Accident Analysis

Submitted by Prisly Mary Jacob, Stanley Saji George, Susan Jacob

Guided by Prof. Siju Swamy

SAINTGITS COLLEGE OF ENGINEERING (AUTONOMOUS), KERALA

Abstract

Studies reveal that a mere 2-second early warning can prevent 99% of accidents, highlighting the urgency for proactive safety measures due to over 80% of traffic collisions being attributed to human errors. ADAS (Advanced Driver Assistance System) serves as a vigilant guardian, utilizing advanced technologies like Artificial Intelligence (AI) to scan the road for hazards and promptly alert drivers, eliminating issues like driver fatigue and distraction. We utilize Tableau to import, analyze, and visualize the dataset containing attributes such as latitude, longitude, date, time, speed, and ADAS-generated events, enabling us to uncover insights into accident prevention and driver safety, and effectively present our findings through interactive dashboards and visualizations. We explore patterns, and trends, and propose solutions to enhance road safety, emphasizing ADAS's pivotal role in reshaping safety standards in our fast-paced world.

1 Introduction

This report presents a comprehensive analysis of data collected from 12 vehicles, categorized into four distinct types, spanning a duration of two months in the Chennai area. The fact that a total of 500 vehicles were involved in road accidents in Chennai city in 2022 and 508 people lost their lives last year, according to data by the Greater Chennai Traffic Police (GCTP), further emphasises the need for better road safety and accident prevention methods. The dataset used in this study primarily focuses on on-road events detected by AI-based Advanced Driver Assistance Systems (ADAS) devices, specifically collision alerts. The study encompasses city roads and national highways in Tamil Nadu, providing insights into vehicular safety and incident prevention. This formal analysis aims to assess the observed data and its implications concisely.

2 Literature Review

Our research goals are mainly to explore the various methods to study the spatial distribution of accidents and identify traffic accident hot spots for a certain region. Masello et al. (2022) assessed the potential of Advanced Driver Assistance Systems (ADAS) in reducing road accidents, highlighting their effectiveness in specific driving conditions. By analyzing UK road safety data, it was concluded that deploying key ADAS technologies could reduce accidents by 23.8%, with Automatic Emergency Braking proving most impactful in mitigating frequent accident types. Ayoun et al. (2022) from their literature review of over 72 papers identified some limitations of ADAS, which could collectively impact its performance and reliability. It categorizes these limitations into three main areas: human factors (including driver misuse, overtrust, and disuse), environmental factors (such as adverse weather, lighting, and road conditions affecting sensor effectiveness), and vehicle-related issues (sensor limitations, compatibility with vehicle modifications, and cybersecurity concerns). Solutions for human factors involve driver behavior monitoring, intention recognition, and pedestrian detection improvement. Environmental factor solutions include machine learning models for sensor support and road condition classification. Vehicle-related solutions focus on sensor fusion, hardware enhancements, and software-based methods and algorithms to improve ADAS performance.

The identification of hazardous road sections is one of the main parts of any successful road safety management process. The identification of hazardous road sections, high-risk accident locations or black spots (BS) receives great interest from road agencies and safety specialists (Ghadi et al. 2019).

3 Analysis

The provided data set includes details about 12 vehicles over a period of two months covering a distance of 35,000 kilometers. This information was collected using Advanced Driver Assistance Systems (ADAS) devices based on AI technology. These devices were strategically placed in the vehicles as they traveled through streets and highways. Upon analysis, it was found out that the longitudes and latitudes given in the dataset correspond to highways in the Chennai-Tambaram area, Tamil Nadu.

We used Tableau software to import, format, and analyze the dataset, employing color-coded labels for clarity. Tableau is a robust data visualization and business intelligence tool known for simplifying complex datasets into accessible visuals. Unlike traditional GIS tools, it offers a b roader r ange o f data analysis features beyond spatial data, enabling interactive dashboards, advanced statistics, and seamless data integration from diverse sources.

3.1 Pivot Table Analysis

Vehicle	Alert	AVERAGE of Speed	COUNT of Alerts
805	cas_fcw	33.87974684	158
	cas_hmw	34.40809084	4227
	cas_ldw	49.55945419	2052
	cas_pcw	17.81278539	438
805 Total		37.86094545	6875
1995	cas_fcw	0	1
	cas_hmw	14.5	8
	cas_ldw	42.625	8
	cas_pcw	0	1
1995 Total		25.38888889	18
2846	cas_fcw	39.6137931	145
	cas_hmw	37.57824824	2409
	cas_ldw	51.63918278	2741
	cas_pcw	18.63682864	391
2846 Total		43.10587408	5686
3143	cas_fcw	33.63414634	82
	cas_hmw	34.67134652	1567
	cas_ldw	51.35045662	876
	cas_pcw	18.9182058	379
3143 Total		37.61742424	2904
5339	cas_fcw	37.25980392	204
	cas_hmw	35.21204761	4117
	cas_ldw	51.62599469	754
	cas_pcw	16.13428944	767
5339 Total		34.89729545	5842

Figure 1: Pivot Table showing average speed and number of alerts of each vehicle type.

From the pivot table analysis, it's clear that vehicle type 805 has the highest number of alerts, totaling 6875. It becomes apparent that this particular vehicle type has encountered a substantial number of incidents or events warranting warnings, specifically related to headway monitoring and warning (HMW). However, an intriguing anomaly appears in the dataset for vehicle type 1995. Despite this vehicle's average speed registering as 0 for Forward Collision Warning (FCW) and Pedestrian Collision Warning (PCW) alerts, there is a singular instance recorded for each of these alerts.

This discrepancy could stem from:
1. Data Entry Error: There may have been an error during data entry, leading to inaccurate information for vehicle type 1995.
2. Sensor or Device Malfunction: The sensors or AI-based ADAS devices in vehicle type 1995 might have experienced technical issues during data collection, resulting in inaccurate or missing data for FCW and PCW alerts.
3. Operating Conditions: Certain conditions or scenarios could suppress FCW and PCW alerts, such as the vehicle being stationary or operating in a mode with collision warnings intentionally disabled.
4. Outlier: These anomalies may represent outliers within the dataset, indicating unique or exceptional situations that warrant further investigation.

3.2 Weekly ADAS Alert Overview

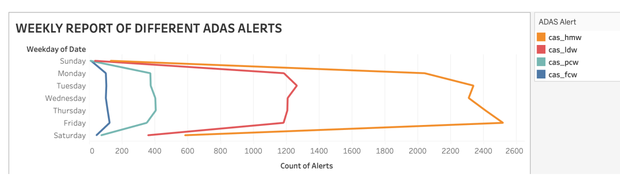

Figure 2: Weekly report of different alerts

On examining the weekly report of various ADAS alerts, it's apparent that Headway Monitoring (HMW) consistently holds the highest alert count, while Forward Collision Warning (FCW) registers as the lowest. This discrepancy can be attributed to several factors.

The relatively low count for FCW alerts could be indicative of several possibilities. Firstly, FCW alerts typically activate when a vehicle is in close proximity to the one ahead, implying that drivers might generally maintain safe following distances or engage in less aggressive driving behaviors. Moreover, modern vehicles are often equipped with advanced safety features, which could contribute to a reduction in FCW alerts as these systems effectively prevent or mitigate potential forward collisions.

Observing the weekly trend, it becomes evident that alert counts for all ADAS categories remain relatively high from Monday through Friday. However, HMW displays a notable uptick on Fridays, reaching a count of 2518. Lane Departure Warning (LDW) experiences a spike on Tuesdays with 1263 alerts, possibly indicating varying driver behaviors early in the week. Additionally, Pedestrian Collision Warning (PCW) alerts peaked on Thursday reaching a count of 404 and FCW peaked on Friday reaching a count of 123. The decrease in alert counts over the weekend may indeed be attributed to reduced vehicular activity, as people tend to spend more time at home during that time.

3.3 Vehicle Alert Time Distribution Analysis

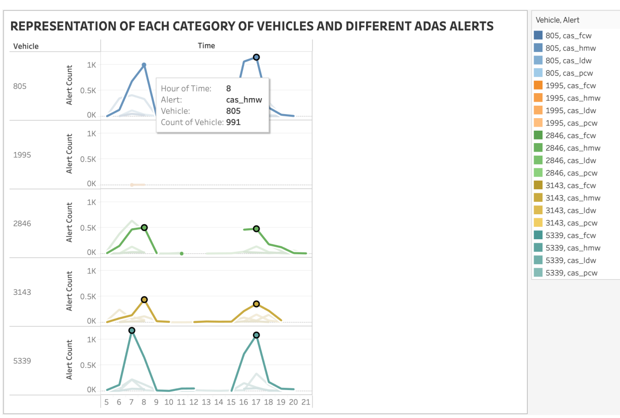

Figure 3: Vehicle Alert-Time Distribution

In Figure 3, we can observe the different alerts generated by the vehicles over the time period from 5 a.m. - 8 p.m. The greatest number of alerts corresponded to HMW alerts across all vehicle types, which have been highlighted in the figure. These HMW alerts exhibited significant peaks during two distinct time periods: 7-8 am and 4-5 pm. These specific timeframes correspond to the morning and afternoon rush hours, which are characterized by heightened traffic activity due to work and school-related commutes.

Several factors contribute to the prominence of HMW alerts during these rush hour periods. First and foremost, traffic congestion is a common occurrence during these times, making it challenging for drivers to maintain a safe following distance between vehicles. The increased vehicle density on the road during rush hours also raises the likelihood of scenarios that trigger HMW alerts, such as tailgating and abrupt braking.

Additionally, the morning and afternoon rush hours are closely associated with school and work commutes. School buses, parents dropping off children, and commuters hurrying to their workplaces all contribute to the surge in traffic vo lume du ring these hours. Consequently, this heightened traffic activity is accompanied by an increased frequency of HMW alerts.

Driver behavior also plays a significant r ole. During rush hours, drivers may exhibit behaviors such as aggressive driving, impatience, or distractions due to time constraints. These behaviors can lead to situations where drivers follow other vehicles too closely, resulting in the triggering of HMW alerts.

Moreover, the dataset used in this analysis reflects urban road conditions, as it pertains to Chennai highways. Urban areas typically experience higher traffic volumes and congestion, especially during peak commuting hours.

3.4 Analysis of the Blackspots

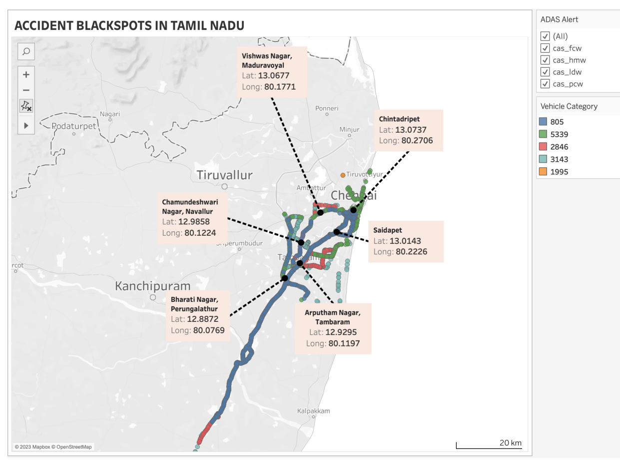

Figure 4: Figure depicting blackspot areas

The provided Figure 4 delineates the blackspots situated along the national highway and city roads. In the context of road safety, "blackspots" denotes specific locations or segments of the road network where a heightened frequency of traffic incidents, accidents, or safety-related issues is documented. Upon scrutinizing Figure 4, it becomes evident that the areas with the highest frequency of alerts encompass Vishwas Nagar, Chintadripet, Saidapet, Arputham Nagar, and Bharati Nagar. Additionally, the presence of an outlier, denoted by a conspicuous yellow spot, corresponds to vehicle type 1995. This data furnishes valuable insights for enhancing safety measures like deploying targeted safety interventions and infrastructure improvements within these blackspot areas.

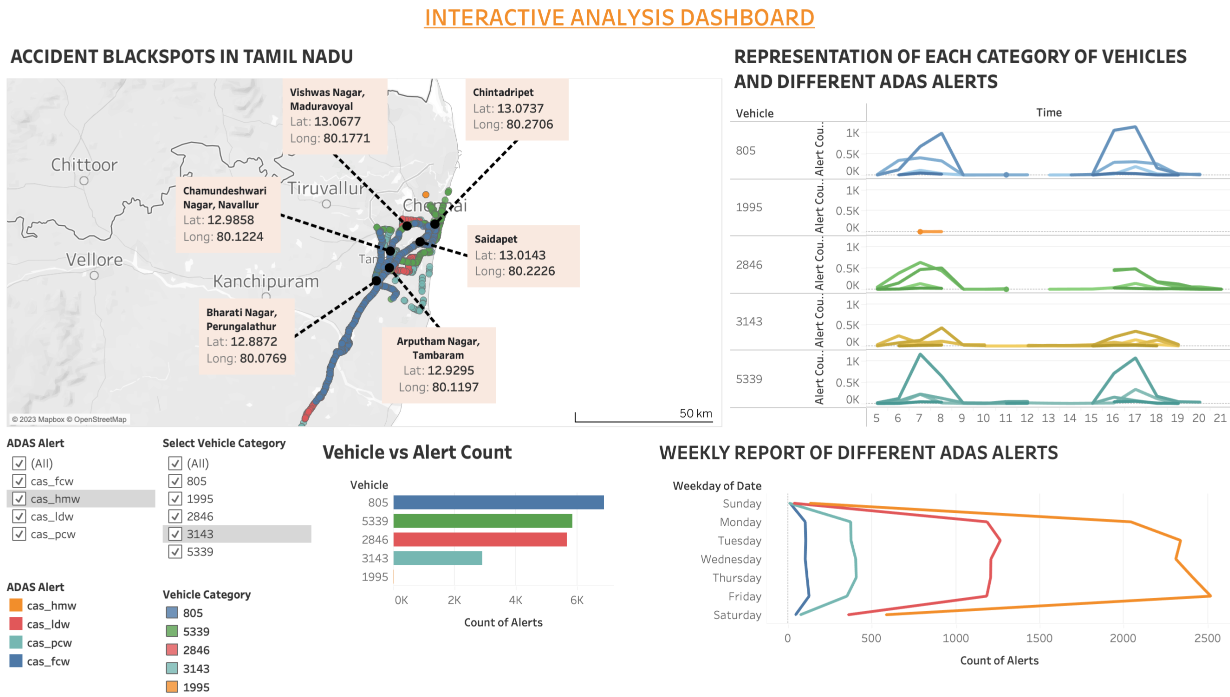

Figure 5: Dashboard showing all analyses results

4 Conclusion

In conclusion, our analysis revealed that vehicle 805 was responsible for generating the highest number of ADAS alerts, predominantly during the peak hours of 7-8 am and 4-5 pm on weekdays. Notably, Headway Monitoring and Warning (HMW) alerts were the most frequently triggered. Furthermore, our examination identified specific "blackspots" along the national highway and city roads, denoting locations with elevated incidents and safety concerns. These blackspots, including Vishwas Nagar, Chintadripet, Saidapet, Arputham Nagar, and Bharati Nagar, demand targeted safety interventions and infrastructure improvements to enhance road safety.

To address these challenges, it is essential to consider potential solutions. Implementing stricter enforcement of speed limits and safe following distances during peak hours can help mitigate the frequency of HMW alerts and reduce the risks associated with congested traffic. Additionally, road infrastructure improvements, such as better signage, improved road markings, and enhanced lighting in identified blackspot areas, can contribute to safer road conditions. Furthermore, continuous monitoring of ADAS system performance, especially for outlier cases like vehicle type 1995, can lead to early detection and resolution of sensor or device malfunctions, ensuring the accuracy of alert data. In embracing these solutions, we can work towards a safer and more efficient road network for all commuters.

5 URL

Our analysis can be viewed by clicking on the following link: Final Analysis of ADAS alerts.

6 References

[1]Masello, L., Castignani, G., Sheehan, B., Murphy, F., McDonnell, K. (2022). On the road safety benefits of advanced driver assistance systems in different driving contexts. Transportation Research Interdisciplinary Perspectives, 15, 100670. https://doi.org/10.1016/j.trip.2022.100670

[2] Ayoub, J., Wang, Z., Li, M., Guo, H., Sherony, R., Bao, S., Zhou, F. (2022). Cause-and-Effect Analysis of ADAS: A Comparison Study between Literature Review and Complaint Data. ArXiv. /abs/2208.00249

[3] Ghadi, M., Török, Á. (2019). A comparative analysis of black spot identification methods and road accident segmentation methods. Accident Analysis Prevention, 128, 1-7. https://doi.org/10.1016/j.aap.2019.03.002