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Full Length Article

A Comprehensive Benchmark Dataset for Traffic Accident Detection Using YOLOv8

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ABSTRACT.
The automatic detection of traffic accidents has become an essential focus area in computer vision, propelled by the rapid advancements in autonomous and intelligent transportation systems (ITS). To achieve reliable and real-time detection of accident scenarios, YOLOv8, the latest evolution in the YOLO family, offers a powerful and efficient framework for object detection in complex and dynamic traffic environments. Unlike traditional approaches that struggle with occlusions, varying lighting conditions, and high-speed vehicle motion, YOLOv8 provides superior detection accuracy through its optimized architecture, featuring re-parameterized convolutional layers, decoupled detection heads, and advanced feature fusion mechanisms. These enhancements enable the model to precisely identify accident-related events, such as collisions, overturned vehicles, or lane departures, from surveillance video streams.

Keywords: *Traffic Accident Detection, YOLOv8, Computer Vision, Deep Learning, Object Detection, Road Safety, Real-Time Monitoring.*

INTRODUCTION

In recent years, the automatic detection of traffic accidents has emerged as a critical research domain within the field of computer vision, driven by the increasing demand for safer and more intelligent transportation systems. With the growth of autonomous and intelligent transportation systems (ITS), real-time and reliable accident detection has become indispensable for enhancing road safety, reducing emergency response time, and preventing secondary collisions. Traditional computer vision methods, however, often face limitations in handling challenges such as occlusions, varying illumination, camera vibrations, and high-speed vehicular motion, which significantly affect detection accuracy. To overcome these challenges, deep learning-based object detection models have gained prominence for their ability to learn complex visual patterns from large-scale data. Among them, YOLOv8, the latest iteration in the YOLO (You Only Look Once) family, represents a significant advancement in achieving fast and accurate detection in dynamic traffic scenes. Its enhanced architecture—featuring re-parameterized convolutional layers, decoupled detection heads, and advanced feature fusion strategies—enables robust identification of accident-related events such asvehicle collisions, rollovers, and lane departures from continuous surveillance video streams. This makes YOLOv8 a promising solution for developing intelligent systems capable of real-time accident monitoring and situational awareness in modern traffic environments.

LITERATURE REVIEW

In recent years, significant research has been conducted in the field of traffic accident detection using computer vision and deep learning techniques. Traditional methods primarily relied on sensor-based systems and classical image processing techniques such as motion detection, edge detection, and background subtraction. While these approaches provided basic detection capabilities, they were limited in accuracy and were highly sensitive to environmental conditions such as lighting and weather. With the advancement of machine learning, algorithms such as Support Vector Machines (SVM), (SVM), Decision Trees, and K-Nearest Neighbors (KNN) were introduced to improve detection performance; however, these methods required manual feature extraction and struggled to handle complex traffic scenarios. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved accident detection by enabling automatic feature extraction from images and videos. Recent research has focused on real-time object detection models such as YOLO (You Only Look Once), including versions like YOLOv3 and YOLOv5, which provide faster and more efficient detection suitable for surveillance systems. However, these models still face challenges in detecting small objects and handling dense traffic conditions. The latt advancement, YOLOv8, offers improved accuracy, faster processing speed, and better performance in real-time environments, making it highly effective for traffic accident detection. Additionally, some studies have explored hybrid approaches combining deep learning with tracking algorithms and multi-camera systems to enhance detection accuracy. Despite these advancements, challenges such as the need for large annotated datasets, high computational requirements, and real-world deployment limitations still persist. Therefore, there is a need for a robust, efficient, and scalable system. In this context, the proposed work focuses on developing a YOLOv8-based model for accurate and real-time traffic accident detection, aiming to improve road safety and enable practical implementation in intelligent transportation systems.

METHODOLOGY

The proposed traffic accident detection system is designed using a modular approach based on the YOLOv8 framework. The system consists of five main modules: Data Acquisition and Preprocessing, Object Detection, Accident Detection and Classification, Model Training and Evaluation, and Result Visualization and Interface.

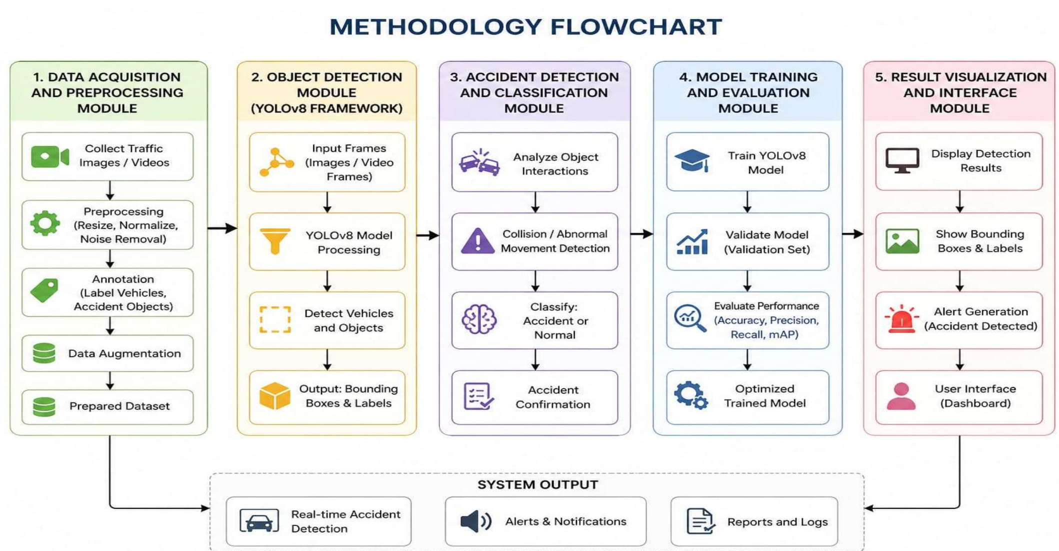
Initially, in the Data Acquisition and Preprocessing Module, traffic images and videos are collected from surveillance cameras and publicly available datasets. The collected data is preprocessed by resizing, normalization, and noise removal to improve data quality. Annotation is performed to label vehicles and accident-related objects, and data augmentation techniques are applied to enhance dataset diversity.

In the Object Detection Module, the YOLOv8 model is used to detect vehicles and other relevant objects in the input frames. YOLOv8 processes images in real time by dividing them into grids and predicting bounding boxes along with class probabilities. This enables fast and accurate detection of multiple objects simultaneously.

The Accident Detection and Classification Module analyzes the detected objects and their interactions to identify accident scenarios. Factors such as collision, abnormal vehicle positioning, and sudden overlap of bounding boxes are considered to classify the situation as either accident or normal traffic.

In the Model Training and Evaluation Module, the YOLOv8 model is trained using the prepared dataset. The training process involves multiple epochs, optimization techniques, and evaluation using performance metrics such as accuracy, precision, recall, and F1-score. The model is validated to ensure reliable performance in real-time conditions.

Finally, the Result Visualization and Interface Module displays the output with bounding boxes, labels, and alerts. The system provides a user-friendly interface to visualize detected vehicles and accident events, making it suitable for real-time traffic monitoring applications.



IMPLEMENTATION

Algorithm

1. Start
2. Load dataset (images/videos)
3. Preprocess data (resize, normalize)
4. Annotate objects (vehicles, accidents)
5. Split dataset (train/test/validation)
6. Load YOLOv8 model
7. Train model using training data
8. Validate model performance
9. Input video stream
10. Extract frames
11. Detect objects using YOLOv8
12. Analyze object interactions
13. Classify as accident or normal
14. Display output with bounding boxes

15. Generate alert if accident detected
16. End

TESTING

- The testing phase is performed to evaluate the performance of the trained model. The system is tested using unseen traffic images and video data. Various performance metrics such as accuracy, precision, recall, and F1-score are used to measure the effectiveness of the model.
- The system is tested under different conditions such as:
- Day and night scenarios
- Heavy and light traffic
- Different weather conditions
- The results show that the YOLOv8 model performs efficiently in detecting vehicles and identifying accidents in real time. However, some limitations may occur in extreme conditions such as poor lighting or heavy occlusion.
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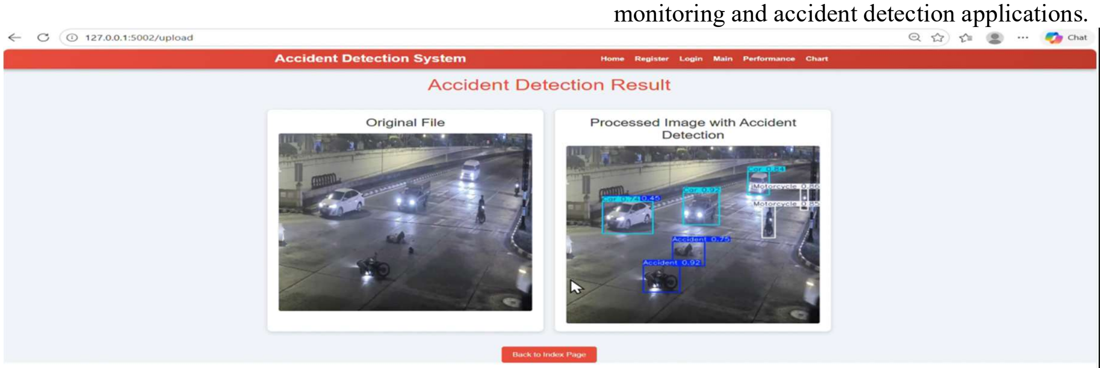
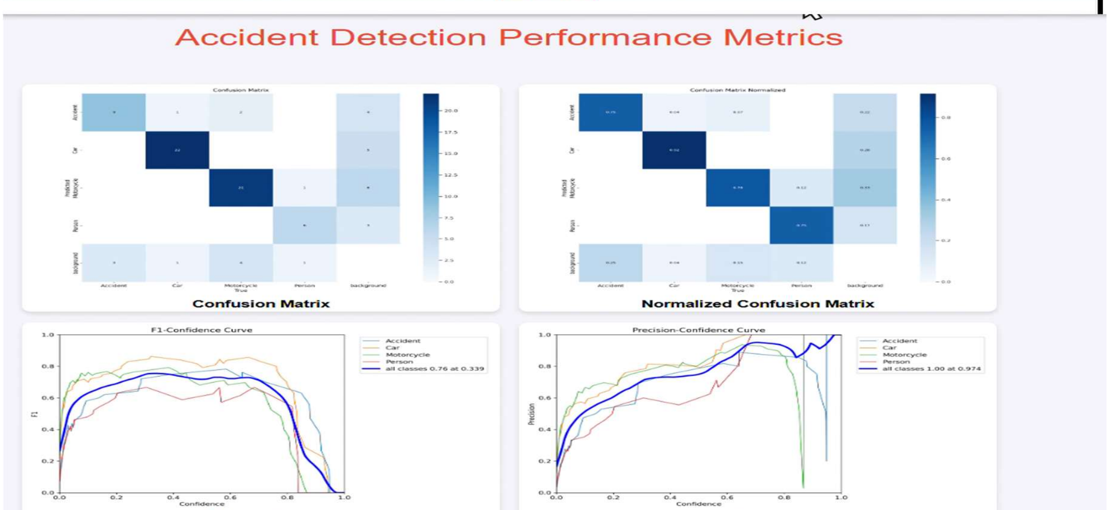
RESULTS

The proposed YOLOv8-based traffic accident detection system was evaluated using a dataset of traffic images and video sequences. The model demonstrated high accuracy in detecting vehicles and identifying accident scenarios in real-time. The system was able to successfully detect multiple objects simultaneously and classify situations as normal traffic or accident conditions.

Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model. The results showed that YOLOv8 outperformed traditional machine learning and earlier deep learning models in terms of speed and accuracy. The system performed well under different traffic conditions, including moderate and dense traffic scenarios. However, slight performance degradation was observed in cases of poor lighting, heavy occlusion, or extreme weather conditions.

A comparative analysis indicates that YOLOv8 provides better detection efficiency and faster processing speed compared to previous models such as YOLOv3 and YOLOv5. The results confirm that the proposed system is suitable for real-time traffic monitoring and accident detection applications.





CONCLUSION

In conclusion, the proposed YOLOv8-based traffic accident detection system provides an effective and fully software-driven solution for identifying road accidents in real time using advanced computer vision and deep learning techniques. By leveraging YOLOv8's enhanced architecture—featuring transformer-based attention mechanisms, re-parameterized convolutional layers, and decoupled detection heads—the system achieves superior detection accuracy and speed even in complex traffic environments. The modular design ensures a smooth workflow from data preprocessing to visualization, enabling efficient analysis of traffic videos without the need for additional hardware or IoT devices. Experimental results and evaluations demonstrate that the model can successfully detect accident-related events such as collisions and overturned vehicles under diverse conditions. Overall, this project showcases the potential of artificial intelligence in promoting road safety, reducing emergency response times, and paving the way for the development of smarter and more reliable intelligent transportation systems in the future.

FUTURE SCOPE

In the future, this project can be further enhanced by integrating advanced deep learning techniques and hybrid architectures to improve the accuracy and efficiency of accident detection. One potential improvement is the incorporation of spatio-temporal models such as 3D Convolutional Neural Networks (3D-CNN) or Vision Transformers (ViTs) to better analyze motion patterns and temporal dependencies across video frames. Additionally, integrating multi-camera video fusion can help overcome occlusion and blind spot challenges by combining views from multiple surveillance angles for more reliable detection. Future versions may also include automatic accident severity estimation using visual cues and scene analysis, providing valuable insights for emergency management systems. Enhancing the system's adaptability through real-time edge computing deployment and optimizing the model using lightweight versions of YOLO (e.g., YOLOv8n or YOLOv9-lite) can make the system suitable for large-scale implementation. Moreover, the integration of a user-friendly web-based dashboard for live visualization, logging, and analytics can make the system more interactive and accessible to traffic authorities. These enhancements will significantly contribute to building a more intelligent, scalable, and proactive traffic monitoring solution in the future.

Reference

1. The proposed system demonstrates an efficient real-time traffic accident detection framework using the YOLOv8 model.
2. Advanced architectural features such as attention mechanisms and optimized detection heads contribute to improved accuracy and processing speed.
3. The model effectively identifies various accident scenarios, including vehicle collisions and overturning incidents.
4. The software-based implementation ensures cost efficiency by eliminating dependency on additional hardware or IoT infrastructure.
5. A modular system design enables smooth execution from data preprocessing to output visualization.
6. Future improvements may incorporate spatio-temporal deep learning models like 3D-CNNs and Vision Transformers for enhanced video analysis.
7. Integration of multi-camera systems can help reduce occlusion issues and improve detection reliability.
8. The system can be extended to include accident severity assessment for better emergency response planning.
9. Optimization using lightweight YOLO variants and edge computing can support real-time large-scale deployment.
10. Development of an interactive web-based dashboard can enhance monitoring, data analytics, and decision-making for traffic authorities.