.02%)	31,368 (47.63%)
Female	12,836 (46.84%)	34,489 (52.36%)
Unknown	37 (0.14%)	7 (0.01%)
Race		
Black/African American	19,256 (70.27%)	47,993 (72.87%)
Asian	166 (0.61%)	548 (0.83%)
White	5,278 (19.26%)	9,695 (14.72%)
Hispanic	104 (0.38%)	361 (0.55%)
Others	1,449 (5.29%)	4,984 (7.57%)
Decline/Do not know	1,149 (4.19%)	2,283 (3.47%)
Emergency severity index		
1: Immediate life-threatening condition	3,441 (12.56)	1,307 (1.98%)
2: High-risk condition	15,951 (58.21%)	33,012 (50.12%)
3: Urgent condition	6,954 (25.38%)	29,137 (44.24%)
4: Less urgent condition	327 (1.19%)	1,761 (2.67%)
5: Non-urgent condition	33 (0.12%)	120 (0.18%)
ED length of stay, average in hours	12.67	9.77
ED disposition		
Admitted	8,654 (31.58%)	11,588 (17.59%)
Discharged	12,466 (45.49%)	43,364 (65.84%)
Left without being seen	1,649 (6.02%)	3,406 (5.17%)
Died	216 (0.79%)	42 (0.06%)

SD: Standard deviation; ED: Emergency department

The average age of EMS patients was 53.07 years, with a standard deviation (SD) of 18.84 years. 46.84% (12,836) of patients were female, and 70.27% (19,256) identified as Black. The average ED length of stay for EMS patients was 12.67 hours. Less than half of the patients, approximately 41.0%, used Medicaid HMO as their insurance provider. The four most common reasons (i.e., patient chief complaints) for ambulance transport to the ED were shortness of breath (7.90%), abdominal pain (6.93%), fall (4.13%), and chest pain (3.62%). Figure 1 illustrates the ambulance arrival patterns for morning, afternoon, evening, and night shifts during the study period. The average daily arrivals show distinct patterns, with 11.33 (SD 3.98) patients arriving in the morning, 12.16 (SD 4.31) in the afternoon, and 12.48 (SD 4.37) in the evening. Notably, the night shift experiences a higher influx of patients, averaging 21.96 (SD 6.50) daily ambulance arrivals.

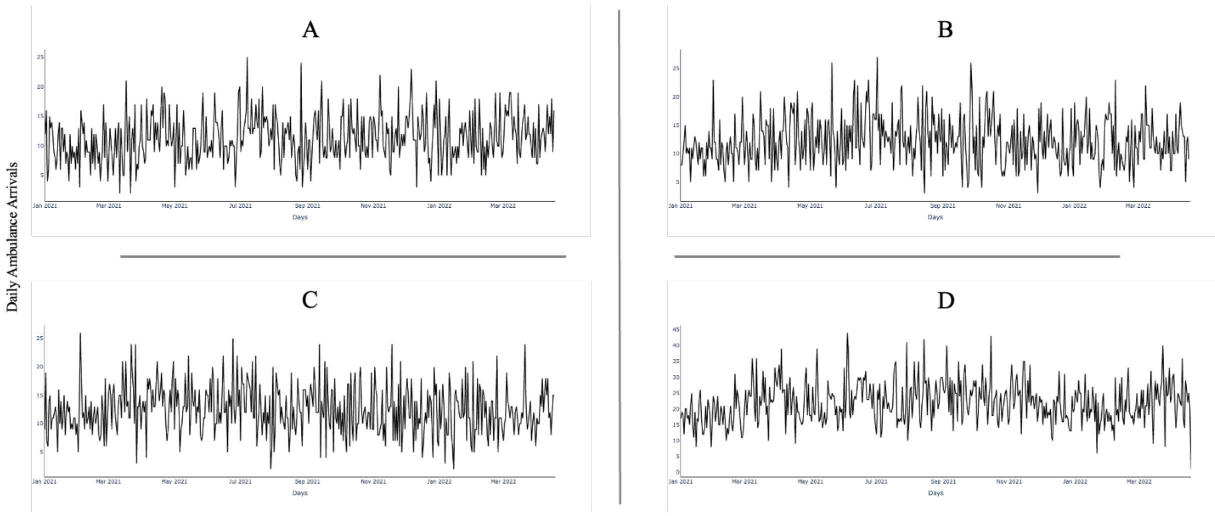

Figure 1. Daily ambulance arrival patterns – (a) morning, (b) afternoon, (c) evening, and (d) night shifts for January 1, 2021 to April 18, 2022.

A non-parametric Kruskal-Wallis test was used since the EMS arrival data does not follow a normal distribution. The results indicate a statistically significant difference in ambulance arrivals across the periods ($\chi^2 = 717.4$, $p < 0.001$). Based on the pairwise comparison results adjusted using the Bonferroni method, we observed statistically significant differences in ambulance arrivals between the following periods: morning and afternoon (11.33 vs. 12.16, $p = 0.042$), morning and evening (11.33 vs. 12.48, $p < 0.001$), morning and night (11.33 vs. 21.96, $p < 0.001$), afternoon and night (12.16 vs. 21.96, $p < 0.001$), and evening and night (12.48 vs. 21.96, $p < 0.001$). However, no significant difference was found between the afternoon and evening periods ($p > 0.05$).

Figure 2 shows the observed and predicted daily ambulance arrivals for different periods. In the morning period (Figure 2a), the LGBM model has a MAPE of 33.86%, which means that, on average, the predictions are off by about 34% from the actual number of patient arrivals. The RMSE for the morning period is 4 patients, reflecting an average deviation of 4 patients in the model's predictions. For the afternoon period (Figure 2b), the model achieves a slightly lower MAPE of 30.15%, suggesting that the predictions are off by 30% from the actual ambulance arrivals. With an RMSE of 4 patients, the afternoon period shows a similar level of deviation as the morning period. The model performs better in the evening (Figure 2c), with a reduced MAPE of 21.16% and an RMSE of 4 patients, which implies that the predictions for the evening period are more accurate compared to the morning and afternoon, with the predictions deviating from the actual values by an average of 4 patients. Lastly, for the night period (Figure 2d), the model achieves the lowest MAPE of 18.53%, meaning that the predictions are the most accurate in this period, with an average error rate of 19%. However, the RMSE for the night period is 5 patients, which is higher than the other periods, suggesting that the model's predictions are more accurate on average; there might be a few instances where the deviations from the actual values are larger.

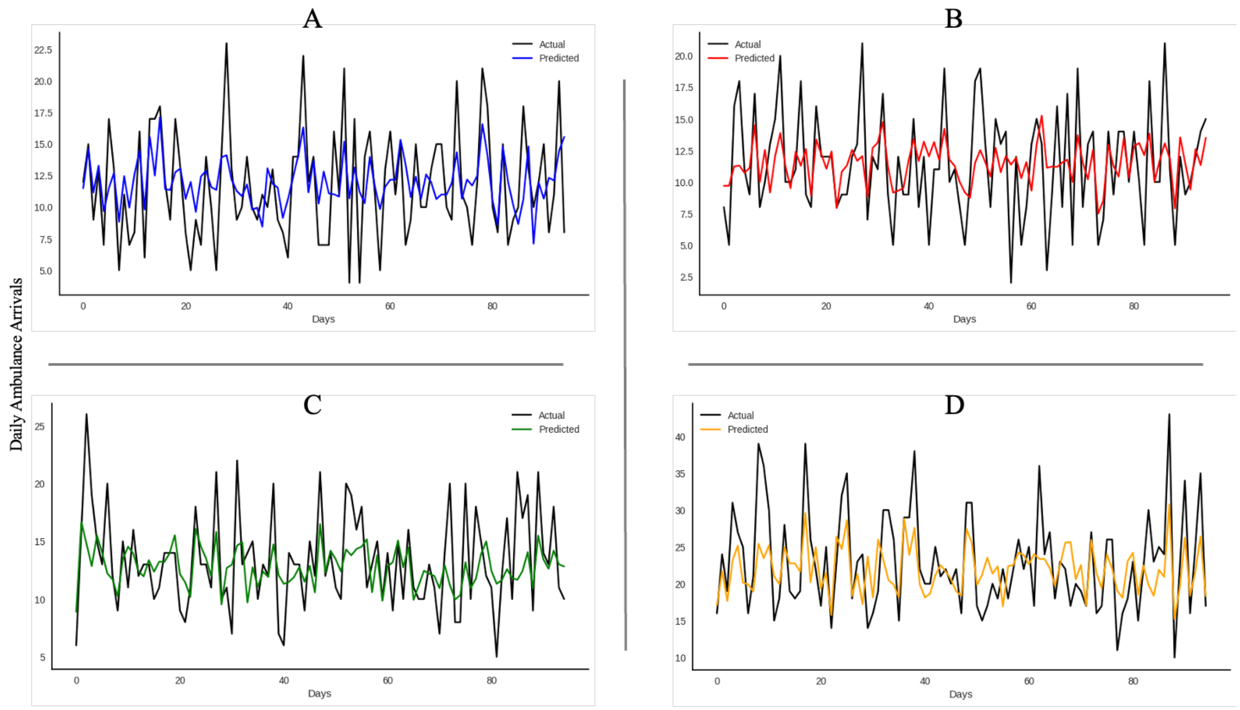

Figure 2. Observed and predicted daily ambulance arrivals for (a) morning, (b) afternoon, (c) evening, and (d) night shifts. The test data is from January 14, 2022 to April 18, 2022.

4. Discussion

The key findings from this study are promising and provide valuable insights into ambulance arrival patterns across different periods or shifts in an urban, academic ED. Analyzing historical data and applying machine learning techniques allowed us to develop a forecasting model tailored to EMS demand. Our results show that ambulance arrivals exhibit distinct patterns throughout the day, with a higher influx of patients at this tertiary trauma center during the night shift. Additionally, our model demonstrated moderate to high accuracy in predicting ambulance arrivals for different periods, with the evening and night periods showing the most accurate forecasts.

These findings have significant implications for ED and hospital resource allocation, preparedness, and throughput, ultimately impacting patient outcomes and quality of care. Accurate forecasting of ambulance arrivals for different periods allows healthcare administrators and emergency responders to allocate resources more effectively. For example, by knowing the expected influx of ambulance patients during specific shifts, hospitals can ensure adequate staff, equipment, and specialized medical and surgical on-call care are available when needed. This proactive resource allocation enhances preparedness and response to acute emergencies, leading to improved patient outcomes.

The importance of accurate forecasting in managing patient flow and reducing overcrowding in EDs has been demonstrated in previous literature. For instance, studies have shown that when hospitals employ forecasting models to anticipate patient arrivals, they can better optimize bed utilization and decrease wait times for medical and surgical specialty teams (Shah et al. 2021; Ordu et al. 2021). Hospitals can proactively coordinate with these specialty teams by accurately predicting ambulance arrivals, ensuring that patients receive timely and appropriate care. This coordinated approach streamlines the patient's journey through the healthcare system, minimizing delays and improving overall efficiency and throughput in the ED.

Understanding the specific timings of EMS arrivals during different shifts presents unique opportunities for optimizing throughput in the ED. Healthcare teams can gather valuable data that informs throughput and utilization strategies by overlaying EMS traffic patterns with overall ED volume patterns. This granular understanding is crucial, considering that EMS patients often have higher ED ESI scores and critical care resource needs. For instance, hospitals can implement targeted measures by knowing that EMS arrivals peak during overnight shifts when ED staffing and specialty medical and surgical teams may not be fully staffed. These measures could involve adjusting staffing levels during those periods, ensuring the availability of specialized care resources, and optimizing the allocation of critical care beds. By proactively addressing these shift-specific challenges, hospitals can mitigate vulnerabilities, enhance patient safety, and improve the overall efficiency of emergency care delivery.

The study findings also highlight important characteristics and considerations related to EMS patients in the ED, offering insights that can inform improvements in care delivery and resource allocation. Notably, EMS patients exhibited high acuity levels, as evidenced by approximately 58% receiving an ESI acuity score of 2 and 13% with an ESI score of 1. It is crucial to recognize that the healthcare resource needs for ESI level 1 or 2 patients are dramatically greater than those of ESI 3, 4, and 5 patients. Additionally, the study revealed a 32% admission rate among EMS patients and an ED length of stay of nearly 13 hours. Like ESI, increased ED and inpatient hospital needs are required for admitted versus discharged patients, underscoring the importance of optimizing bed capacity and staffing to effectively manage their care requirements. Among the top complaints reported by EMS patients were dyspnea (i.e., shortness of breath), abdominal pain, falls, and chest pain, which provide valuable information for targeted interventions and preparedness planning. For instance, the identification and awareness that dyspnea accounts for 7% of EMS visits can guide the allocation of resources such as non-invasive and invasive positive pressure ventilators and the availability of respiratory therapists during surge periods. These findings emphasize the opportunity for tailored approaches and proactive measures to optimize outcomes and enhance the overall efficiency of ED operations when managing EMS patients.

Our study's methodology and machine learning approach provide a solid foundation for accurate ambulance arrival forecasting. The use of advanced machine learning techniques, specifically the LGBM model, allowed us to leverage historical data and incorporate relevant factors such as time of day and day of the week into the forecasting model. The LGBM model, known for its fast-training speed and high accuracy in time series forecasting, demonstrated its effectiveness in predicting ambulance arrivals for different periods. By incorporating lagged variables and time-related features, we accounted for potential temporal dependencies and seasonality, further enhancing the model's performance and robustness. Despite the strengths of our study, there are limitations to consider. First, our analysis focused on a single urban, academic ED with a predominantly Black patient population, which may limit the generalizability of our findings to other settings and patient populations. Additionally, while our model demonstrated moderate to high accuracy, there is still room for improvement, as reflected in the RMSE values. External factors beyond the scope of our study, such as major public events or community outbreaks, could influence ambulance arrivals and were not accounted for in our model. Furthermore, the retrospective nature of our study limits our ability to establish causality and fully capture the complexity of emergency healthcare dynamics.

This study serves as foundational work for future models and opportunities to create forecasting and analytic approaches that aid healthcare, specifically ED teams. The accurate forecasting of ambulance arrivals and the effective allocation of resources is crucial for improving emergency care delivery. Our study provides insights into the patterns and variations of ambulance arrivals, emphasizing the need for specialized care during different periods. These findings can inform the development of more sophisticated predictive models and decision support systems that leverage advanced analytics to optimize resource allocation, enhance preparedness, and improve patient outcomes in EDs and health systems.

5. Conclusion

This research successfully achieves its objectives of identifying significant differences in ambulance arrivals across various periods and employing machine learning to forecast daily EMS arrivals. Our data, collected from an urban, academic ED, revealed distinct patterns in ambulance arrivals, with the most significant patient influx occurring during the night shift. Furthermore, there were significant differences in arrival times between morning and afternoon, morning and evening, morning and night, afternoon and night, and evening and night periods. Interestingly, no substantial difference was found between the afternoon and evening periods. The developed LGBM model displayed moderate to high accuracy, especially during the evening and night periods, with 21% and 19% MAPE, respectively. The unique contribution of this study lies in its comprehensive examination of ambulance arrival patterns and the application of machine learning to forecast daily EMS arrivals. It underscores the necessity for specialized care across different periods and the potential benefits of predictive models in ED management. In conclusion, understanding and predicting ambulance arrival patterns can have significant implications for the efficient management of EDs, which may ultimately lead to more effective patient care and improved health outcomes. This research provides a firm foundation for future studies to refine forecasting models and further explore the implications of ambulance arrival patterns on emergency care.

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