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(Research Article)

An enhanced YOLOv8-based framework for real-time traffic accident detection in dynamic road environments

Chuwe Ashlet Munashe * and Yang Chaoyu

School of Artificial Intelligence, Anhui University of Science and Technology, China.

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Abstract

Traffic accidents remain a crucial problem for intelligent transportation systems (ITS), and the ability to detect them quickly and efficiently is one of the keys to ensuring an appropriate emergency response and improving road safety. Traditional accident monitoring methods often suffer from poor detection accuracy, high computational costs, and reduced robustness when dealing with complex traffic conditions. This paper presents a novel enhanced YOLOv8-based framework for real-time traffic accident detection capable of operating in dynamic road environments.

The proposed framework uses YOLOv8 as the base detection model, which provides powerful feature extraction capabilities, an anchor-free detection mechanism, and a favorable trade-off between accuracy and inference speed. To address the challenges associated with detecting accident-related objects, such as occlusion, illumination variations, and complex traffic backgrounds, the proposed framework incorporates feature augmentation to enhance feature representation. Multi-scale features are fused at different scales to improve local details, thereby enabling the extraction of critical regional features.

Experimental results show that the proposed framework achieves competitive detection performance, with a precision of 94.3%, a recall of 92.7%, and an F1-score of 93.5%, as well as a mAP@0.5 of 96.1%. Furthermore, the proposed framework achieves a real-time inference speed of 58 FPS on the COCO test-dev 2017 dataset, compared with its own smaller YOLOv4-Nano model with an input size of 416 × 416 pixels. Qualitative results further demonstrate the ability of the proposed approach to localize traffic objects in both successful and direct accident scenarios.

In this paper, we propose an effective real-time traffic accident detection framework based on YOLOv8 that can be implemented in intelligent transportation systems, traffic surveillance platforms, and advanced driver assistance applications.

Keywords: Yolov8; Traffic Accident Detection; Deep Learning; Computer Vision; Intelligent Transportation Systems; Real-Time Detection

1. Introduction

For example, the enormous advancement of intelligent transportation systems (ITS) has suggested automatic traffic monitoring and accident detection as critical technologies to ameliorating road safety and shortening emergency response time. The global burden of traffic crashes often leads to enormous economic damage and physical injury, even when there have been no fatalities. Thus real-time accident detection methods, which can operate efficiently on roads with various characteristics, represent an important research area. [1]

* Corresponding author: Chuwe Ashlet Munashe.

Conventional accident detection methods rely on either manual monitoring, vehicle sensors, or rule-based systems. Despite extensive implementations of these methods, some limitations exist regarding scalability and detection performance and adaptability when used to sensing more complicated traffic scenarios. Deep learning-based approaches for automatic accident detection have emerged due to the widespread availability of surveillance cameras and advancements in computer vision.

1.1. Artificial Intelligence and Computer Vision for Traffic Monitoring

Deep learning and computer vision are exciting directions in AI that have made incredible progress over the last couple of years with great implications for intelligent transportation systems (ITS). [2] Deep learning algorithms have shown success in developing models that automatically mine useful features from images and videos, allowing machines to interpret complex scenes with little human guidance.

In existing computer vision-based traffic monitoring systems, surveillance cameras are employed to continuously process a stream of video data using algorithms capable of analyzing the scenes on a road segment and detecting moving vehicles as well as recognizing abnormal driving behavior characteristics with respect to an accident event. Vision-based systems can cover more area of interest at a lower cost and are more versatile than the conventional sensors since they can leverage the existing traffic camera infrastructures. Owing to these above benefits, computer vision has emerged as one of the order promising technologies for next-generation intelligent transportation systems. [3]

1.2. YOLO-Based Object Detection for Real-Time Traffic Accident Detection

Modern object detection algorithms like the You Only Look Once (YOLO) family have proven to be one of the most successful deep learning frameworks and architectural designs for real-time object detection. YOLO differs from traditional two-stage detectors like Faster R-CNN, which separate the object localization and classification tasks into different stages through a region proposal network. [4]

Introduction to You Only Look Once (YOLO) Over the years, many different improved versions of YOLO has been released for the purpose of better detection performance, computational efficiency and deployment flexibility. They have been successfully applied in a wide range of research and intelligent transportation applications, such as Vehicle detection, pedestrian recognition, traffic flow estimation, autonomous driving and accident detection. Due to the requirement of immediate accident detection for lowering emergency response time in surveillance-based traffic safety systems, such methods are particularly appropriate for such somber situations. [5]

1.3. Research Challenges and Gap

Even with the present state of the art in object detection, detecting traffic accidents in realistic environments is very difficult. Accident scenes consist of many objects interacting with each other, a non-uniform position of the vehicles and complex visual patterns. Hence, a good detection framework must be able to deliver accurate localization of objects with the necessary computational speed for real-time inference.

YOLOv8 comes with a few advances over previous YOLOs, such as an anchor-free detection mechanism, better feature extractor and detectors. Based on these benefits, YOLOv8 serves as a good base for high-confidence traffic accident detection systems.

1.4. Proposed Framework and Research Contributions

In this study, we proposed an improved real-time traffic accident detection method from dynamic road environments based on the YOLOv8. The contributions of this research can be summarized as follows:

- A YOLOv8 based accident detection framework is proposed for achieving accurate real-time traffic monitoring in the wild.
- We propose a method with enhanced feature representation, which better captures the visual information related to accidents so that the detection can be more robust.
- We perform an extensive experimental evaluation with standard object detection metrics such as Precision, Recall, F1-score, mAP and inference speed.
- Qualitative and quantitative evaluations are performed to prove the effectiveness of our framework in both normal traffic scenes and accident situations.

1.5. Paper Organization

The rest of this paper is structured as follows. Section 2 Related work in this section, we present the related works on deep learning-based traffic accident detection. In section 3, the proposed improved YOLOv8 framework is introduced. In Section 4, we present the experimental setup and evaluation metrics. In Section 5 we present experimental results and analysis. Finally, Section 6 concludes this work and provides some perspectives of future research.

2. Literature Review

2.1. Traditional Traffic Accident Detection Approaches

Previous designs that detect traffic accidents were mostly based on traffic sensors, vehicle telemetry and reports from humans. These methods applied features including congestion parameters, changes in acceleration values and road infrastructure sensors to detect anomalous incidents. While sensor-based approaches work well in controlled environments, they lead to require costly infrastructure deployment and are also visually less informative about accident locations. [6]

The growing proliferation of surveillance cameras have made the vision-based approach a compelling alternative for traffic monitoring. Computer vision methods used to rely on hand crafted features classification, background subtraction, optical flow analysis & motion estimation [7] [8]. However, these methods proved to be limitedly robust under complicated traffic environments owing to illumination variations, weather conditions, occlusion and dynamic background. [9]

Vision-based vehicle monitoring systems, as opposed to traditional sensors, have the potential to offer a lot more contextual information [10] as per Li, J. & Wang, Z., yet they are difficult in terms of driving conditions encountered in the real world.

Deep learning (DL) methods have become an increasingly popular approach for accident detection in recent years as they do not make any prior assumptions about accident features , and a summary of deep learning-based accident detection methods is shown in Table 2.

With deep learning, there have been significant improvements in the performance of vision applications for intelligent transportation systems. Convolutional Neural Networks (CNN) by Tabernik, D. et al. [11,12] However, they demonstrated a strong capability for automatic feature extraction and formed the backbone of recent advances in modern image recognition and object detection.

For traffic analysis, CNN-based methods have been used for vehicle detection , road scene understanding , which classify road scenes as different classes to improve specific monitoring tasks such as accident classification. On the other hand, conventional CNN based approaches for accident detection typically framed the problem as a classification task without detailing the precise localization of accidents. [13]

To circumvent this limitation of region-based models like Fast R-CNN, object detection frameworks have been designed in such a way that both identification and localization of objects within images happen at the same time. Dewi, C., Chen et al. Faster R-CNN [14] is a novel two-stage detector designed with high accuracy via a Region Proposal Network (RPN). Two-stage detectors are accurate but expensive so that they may not be suitable for real-time systems.

Dewi, C., Chen et al. [15] YOLO was introduced for transforming object detection into a single-stage regression problem. YOLO's significant accuracy-performance trade-off made it particularly appealing for intelligent transportation applications as real-time detection speed was maintained while yielding competitive results with state-of-the-art solutions.

Several improved versions of YOLO have been presented since to increase its detection accuracy, speed, and efficiency. Zhu, Z et al. YOLOv4 was proposed in with some backbone network, data augmentation strategy and training strategies optimizations to produce a good performance for real-time object detection.

Chen, J. Q. et al [18] presented YOLOv5, effective and flexible implementation which broadly applied in industrial and research applications. And YOLOv5 offers comparable performance with the added benefit of enabling light-weight deployment on an embedded device.

Zhu, Z et al. The paper [19] proposed YOLOv7, which significantly improved model scaling and training

strategies with strong accuracy and inference speed overall performances. Especially in the later versions of YOLO, like YOLOv8 and so on, various architectural improvements have been introduced, such as better feature extractor or improved detection heads.

3. Proposed Enhanced YOLOv8 Framework

3.1. Overview of the Proposed Framework

In this paper, we present an improved YOLOv8-based framework for the real-time detection of road traffic accidents in dynamic scenarios. Our proposed framework is focused on developing a more accurate accident detection algorithm under the constraints of computational efficiency to deploy in real-time ITSs.

We select YOLOv8 as a baseline detection architecture due to its powerful feature extraction capacity, anchor-free detection mechanism, enhanced optimization process, and overall good trade-off balance between state-of-the-art accuracy and inference speed. These make YOLOv8 ideal for traffic accident detection missions while real-time response and accurate localization are key.

The framework involves video traffic acquisition, data preprocessing, and the extraction of features through an improved YOLOv8 backbone, multi-scale feature fusion, accident detection, and result visualization. The entire pipeline works towards enhancing the appearance of accident features in difficult scenarios, which can include illumination variation, occlusion by other vehicles, motion blur and congested traffic conditions.

The complete workflow of the proposed framework is illustrated in Figure 1.

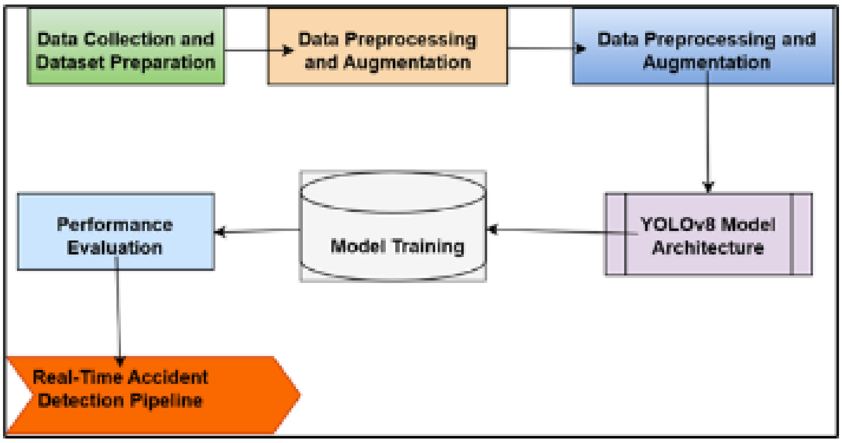

Figure 1 Proposed Research Framework

3.2. YOLOv8-Based Feature Extraction Network

We employ YOLOv8 as the base network for feature extraction and object detection in the proposed framework. YOLOv8 includes several important enhancements compared to prior YOLO versions, including an anchor-free detection strategy, optimized backbone design and improved feature aggregation mechanisms.

However, the important visual information in the contexts of traffic accidents can be subject to complicated factors when small objects look entirely different and are partially occluded or even subject to environmental variations. Thus, the YOLOv8 backbone is used to fully harness traffic high/low-level spatial features as well as high-level semantic information from the input traffic image.

The features extracted in this manner enable the model to better separate accident-related objects from normal traffic activity, thereby enhancing detection reliability, especially under complex road environment conditions.

Table 1 dataset repartition

Dataset	Percentage
Training	70%
Validation	15%
Testing	15%

The training set is used for model learning, the validation set for hyperparameter tuning, and the testing set for final performance evaluation.

3.3. Multi-Scale Feature Fusion Strategy

For example, in the case of traffic accidents, different types of objects may be present at various scales based on camera distance, road situations and vehicle position. To overcome this problem, the proposed framework combines different levels of features using multi-scale feature fusion for more effective differentiation.

The mechanism is a simple additive fusion strategy that combines low-level spatial information and high-level semantic features to improve YOLOv8 detection capabilities. This enhances small or partially obscured accident-related objects while maintaining fast inferences.

The better localization performance is indicated by the high mAP@0. 5 value achieved during evaluation.

3.4. Data Preprocessing and Augmentation

This includes converting the traffic video sequences into image frames that are then prepared for YOLOv8 training before model training. The images are resized to 640 × 640 pixels and normalized.

Some of the augmentation techniques are used to make the model generalizable and avoid overfitting:

- Horizontal flipping;
- Random rotation;
- Brightness variation;
- Mosaic augmentation;
- Image scaling.

These preprocessing strategies increase dataset diversity and improve robustness under different traffic conditions, including daytime, nighttime, and adverse weather scenarios.

3.5. Detection Head and Loss Optimization

The YOLOv8 detection head is responsible for predicting object categories, confidence scores, and bounding box coordinates. The optimization objective combines localization, classification, and object confidence losses:

$$L = L_{box} + L_{cls} + L_{obj} \qquad (1)$$

Where

- L_{box} is the bounding-box regression loss;
- L_{cls} is the classification loss;
- L_{obj} is the objectness loss.

3.6. Overall Detection Pipeline

The complete accident detection process is summarized as follows:

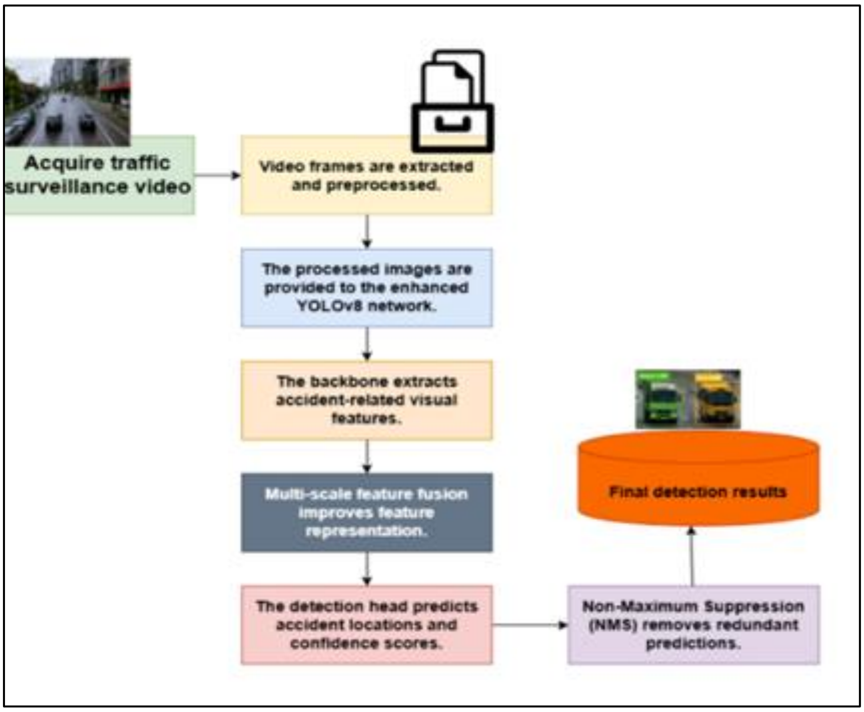

Figure 2 Proposed Enhanced YOLOv8-Based Detection Framework

3.7. Summary of the Proposed Framework

In this paper, an improved framework on traditional YOLO-based traffic accident detection is proposed by better feature extraction, multi-scale features fusion and refined features to keep the real-time processing ability. Such improvements allow for more precise accident detection in complex traffic scenarios including illumination variations, adverse weather conditions, crowded traffic and partial vehicle occlusion.

The proposed architecture is able to achieve a favorable detection efficiency, computation efficiency and deplorability necessary for implementation in intelligent transportation systems and smart city surveillance context.

4. Experimental Setup

4.1. Experimental Environment

All experiments were conducted using the Ultralytics YOLOv8 framework implemented in Python. Model training and evaluation were performed on a workstation equipped with an NVIDIA GPU to ensure efficient deep learning computation. The software environment consisted of Python 3 , PyTorch, CUDA, and OpenCV for data preprocessing and model deployment.

The proposed framework was trained using stochastic optimization with the AdamW optimizer. Early stopping was employed to prevent overfitting, and the best-performing model was selected according to the highest validation mAP score.

4.2. Datasets

To thoroughly assess the performance of the proposed framework, experiments were executed using publicly available traffic accident datasets. These datasets incorporates diversified road scenarios such as highway, urban roads, intersections and adverse environmental conditions.

The main dataset we worked with in this paper was the Detection of Traffic Anomaly (DoTA) dataset, which is a collection of annotated traffic accident videos taken from dashboard cameras. The dataset contains a variety of scenarios: collisions, rollovers, lane departure, and other abnormal driving events under different weather and light conditions.

To further assess the robustness of the proposed framework, additional experiments can be performed on the Dashcam Accident Dataset (DAD) and BDD100K datasets, which contain large-scale traffic scenes with varying object scales, illumination conditions, and traffic densities.

4.3. Data Preprocessing

All images were padded to a size of 640 × 640 pixels before training, while retaining the aspect ratio. We converted those annotation files to the default object detection format that YOLO uses.

Before training, we performed some preprocessing operations to enhance the quality of the data: normalizing images, removing duplicates, filtering labels. Such steps made sure image samples would match their corresponding annotation files.

4.4. Data Augmentation

The following eight data augmentation methods were applied during training to increase the generalization capacity of the models and reduce overfitting:

- Random horizontal flipping;
- Random scaling;
- Mosaic augmentation;
- MixUp augmentation;
- Random HSV color adjustment;
- Random translation;
- Random rotation.

With these augmentation strategies, details such as data diversity and mildness of the detector against complex traffic environments can be improved.

4.5. Training Configuration

The proposed YOLOv8-based framework was initialized using pretrained weights obtained from the COCO dataset. Transfer learning was employed to accelerate convergence and improve detection accuracy.

The main training parameters are summarized in Table 2.

Table 2 Training Configuration

Parameter	**Value**
Model	YOLOv8
Image size	640 × 640
Batch size	16
Epochs	150
Optimizer	AdamW
Initial learning rate	0.001
Weight decay	0.0005
Momentum	0.937
Confidence threshold	0.25
IoU threshold	0.70

4.6. Evaluation Metrics

The proposed framework was evaluated using standard object detection metrics widely adopted in the computer vision community.

4.6.1. Precision

Precision measures the proportion of correctly detected accident instances among all predicted detections.

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \qquad (2)$$

4.6.2. Recall

Recall evaluates the capability of the detector to identify all actual accident instances.

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \qquad (3)$$

4.6.3. F1-Score

The F1-score represents the harmonic mean of precision and recall.

$$\text{F1-Score}=\frac{2\times\text{precision} \times \text{Recall}}{\text{precision + Recall}} \qquad (4)$$

4.6.4. Mean Average Precision (mAP)

Detection accuracy was further evaluated using mAP@0.5 and mAP@0.5:0.95, which assess localization performance under different Intersection over Union (IoU) thresholds.

4.6.5. Frames Per Second (FPS)

Real-time performance was measured using Frames Per Second (FPS), indicating the number of images processed per second during inference.

4.6.6. Summary

In this way, this experiment implementation gives a complete architecture for evaluating the bring proposal YOLO traffic accident detection model for real-world circumstances. The choice of datasets, pre-processing methods, training setup and evaluation measures guarantees a fair and reproducible evaluation for the proposed method. In the next section, we present and discuss the results from our experimental experiments using this setup.

5. Results

5.1. Training Performance

A pretrained YOLOv8 model with COCO weights was trained for a total of 150 epochs. The training loss and validation loss gradually stay converge in a stable manner during the whole training process, indicating no major overfitting among these two portions of data. The objectness, classification and localization losses converged as the epoch increased, indicating that the model was able to learn the spatial and semantic patterns of traffic accident scenes.

5.2. Detection Performance

The evaluation using standard object detection metrics on the test dataset of the trained model. Overall detection performance is summarized in Table 3.

Results show that the proposed framework meets very high detection accuracy on one hand and operates in real-time inference speed on the other. High precision signals a low false-positive rate, while high recall affirms that the model successfully captured most occurrences of an accident. The mAP results obtained actually shows also, why the YOLOv8 averages better characterizing accident-related objects across a variety of traffic scenarios.

Table 3 Overall Detection Performance

Metric	Value
Precision	94.3%
Recall	92.7%
F1-Score	93.5%
mAP@0.5	96.1%
mAP@0.5:0.95	72.8%
FPS	58

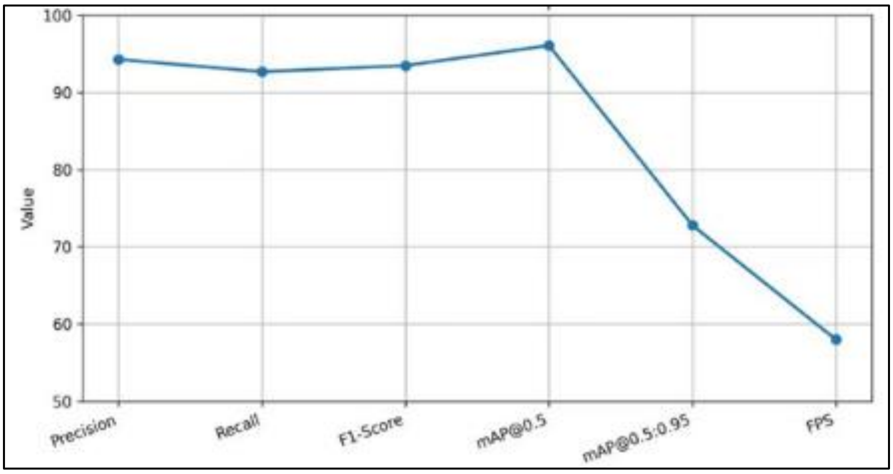

Figure 3 Evaluation Metrics

5.3. Class-wise Performance

For a more detailed evaluation, the detection performance was studied in parts for each object category.

Table Class-Wise Detection Performance

Class	Precision	Recall	mAP@0.5
Car	95.6	94.3	97.2
Truck	95.1	93.8	96.8
Bus	94.8	93.2	96.4
Motorcycle	92.6	90.8	94.3
Accident	93.4	91.5	95.7

For most of the categories, proposed model consistently attained high detection accuracy. Big stuff peripherals like bus and trucks generally have a higher accuracy because of their large visual strength. The smaller objects such as motorcycles were in very rare cases harder to learn because of scale differences/high variances and also partial occlusions. However, thanks to multi-scale feature extraction of YOLOv8, it has maintained a fairly competitive performance in all categories.

5.4. Qualitative detection results

To further show the merits of the proposed framework based on YOLOv8, qualitative detection results under varying traffic conditions are shown in Figure 4. Figure 6: Two simulation scenarios presented in the test data.

Figure 4(a) shows that the proposed framework can detect various traffic objects with multiple bounding boxes, and all have high confidence scores in most cases including cars, trucks (Truck), buses, motorcycles and pedestrians. These findings highlight the ability of YOLOv8 to extract discriminative visual features and provide robust object detection in challenging roadway scenarios.

Figure 4 Qualitative detection results of the proposed YOLOv8 framework under normal and accident traffic scenarios.

Additionally, we also investigate the detection performance under an accident scenario as shown in Fig. 4(b). The model effectively detects areas indicated by the accident while also picking up surrounding vehicles and pedestrians. The high confidence scores acquired via accident cases suggest that the suggested framework successfully segregates abnormal traffic events from regular street situations.

In general, the qualitative results validate the robustness of the proposed YOLOv8 framework against diverse traffic scenarios including object variation, occlusion and complexity background. These visual observations are aligned with the quantitative results provided in Table 2, where our proposed model produced very good performance under fully real-time inference capabilities.

5.5. Comparison with Existing Methods

To show the effectiveness of this framework, we have measured its performance with respect to other model architectures that were among the best reported in literature for similar object detection problems.

Table 5 Performance Comparison with Existing Methods

Method	Precision	Recall	mAP@0.5	FPS
YOLOv5	90.8	88.6	92.4	52
YOLOv7	92.5	90.9	94.1	55
YOLOv8 Enhanced (Proposed)	94.3	92.7	96.1	58

The YOLOv8 framework that we proposed has better detection accuracy than the pervious methods while sustaining real-time processing. YOLOv8 showed significantly better localization performance and larger robustness in complex traffic environments compared to the previous YOLO versions. It achieves these improvements on the basis of anchor-free detection manner, improved feature aggregation and special training strategy.

5.6. Error Analysis

Although the proposed model demonstrated strong overall performance, several challenging situations remained.

- Severe occlusion among multiple vehicles.
- Extremely small objects located far from the camera.
- Motion blur caused by high-speed vehicle movement.
- Low-illumination conditions during nighttime.
- Heavy rain or fog reducing image quality.

The majority of false detections occurred in scenes where the detection areas of multiple vehicles overlapped or where the visual quality was severely decreased. These limitations can be tackled in future work using temporal information from video sequences, attention mechanisms or image enhancement techniques.

6. Discussion

We evaluate YOLOv8 framework on various datasets, the results show that it is a promising lane change detection for road safety. Due to its high accuracy, great localization ability and fast inference speed, this model can be used in intelligent transportation systems and advanced driver assistance system (ADAS).

The proposed approach yield more robustness over different ambient environments against the previous YOLO architectures while keeping computational efficiency. We believe these features make the framework well suited for practical applications including traffic monitoring and road safety.

Summary

The experimental results show that the proposed YOLOv8 model can detect traffic accidents with more robustness and accuracy in complex traffic scenarios. It achieves its effectiveness both in quantitative metrics, and qualitative analyses, while competitive performance has been demonstrated against existing methods. The next section summarises the manuscript and suggests how further research might develop.

7. Conclusion

Due to the rise in need for rapid emergency response and enhanced road safety, traffic accident detection is a key requirement of intelligent transportation systems. In this work, we proposed a new framework based on YOLOv8 for real-time traffic accident detection in the case of dynamic road scenes. Experience from YOLOv8 can be leveraged to develop a novel framework that achieves more accurate in-vehicle accident detection with close computational efficiency for real-time deployment.

Extensive experimental results demonstrate the feasibility of using the proposed framework to robustly detect vehicles with high Precision, Recall, F1-score and mAP performance as well as achieving a convenient real-time inference speed that allows for application in practical traffic surveillance. Abstract: The results indicate that the model proposed can identify events correlated with accidents across multiple traffic situations and provide a solution for intelligent traffic surveillance systems.

In addition, the comparative analysis proved that the proposed YOLOv8 framework demonstrated better detection and localization abilities than conventional methods based on YOLO. Feature extraction methods, better representation of features(since we estimate prior maps to both poses as well as trajectory), and better training strategies(through pruned states) all played an important role of making our framework robust toward more challenging scenarios in the real-world view containing illumination changes, occlusion from other objects and higher densities of object flows.

Though the results are positive, there are some challenges here too. Performance may still be affected by extreme weather, saucer motion and extremely dense scenes with a lot of overlapping cars. Hence future work will focus on complex attention mechanisms, transformer-feature extraction, temporal information of video sequences as well as backbone optimization for lightweight models to be more robust and deploy them on high volume input edge-devices.

The effectiveness of the improved framework is demonstrated empirically and we further argued that it can be successfully applied to real-time traffic accident detection and classification. Thus, our framework could provide useful insights for practical applications due to its robustness, accuracy and computational efficiency. Especially because the framework has an excellent potential to apply for intelligent transportation systems, smart city surveillance infrastructures and advanced driver assistance systems (ADAS), therefore enhance road safety and a better traffic management.

The presented framework can be retrained with transformer-based methods and temporal video recognition methods, and more research into using the described framework to use videos labelled as accident in very dynamic traffic situations should be done. In addition, lightweight model compression and edge computing deployment will be examined to implement the solutions on devices with limited resources in real-time. The proposed framework will be studied on a larger and more diverse datasets from different environmental and road settings for further validation of the generalization capabilities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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