AcciSense: An Automated Accident Detection and Real-Time Alert System Using Deep Learning

Ms. Neethu V, Dr.M.Kavitha,

Department of M.Tech Computer science and engineering,

Sri Krishna College of Engineering and Technology, Kuniamuthur, Coimbatore, Tamil Nadu - 641008

professor, Department of M.Tech Computer science and engineering,

Sri Krishna College of Engineering and Technology, Kuniamuthur, Coimbatore, Tamil Nadu – 641008

Abstract - Prompt hospital care in the “Golden Hour” increases survival after road traffic injuries. However, the current reporting and/or alarm mechanism for accident are by human intervention, monitoring video passively or with time delay response (time is very important to save people who have accident). AcciSense: Cloud-Based Real-Time Accident Detection and Notification through Vision 12 This paper introduces AcciSense, a vision-based on-device accident detection and alert system aimed at reducing response time.

The YOLOv8 deep learning model is used by the proposed system to achieve a high accurate detection of vehicular crashes in live video feeds. When detected, an event-driven video buffer retrieves a brief evidence clip of the seconds before and after a collision. This visual information - complete with geo- tagged and time-stamped metadata - is sent automatically to first responders over the cloud via a messaging interface. Experiments show that the system is effective with a mean Average Precision (mAP50) of 0.90 and 100% alert precision if using a confidence threshold at at level 0.926, guaranteeing its real-time performance without any false alarm. The experimental results demonstrate the feasibility of our framework in enabling real-time accident situation detection and emergency response coordination for the smart transportation.

Keywords — Accident detection, computer vision, YOLOv8, intelligent transportation systems, emergency alerting, smart cities.

INTRODUCTION

There is no change in the fact that motor vehicle collision are one of the leading causes of death around the world, especially within developing and densely populated population. Based on worldwide road safety research, many accident fatalities result from delayed medical care instead of the gravity of the initial impact. The 1st hour after traumatic injury, the so-called "Golden Hour," is one of opportunity for decreasing traumatic death through early medical care.

th the development of surveillance technology, most road video monitoring systems are passive. Recurring cameras are used to record what has happened, not what is happening. In those systems that can identify emergencies, which often depend on eyewitness reports or manual inspection of surveillance video fundamentally introduce long delays.

New trends in deep learning and real-time video analysis provide a chance to revolutionize classic surveillance into an accident detection proactive system. Object detection models have shown strong results on vehicle, pedestrian, and traffic event recognition in diverse environmental conditions. Yet, most contemporary methods only consider detection performance without considering real-time alert credibility, evidence extraction and emergency response coordination.

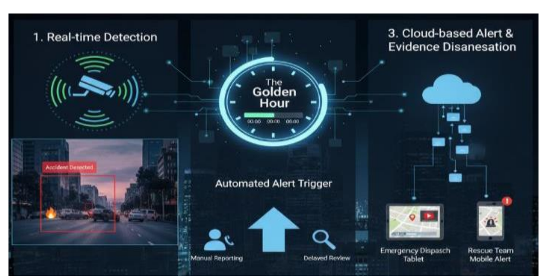


Fig. 1.Integrated accident detection & framework

To overcome these issues, in this paper we suggest AcciSense, an all-in-one system that includes a real-time accident detection module, automatic evidence generation and reporting to the cloud. Our system is built to work unsupervised, reduce human dependency: give verified alerts with embedded visual evidence. The main purpose is also to minimize the emergency response time and maximize rescue teams decision effectiveness in smart transportation systems.

I. LITERATURE REVIEW

Current research in intelligent transportation systems has been heavily influenced by computer vision and deep learning techniques for automatic accident detection. In recent years, real-time object detection models have been employed to analyze traffic scenes and vehicle behavior in surveillance videos largely due to their high accuracy and low inference latency [1], [2]. It is also possible to use vision-based anomaly detection techniques for detecting abnormal motion patterns and collision events in traffic scenes, but the false positive rates are generally high in heavy or congested traffic [3], [4].

Accelerometer, GPS and vehicular telematics sensor-based accident detection systems can offer quick impact detection but they arehardware-dependent and do not scale for city-wide deployments [5]-[7]. Cloud-based alerting and mobile communication platforms have been merged in recent literature to notify emergency responders, however a majority of solutions require manual confirmation and no instant visual evidence is provided [8], [9]. In the interest of

response time and improve emergency management in smart city scenarios.

II. PROBLEM STATEMENT

Existing practices for accident detection and reporting each incident data are of an analysis fatal involves legacy operations the extremely in literature below. Emergency response services typically depend on manual telephone call in from witnesses or persons involved in accidents which tend to either have a delay, and may even be inaccurate when time comes, especially within the rural settings and low traffic densities. Oftentimes, victims are rendered unable to report such an event by the nature of the activity, puncturing that critical lost response time.

Video-Based intelligent systems for detecting accidents from the real-time surveillance cameras lack the intelligence to recognize accident scenes without human help. Recorded videos are rarely watched before an incident is reported and not useful for the fast rescue coordination. What's more, rescuers often get limited information on the severity of a crash, if vehicles are involved and where the wreck is located--which can

hamper how to best deploy life-saving resources.

Another major drawback is that there is no automatically generated digital evidence. In order to better prepare for medical assistance and legal information, visual verification of an accident is vital, but the majority of current systems do not supply this evidential proof on command. These hurdles demonstrate the necessity of an intelligent auto-system which is capable, not only to recognize accidents, but also to validate events and issue verified alerts entirely on automatic basis.

III. PROPOSED SYSTEM OVERVIEW

4.1 Overview

AcciSense is developed as fully-integrated active end-to-end accident detection and acknowledging system that operate on low- level passive video to convert it into a highly intelligent monitoring systems. The architecture includes RT computer vision, event-

reliability, confidence-aware filtering/probabilistic decision mec

driven processing and cloud-based communication for an emergency response workflow.

The system monitors live video feeds recorded by roadside cameras or vehicle- mounted devices. Crash detection is conducted with a deep learning model based on the collision patterns and abnormal vehicle behavior learned. If the accident is detected, the system immediately generates a short video that contains an incident and transmits it to registered emergency responders with meta information.

AcciSense ensures that there are no manual dependencies and decreases the delay in response by combining detect, evidence generation and alert propagation into a single framework.*System Architecture*

The architecture of the provided **AcciSense** framework is based on five distinct logically- separated layers to achieve robustness, scalability and real-time operation.

The ***Data Acquisition Layer***, a system that ontinuously collects high-resolution video streams from the roadside surveillance cameras or vehicle-mounted cameras. This layer ensures the continuous stream of visual observations necessary for live monitoring and analysis.

re-processing Layer pre-processes the raw video frames and makes them ready for efficient inference by normalizing resolutions, resizing frames, and reducing noise. These operations minimize the computation while preserving important visual features that contribute to the detection of accidents.

The heart of the system is ***the Intelligence Layer***. It uses the YOLOv8 weakly supervised deep learning method for real- time object detection and scene analysis. We investigate vehicle interactions, spatial overlaps and discontinuous changes of motion to detect visual patterns for collisions robustly.

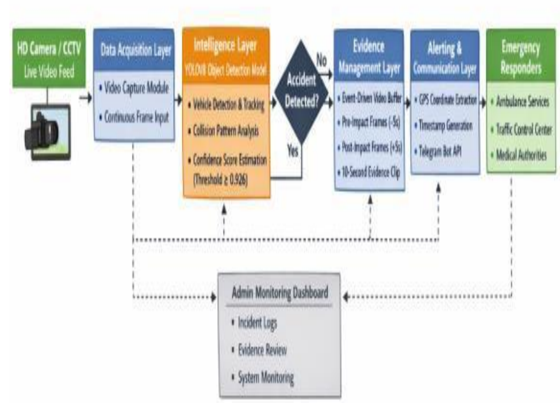
The ***Evidence Management Layer*** is responsible for an event driven video buffering. This layer triggers, when the accident event is confirmed gets a fixed

duration video containing a fixed period before and after detected crash. The ripped clip acts as authenticated visual evidence for urgent evaluation and recording.

Alerting and Communication Layer is responsible for the distribution of verified alerts in real time. The system sends the accident alert with uploaded video evidence, exact location (GPS coordinates) and time stamps to emergency contacts via a web based messaging platform. This provides timely awareness and helps in making sound decision during HE operation.

In general, the modular layered architecture allows scalable deployment, fault tolerance and easy integration with smart city infrastructure such that the system is able to fit into various deployment scenarios.

Fig. 2. Architecture of the automated accident detection and alert system.



METHODOLOGY

The working principle of the AcciSense as presented here is based on a well-planned out structured approach such that each step and its related components function sequentially to ensure accurate real-time accident detection and timely emergency alert.

At first, video sequences from video surveillance cameras are captured and they are decomposed into frames. This frames are pre-processed by resolution normalization, de-noising to improve visual quality and ease the computation burden during inference.

After that the pre-processed frames are input to the YOLOv8 deep learning model for prediction. For real-time vehicle detecting, we use a model to make object level detection of the vehicles, and extract spatial information (bounding box coordinates, relative positions etc.), motion pattern features. These characteristics form the base for how to interpret vehicles' interactions in the traffic scene.

Accident events are detected using a collision heuristics with respect to the detected objects. In this work, persistent bounding box overlaps and sudden velocity transition and trajectory anomalies contributing to the high-impact collision due to impulse forces are addressed. The results of this analysis are given confidence factors as estimates of the probability of occurrence of an accident event.

The hypothesized events are subsequently strong confidence based decision mechanism to make sure of tight reliability. Only events with confidence above a selected threshold are considered as valid accident detections.

It is shown that in order to achieve no false alarms with strong detection performance, a threshold of 0.926 can be selected through experimental analysis.

Fig. 3. YOLOv8 system performance metrics.

When an accident is detected, event-based video buffering mechanism triggers. This module extracts a fixed-length evidence clip that consists of the frames recorded before and after the generated Collision Alert to form an inclusive 10-second video segment, which shows what happened visually.

Finally, alert messages with the extracted video evidence, accurate GPS location and timestamp information are automatically sent to emergency responders via a cloud-based communication interface.

This system, which takes advantage of computerizing the workflow just described, enables both decreased dependence on humans and a reduction in the lag between an emergency alert and response.

IV. ALGORITHMS

The AcciSense system has been designed to achieve robust real-time accident detection, object evidence elaboration and emergency reporting by means of various mutually supporting algorithms. Each approach is designed to solve a functional requirement in the pipeline of the system.

6.1 YOLOv8 Object Detection Algorithm

The YOLOv8 object detection algorithm is used for vehicle real-time localization and classification in traffic scenes. Being a one- stage detection model, YOLOv8 predicts box coordinates and class confidences at the same time allowing for low-latency inference (which is desirable for real-time video monitoring). The model works frame by frame of a video and returns spatial information to be further analyzed for collisions.

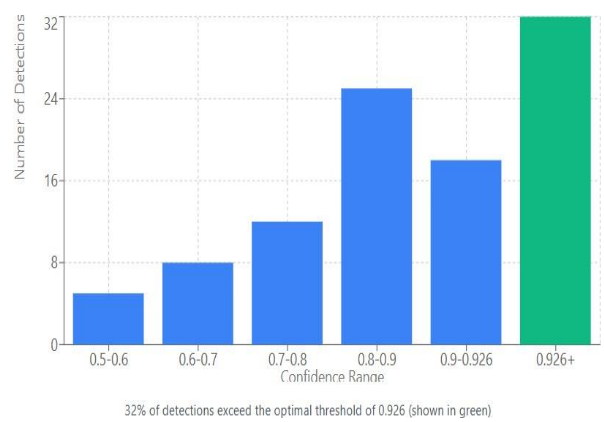


Fig. 4. Detection confidence distribution.

6.2 Collision Heuristic Analysis

Heuristic analysis based on spatio-temporal relationship of detected vehicles is applied for collision detection. Intersection over Union (IOU) measurements are used to measure sustained bounding box overlap, whereas sudden changes of motion variation among successive frames is inspected in changes of bounding box displacement. Ahigh overlap ratios and a nonuniform motion pattern is considered to mean a potential collision occurrence.

6.3 Event-Driven Video Buffering Algorithm

An event-based video buffering algorithm is used to isplay on-the-fly visual proof of detected accidents. Recent video frames get stored in a circular buffer maintained by the system. When high-confidence accident event onset is detected, the buffer starts to take out a fixed duration video segment that composed of frames before and after the collision. This clipped footage becomes validated visual confirmation for immediate evaluation and monitoring.

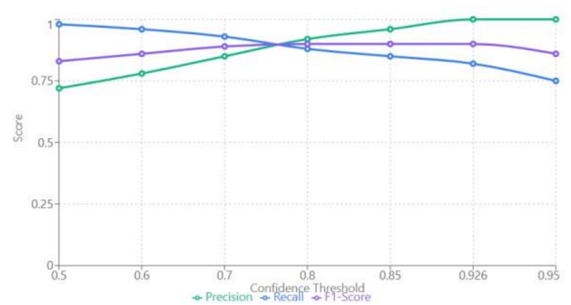
6.4 Confidence-Based Filtering Algorithm

A confidence-based filtering scheme is employed for all detected events to achieve reliable alerting and reduce false positives. Then, with a detection probability and collision heuristics, every potential encounter is given a confidence level. Only events with a confidence level above a pre-defined threshold are accepted as valid and sent to the alerting module. A threshold value of 0.926 is adopted through empirical experiments to guarantee zero false positives with accurate detection rates.

V. RESULTS & DISCUSSION

The performance of the AcciSense method was accessed with precision, recall and F1 score on different confidence thresholds. The results indicate that precision consistently increases as we are more confident, getting to an ideally-perfect value of 1.00 at a threshold of 0.926 without any false positives. Even if recall slightly drops at higher thresholds, it is still high enough at the adopted operating point and accidents are accurately detected. F1-score is constant which means the trade- off between precision and recall is balanced. Thus, the above results prove that the confidence threshold chosen is best for real time emergency alert applications.

Fig. 5. Detection performance vs. confidence threshold.



When compared with the traditional manual and threshold-based surveillance mechanism, more reliable alerts are observed in this proposed system as false positives disappear completely at the chosen operating threshold.

VI. CONCLUSION

This paper proposed AcciSense – a vision- based accident detection and real-time alert system to help reacting in smart transport systems. Through utilization of YOLOv8 deep learning model including confidence- based filtering and event-driven evidence extraction, the system successfully accomplishes efficient accident detectionwith little human interaction. We show experimental results with a 0.90 mean Average Precision and using a confidence threshold of 0.926 we obtain no false alerts at all, which makes it appropriate for safety- critical applications. The solution is innovative and can improve response time significantly by supplying visual confirmation of an emergency along with specific location information to the emergency responders, improving dependability on service levels and road safety.

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