A COMPUTER VISION-BASED FRAMEWORK FOR AUTOMATED ROAD ACCIDENT DETECTION AND RAPID EMERGENCY RESPONSE

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ABSTRACT

Road accidents are a major cause of fatalities and severe injuries worldwide, often due to delays in accident detection and emergency response. With the increasing deployment of surveillance cameras in urban areas, computer vision and deep learning techniques can be utilized for real-time traffic monitoring. This paper proposes a computer vision-based framework for automated road accident detection using CCTV surveillance systems. The system employs deep learning models such as YOLOv8 for object detection, Mask R-CNN for segmentation, and DeepSORT for object tracking to analyze vehicle movements and identify abnormal events like collisions and sudden stops. Upon detecting a potential accident, the system automatically generates alerts and notifies emergency responders with relevant information. Experimental results demonstrate that the proposed framework achieves high detection accuracy while maintaining real-time performance, enabling faster emergency response and improved road safety.

Keywords: Computer Vision, Accident Detection, Deep Learning, CCTV Surveillance, YOLOv8, Intelligent Transportation Systems.

I. INTRODUCTION

Road accidents represent a serious global safety concern, causing millions of injuries and fatalities every year. Rapid urbanization and increased vehicle usage have significantly contributed to the rise in traffic accidents across cities worldwide [1]. One of the major challenges associated with road accidents is the delay in detecting incidents and informing emergency response teams.

Traditional accident reporting methods rely heavily on manual observation or eyewitness reporting. These approaches often lead to delayed emergency responses, which can significantly increase the severity of injuries and fatalities. Therefore, automated accident detection systems are essential to enhance road safety and reduce response time [2].

Recent advancements in artificial intelligence and computer vision have enabled machines to interpret and analyze visual data effectively. Deep learning techniques have demonstrated remarkable success in various applications such as object detection, image classification, and video surveillance. These technologies can be utilized to analyze traffic video streams and automatically detect the accidents.

These technologies can be utilized to analyze traffic video streams and automatically detect abnormal events that may indicate road accidents. By continuously monitoring vehicle movements, speed variations, and interactions between road users, intelligent systems can identify unusual patterns such as sudden collisions, abrupt stops, or irregular vehicle trajectories. Integrating deep learning–based object detection and tracking techniques enables accurate identification of vehicles and their motion behavior in complex traffic environments. Such automated accident detection frameworks can significantly improve real-time traffic monitoring and support faster emergency response [3]. Therefore, developing an intelligent and automated accident detection system is essential for improving road safety.

II. LITERATURE SURVEY

Road accident detection systems have gained significant attention in recent years due to the increasing number of traffic accidents and the need for rapid emergency response [4]. Researchers have explored various computer vision, deep learning, object detection, and traffic monitoring techniques to automatically identify accidents in real-time. Many studies focus on improving detection accuracy, reducing response time, and enhancing traffic safety using intelligent transportation systems. This section provides an overview of key research papers related to automated road accident detection using computer vision and deep learning approaches [5].

The study [6] proposes a deep learning–based approach for detecting road accidents from traffic surveillance cameras. The system uses convolutional neural networks (CNNs) to analyze video frames and identify abnormal events such as vehicle collisions or sudden stops. Experimental results show that the model achieves high detection accuracy while maintaining real-time performance. The research also highlights the importance of integrating automated alert systems to notify emergency responders immediately after accident detection. Overall, the study demonstrates that deep learning techniques can significantly improve automated accident monitoring systems.

Research on YOLO-based object detection combined with DeepSORT tracking [7-9] shows promising results in real-time traffic monitoring applications. The YOLO model is used to detect vehicles and pedestrians in video frames, while DeepSORT tracks their movements across multiple frames. The system analyzes vehicle trajectories and motion patterns to identify abnormal behavior that may indicate potential accidents. Experimental evaluations demonstrate high precision and recall in detecting moving objects and maintaining tracking consistency. The study emphasizes that combining object detection with multi-object tracking significantly improves accident detection reliability.

Studies [10-11] on Mask R-CNN highlight its effectiveness in identifying precise object boundaries in complex traffic scenes. The model performs instance segmentation to detect vehicles, pedestrians, and road objects with high accuracy. By identifying the exact region of each object, the system can better analyze spatial relationships and collision scenarios between vehicles. The research indicates that segmentation-based approaches improve scene understanding compared to traditional bounding-box detection methods. Overall, the study demonstrates that instance segmentation plays a crucial role in accurate traffic incident detection.

This research [12] introduces a computer vision–based system for detecting traffic incidents from surveillance camera footage. The system analyzes vehicle speed, direction, and motion patterns to identify abnormal events such as sudden braking or collisions [13]. Machine learning algorithms are applied to distinguish between normal traffic flow and accident scenarios. Experimental results show that the proposed approach improves detection accuracy and reduces false alarms compared to traditional rule-based systems. The study highlights the potential of intelligent video analytics for enhancing road safety and traffic management.

This study [14-17] explores the use of deep learning and artificial intelligence for smart city traffic monitoring applications. The system integrates object detection, motion analysis, and anomaly detection to automatically identify road accidents and traffic congestion. Experimental results demonstrate that deep learning models can process real-time video streams efficiently while maintaining high detection accuracy [18]. The research also emphasizes the importance of integrating automated alert mechanisms to support faster emergency response. Overall, the study highlights the role of AI-driven systems in improving intelligent transportation infrastructure [19].

Overall, the common limitations identified across these research studies reveal several challenges in existing accident detection systems. Many approaches struggle with complex traffic scenarios involving multiple vehicles, occlusions, and varying lighting conditions. Some systems rely heavily on motion-based detection, which may produce false positives in dense traffic environments. Additionally, real-time processing of high-resolution video streams requires significant computational resources, making deployment challenging in large-scale surveillance systems. The surveyed works highlight that improving detection accuracy, reducing false alarms, and ensuring real-time performance remain key challenges in automated road accident detection systems.

III. PROPOSED METHODOLOGY

1. Video Input Acquisition

The proposed system begins with capturing real-time video streams from CCTV surveillance cameras installed at road intersections and highways. These cameras continuously monitor traffic activity and provide video input to the processing system. The video stream is divided into

individual frames for further analysis.

2. Frame Preprocessing

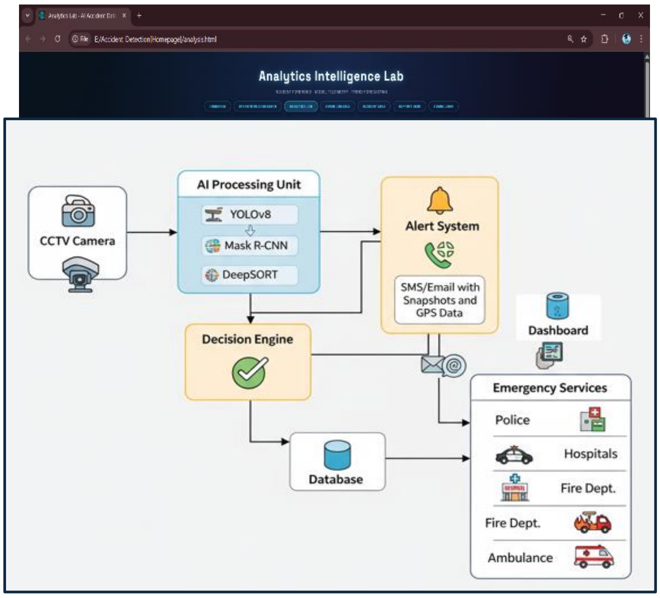
Before performing object detection, the captured frames undergo preprocessing to improve image quality and ensure accurate analysis. Preprocessing techniques such as resizing, noise reduction, and normalization are applied to standardize the input frames. These steps help reduce unnecessary variations caused by lighting conditions, camera noise, or environmental factors. By preparing the frames properly, the deep learning models can perform more efficiently and deliver better detection accuracy. This stage ensures that the system processes clean and consistent visual data.

Fig.3.1. *"Annotated video frames with bounding boxes and segmentation masks used for training"*

3. Object Detection using YOLOv8

The system uses the YOLOv8 deep learning model to detect and classify objects present in each frame. YOLOv8 is a real-time object detection algorithm capable of identifying vehicles, pedestrians, and other traffic participants. The model generates bounding boxes around detected objects and assigns class labels with confidence scores. This detection process enables the system to understand the traffic environment and identify vehicles involved in potential accidents. YOLOv8's fast processing speed makes it suitable for real-time surveillance applications.

4. Instance Segmentation using Mask R-CNN



To improve the understanding of traffic scenes, the system applies Mask R-CNN for instance segmentation. Unlike traditional object detection, Mask R-CNN identifies the precise pixel-level boundaries of objects within the frame. This allows the system to determine the exact position and shape of vehicles involved in traffic scenarios. Accurate segmentation helps analyze spatial relationships between vehicles and detect collisions more effectively. This component enhances the system's ability to recognize accident regions within complex traffic environments.

5. Object Tracking using DeepSORT

The system incorporates DeepSORT to track detected objects across consecutive video frames. DeepSORT assigns unique IDs to vehicles and follows their movement trajectories throughout the video sequence. Tracking vehicle motion enables the system to analyze behavioral patterns such as speed, direction, and interactions between vehicles. By observing movement over time, the system can detect abnormal behavior such as sudden stops or irregular motion paths. This temporal analysis improves the reliability of accident detection.

6. Accident Detection and Event Analysis

After detecting and tracking vehicles, the system analyzes motion patterns to identify potential accident events. Abnormal traffic patterns such as sudden collisions, rapid deceleration, unusual vehicle positioning, or unexpected stops are treated as indicators of accidents. The system evaluates spatial relationships between vehicles and their movement trajectories across frames. When these abnormal conditions exceed predefined thresholds, the system flags the event as a possible accident. This automated detection mechanism ensures rapid identification of traffic incidents.

Fig.4.1 "Event analysis and Detection Dashboard"

Fig.4.2. *"Event analysis and Detection Dashboard"*

7. Emergency Alert Generation

Once an accident is detected, the system automatically triggers an emergency alert mechanism. The alert includes important details such as the accident timestamp, location information, and captured visual evidence. Notifications are sent to emergency responders or traffic management centers for immediate action. The system can also store accident footage for further investigation and analysis. This automated alert process significantly reduces the delay between accident occurrence and emergency response. This rapid alert generation mechanism ensures timely assistance and helps reduce the severity of injuries by enabling quicker emergency response.

IV. ARCHITECTURE

The system architecture is designed to automatically detect road accidents from traffic surveillance video streams and generate rapid emergency alerts. The architecture **Fig.4.1** consists of several components including video input acquisition, frame processing, object detection, object tracking, accident analysis, and emergency alert generation. Each component works together to analyze traffic activity in real time and identify abnormal events that indicate potential accidents.

a) Video Input & Data Acquisition

The process begins with capturing live video streams from CCTV cameras installed at road intersections, highways, or traffic monitoring points. These surveillance cameras continuously monitor traffic conditions and transmit video feeds to the accident detection system. The system extracts individual frames from the incoming video stream at regular intervals for analysis. Input validation ensures that the video feed is stable and compatible with the processing pipeline. This stage provides the raw visual data required for detecting vehicles and analyzing traffic behavior.

b) Frame Processing & Data Preparation

Once the video frames are captured, they undergo preprocessing to improve image quality and ensure consistent input for deep learning models. Techniques such as resizing, normalization, and noise reduction are applied to standardize frame dimensions and reduce unwanted distortions. These preprocessing steps help the detection models focus on relevant visual features. Proper frame preparation improves computational efficiency and enhances the accuracy of the detection system. This stage prepares the input data for reliable object detection and tracking.

c) Object Detection using YOLOv8

After preprocessing, the system applies the YOLOv8 deep learning model to detect objects present in each frame. YOLOv8 identifies vehicles, pedestrians, and other traffic participants by generating bounding boxes and classification labels. The model operates in real time, enabling fast detection even in high-traffic environments. By accurately locating vehicles in the scene, the system can analyze traffic flow and interactions between vehicles. This stage forms the foundation for identifying vehicles potentially involved in accident scenarios.

d) Instance Segmentation using Mask R-CNN

To improve scene understanding, the system utilizes Mask R-CNN for instance segmentation. Unlike basic detection methods, Mask R-CNN identifies the precise pixel-level boundaries of detected objects. This helps determine the exact shape and region occupied by each vehicle in the frame. Accurate segmentation allows the system to analyze spatial relationships between vehicles and detect collisions more effectively. This stage enhances the system's ability to understand complex traffic scenes.

e) Object Tracking using DeepSORT

After detecting objects in each frame, the DeepSORT tracking algorithm is applied to track vehicles

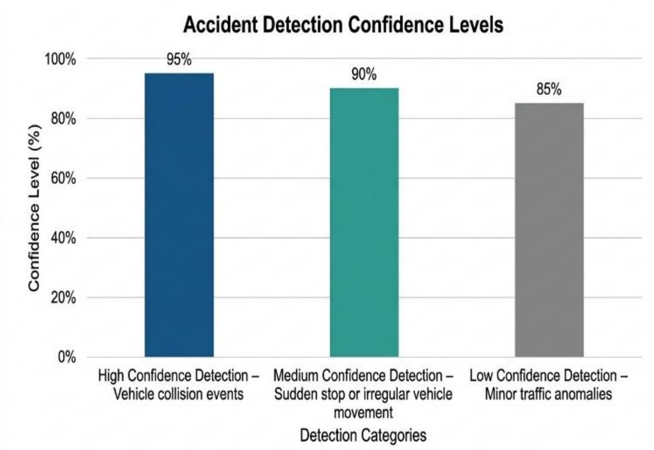


Fig.5.1. Confidence level distribution for detected accident events.

across consecutive frames. DeepSORT assigns a unique identifier to each detected vehicle and monitors its movement over time. This tracking process helps analyze vehicle trajectories, speeds, and interactions with nearby vehicles. By studying motion patterns, the system can identify unusual behavior such as sudden stops, abnormal turns, or vehicle collisions. Tracking provides the temporal context required for reliable accident detection

f) Accident Detection & Event Analysis

The system continuously analyzes vehicle trajectories and spatial relationships to detect abnormal traffic behavior. Events such as sudden collisions, abrupt deceleration, irregular vehicle positions, or unexpected stops are considered potential indicators of accidents. When such abnormal patterns are detected, the system classifies the event as a possible accident. Advanced analysis techniques help reduce false positives while ensuring accurate identification of incidents. This stage plays a critical role in recognizing real accident scenarios in real time.

g) Emergency Alert Generation & Reporting

Once an accident is detected, the system automatically generates an emergency alert notification. The alert includes important information such as the accident timestamp, location details, and visual evidence from the surveillance footage. Notifications are sent to emergency responders, traffic authorities, or monitoring centers to enable rapid intervention. The system can also store accident footage and generate reports for further investigation and documentation. This automated alert mechanism significantly reduces response time and improves overall road safety.

V. RESULT

The proposed system was evaluated using traffic surveillance video datasets to analyze its ability to detect road accidents in real time. The system successfully processed continuous video streams and accurately identified vehicles, pedestrians, and other traffic participants within the scene. Object detection using the YOLOv8 model effectively identified vehicles in each frame, while Mask R-CNN provided precise segmentation of vehicle regions. DeepSORT tracking enabled the system to monitor vehicle movements across consecutive frames and analyze motion patterns. The integrated framework demonstrated reliable performance in detecting abnormal traffic events and potential accident scenarios.

The accident detection module analyzed vehicle trajectories and identified unusual traffic patterns such as sudden collisions, abrupt stops, and irregular vehicle movements. When such events were detected, the system flagged them as potential accidents and triggered the emergency alert mechanism. Each detected event was assigned a confidence score **Fig.5.1** based on the probability generated by the detection models.

a. **High-confidence detections** corresponded to clear collision events between vehicles.
b. **Medium-confidence detections** included sudden stops or unusual vehicle positioning.
c. **Low-confidence detections** represented minor anomalies or temporary traffic disturbances.

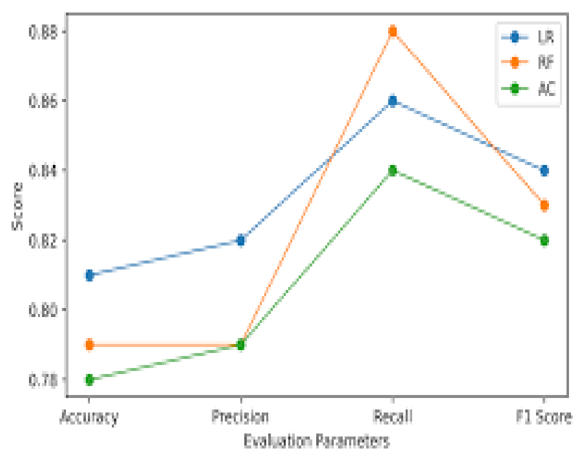


Fig.5.2 "Evaluation parameters for different metrics"

The evaluation metrics were calculated to measure the performance of the proposed framework. The system achieved high accuracy across key performance indicators such as precision, recall, F1-score, and mean Average Precision (mAP). These results demonstrate the effectiveness of combining object detection, segmentation, and tracking models for automated accident detection **Fig.5.2**.

Fig.5.3 "compariosion between baseline model and proposed model"

The comparison graph **Fig.5.3** illustrates the performance improvement of the proposed model compared with traditional accident detection approaches. The proposed framework consistently achieves higher accuracy across all evaluation metrics. The results indicate that integrating YOLOv8, Mask R-CNN, and DeepSORT significantly improves detection reliability and reduces false positives. Overall, the experimental evaluation confirms that the proposed system can effectively detect road accidents in real time and support faster emergency response in intelligent transportation systems.

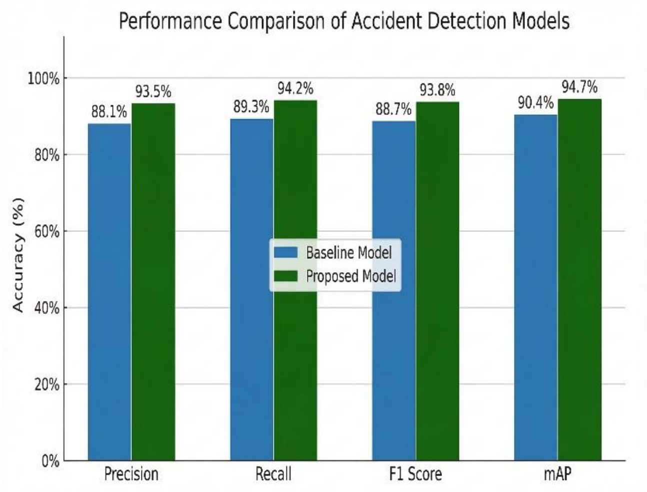
VI. CONCLUSION & FUTURE SCOPE

This project presents an intelligent computer vision–based framework for automated road accident detection using CCTV surveillance systems. By integrating advanced deep learning models such as YOLOv8 for object detection, Mask R-CNN for segmentation, and DeepSORT for object tracking, the system can continuously monitor traffic activity and detect accidents in real time. The proposed framework effectively analyzes vehicle movements, identifies abnormal traffic behavior, and detects collision events with high accuracy. Once an accident is detected, the system automatically generates emergency alerts and provides relevant information to responders. This automated approach significantly reduces the delay in accident reporting and enables faster emergency response.

The system demonstrates strong potential in improving road safety by providing continuous traffic monitoring and reliable accident detection. Unlike traditional manual reporting methods, the proposed framework operates autonomously and can detect incidents even in the absence of human supervision. The integration of multiple deep learning models improves detection reliability while minimizing false alarms. Additionally, the ability to record accident footage provides valuable evidence for further investigation and traffic management analysis. This intelligent monitoring system can play a vital role in supporting smart city infrastructure and intelligent transportation systems.

In the future, the proposed system can be further enhanced by integrating GPS-based location identification to provide precise accident location information. Advanced AI techniques such as behavior prediction models can be implemented to identify potential accident risks before collisions occur. The system can also be connected to cloud-based traffic monitoring platforms to enable large-scale deployment across multiple cities. Integration with emergency service networks and traffic control centers can further improve the speed and efficiency of rescue operations. Additionally, expanding the system with drone surveillance and edge computing technologies could improve coverage and reduce processing latency.

Overall, the proposed framework demonstrates the effectiveness of combining computer vision and deep learning technologies for real-time accident detection and



rapid emergency response. With further enhancements and large-scale deployment, such intelligent monitoring systems can significantly contribute to reducing road accident fatalities and improving overall transportation safety.

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