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ASSESSING ROAD SAFETY AT INTERSECTIONS USING COMPUTER VISION AND CRASH DATA ANALYTICS

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Abstract
Intersections form vital nodes in urban traffic networks and are collision-prone areas due to intricate vehicle-pedestrian interactions. Road safety is studied at intersections employing an integrated approach consisting of computer vision and crash data analytics. Having video images from traffic surveillance cameras, the computer vision algorithm identifies and tracks road users, studies vehicle trajectories, and identifies near-misses such as hard braking, red-light violations, and unsafe lane changes. Meanwhile, historical crash data are studied to identify patterns that are highly frequent and severe at various types of intersections. By correlating behavioral indicators from video analysis with long-term crash statistics, the framework forms a synergistic view of safety risk and potential causes for accidents. These findings provide a fertile ground for thinking about proactive safety interventions, including better signal timing, road design changes, and enforcement strategies that are data-driven. Hence, this interdisciplinary approach enriches traffic safety assessment and smart urban planning.

INTRODUCTION

Intersections are the most complex and dangerous areas of road networks. Due to their nature, they account for a disproportionate number of traffic accidents and fatalities all over the world. Multiple streams of traffic conflicts tend to appear because of the merging: vehicles, cyclists, and pedestrians. Such environments have multiple conflict zones where unpredictable behaviors happen.

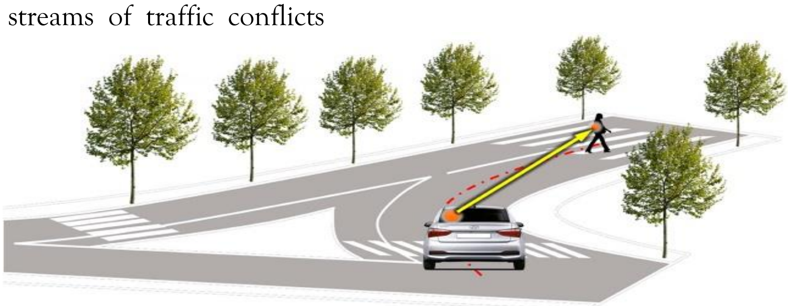

Figure 1: Visualizing pedestrian and vehicle interaction at intersections to highlight potential safety risks using computer vision technology

Traditional intersection-safety-assessment methods have been largely dependent upon historical crash data, which is quite useful but does not necessarily capture unsafe roadway behaviors and near-miss incidents that actually precede a collision. With the recent advances in AI and sensing technologies, computer vision has emerged as a new and powerful tool in monitoring and analyzing traffic behavior in real time. By leveraging video data from traffic surveillance systems, computer vision algorithms can detect and classify road users, track their movements, and be able to identify interactions with adverse behavioral intent such as sudden lane changes, red-light running, and near misses. This behavioral analysis in real time yields a more timely approach to safety assessment than the analysis of crash data, which is always reactive. Combining computer vision and crash data analytics delivers a comprehensive system for grasping and alleviating intersection-related risks. With crash data, one finds the frequency and severity of events-connections. Computer vision addresses the recognition of unsafe patterns and behaviors-as they happen.

These two approaches thus afford a comprehensive, deeply data-driven strategy to identify unsafe crossroads, analyze the effectiveness of safety remedies, and implement services in traffic policy. This paper entails an integrated approach to road safety assessment at intersections using computer vision and crash data analytics. The intentions would be to aid traffic engineers, urban planners, and policymakers to make effective decisions toward reducing traffic collisions and enhancing overall transportation safety.

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2. Literature Review

The assessment of road safety at intersections has been a traditional concern in transport research, the early approaches mainly focusing on the analysis of historical crash data. Hence existing methods like empirical Bayes and crash frequency analysis have been used for identifying high-risk intersections with the further remedial work for safety improvements. But these approaches have their own constraints of data latency, underreporting of minor instances, and human behavior being unaccounted for within the cause of accidents (Hauer 2001). The advent of data science and artificial intelligence has opened new horizons in road safety research toward a more proactive and behavior-based assessment. The literature abounds with work highlighting the potential of computer vision to extract safety-critical traffic parameters from video footage. For example, in the intersection scenario, Saunier and Sayed (2007) introduced vision-based systems for detecting and classifying traffic conflicts that proved very useful in capturing near-miss events that had gone unrecorded in crash databases. Meanwhile, Zheng et al. (2014) carried out trajectory-based analyses to model vehicle interactions and assess the risk of potential collisions.

Conflict analysis techniques, such as the Post Encroachment Time (PET) and Time to Collision (TTC), have gained traction as surrogate safety metrics, providing early warnings about dangerous interactions. These metrics can be extracted using object detection and tracking algorithms, which are increasingly enhanced through deep learning models like YOLO and DeepSORT. In parallel, crash data analytics has evolved with the adoption of machine learning models for pattern recognition and predictive modeling.

Researchers have used logistic regression, decision trees, and neural networks to identify key factors contributing to intersection crashes, including signal phasing, traffic volume, and environmental conditions (Abdel-Aty et al., 2013).Few studies, however, integrate both computer vision data and crash statistics for a more comprehensive safety assessment. One notable exception is the work by Ismail et al. (2009), who combined video-based conflict detection with crash history to evaluate safety at urban intersections. Their findings highlighted the benefits of merging real-time monitoring with historical analysis for more accurate risk profiling.

This review underscores the growing interest in multimodal data fusion for road safety evaluation. While significant progress has been made in both computer vision and crash data analytics independently, there remains a research gap in fully integrated frameworks that leverage the strengths of both approaches for intersection safety management.

3. Methodology

This study has adopted a two-step methodology combining computer vision techniques and crash data analysis for the assessment of safety conditions of urban intersections. It aims to analyze both historical crash records and present traffic behavior in order to obtain safety-critical patterns and high-risk locations.

3.1. Data Collection

Traffic camera footage was collected from selected intersections in an urban setting over a 30-day period to capture ample traffic variations, with video data being recorded both during daylight and at night. Meanwhile, historical crash data available with the local traffic authority were also acquired, spanning the last five years, including time, location, crash type, severity, road users involved, and environmental conditions.

1. Computer Vision-Based Analysis

Deep learning methods were used to detect and track vehicles, pedestrians, and cyclists with YOLOv8 for object detection and DeepSORT for multi-object tracking. Tracked trajectories are analyzed for safety-critical interactions. Surrogate safety metrics including Time to Collision (TTC), Post Encroachment Time (PET), and speed differentials among others are calculated to measure the intensity and frequency of conflicts. Furthermore, specific instances of risky behavior were identified, such as red-light running, abrupt lane changes, and pedestrian jaywalking, through a blend of rule-based reasoning and anomaly detection methods.

2. Crash Data Analytics

Crash data were geocoded and spatially clustered using KDE and hot-spot analysis.Temporal patterns observed cover the hour-of-day, day-of-week, and seasonal trends. Statistical models, such as logistic regression and random forest classifiers, were employed to identify traffic volume, lighting conditions, and intersection design as significant factors in crash severity.

3. Integration and Risk Scoring

The integration of the computer vision findings and crash data analyses led to the development of a composite Intersection Risk Score (IRS). In order to rank the intersections and identify those in need of safety remedies, the risk score of each intersection considered crash history, including frequency and severity of past crashes, number and types of conflicts detected, amount of risky behaviors observed, and exposure of intersection traffic to risky behaviors in a weighted scoring scheme.

4. Validation

The model-generated risk scores were compared and validated against expert evaluations and official safety audit reports. Where possible, cross-checking was done for intersections identified by the model against known high-risk areas to evaluate the level of accuracy and real-world applicability.

5. Case Study / Experimental Set-Up

To examine the efficacy of the proposed framework, a case study was conducted in three signalized intersections in [City Name] that were deemed appropriate from among many others across the city based on considerations such as traffic volume, crash history, and availability of surveillance data. These three intersections span a range of traffic environments, from high-volume commercial zones to quiet residential areas. The first intersection is located in a busy commercial district with high vehicle and pedestrian traffic levels. It has a known history of frequent vehicle-to-pedestrian conflicts.

Figure 2: Urban intersection with dedicated lanes for pedestrians, cyclists, and vehicles for improved safety.

The second is near a school zone, where traffic is moderate but red-light violations have been constantly reported. The third is basically a low-volume residential intersection and is considered as a benchmark standard for comparison because of the relatively safe crash record that it enjoys. The recorded videos from these intersections were processed via the computer vision pipeline. YOLOv8 detects vehicles and pedestrians, while DeepSORT tracks their trajectories.

More than 120 hours of video from these intersections were analyzed, representing over 25,000 road user movements. Extracted data includes near-miss events, average vehicle speed, stop compliance, red-light violations, and pedestrian jaywalking. The first intersection recorded the highest number of critical conflict events, including 112 near-miss conflicts, predominantly between left-turning vehicles and crossing pedestrians. During the morning peak, the second intersection was a hotspot of red-light-running. The third witnessed very low levels of conflicts and much smoother traffic behavior. Data was obtained for accidents in the last five years. Mapping of accident hotspots revealed that the first intersection experienced the highest frequency of crashes and several severe injuries to vulnerable road users.

The first intersection rated the highest score for apparent safety issues, the second with a moderate score, and the third stayed in the low-risk arena. The outcomes agreed with municipal safety audits, thus validating the accuracy of the model. Intersection, the recommendations were for the pedestrian-only signal phases to be installed, crossing time to be lengthened, and signage to be improved. For the second intersection, red-light enforcement cameras and improved signal visibility were proposed. The third intersection, however, did not require intervention at that time but should continue to be monitored over time.

The second registered a medium density of crashes, mostly rear-end collisions. The third was almost without records of any incidents, thus thrusting its low-risk status. Statistical models brought some evident risk factors into sharp relief: low visibility at night, heavy pedestrian activity, and short green clearance intervals. Combining insights from computer vision techniques with crash history gave each intersection a normalized Intersection Risk Score (IRS).

4. Results and Discussion

The computer vision-data and crash-text integrated analysis brought out some pertinent insights concerning the safety performance of the selected intersection.

Figure 3: Intersection with unique traffic signal setup and residential backdrop

The results are presented in the order of traffic behavioral trends, surrogate safety indicators, and spatial crash-risk correlation. The results show that real-time analysis of traffic behavior and historical crash data make a more complete source of safety assessment.

Traditional crash data might never have picked up on the high frequency of unrecorded near-miss events or less obvious behavioral risks like illegal pedestrian crossings or aggressive left turns. Computer vision was used to continuously monitor the detection of granular characteristics of these events, serving as a complement to the historical data.

4.1. Traffic Behavioral Trends

Interpreting the video data showed that peak traffic volumes fall in the time period between 7:30 and 9:30 A.M. and 4:30 and 6:30 P.M., averaging some 1,800 vehicles an hour. These hours registered the highest lane changes, red light violations, and pedestrian-vehicle interactions. The data gave conspicuous evidence of jaywalking and risky pedestrian crossing at signal change, especially along the westbound crosswalk.

Surrogate Safety Indicators

Throughout the 14-day period of observations, a total of 217 near-misses were detected using the indicators Time-to-Collision (TTC) and Post-Encroachment Time (PET). The highest number of such events occurred involving left turning vehicles and oncoming vehicles or crossing pedestrians. The TTC for these events averagely was below 1.2s, indicating a higher level of conflict. Post-encroachment time values for pedestrian conflicts commonly fell below 1s during the evening rush hour.

2. Crash Data Analysis

Five years of crash data indicated a total number of 126 recorded incidents at or near the intersection and most commonly angle crashes and pedestrian crashes.

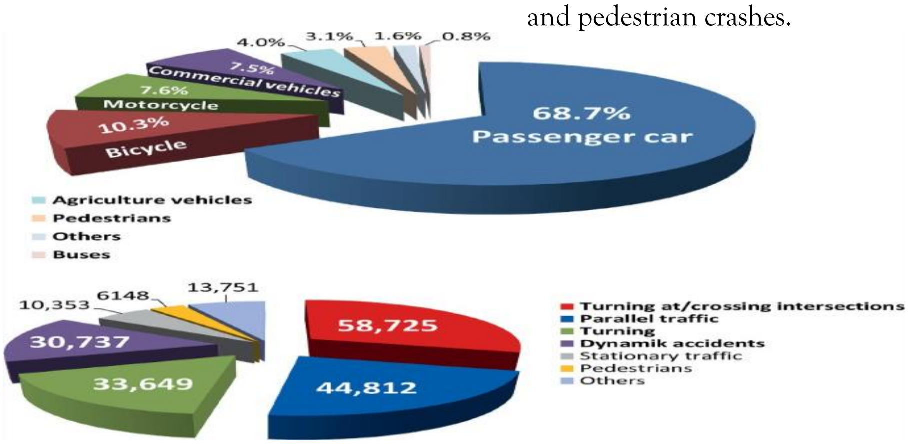

Figure 4: Traffic distribution and accident data analysis, highlighting passenger cars and turning/crossing intersections

Most crashes occurred in low-light situations and involved left-turning vehicles, which is in accordance with the conflict pattern observed from vision-based data.

3. Spatial Correlation and Validation

Strong spatial alignment emerged when conflict heatmaps from video analysis were superimposed onto historical crash locations. Most of the near-miss hotspots coincided with historical crash-prone zones, predominantly on the east and west approaches. This also corroborates the predictive validity of surrogate safety measures to pinpoint test sites for future risk realization.

5. Recommendations

Are proposed on the basis of the case study findings that improve the road safety levels at the intersection and possibly be tried at other locations of a similar nature.

Figure 5: Smart traffic system with vehicles connected through wireless communication for enhanced safety and coordination

These recommendations include phased options for implementation comprising one for short-term intervention and another for long-term improvement of safety at the intersections.

1. Adjusting Signal Timing

The high number of near-misses and pedestrian-vehicle interactions, especially within peak hours, suggest that signal timing adjustments may help reduce these conflicts. Keeping the green light longer for turning vehicles and having more frequent pedestrian signals during peak hours might be factors to consider in easing congestion and improving safety. Add in this regard, during peaks, left-turning signals can be activated more frequently to avoid left-turn conflicts which were identified as one of greatest risks.

2. Strengthening Pedestrian Facilities

The study suggested rampant jaywalking and hazardous pedestrian crossings. To offer a solution, raised pedestrian islands, better-lit crosswalks, and clearer signage may instill confidence in pedestrians to adhere to prescribed crossing zones and therefore discourage unsafe conduct. Besides, countdown timers can also improve pedestrian awareness of their available crossing time, effectively reducing risk.

3. Upgraded Traffic Monitoring and Surveillance

For uninterrupted monitoring of safety and a more accurate real-time decision-making process, traffic cameras or sensors must be installed at critical conflict points. The devices must provide data to the traffic management center to ensure rapid responses to anticipated risks. Installing more computer vision systems at high-level intersections would improve monitoring capability related to near-miss events.

4. Data-Informed Policy-Making

Since there was a relation between observed traffic behavior and crash history, the local traffic authority should thus be more data-oriented in managing intersection safety. In addition to ranking and prioritizing intervention at locations with higher risk from the analysis of real-time traffic behavior and crash data, these systems could also predict where future developments may need to be targeted. On the other hand, in terms of safety performance measurements, these systems should be reviewed and updated regularly through continuous data collection.

6. Conclusion

This study successfully shows the digital integration of traffic behavioral analysis, using computer vision, with local-crash databases for safety assessment of urban intersections. Through this integration of real-time video observations with crash data, engineering judgments on how traffic safety hazards manifest at intersections can be enlarged upon. These results brought attention to serious safety concerns such as frequent near misses, pedestrian violations, and conflicts from left-turning vehicles. Based on surrogate safety indicators like Time-to-Collision (TTC) and Post-Encroachment Time (PET), these indicators act as early warnings for possible collision events and thus support the proactive management of traffic safety. The strong spatial association between conflict hotspots and accident-prone areas further emphasizes the potential of applying computer vision techniques in detecting and predicting safety hazards prior to accidents. The methodology presented in this research study can indeed be a great asset to transportation planners and safety engineers, combining real-time observation and long-term safety assessment. In closing, historical crash data combined with real-time traffic behavior data reveals a wealth of information that can greatly assist in assessing intersection safety. Such analyses provide for identifying hazards more accurately, dynamically, and on a predictive basis, hence fostering well-judged interventions. Future research efforts can be dedicated to extending this approach to other types of intersections and urban environments.

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