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Large Data Analysis: How Can Accidents Be Detected Based on Probe Vehicle Data?

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Abstract

Accidents continue to affect both the people involved and the flow of traffic. Timely and accurate accident detection can greatly benefit emergency services and traffic management, as a delay of minutes can determine the difference between life and death. This study introduces a method for detecting accidents using floating car data. The algorithm analyzes vehicle trajectories based on criteria derived from Kerner's three-phase traffic theory, determining a high likelihood of an accident at a specific time and location. Validation using third-party data confirms the occurrence of real accidents. Empirical examples from a large fleet of connected vehicles demonstrate the method's effectiveness: it can swiftly and accurately detect freeway accidents, distinguishing them from normal congestion. A median improvement in detection time of 6.5 minutes is achieved compared to ground truth.

Keywords: accident detection; three-phase traffic theory; floating car data; vehicle trajectories

1. Introduction

Accidents continue to pose significant risks to both the individuals involved and the overall flow of traffic. Rapid and accurate accident detection is crucial, as it can greatly benefit emergency services and traffic management (WHO, 2023). This study introduces a novel method for detecting accidents using floating car data, which involves vehicles transmitting their positional data to a central server. By analyzing vehicle trajectories using criteria derived from Kerner's three-phase traffic theory, the system can accurately identify high-likelihood accidents at specific times and locations. Previous research indicates that a penetration rate of 2% of the traffic flow is sufficient for detecting traffic patterns and accidents (Paczia et al., 2023). This method has been validated with third-party data, confirming its ability to detect real accidents effectively. Empirical examples from a large fleet of connected vehicles demonstrate the system's ability to swiftly and accurately detect freeway accidents and differentiate them from regular congestion.

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2. Related Work

The literature on accident detection encompasses a wide range of methodologies. Traditional car accident detection methods can be broadly categorized into two main approaches: those that rely on accident video features, and those that analyze trajectory parameters derived from fleet data, such as acceleration and velocity. These methods generally rely on vehicle-to-infrastructure communication and obtain their information from road infrastructure, including video cameras and radar sensors (Tian et al., 2019). This limits the application to only specific road sections and the expansion of such systems is costly. Recent studies have shifted towards using data-driven approaches for accident detection. Video based approaches include incorporating dash cameras and other video sources inside vehicles to detect accidents (Yao et al., 2019), (Chan et al., 2017). Additionally, road infrastructure like traffic cameras can be used to detect accidents (Shah et al., 2018), (Tian et al., 2019). Video based approaches are limited to specific road sections or vehicles and require a high amount of data to be processed. Connected vehicle data can be used to detect accidents in a more general way, as the data is available for a larger area and can be processed in real-time. For example, Zhang et al. (2023) and Yang et al. (2021) have explored the use of floating car data (FCD) for freeway accident detection. Accidents cause significant changes in a vehicle's motion state, prompting researchers to propose various detection methods that monitor motion parameters like acceleration and velocity. Amin et al. (2012) developed a detection and reporting system integrating Global Positioning System (GPS), General Packet Radio Service (GPRS), and Global System for Mobile Communications (GSM) technologies. This system leverages the vehicle's speed, obtained from a high-sensitivity GPS receiver, as the primary indicator for accident detection. The paper focuses on accident detection based on singular vehicle data, thus the vehicle involved in an accident needs to be connected to a central server in order for the method to work. In the European Union, a comparable system has been mandated since 2018, requiring all new cars to be equipped with an eCall system (Blancou et al., 2016). In contrast, the proposed method leverages domain knowledge to identify traffic accidents based on vehicle trajectory details. Accidents cause significant changes in a vehicle's motion state, prompting the development of various detection methods that monitor parameters such as acceleration and velocity. Unlike traditional methods, this approach emphasizes the traffic impact of accidents by analyzing the trajectories of connected vehicles. The method allows for accurate accident detection by reconstructing the time and location based on connected fleet data, even if the involved vehicles are not connected to a central server. It requires less data compared to single-vehicle solutions like Amin et al. (2012), as it only requires position data transmitted at intervals of 2 to 10 seconds. Video-based systems require continuous streaming of high-resolution video data, e.g., at 30 frames per second (FPS), resulting in significant data usage Ijjina et al. (2019). In contrast, GPS-based systems transmit small data packets at intervals of 2 - 10 s, resulting in minimal bandwidth usage and more efficient data transmission and storage. These data packages are already transmitted by connected vehicles today for navigation systems, making the proposed method cost-effective and efficient, with no additional hardware requirements in the vehicle.

2.1. Accident Types

The proposed approach focuses on accidents with high traffic impact and full blockage, as it relies on detecting congestion patterns. It is not designed to detect accidents without traffic impact. Accidents that significantly affect traffic flow are of particular interest due to the high likelihood of needing prompt emergency services support (Zeng et al., 2019). To classify different types of accidents in the ground truth data, the following categories are used:

- **No traffic impact:** Minor accidents that do not obstruct traffic flow or cause delays.
- **Low traffic impact:** Accidents causing slight delays or minor congestion, requiring limited intervention.
- **High traffic impact:** Significant disruptions of the traffic flow, causing delays and congestion. They typically involve severe collisions, multiple vehicles, or occur at critical points in the traffic network, such as intersections or highways.
- **Full blockage:** Severe incidents completely obstructing traffic, necessitating road closure and urgent intervention.

2.2. Three Phase Traffic Theory

The Three-Phase Traffic Theory focuses on modeling traffic breakdown and explaining congestion phenomena. Traffic breakdown is a transition from free flow to congested traffic in a traffic network. It usually occurs at a network bottleneck and limits highway capacity. Kerner's theory divides congested traffic into two distinct phases: Synchronized Traffic and Wide Moving Jam (WMJ). The three traffic phases can be defined as following (Kerner, 2004):

1. Free Flow Phase (F): In this phase, vehicles move freely without significant interaction. Traffic density is relatively low, and vehicles can maintain a steady speed close to the speed limit with variable overtaking and lane changing.
2. Synchronized Flow Phase (S): The synchronized flow phase in congested traffic refers to a state where traffic congestion is characterized by continuous traffic flow without significant stoppage and a tendency towards synchronization of the vehicle speeds across different lanes, typically observed at moderate to high densities. In this phase, the congestion's downstream front is usually concentrated at specific bottleneck locations along the roadway. These bottleneck sites serve as focal points for the formation and dissipation of traffic congestion.
3. Wide Moving Jam Phase (J): Within synchronized flow phases, disturbances can lead to the spontaneous emergence of wide moving jams (WMJs). A WMJ in congested traffic is characterized by low-speed congestion not localized at a specific bottleneck and propagates across the roadway with the average velocity v_g of the downstream jam front. On highways, heavy bottlenecks can appear, limiting the average flow rate upstream to such low values that all WMJs merge into a mega-jam. A mega-jam is a WMJ with an extremely large width (in the flow-direction) growing often over time.

3. Conceptual Approach

The concept focuses on traffic features as described in Kerner's three-phase traffic theory, see empirical examples also in Rehborn et al. (2021). A traffic breakdown based on normal driving maneuvers in dense traffic is defined as phase transition from free to synchronized traffic flow. In the further emergence of such a congestion, small narrow moving jams can develop, which can further evolve into wide moving jams emanating from the localized synchronized flow area. A visualization of such a local congestion without any accident is shown in Fig. 1 (left): two WMJs originate from the S region which is fixed at the bottleneck. In contrast, the traffic breakdown in case of an accident is different and can, therefore, be distinguished based on an automated algorithm (Fig. 1 (right)). Key finding of the paper are the feasibility and features of such an algorithm illustrated for several empirical examples of analyzing connected vehicle data. The following sections introduce the algorithm and its validation based on real accident data.

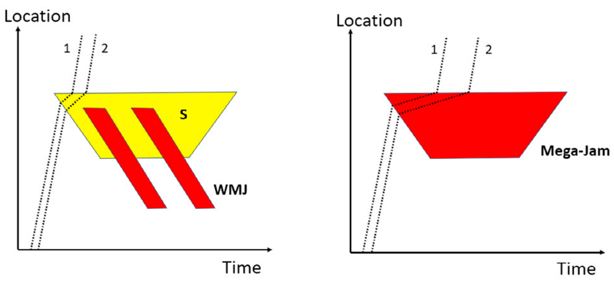


Fig. 1: Principal approach for automatic accident detection in a time-space-diagram: vehicle trajectories marked with "1" and "2" in case of normal congestion (left) and an accident (right)

4. Methodology

A previously established methodology, drawing from the principles of three-phase traffic theory as outlined in studies by Haug et al. (2007), Palmer et al. (2011) is adapted for comprehensive traffic analysis. This adaptation focuses on two critical processes: firstly, the delineation of distinct traffic states at each spatio-temporal position of vehicles using probe vehicle data from connected vehicles, and secondly, the integration of these states into various traffic phases. The analysis examines individual vehicle trajectories assigning unique traffic states to each spatio-temporal position. Subsequently, the system autonomously identifies traffic jam fronts by detecting transitions in traffic states corresponding to vehicles entering and exiting specific traffic phases (Fig. 1). A distributed method for spatio-temporal traffic pattern recognition is then introduced. This method consolidates traffic state transitions indicative of congestion fronts, autonomously detected by all vehicles, into a unified database. By analyzing the underlying processes and metrics of traffic events, it identifies individual traffic phases. These identified WMJs are then further analyzed to determine the likelihood of an accident occurring.

Phase Transitions. The process of traffic state detection involves analyzing a vehicle's speed over time at each spatio-temporal position and assigning a specific traffic state based on predefined criteria. Trajectory data is categorized into three traffic phases, as outlined by Palmer et al. (2011), using both velocity and minimum duration conditions.

- **Velocity Condition (v):** Each transition between phases is determined by a designated velocity threshold. For example, the shift from free-flow to synchronized flow (F → S) occurs when a vehicle's velocity falls below a predefined threshold.
- **Minimum Duration Condition (Δt):** To ensure accurate phase classification, transitions must persist for a minimum duration. This criterion helps differentiate genuine phase changes from temporary traffic fluctuations. The minimum duration for the transition from free-flow to synchronized-flow is denoted as Δt_{FS}.

Accident Detection. The process of accident detection involves a detailed examination of WMJ's, focusing on several critical factors that significantly influence the probability of an accident within traffic flows. These factors are analyzed based on their spatio-temporal characteristics and behaviors as follows:

1. **Spatio-Temporal Extent of Synchronized Traffic Phase Prior to the WMJ:** This criterion assesses the duration and spatial coverage of the synchronized traffic phase that precedes the formation of a WMJ. A large, synchronized phase that forms at a bottleneck allows for normal congestions to form spontaneous. An accident thereby can be an exception to the theory of F → S → J transition as it can occur spontaneous even in free flow. The criterium is denoted in eq. 1, with $A_{\mathrm{S},max}$ being the threshold to for the spatio-temporal extend.

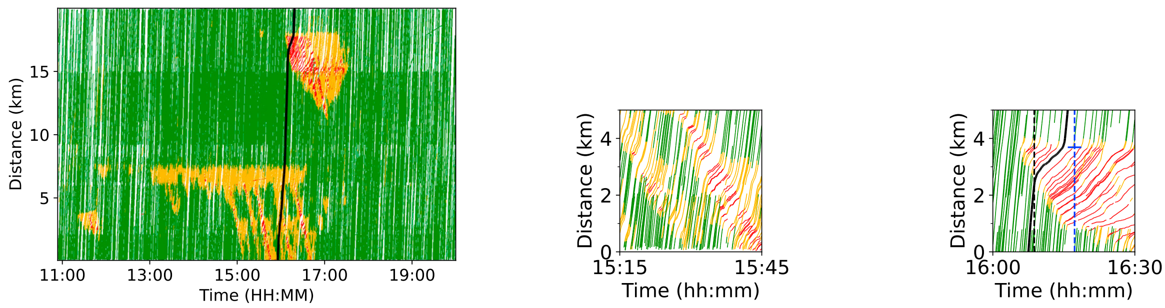
$$A_s = \int_{t_1}^{t_2} d\,(t)\,dt < A_{\mathrm{S},max} \tag{1}$$

2. **Spatial Fixation (SF) of the Downstream Front at the Emergence of the WMJ:** The concept of spatial fixation refers to the phenomenon where the downstream front of a traffic jam exhibits minimal spatial movement over time, essentially becoming 'fixed' in place. The presence of spatial fixation at the onset of a WMJ suggests a persistent bottleneck or other disruption in traffic flow, which may be due to an accident on the driving lanes. The spatial fixation can be measured either by a deviation in the downstream velocity of the phase (eq. 2) or directly through the fixation of the front. The formula can be seen in eq. 3. Thereby T_i denotes a "j-downstream" transition of a single trajectory, SF the spatial fixation and d_{max} the threshold.

$$v_d > V_{lim} \tag{2}$$

$$SF = (T_0 - T_{n-1}) < d_{max} \tag{3}$$

3. While the two conditions above are sufficient for fast and reliable accident detection, the jam area can be further analyzed for a better detection rate at the cost of a longer duration. In practice a warning due to the first two criteria can be issued, and then updated after the certainty is backed by further met conditions, like size of the jam and duration of a vehicle in the jam.



(a) Overview of vehicle trajectories showing multiple congestions

(b) traffic congestion

(c) accident

Fig. 2: Traffic pattern on freeway A81 in Germany on 18th March, 2022. (a) Full traffic pattern, (b) Cutout of the WMJ at 7 km, (c) Cutout of the accident at 18 km.

5. Validation

5.1. Empirical Findings

Fig. 2a shows 2997 vehicle trajectories in a time distance diagram on freeway A81 in Germany on 18th March, 2022. The trajectories are colored according to Kerner's traffic phases, with the time of accident detection of the algorithm (black) and the public services (blue) marked. Congested patterns are observed at 7 km from approx. 11:00-17:00 h and at 18 km from approx. 15:40-18:00 h in Fig. 2a. For better comparison of WMJ and mega jam Fig. 2b, Fig. 2c show cutouts. Criteria (i) to (iii) conclude an accident in Fig. 2c 90s after the first slowdowns of connected vehicles at 16:07h at the accident's location. Ground truth accident data is received from traffic service information provided by public authorities and private sources, sent on 22nd April at exactly 16:17h. The proposed algorithm detects the accident at 16:08:30h, imporivng service by approx. 8 min compared to public message channels. Fig 2a shows, that the detection algorithm can distinguish between normal congestion and congestion due to accidents. The algorithm is neither triggered in the congestion pattern at 4km from approx. 11:00-11:30h nor in the multiple WMJ at 7 km from approx. 14:00-17:00. The thick black line in Fig. 2a marks a single trajectory of a vehicle that passes both the WMJ congestion and the accident congestion. It then exits the highway at 22 km. Fig. 3 shows the velocity-distance and the acceleration-distance diagram of the vehicle trajectory marked in Fig. 2a. The acceleration is smoothed, to account for the sparsity of the data. The trajectory passes both the WMJ congestion and the accident congestion. The vehicle passes the two WMJ's between 0 km and 7 km. It then passes the accident at 17 km. The maximum deceleration value when approaching the accident congestion is higher than the needed deceleration in the synchronized phase, since the vehicle is already in a synchronized traffic phase when approaching the WMJ. The vehicle remains longer in the accident congestion than in the WMJ congestion. Single trajectory-based distinction of the accident and WMJ is error-prone; hence, a multi-trajectory approach, as introduced, is needed.

Accidents in Different Countries. Fig 4 shows examples of accidents on freeways in the USA and England in 2022 and 2024. The examples demonstrate the algorithm's ability to detect accidents in different countries and infrastructure. All chosen examples show the detection of accidents with high traffic impact. The examples in Fig. 4a and Fig. 4b show accidents in the USA, while the examples in Fig. 4c and Fig. 5c illustrate accidents in England. The U.S. examples, derived from multiple connected vehicle fleets and devices, exhibit a higher trajectory density. However, this multi-source collection method leads to heterogeneous data quality, resulting in noisier traffic patterns. The British examples exhibit a lower trajectory density and uniform data quality because they originate from a single connected vehicle fleet, resulting in clearer and equally well detectable traffic patterns. Paczia et al. (2023) showed that a penetration rate of 2% of traffic flow is sufficient for detecting traffic patterns and thus detecting accidents. The U.S. examples depict a significant issue with current implementations. Public response times can be quick when accidents involve connected vehicles or fast third-party reports, but slow without connected vehicle involvement. The algorithm offers a remedy by ensuring consistent and swift accident detection.

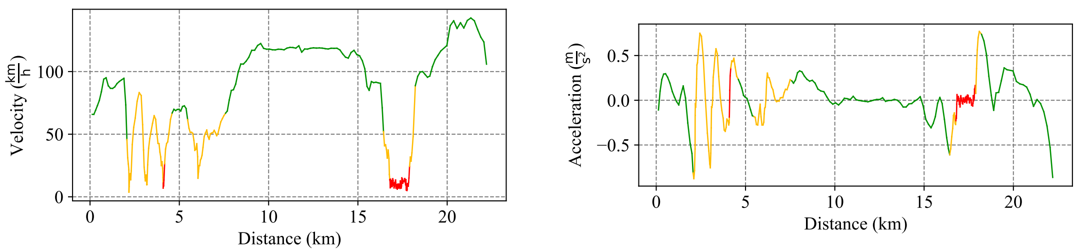
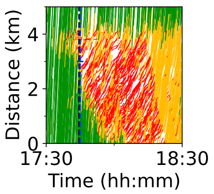
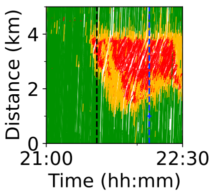


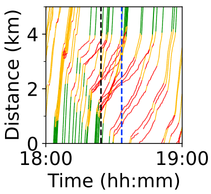
Fig. 3: Velocity and acceleration over distance of the highlighted single trajectory in the traffic pattern on freeway A81 in Germany on 18th March, 2022



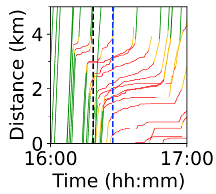
(a) 2024-02-28, I-294, Chicago, USA



(b) 2024-03-03, NJ-3, New York, USA

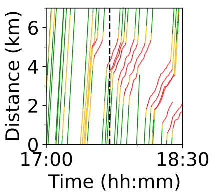


(c) 2022-03-20, M1, Leicester, UK

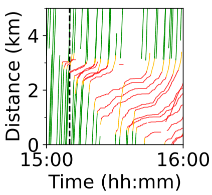


(d) 2022-03-19, M1, Northampton, UK

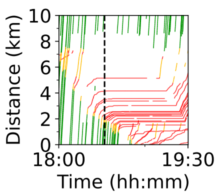
Fig. 4: Examples of accidents on freeways in the USA and England, 2024



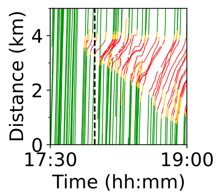
(a) 2022-03-18, M20, London, GB



(b) 2022-03-20, A3, Frankfurt, DE



(c) 2022-03-21, M1, Nottingham, UK



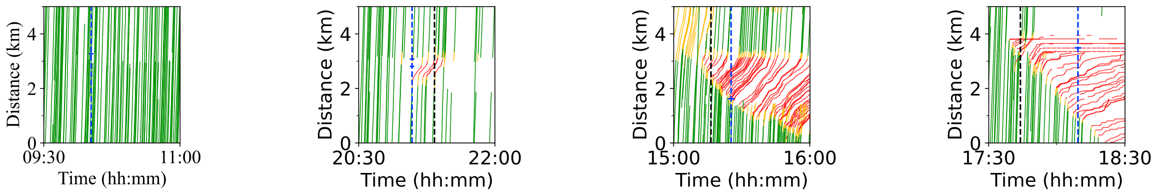
(d) 2022-03-25, A7, Ulm, DE

Fig. 5: High likelihood accidents on freeways in England and Germany, 2022

Undetected Accidents. A great strength of the algorithm is its ability to detect accidents with a high traffic impact and full blockage, thereby detecting traffic patterns with a high accident likelihood that are not reported by public sources. Such unreported high-likelihood accidents have the potential to significantly improve the current accident detection system and allow for timely reactions by traffic management systems, reducing traffic congestion and individual travel times. Fig. 5 shows examples of such high likelihood traffic patterns that were not reported by public sources. By detecting unreported incidents, the algorithm significantly enhances the robustness of traffic monitoring systems.

5.2. Ground Truth Data

The data for validating the accident detection algorithm is sourced from both public authorities and private entities. This data is crucial for assessing the algorithm's accuracy in determining the timing of accident detection. Figure 6 categorizes various accident types by their impact on traffic along German freeways in May 2022, a classification detailed previously in Chapter 2.1. Analysis of incidents depicted in Figures 6a and 6b highlights limitations of the current algorithm when dealing with accidents that have minimal or no impact on traffic. In scenarios where traffic



(a) No traffic impact (b) Low traffic impact (c) High traffic impact (d) Full blockage

Fig. 6: Different ground truth accident types categorized by traffic impact on German freeways May, 2022

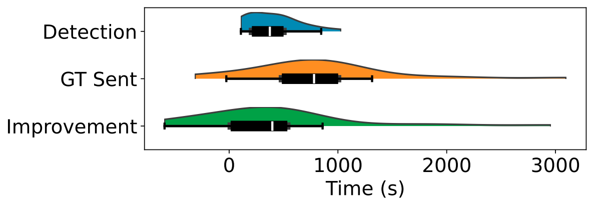


Fig. 7: Statistical analysis of 30 accidents on German, British and United States freeways in March 2022 and spring 2024

flow remains unimpeded, the algorithm fails to activate, as it relies on the detection of traffic patterns. In case of low traffic impact it may be outpaced by conventional reporting through involved parties or bystanders. Often, these low traffic impact incidents are resolved before they generate noticeable traffic patterns, as illustrated in Figure 6b where the algorithm detected the incident at 21:22 h, 13 min after the official report at 21:09 h and just prior to the resolution of the congestion pattern. Conversely, Figures 6c and 6d demonstrate the algorithm's effectiveness in recognizing accidents with significant traffic disruption or complete blockage, often before these are reported by official sources. In these cases, the algorithm proves particularly beneficial, enhancing the responsiveness of emergency services and the overall management of traffic flow.

5.3. Statistical Analysis

A statistical analysis supports the significance of the proposed method. Thirty examples from German, British, and U.S. freeways in March 2022 and spring 2024 are analyzed, focusing on accidents with high traffic impact and full blockage. Of these, 79% are high-impact and 21% are full blockage accidents. The analysis examines three key performance indicators (KPIs): detection, ground truth (GT) sent, and improvement. Violin plots (Fig.7) illustrate the distribution of these KPIs, combining features of box plots and density plots. Colors indicate the distribution over time, white vertical line the related median of the KPI and black boxes indicate the box plot with interquartile range.

- Detection: Measures time to detect an accident. Most accidents are detected quickly, with high density around lower time values.
- GT Sent: The time of the ground truth data sent, relative to the formation of a traffic pattern. Shows greater variability due to factors like detection complexity without connected vehicles or third-party reports.
- Improvement: Measures time saved between detection and sending of GT information.
- The distribution is skewed towards lower time saved, with most cases showing modest improvements and a few significant savings.

Notably, some ground truth data indicates that accident information is sent before traffic patterns form, likely due to direct reports from connected vehicles, for example via eCall. The average saved detection time across all accidents is 6:37 min, a 51.6% improvement.

6. Conclusion and Outlook

The paper presents an innovative automated accident detection method utilizing fleet data, offering significant improvements over current incident reporting channels. The method demonstrates reliability and efficiency, being approximately 6:37 min faster than traditional channels. Notably, it circumvents the necessity for vehicles involved in the accident to be connected, focusing instead on analyzing the traffic impact resulting from the accident. This approach enables a precise reconstruction of the time and location of the accident. The detection method relies on the impact of accidents on traffic flow, which limits the detectable accidents to those having an impact on other cars, i.e., those occurring on a road lane rather than an emergency lane. Future work may further elaborate on the potential of traffic impact detection by predicting the future impact of a congestion. While the method focuses on real-time accident detection, its principles could be adapted for predictive applications. Analyzing vehicle trajectory patterns over time could identify high-risk areas and times for accidents, aiding proactive traffic safety. This involves extending the analysis to historical data to find recurring accident patterns. Incorporating surrogate measures like near-miss incidents and traffic conflicts would improve predictive capability. Although it has predictive potential, the primary aim is to detect accidents post-occurrence and improve the response time of emergency services or traffic management systems. Post-occurence detection ensures that false-positive detections can be minimized, as the traffic pattern is already formed. In summary, this automated accident detection method presents a promising tool for improving traffic incident reporting and response times. Future research should explore predictive capabilities and the incorporation of near-miss and traffic conflict data to enhance traffic safety further.

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