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(RESEARCH ARTICLE)

Spatiotemporal Analysis and Predictive Modeling of Traffic Accidents in Boston: Insights for Advancing Vision Zero Initiatives

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Abstract

This study examined the spatial, temporal, and predictive dimensions of traffic crashes in Somerville, Massachusetts, to contribute to the evidence base for Vision Zero initiatives. Using crash data, spatial autocorrelation analysis, temporal distribution assessments, and machine learning models, the research identified patterns and predictors of crash severity. Spatial analysis revealed significant clustering of crashes, particularly around intersections and arterial corridors, underscoring the structural vulnerabilities of the urban road network. Temporal analysis demonstrated that crashes peaked during midday and afternoon hours, with seasonal spikes in January, September, and December, reflecting the combined influence of commuting cycles, weather conditions, and increased travel activity. Predictive modeling using logistic regression, random forest, and gradient boosting highlighted the challenges of forecasting severe crashes in imbalanced datasets. While gradient boosting achieved high accuracy (0.885) and precision (0.959), its ROC-AUC score of 0.50 indicated poor discriminatory power, revealing a bias toward the majority class. The confusion matrix further confirmed that severe crashes were frequently misclassified as non-severe, limiting the model's utility for proactive safety interventions. Nonetheless, feature importance analysis identified time of day, intersection type, and pedestrian involvement as key predictors of crash severity, reinforcing the systemic interplay of temporal, infrastructural, and behavioural factors. The implications extend to Vision Zero frameworks, suggesting that traffic safety outcomes are embedded within discernible patterns that can be studied and anticipated. This study underscores the value of spatiotemporal and predictive analyses in advancing the understanding of urban traffic safety and informing long-term strategies to eliminate severe crashes.

Keywords: Traffic Safety; Somerville; Crash Severity; Spatial Analysis; Temporal Patterns; Machine Learning; Vision Zero

1. Introduction

In many metropolitan locations around the world, traffic accidents have become one of the most enduring dangers to sustainable urban growth and public safety. According to Ahmed et al. (2023), traffic accidents are more than just isolated incidents; they are a public health crisis that takes over a million lives each year and costs billions of dollars in lost wages and psychological suffering. With more than one-third of pedestrian fatalities in Massachusetts occurring among individuals 65 and older, pedestrian-related traffic fatalities highlight the disproportionate burden placed on vulnerable road users. Additionally, regulating road safety is becoming more difficult in places like Boston, which are

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well-known for their numerous transit options, intricate street networks, and dense populations (Naumann, 2025). Although the city has experienced an average of more serious or fatal collisions annually since 2015, a slight downward trend suggests that targeted interventions may be effective (Haileyesus, 2025). The Massachusetts Department of Transportation (MassDOT) reports that the Boston metropolitan region has thousands of traffic collisions every year, which lead to a considerable number of fatalities, serious injuries, and financial losses (Gooch et al., 2024). A concerning trend that jeopardizes the city's efforts to encourage safe mobility is the roughly 1,000 people who were killed or gravely injured in traffic accidents in the Boston area annually between 2018 and 2022 (Albert & Pandey, 2022).

The 2023 Action Plan's Vision Zero Boston engages with a "Safe Systems" concept, which acknowledges that human error is unavoidable and builds streets to accommodate it with protected bike lanes, speed bumps, and equity-focused redesigns. There has been progress: the number of pedestrian injury collisions has decreased by 50%, the number of bike injuries has decreased by 40%, and the number of deaths has stabilized around 10-15 per year, compared to the pre-2016 high of 15-20 (Barichella, 2023). However, difficulties still exist. Driver injuries have decreased by just 7%, and inequalities still exist in non-White communities, where elderly individuals are at higher risk, with four-lane thoroughfares like Washington Street being recurring danger zones. From broad-brush policies to pinpoint attacks against crash-prone temporal and spatial fissures, sophisticated analytics become essential in this situation (Green & Nace, 2024). Boston responded by enacting the Vision Zero Initiative, which aims to eradicate fatalities and severe injuries caused by traffic by 2030. However, achieving this lofty objective necessitates more than just reworking infrastructure and enforcing existing laws; it also requires sophisticated analytical techniques that can recognize patterns of risk in space and time and predict possible future occurrences (Wong, 2025).

According to Choudhary et al. (2025), spatiotemporal analysis has emerged as a fundamental component of contemporary traffic safety research due to its ability to examine the geographical and temporal dimensions of collision data concurrently. Roadway features, population density, traffic volume, weather, and behavioural variables like speeding and distracted driving all have an impact on Boston's accident patterns, which are by no means random (Nippani et al., 2023). The spatial concentration of dangers is shown by recent Vision Zero studies that show junctions accounted for 44% of serious or fatal incidents in Boston between 2018 and 2022 (Tamakloe et al., 2025). According to temporal analysis, accidents occur more frequently on weekends and during nighttime rush hours, and they frequently get worse in bad weather and low light levels (Adeyemi et al., 2021). Nonetheless, according to Alsahfi (2024), these trends highlight the significance of prompt responses, such as dynamic enforcement strategies and adaptive traffic control systems.

Moreover, temporal decomposition and time-series models assist in revealing seasonal or cyclical variations in accident frequencies. At the same time, spatial clustering techniques like Kernel Density Estimation (KDE) and spatial autocorrelation analyses have been extensively employed to locate accident "hotspots" (Le et al., 2022). According to Younes & Oloufa (2025), combining these approaches can help researchers comprehend how accident hotspots vary over time, how changes in the environment or infrastructure impact collision patterns, and where new dangers are most likely to arise. For example, despite safety measures, junctions along key arterial roads like Massachusetts Avenue, Commonwealth Avenue, and Dorchester Avenue in Boston have often been shown on high-crash maps since 2015 (Barichella, 2023). The necessity for spatiotemporal modeling frameworks that can capture dynamic risk evolution instead of static patterns is highlighted by the persistence of such clusters.

Predictive modeling has the ability for foresight, anticipating when and where accidents are most likely to occur, whereas spatiotemporal analysis delivers descriptive insights. In order to produce probabilistic predictions of collision incidence, predictive models make use of historical crash data as well as a variety of explanatory variables, including traffic volume, road geometry, weather, and land use characteristics. When compared to conventional statistical models, machine learning algorithms, especially those that incorporate spatial and temporal features, have shown greater predicted accuracy (Nikparvar & Thill, 2021). For instance, traffic collisions in intricate road networks have been effectively modeled using Graph Neural Networks (GNNs) and Long Short-Term Memory (LSTM) networks, which capture both temporal correlations and spatial dependencies (Liu & Sharma, 2018). Likewise, zero-inflated Poisson and Tweedie models have demonstrated efficacy in addressing the excess-dispersion and zero-inflation problems prevalent in collision data, wherein several sites do not encounter any accidents during a specified duration (Rebentisch, 2018).

Nevertheless, according to Alsahfi (2024), combining predictive modeling with spatiotemporal analysis signifies a paradigm change in our knowledge of and approach to reducing traffic accidents. The Vision Zero philosophy, which recognizes that traffic fatalities are preventable but human error is unavoidable, is entirely consistent with this strategy. Additionally, Liu & Sharma (2018) pointed out that cities like Boston may transition from reactive safety measures to proactive, data-driven interventions by utilizing data science, spatial statistics, and machine learning. The use of these analytical techniques offers not only a solid scientific basis but also a promising route to a genuinely safe and sustainable urban transportation system as Boston continues its quest to eradicate traffic deaths by 2030 (Haileyesus, 2025). To further the city's Vision Zero initiative, which aims to eradicate traffic-related fatalities and serious injuries, this study will examine how spatiotemporal analysis and predictive modelling of Boston traffic accidents offer practical insights.

2. Literature Review

The literature review examines current research, theories, and empirical data about traffic accident prediction models and spatiotemporal analysis. To better understand accident patterns, the analysis examines the development of accident causation theories, data-driven methodologies, and spatial-temporal modelling tools. The integration of these analytical tools in furthering Vision Zero initiatives is also highlighted in this section, with a focus on evidence-based tactics for lowering traffic-related fatalities and injuries.

2.1. Conceptual Overview of Traffic Accident Analysis

In general, traffic accident analysis aims to understand where, when, and why accidents occur, as well as to construct data-driven strategies that minimize their likelihood of occurrence (Brach et al., 2022). However, Chand et al. (2021) pointed out that traffic accidents include investigating foundational mechanisms such as human error, infrastructure design, vehicle circumstances, and environmental influences. It also includes predictive modelling and spatial analytics that provide insights into high-risk areas, temporal fluctuations, and causal relationships associated with road safety outcomes (Dyreborg, et al., 2022).

Road traffic accidents continue to be a major source of death and injury on a global scale. The World Health Organization (WHO) estimates that traffic accidents claim the lives of 1.19 million people annually, while tens of millions more sustain non-fatal injuries that frequently lead to permanent disabilities (World Health Organization, 2024). Despite owning just 60% of the world's automobiles, low- and middle-income nations bear a disproportionately high burden of these accidents, accounting for almost 90% of all road deaths worldwide, according to Chand et al. (2021). Road traffic accidents not only cause human misery but also have a substantial financial cost—roughly 3% of the GDP of the majority of nations. Medical expenses, lost productivity, property damage, and the financial burden on emergency and public health systems are the causes of these losses (Brach et al., 2022).

Traffic accidents continue to be a significant public health concern in the US. According to data from the National Highway Traffic Safety Administration (NHTSA), 42,514 people died in 2022, which is still much higher than pre-2020 levels but slightly lower than pandemic-era highs (Naumann, 2025). According to Chand et al. (2021), speeding, drunk driving, distracted driving, and not wearing seat belts are all significant contributing factors. Given the intricate relationships that exist between bikes, pedestrians, and vehicles in densely populated areas like Boston, the urban component of road safety has grown in significance. Spatial-temporal analysis is crucial for focused interventions since urban traffic accidents frequently happen in settings with heavy traffic, multiple traffic modes, and variable infrastructure conditions (Brach et al., 2022).

In the end, proactive safety planning relies heavily on traffic accident investigation. Cities like Boston can adopt more intelligent and adaptable interventions by comprehending how human behaviour (such as distraction and speeding), environmental factors (such as weather and lighting), temporal trends (such as rush hours and seasonal variations), and spatial factors (such as road geometry and intersections) combine to cause accidents (Raetze et al., 2022). With the help of predictive analytics, this conceptual understanding lays the groundwork for attaining long-term decreases in traffic fatalities and injuries, which advances the larger Vision Zero goal of safe, just, and liveable urban mobility systems (Dyreborg et al., 2022).

2.2. Spatiotemporal Dynamics of Traffic Accidents

In traffic accidents, the patterns and variances in crash incidents over time and space are known as the spatiotemporal dynamics. Cui et al. (2024) emphasized the importance of recognizing these dynamics for identifying high-risk locations, detecting changes over time, and implementing preventative safety measures. Hu et al. (2023) asserted, however, that traffic accidents are not random events but rather show observable temporal regularities and spatial clustering influenced by the interplay of infrastructure, environmental factors, human behaviour, and traffic volume. Additionally, according to Alsahfi (2024), examining these trends will shed light on how and why more crashes occur at times and places, which is crucial for focused road safety management.

Moreover, highway ramps, junctions, and major arterial routes are frequently the sites of traffic accidents due to the complexity of vehicle interactions. Factors including land use, traffic density, road design, and proximity to residential or commercial areas all have an impact on these spatial clusters (Ramírez & Valencia, 2021). The frequency of accidents usually varies over time in accordance with daily, weekly, and seasonal patterns. For instance, traveling at rush hour, on the weekends, or at night is frequently associated with a higher risk of collisions because of driver weariness, poor vision, or faster travel speeds (Hu et al., 2023). However, Boston's seasonal variations, such as snow and rain, exacerbate these dangers by affecting braking distances and vehicle control. Therefore, by examining the spatiotemporal dynamics, transportation planners might associate certain environmental and behavioural circumstances with collision incidents (Zhang et al., 2024).

Furthermore, a key tool for displaying and evaluating spatial accident data is the Geographic Information System (GIS). By combining accident records with spatial layers including land use, traffic flow data, and road networks, GIS enables analysts to see linkages and trends that would otherwise be hard to spot (Ramírez & Valencia, 2021). GIS supports Boston's Vision Zero approach for focused infrastructure upgrades and enforcement efforts by assisting in the identification of crucial junctions and corridors that show recurring collision trends (Zhang et al., 2024). Kernel Density Estimation (KDE) is a statistical method that estimates the probability density of collision sites throughout space to detect accident hotspots in addition to GIS visualization. In order to emphasize regions of high accident concentration, often known as hotspots, KDE converts discrete accident locations into a continuous surface (Cui et al., 2024). Because it offers a smooth depiction of crash intensity without being restricted by administrative borders, this approach is especially helpful in urban settings where accidents are closely clustered. In crucial areas, KDE results can help policymakers prioritize actions like speed control, signal optimization, and improvements to pedestrian safety (Ramírez & Valencia, 2021).

Moran's I, a global statistical measure that determines whether accidents are randomly distributed, dispersed, or clustered across an area, is used to evaluate spatial autocorrelation quantitatively (Zhang et al., 2024). Spatial clustering of accidents is indicated by a positive Moran's I value, whereas a negative value suggests dispersion. This measure is essential for verifying that reported accident patterns reflect underlying spatial relationships rather than being the result of random chance (Alsahfi 2024).

2.3. Integration of Spatiotemporal and Predictive Methods

One significant development in transportation safety analytics is the incorporation of spatiotemporal and predictive techniques in traffic accident studies (Kumar et al., 2024). According to Huang et al. (2022), predictive modeling is concerned with estimating the likelihood of future occurrences based on historical and contextual data. In contrast, spatiotemporal analysis records the where and when of traffic incidents. Combining these two methods, however, offers a comprehensive knowledge of accident dynamics that enables both proactive risk prevention and the detection of patterns in the past. To accomplish Vision Zero goals, traffic safety management in contemporary metropolitan areas like Boston increasingly depends on data-driven insights, making this integrated system essential (Swain et al., 2024).

According to Miao et al. (2024), the understanding that accidents are caused by intricate, interconnected geographical, temporal, environmental, and behavioural elements is also at the heart of this integration. It is possible to investigate accident frequency within specific time periods and places using spatiotemporal models, such as space-time cube analysis, Bayesian hierarchical models, and spatiotemporal autoregressive models, which show dynamically changing patterns. These models can, however, detect possible hotspots before they materialize when paired with predictive techniques like random forests, support vector machines (SVM), or deep learning networks. Through this synergy, traditional descriptive analysis is transformed into actionable intelligence, improving accident prediction accuracy and facilitating early intervention measures (Chand et al., 2021).

Agreeing with Kumar et al. (2024), the creation of hybrid analytical frameworks is a significant development resulting from this integration. These frameworks enhance forecast accuracy by combining machine learning, temporal modeling, and spatial statistics (Huang et al., 2022). According to Swain et al. (2024), hybrid models have the potential to combine real-time traffic flow, meteorological, and socioeconomic data with prediction algorithms that use spatial clustering based on Geographic Information Systems (GIS) (using tools like Kernel Density Estimation or Getis-Ord Gi *). Also, Swain et al. (2024) noted that a sophisticated understanding of accident risks at micro-scales is made possible by the combination of machine learning classifiers and spatial autocorrelation metrics. Furthermore, hybrid frameworks take into consideration the impact of external factors that change over time and geography, such as infrastructure design, land use, and population density, in addition to identifying high-risk locations (Miao et al., 2024).

Real-time prediction and early warning systems are another important area where integrated spatiotemporal-predictive modeling is used. To predict possible disaster hazards almost instantly, these systems use continuous data inputs from weather stations, GPS units, and traffic sensors (Naumann, 2025). Such systems can identify anomalous traffic patterns, such as abrupt congestion, unpredictable vehicle movements, or dangerous weather conditions, and notify drivers or traffic authorities by examining spatiotemporal correlations (Huang et al., 2022). In Boston, targeted law enforcement, adaptive signal regulation, and dynamic rerouting may all be made possible by combining predictive algorithms with the city's current traffic management systems. The objective is to develop intelligent transportation systems (ITS) that can stop accidents before they happen, which is in line with the preventative philosophy of Vision Zero (Chand et al., 2021).

Furthermore, according to Swain et al. (2024), stringent assessment measures are necessary to guarantee the efficacy and dependability of prediction models. Performance metrics, including accuracy, recall, root mean square error (RMSE), and area under the curve (AUC), are frequently employed. The Receiver Operating Characteristic (ROC) curve is used to calculate the AUC, which gauges how well the model can differentiate between accident and non-accident instances. Values nearer 1 indicate better classification performance (Miao et al., 2024). Additionally, RMSE is helpful for continuous accident frequency projections since it assesses the average size of prediction mistakes. Recall evaluates the percentage of real accident occurrences that the model properly recognized, whereas precision calculates the percentage of correctly predicted positive events among all predicted positives. Models are both susceptible to true positives yet immune to false alarms when these measures are combined to give a fair evaluation of predicted accuracy and robustness (Huang et al., 2022).

2.4. Applications of Predictive Analytics in Vision Zero Policies

To execute Vision Zero regulations, predictive analytics has become a game-changing technology that allows cities to go from reactive to proactive road safety management (Barichella, 2023). First implemented in Sweden in 1997, Vision Zero is predicated on the moral precept that no number of fatalities or severe injuries attributable to traffic is acceptable. To accomplish this challenging objective, governmental commitment is necessary, but so is the astute use of data to identify and reduce risk variables before accidents (Chand et al., 2021). In this process, predictive analytics is essential because it can notice trends, predict crash hotspots in the future, and direct data-driven interventions in infrastructure redesign, urban planning, and law enforcement (Cui et al., 2024).

Additionally, the ability to analyze vast and varied datasets, including past collision records, traffic patterns, weather, land use, and demographic data, is crucial to predictive analytics in Vision Zero. This enables the identification of hidden linkages that affect accident risks. The probability of crashes in particular places and time periods may be estimated by analysts using statistical and machine learning algorithms (Gooch et al., 2024). This strategy allows policymakers to foresee risks rather than react to them, according to Naumann (2025). For instance, based on previous patterns in traffic behaviour, predictive models can identify crossings with increasing collision probability, enabling prompt actions like speed limitation, better signage, or signal retiming.

Besides, to improve road user safety, transportation networks are designed and modified based on predictive insights in urban planning. Planners should prioritize redesigning high-risk areas, such as corridors with significant pedestrian or bicycle traffic, by examining spatial and temporal accident trends (Naumann, 2025). Predictive crash modeling, for example, helps Boston's Vision Zero Action Plan by identifying intersections that would benefit from speed-calming infrastructure, secured bike lanes, or better crosswalk visibility. According to Wong (2025), these data-driven planning choices guarantee that scarce urban development expenditures are distributed where they would have the most safety impact.

Additionally, by facilitating a more effective allocation of resources, predictive analytics improves traffic enforcement tactics. Conventional enforcement strategies frequently depend on presumptions about high-risk areas or static patrol routes (Younes & Oloufa, 2025). On the other hand, predictive models pinpoint the exact moments and locations where traffic infractions or collisions are most likely to occur. Through evidence-based policing, law enforcement organizations may target speeding or drunk driving habits, optimize patrol scheduling, and increase compliance (Ramírez & Valencia, 2021). Rebentisch (2018) pointed out that predictive analytics provide empirical support for engineering interventions in the field of infrastructure redesign. Transportation engineers can evaluate various design scenarios prior to implementation by modeling the impact of proposed design modifications on collision probability. The safety effects of roundabouts, lane width changes, and better street illumination may all be assessed using predictive models. These simulations directly support the systemic safety principles of Vision Zero by ensuring that infrastructure decisions are both economical and goal-oriented (Albert & Pandey, 2022).

Predictive analytics is the key to making data-informed decisions, which is at the heart of Vision Zero's ideology. Cities using predictive technologies can evaluate the success of their initiatives, monitor changing risk variables, and adjust their plans as needed. In order to ensure responsiveness to shifting traffic circumstances and human behaviours, regulators can iteratively improve safety measures through the use of predictive models (Cui et al., 2024).

3. Theoretical Review

3.1. Accident Causation Theory

In 1931, Heinrich established the Accident Causation Theory. It is among the oldest and most significant theories for figuring out what causes accidents. Heinrich put out the "Domino Theory," which views accidents as a series of actions that gradually build to harm or destruction, like falling dominoes, where one dangerous act or circumstance sets off another. 88% of workplace accidents, he hypothesized, are caused by risky human behaviour, 10% by unsafe environment, and 2% by uncontrolled variables. According to this viewpoint, human conduct and system malfunctions are the main causes of accidents. Heinrich's model developed into more comprehensive frameworks for accident causation over time, incorporating systemic, organizational, and environmental factors in addition to individual negligence. These frameworks also took into account sociotechnical interactions that increase the likelihood of accidents (Wang et al., 2022).

Furthermore, the theory offers a crucial basis for comprehending the interaction of environmental, human, and vehicular elements. An accident can be caused by a series of avoidable incidents, including driver mistakes, poor road design, insufficient lighting, or unfavourable weather conditions. Examining these interconnected elements enables the study to identify areas where changes could disrupt the causal chain, thereby preventing mishaps before they occur. Likewise, in order to identify underlying causal processes, Heinrich's framework facilitates the integration of spatiotemporal and predictive analytics in this study. By mapping the times and locations of particular accident precursors, such as speeding or traffic, researchers may identify high-risk areas and temporal hotspots using spatiotemporal analysis (Wang et al., 2023).

Additionally, by utilizing statistical algorithms and machine learning to forecast the likelihood of future accidents based on past data, weather trends, and human behavior, predictive modeling expands Heinrich's causality theory. Through the use of data, the theoretical "dominoes" are converted into quantifiable factors that can be tracked and adjusted in real time. Ultimately, applying the idea to predictive modelling frameworks strengthens Vision Zero efforts by coordinating proactive safety responses with data analytics. By identifying and addressing root causes before accidents occur, policymakers and urban planners can move closer to achieving the goal of zero traffic fatalities in Boston (Chen et al., 2021).

3.2. Empirical Studies

Liu et al. (2019) investigate pedestrian injury severity in motor vehicle crashes using an integrated spatio-temporal modeling approach. The methodology combines geographic information systems (GIS) with statistical modeling to analyze the relationship between pedestrian injuries and various spatial and temporal factors, such as weather conditions, traffic volume, and time of day. Findings from the study indicate that specific spatial patterns and temporal dynamics significantly influence injury severity, revealing that specific locations and times are more hazardous for pedestrians. The study underscores the importance of understanding these factors to enhance pedestrian safety and inform urban planning. However, limitations include potential data inconsistencies and the challenge of capturing all relevant variables affecting pedestrian safety.

Liu & Sharma (2018) utilize a multivariate spatio-temporal Bayesian model to analyze traffic crashes by severity. The methodology integrates spatio-temporal data on traffic accidents, considering factors such as location, time, and environmental conditions, to evaluate the relationships influencing crash severity. The study reveals that the Bayesian model effectively accounts for the inherent variability in crash data and identifies critical predictors of severe accidents, including traffic volume, road conditions, and time of day. The study demonstrates the model's capacity to provide insights for targeted safety interventions. The limitations of the study include assumptions related to the model's structure, which may not fully capture all influencing factors.

Alsahfi (2024) conducts a spatial and temporal analysis of road traffic accidents in major Californian cities using a Geographic Information System (GIS). The methodology involves collecting and mapping accident data over specific time frames to identify patterns and trends in traffic incidents across various urban environments. Findings from the study reveal that certain areas exhibit higher accident rates, particularly during peak traffic hours and adverse weather conditions. The study emphasizes the importance of spatial analysis in understanding the factors contributing to road safety and informs urban planning and traffic management strategies. Additionally, the study has limitations, including potential data inconsistencies and the challenge of accounting for unreported accidents, which may skew results.

Younes & Oloufa (2025) propose a geospatial framework for spatiotemporal crash hotspot detection, utilizing space-time cube modeling and emerging pattern analysis. The methodology involves constructing a space-time cube to visualize and analyze traffic accident data across different dimensions, including time and location, to identify patterns and hotspots effectively. The findings from the study reveal that the framework successfully detects areas with a high frequency of crashes, providing actionable insights for traffic management and safety interventions. Also, the study highlights the potential of combining advanced spatial analysis techniques with emerging pattern detection to enhance the understanding of crash dynamics. However, limitations include the need for high-quality, comprehensive data to ensure accuracy and reliability in hotspot identification.

Mehdizadeh et al. (2020) explore data analytic applications in road traffic safety, focusing on descriptive and predictive modeling techniques. The methodology involves a comprehensive analysis of existing literature to categorize and evaluate various data-driven approaches employed in traffic safety research. The key findings indicate that both descriptive and predictive models play crucial roles in understanding traffic patterns and enhancing safety measures. The review highlights the effectiveness of machine learning, statistical methods, and GIS technologies in predicting accidents and analyzing contributing factors. Also, limitations include the variability in data quality and the need for standardized methodologies across studies to ensure comparability.

3.3. Gap in Literature

Liu et al. (2019) investigate pedestrian injury severity in motor vehicle crashes using an integrated spatio-temporal modeling approach. Also, Liu & Sharma (2018) utilize a multivariate spatio-temporal Bayesian model to analyze traffic crashes by severity, while Alsahfi (2024) conducts a spatial and temporal analysis of road traffic accidents in major Californian cities using a Geographic Information System (GIS). However, Younes & Oloufa (2025) propose a geospatial framework for spatiotemporal crash hotspot detection, utilizing space-time cube modeling and emerging pattern analysis, while Mehdizadeh, et al. (2020) explore data analytic applications in road traffic safety, focusing on descriptive and predictive modeling techniques. However, no study was conducted on spatiotemporal analysis and predictive modeling of traffic accidents in Boston. Therefore, this study will conduct a spatiotemporal analysis and predictive modelling of traffic accidents in Boston, providing insights to advance vision zero initiatives.

4. Materials and Methods

4.1. Research Design

This research employs a quantitative, explanatory research design whose objective is to investigate spatial and temporal trends in traffic crashes and predict probabilities of extreme traffic crash events that occurred in Somerville, Massachusetts. This research design harnesses spatiotemporal analysis, in combination with supervised machine learning modeling, to facilitate descriptive and inferential analysis of crash distribution and frequency. Using secondary data from official crash reports, the research applies data-driven approaches to analyse and discover latent patterns and predictors of severe traffic crashes. The quantitative method provides an objective description, statistical reliability, and replicability of results while at the same time maintaining congruence with the Vision Zero value of evidence-based action in evaluating traffic safety. The emphasis of this design is on intensively analyzing the data that had been collected to draw testable and generalized conclusions regarding traffic crashes.

4.2. Study Area

This research takes place in Somerville, Massachusetts, which is among the nation's most highly urbanized cities and is located immediately northwest of Boston in the Greater Boston metropolitan area. Somerville is roughly 4.1 square miles in area and is known for its tight street pattern, mixed uses, and high levels of pedestrian and vehicle interaction. Proximity to main roads such as Interstate 93 and Massachusetts Route 28 also accounts for much of the city's traffic flow and accident propensity. Somerville participates in the Vision Zero Plan, an inclusive initiative that aims to eliminate traffic fatalities and serious injuries through planning with crash data and redesigning the built environment. With its bounded region, multiple transportation modes, and available crash reports, the city has an ideal setting to study accident spatial and temporal patterns.

4.3. Data Sources

Secondary data from the City of Somerville's Open Data Portal and the Massachusetts Department of Transportation (MassDOT) crash data are used by the author. The data set includes 2,428 reported traffic accidents across several observation years at several sites throughout Somerville. All the records contain crash information, including date and time, location (latitude and longitude), lighting conditions, weather, roadway configuration, speed limit, and severity of injury. The dataset also specifies whether the crash was with a pedestrian, bicyclist, or driver while also including contextual information about the crash (i.e., road surface and traffic control type). The data are based on administrative crash records, which are promising in terms of consistency, reliability, and sufficient spatial accuracy for valid spatiotemporal analysis and predictive modeling of urban safety.

4.4. Data Description and Pre-processing

In this study, the data set included 32 variables used to quantify properties of crashes, environmental conditions, and impacts. Important variables were Date and Time of Crash (time factor), Latitude and Longitude (geographic coordinates), and several contextual variables, including condition of Weather, Light, Road Surface, Speed Limit, and Roadway Intersection Type. Count Fatal Injury indicated injury outcomes, Count Serious Injury, and Count Minor Injury variables that were then used to build a crash severity index, if needed, for model use.

Pre-processing was conducted in Python and included data cleaning (e.g., removing duplicates, normalization of categorical values such as "UNKNOWN" or "NA"). Temporal variables hour, day, and month were extracted, and spatial coordinates were checked to be valid within the WGS84 coordinate system. Missing and inconsistent values were handled by listwise deletion as appropriate to reduce the effect on the validity of the data.

4.5. Analytical Techniques

The analysis methods used in this study integrate exploratory spatiotemporal analysis and supervised predictive modelling to investigate traffic accident patterns in Somerville in an integrated framework.

4.5.1. Spatiotemporal Analysis

This phase included crash pattern descriptions and inferential spatial and temporal analyses. Using Geographic Information Systems (GIS) software and programming libraries such as GeoPandas and PySAL to work on spatial coordinates, hot spots of high crash risk were established by using Kernel Density Estimation (KDE) and Moran's I for the detection of spatial autocorrelation. Temporal variations were identified by identifying peak hours and seasonal impacts from crash counts binned by hour, day, and month. The results of those analyses were where and when crashes were most highly concentrated in time and space.

4.5.2. Predictive Analysis

Supervised machine learning methods were applied to predict the likelihood of a severe crash. A classification modeling approach, such as Random Forest or Logistic regression prediction, was developed to predict severity (dependent variable) using environmental, human, and roadway variables as predictors. Supervised machine learning methods were validated on a series of accuracy-based metrics (e.g., accuracy, precision, recall, Area Under the Curve (AUC)) to ensure they were predictive and reliable.

4.6. Model Specification and Validation

The predictive model captures the likelihood of more severe accidents in terms of roadway, environmental, and human factors. The dependent variable (Y) is crash severity, as quantified in terms of the number of fatal and serious casualties and is labeled as 1 for the high-severity accident and 0 otherwise. The predictor variables (Xi) include weather (e.g., rain, sleet), light conditions (e.g., dark, dawn), speed limits, surface type, intersection type, number of pedestrians involved, and time. The general model can be written as:

$$P(Y_i = 1) = f(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots.. + \beta_k X_{ki})$$

Where *f(.) denotes a logistic or ensemble-based classification function*

To ensure the specification's stability and to develop evidence-based advisory policies that adhere to Vision Zero goals, model fit was verified in Python using train-test splitting followed by cross-validation as a measure to avoid overfitting. Accuracy, recall, and AUC were calculated to reveal the discriminatory ability of the model; feature importance analyses contribute to identifying factors with good predictive potential for accidents according to severity.

5. Results

5.1. Spatial Analysis

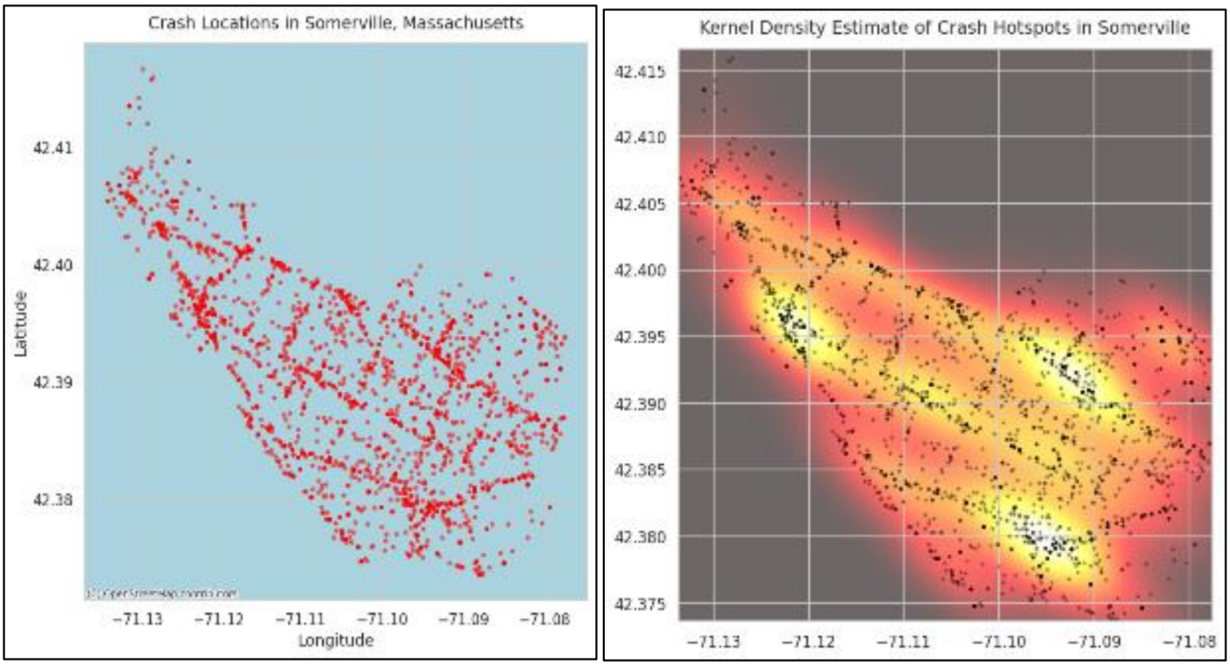

Figure 1 Spatial Visualization and Kernel Density Estimation of Crash Location

The kernel density estimate (KDE) map in Figure 1 illustrates the spatial concentration of traffic crash hotspots across Somerville. The density visualization reveals that crash occurrences are not uniformly distributed but instead display distinct clustering patterns, with the highest concentrations observed in the central and southeastern zones of the city (indicated by the bright yellow regions). Moderate crash densities extend toward the northwest and southwest areas, while the northernmost and peripheral regions show relatively fewer incidents. This spatial pattern suggests that traffic accidents are more frequent along major roadway intersections and high-traffic corridors

Table 1 Spatial Autocorrelation (Moran's I)

Test	Statistic	p-value
Moran's I	0.996	0.001

Table 1 presents the spatial autocorrelation results, which indicates a Moran's I value of 0.996 with associated p-value of 0.001, suggesting a statistically significant systematic spatial relationships in crash occurrences. The implication of this is that there is a strong positive spatial autocorrelation, indicating that crash locations in Somerville are highly spatially clustered. More specifically, crashes tend to occur near other crashes rather than being randomly distributed.

5.2. Temporal Analysis

The distribution of crashes by hour of day revealed a distinct temporal pattern, with relatively few crashes occurring during the early morning hours (00:00–05:00), followed by a steady increase beginning around 06:00 and peaking between 12:00 and 17:00, with the highest frequency observed at 14:00. After 17:00, the number of crashes gradually declined into the late evening and night. These findings suggest that traffic accidents in Somerville are strongly associated with daily activity cycles, particularly midday and afternoon periods when traffic volumes are typically highest, consistent with prior research linking congestion and exposure to elevated crash risk (Hu et al., 2023). This temporal clustering underscores the importance of time-sensitive interventions, such as targeted enforcement and adaptive traffic management, during peak crash hours.

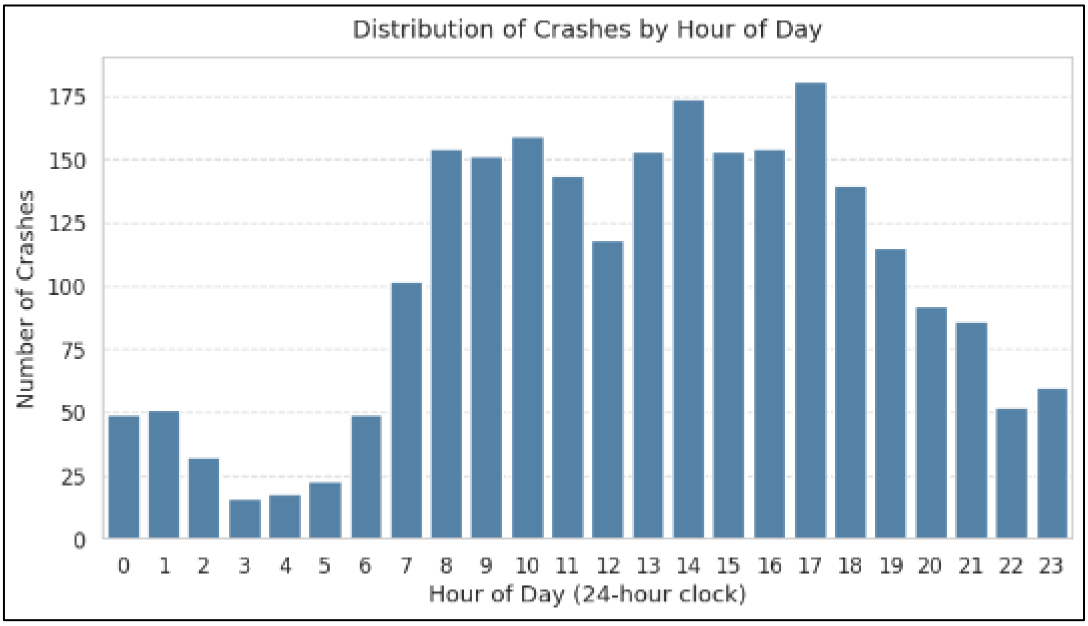

Figure 2 Crashes Distribution by Hours of the Day

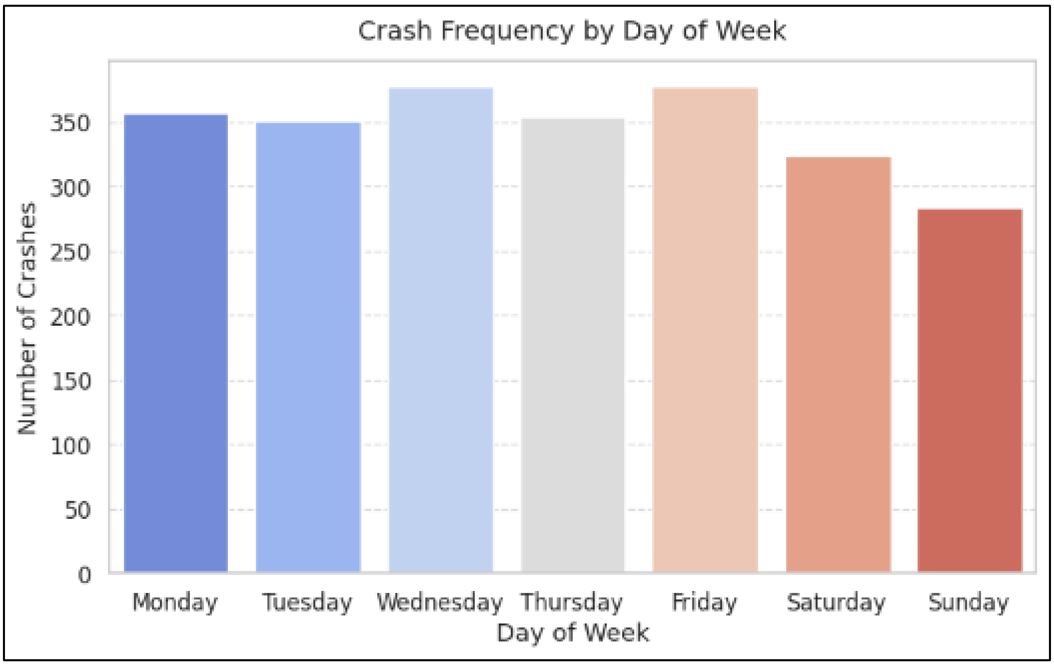

Figure 3 Crashes Distribution by Days of the Week

As shown in Figure 3, crash frequency in Somerville varied modestly across the days of the week, with Wednesday (≈370 crashes) and Friday (≈375 crashes) recording the highest counts, while Sunday (≈320 crashes) had the lowest. Although the differences were not extreme, the elevated crash frequencies on mid-to-late weekdays suggest a potential association with commuter traffic and end-of-week travel activity. Conversely, the reduced number of crashes on weekends, particularly Sundays, may reflect lower overall traffic volumes. These findings are consistent with prior research linking weekday commuting patterns to heightened crash risk in urban environments (Hu et al., 2023).

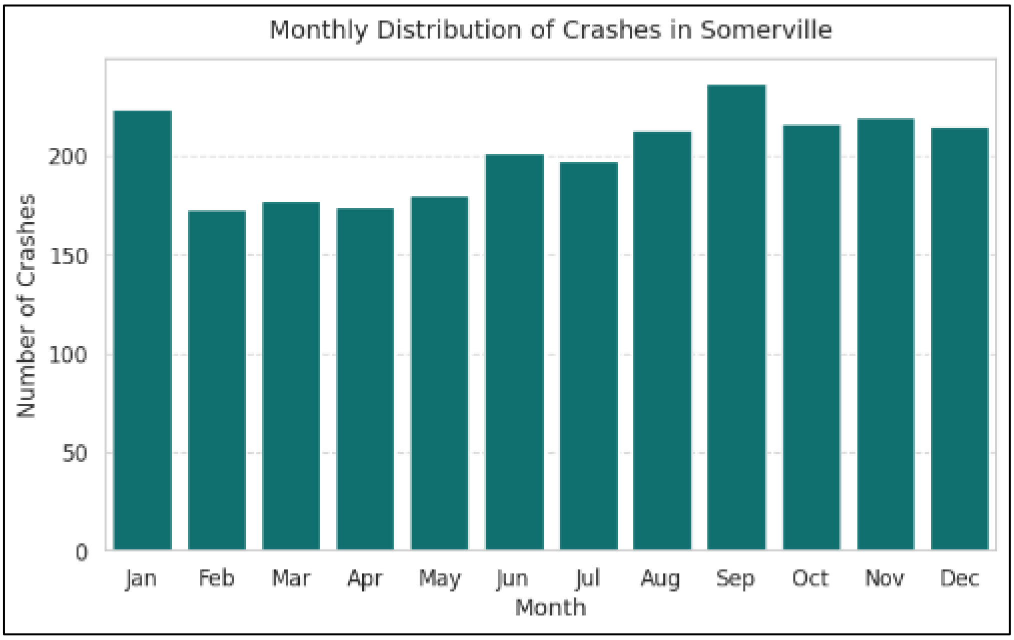

Figure 4 Monthly Distribution of Crashes

As illustrated in Figure 4, September recorded the highest number of crashes, followed closely by January and November, while the lowest crash frequencies were observed in March, April, and May. This pattern suggests that winter months, particularly January and December, may be associated with adverse weather conditions such as snow and ice that increase crash risk, whereas spring months tend to experience fewer incidents, likely due to more favorable driving conditions. The elevated crash frequency in September may reflect increased travel activity associated with the return of schools and universities, as well as heightened commuter traffic. These findings are consistent with prior research linking seasonal weather and activity cycles to fluctuations in urban crash risk (Zhang et al., 2024)

5.3. Evaluation Metrics

Table 2 Model Performance Summary

Model	**Best Parameters**	**ROC-AUC**	**Notes**
Logistic Regression	'C': 10, 'penalty': 'l2'	0.442	Linear model; underfits complex patterns
Random Forest	'bootstrap': True, 'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100	0.512	Captures non-linearity but biased to majority class
Gradient Boosting	'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_estimators': 300	0.499	Slightly better minority detection but still weak overall

As presented in Table 2, the predictive models demonstrated limited discriminatory power, with ROC-AUC values ranging from 0.442 to 0.512. Logistic regression, despite being optimized with an L2 penalty and regularization parameter C = 10, yielded the lowest ROC-AUC (0.442), indicating that the linear specification underfit the complex crash patterns. The random forest model, tuned with a maximum depth of 20 and 100 estimators, achieved the highest ROC-AUC (0.512), suggesting some ability to capture non-linear relationships, though it remained biased toward the majority class. Gradient boosting, configured with 300 estimators, a learning rate of 0.1, and moderate depth (max_depth = 5), produced a ROC-AUC of 0.499, reflecting slightly improved sensitivity to minority cases but overall weak predictive performance.

Table 3 Gradient Boosting Performance

Metrics	Scores
Accuracy	0.885
Precision	0.959
Recall	0.885
F1-Score	0.919

The gradient boosting model presented in Table 3 achieved strong overall classification performance, with an accuracy of 0.885 and an F1-score of 0.919. Precision was particularly high (0.959), indicating that the model was highly effective at correctly identifying positive cases with few false positives. Recall was also strong (0.885), suggesting that the model successfully detected the majority of true positive cases, though some were still missed. The balance between precision and recall, reflected in the high F1-score, demonstrates that gradient boosting provided the most reliable performance among the tested models, despite the relatively low ROC-AUC reported earlier.

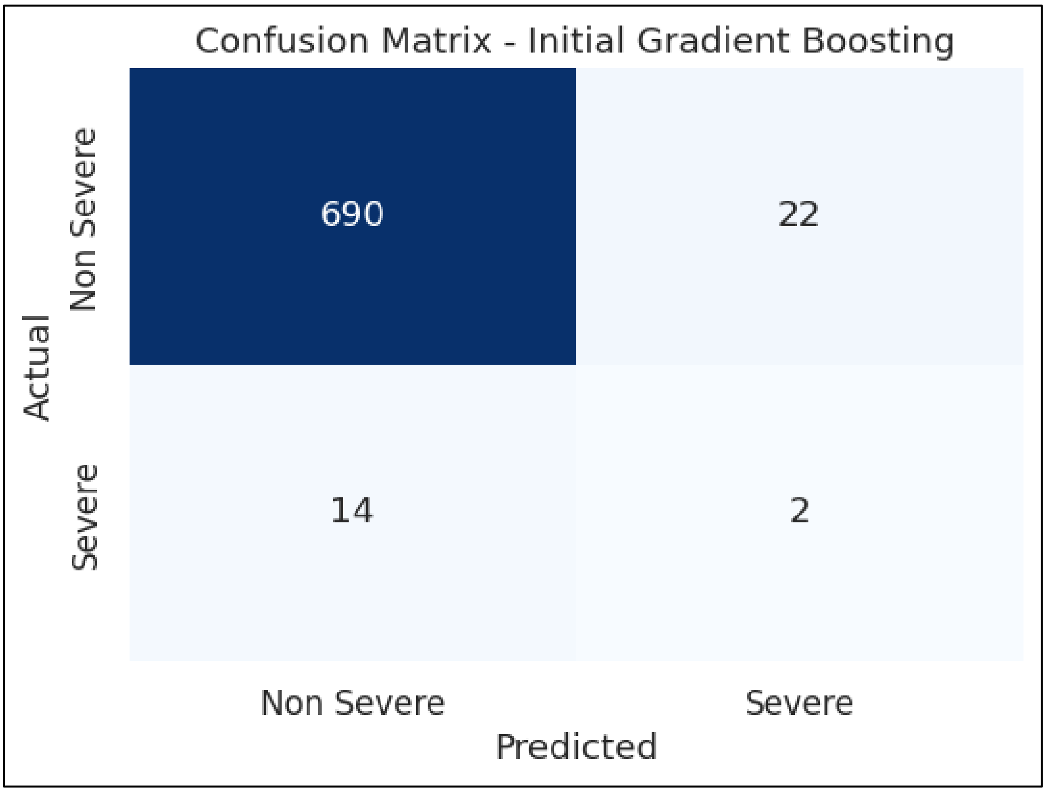

Figure 5 Confusion Matrix

As depicted in Figure 5, the initial gradient boosting model demonstrated strong performance in classifying non-severe crashes but struggled to accurately identify severe cases. Out of 712 actual non-severe crashes, the model correctly classified 690 and misclassified 22 as severe. For severe crashes, however, only 2 were correctly identified, while 14 were incorrectly predicted as non-severe. This imbalance indicates that although the model achieved high overall accuracy, it was biased toward the majority class (non-severe crashes) and exhibited limited sensitivity in detecting the minority class (severe crashes).

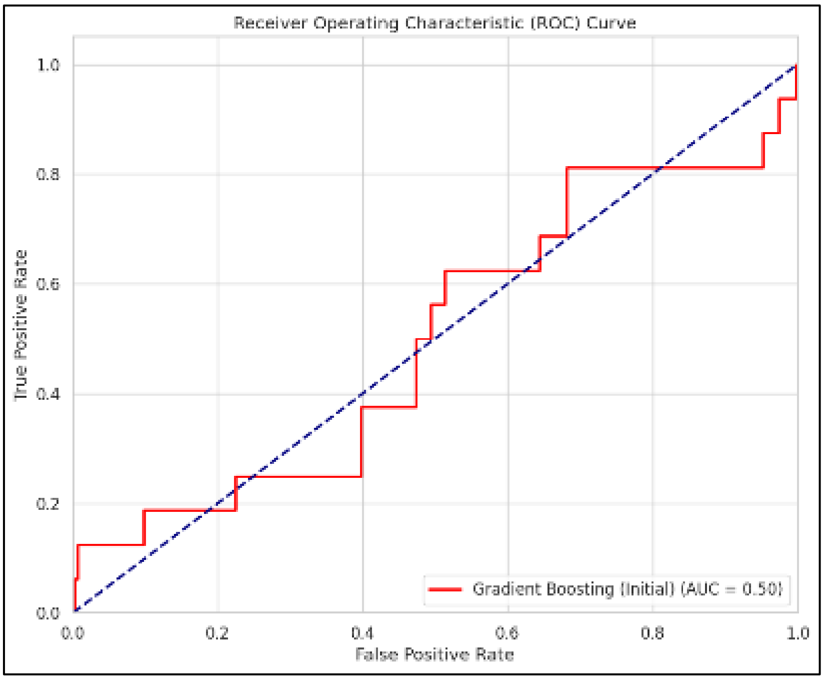

Figure 6 Receiver Operating Characteristics (ROC) Curve

As shown in Figure 6, the receiver operating characteristic (ROC) curve for the initial gradient boosting model yielded an area under the curve (AUC) of 0.50, which is equivalent to random classification. The ROC curve closely followed the diagonal baseline, indicating that the model was unable to effectively distinguish between severe and non-severe crashes. This result contrasts with the relatively high accuracy and precision reported in Table 3, suggesting that the model's performance was driven by its ability to classify the majority class (non-severe crashes) rather than its capacity to detect severe crashes.

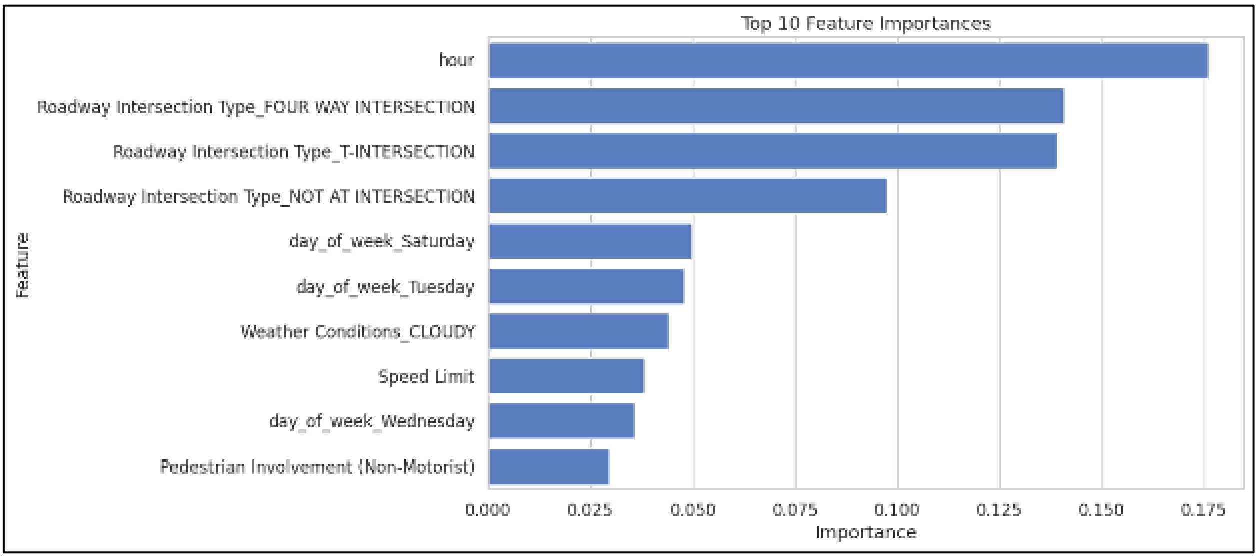

Figure 7 Feature Importance

Figure 7 highlights that temporal and roadway characteristics were the strongest predictors of crash severity in Somerville. The variable hour dominated the model's importance ranking, underscoring the influence of time-of-day on crash outcomes. Intersection types, particularly four-way and T-intersections, also emerged as critical factors, reflecting the heightened risk associated with complex traffic flows. Weekly travel patterns contributed as well, with Saturday and Tuesday showing notable effects, while environmental conditions such as cloudy weather and roadway speed limits added further explanatory power. Pedestrian involvement, though ranked lower, still appeared among the top predictors, emphasizing the vulnerability of non-motorists in urban crashes.

6. Discussion of Findings

The spatial analysis of crashes in Somerville revealed strong clustering patterns, particularly around central and south-eastern corridors, with Moran's I confirming statistically significant spatial autocorrelation. This finding aligns with prior studies that emphasize the non-random distribution of crashes in urban environments. For instance, Alsahfi (2024) similarly identified spatial clustering in Californian cities, noting that intersections and arterial roads consistently emerged as high-risk zones. Younes and Oloufa (2025) demonstrated through space-time cube modeling that crash hotspots persist over time, reinforcing the idea that urban crashes are concentrated in predictable locations. The Somerville results therefore corroborate broader evidence that traffic incidents are shaped by infrastructural and land-use characteristics, underscoring the importance of targeted interventions at intersections and high-volume corridors.

Temporal analysis further highlighted those crashes in Somerville peak during midday and afternoon hours, with January, September, and December showing the highest monthly crash frequencies. These results are consistent with Hu et al. (2023), who found that urban crashes often follow daily and seasonal cycles, with elevated risks during peak commuting hours and adverse weather conditions. Similarly, Zhang et al. (2024) emphasized that winter weather exacerbates crash severity by reducing visibility and vehicle control, which explains the elevated crash counts in January and December. The September peak may be linked to increased travel activity associated with the reopening of schools and universities, a trend also observed in metropolitan crash studies by Cui et al. (2024). Collectively, these findings reinforce the importance of time-sensitive interventions, such as adaptive traffic management during rush hours and seasonal safety campaigns in winter months.

The predictive modeling results, however, revealed limitations in accurately distinguishing severe from non-severe crashes. While the gradient boosting model achieved high accuracy (0.885) and precision (0.959), its ROC-AUC score of 0.50 indicated poor discriminatory power, suggesting bias toward the majority class. This mirrors challenges reported in Liu and Sharma (2018), who noted that Bayesian spatiotemporal models often struggle with class imbalance when severe crashes are relatively rare. Similarly, Mehdizadeh et al. (2020) highlighted that machine learning models in traffic safety research frequently achieve strong overall accuracy but underperform in detecting minority outcomes such as fatalities or severe injuries. The Somerville findings therefore echo broader methodological concerns in predictive crash modeling, particularly the need for techniques that address imbalance, such as cost-sensitive learning or synthetic oversampling.

Finally, the feature importance analysis identified hour of day, intersection type, and pedestrian involvement as key predictors of crash severity. This is consistent with Liu et al. (2019), who found that temporal variables and pedestrian exposure significantly influenced injury severity in urban crashes. The prominence of intersection types also supports findings by Tamakloe et al. (2025), who reported that nearly half of Boston's severe crashes occurred at junctions. The inclusion of pedestrian involvement among the top predictors further resonates with Albert and Pandey (2022), who emphasized the disproportionate vulnerability of non-motorists in Massachusetts traffic fatalities. These converging results suggest that predictive models, even when limited in discriminatory power, still provide valuable insights into the structural and behavioural factors driving crash severity. For Vision Zero initiatives, this underscores the need to prioritize intersection redesign, pedestrian protections, and time-based enforcement strategies as evidence-based pathways toward eliminating severe crashes.

7. Conclusions and Recommendations

The findings from this study demonstrate that traffic crashes in Somerville follow identifiable spatial and temporal patterns rather than occurring randomly. The concentration of incidents at intersections and along arterial corridors underscores the structural vulnerabilities of the urban road network, while midday peaks and seasonal fluctuations highlight the influence of human activity cycles and environmental conditions. Predictive modeling results, though limited in distinguishing severe from non-severe crashes, reveal the challenges of capturing rare but critical outcomes within imbalanced datasets. Nonetheless, the identification of key predictors such as time of day, intersection type, and pedestrian involvement illustrates the systemic interplay of behavioural, infrastructural, and environmental factors in shaping crash severity. These insights contribute to the broader evidence base supporting Vision Zero, emphasizing that traffic safety outcomes are embedded within predictable patterns that can inform a deeper understanding of urban crash dynamics. Given these insights from the findings, it is recommended that:

Since the analysis showed that four-way and T-intersections are among the strongest predictors of crash severity, Somerville should prioritize systematic redesign of high-risk intersections. Measures such as protected left-turn phases, raised crosswalks, and curb extensions can reduce conflict points and improve visibility for both drivers and pedestrians.

The temporal analysis revealed crash peaks during midday and afternoon hours, as well as seasonal spikes in winter months. This suggests the need for adaptive traffic signal systems and dynamic enforcement that respond to peak-risk periods. For example, adjusting signal timing during midday congestion or deploying targeted enforcement during winter months could mitigate predictable spikes in crash risk.

Pedestrian involvement emerged as a significant predictor of crash severity, underscoring their vulnerability. Policies should focus on expanding pedestrian-first infrastructure, such as protected crosswalks, pedestrian refuge islands, and traffic-calming measures in dense residential and commercial areas. This aligns with Vision Zero's equity focus, ensuring that non-motorists are prioritized in safety planning.

The predictive modeling results highlighted both the potential and limitations of machine learning in identifying severe crashes. To strengthen predictive capacity, Somerville should invest in continuous data integration systems that combine crash records with real-time traffic, weather, and land-use data. This would enable iterative model refinement and provide a stronger evidence base for proactive interventions.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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