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Kardan Research Journal (KRJ)

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Journal homepage: krj.kardan.edu.af

Enhanced AI Automated Reporting and Alert System for Road Accidents Using the YOLO Backbone Network

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To cite this article: M. Haleem, and A. S. Raufi, "Enhanced AI automated reporting and alert system for road accidents using the YOLO backbone network," *Kardan Research Journal*, vol. 1, no. 1, pp. 63–74, 2024.

Published online: 30 December 2024

Article

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Kardan Research Journal
1 (1) 63–74

Kardan Publications
Kabul, Afghanistan

Received: 28 Sep 24
Revised: 25 Oct 24
Accepted: 28 Nov 24
Published: 30 Dec 24

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Abstract

With the increasing number of road accidents globally, as reported by WHO, there are over 50 million casualties annually, including 1.4 million deaths. This study presents an enhanced AI-based automated reporting and alert system for road accident detection using the YOLO (You Only Look Once) backbone network. Our system integrates YOLO's real-time object recognition capabilities with advanced techniques for detecting irregularities, such as sudden changes in speed, abrupt lane changes, erratic driving patterns, or vehicle collisions, to accurately identify and classify road accidents from CCTV footage. The lightweight and efficient YOLOv5 model was chosen to balance computational efficiency and detection accuracy, particularly suitable for resource-constrained environments. This version of YOLO was selected over others due to its faster frame processing rates, reduced computational demands, and robust performance across diverse traffic scenarios, making it ideal for real-time deployment in constrained systems. By combining YOLO's high-speed object detection with event classification algorithms, our solution minimizes false positives by combining spatial-temporal analysis and cross-frame validation. These techniques ensure detected anomalies, such as abrupt movements or collisions, are consistently verified across multiple frames, reducing the likelihood of false triggers and enhancing overall detection precision. Once an accident is detected, the system promptly generates alerts and notifies relevant authorities through automated email notifications, facilitating a timely emergency response. Comprehensive testing on various CCTV setups demonstrates the system's efficiency in diverse traffic scenarios, including varying lighting and weather conditions. Results exhibit significant improvements in accuracy (92.5%), precision (91%), and recall (89%), underlining the system's potential for saving lives by enabling earlier emergency response times.

Keywords: *Road Accident Detection, Yolov5, Automated Alert System, Real-Time Object Detection, Traffic Safety*

1. Introduction

Road traffic accidents are among the most pressing global public health and safety challenges, claiming the lives of over 1.4 million individuals annually, as highlighted by the WHO. In addition to the tragic loss of human life, millions sustain non-fatal injuries, many of which lead to long-term disabilities. These incidents impose significant economic burdens, including increased healthcare expenditures, loss of productivity, and substantial emotional and social consequences for affected families and communities. Addressing this issue effectively requires a robust system for the timely detection and mitigation of road accidents, which can directly contribute to reducing fatalities and alleviating associated socioeconomic impacts. Conventional methods for detecting road traffic accidents rely heavily on manual processes, such as visual monitoring by traffic personnel or reports from witnesses. Human latency, incomplete data, and potential inaccuracies in reporting inherently limit these approaches.

Additionally, such systems often fail to deliver real-time alerts, leading to significant delays in emergency responses. As a result, the critical window for saving lives and minimizing injury severity is frequently missed. The urgent need for a more efficient, automated, real-time accident detection system underscores the importance of leveraging modern technological advancements.

Recent progressions in computer vision technologies have transformed numerous industries, proposing innovative resolutions to complex problems. In the context of road safety, these technologies provide an unprecedented opportunity to automate accident detection processes. By analyzing real-time video feeds from surveillance systems, AI-powered models can identify potential accidents with high speed and accuracy, significantly enhancing situational awareness for emergency response teams. Among these technologies, the YOLO object recognition network stands out as a state-of-the-art model designed for real-time applications. Its architecture processes video frames through a single-stage detection pipeline, achieving high performance and low latency, critical for time-sensitive tasks such as accident detection. This research focuses on implementing YOLOv5, a cutting-edge iteration of the YOLO family of models. YOLOv5 has gained recognition for its remarkable balance between computational efficiency and detection accuracy, making it suitable for deployment in environments with limited resources, such as urban surveillance networks. Its lightweight architecture ensures rapid inference, while its advanced feature extraction capabilities enable precise detection and classification of objects and events in dynamic scenarios. By incorporating YOLOv5 into an automated accident detection framework, this study aims to address the limitations of traditional systems and offer a scalable solution for real-world deployment.

The proposed system integrates YOLOv5 with advanced event classification algorithms to achieve reliable detection and categorization of road accidents using CCTV footage. This integration is designed to minimize false positives and improve the accuracy of accident identification under diverse environmental conditions, such as varying lighting or weather. Additionally, the system includes an automated alert mechanism that instantly notifies relevant authorities, such as emergency medical services and traffic management agencies. The proposed solution reduces emergency response times by streamlining the alert and response process, thereby increasing the likelihood of saving lives and mitigating injuries.

2. Literature Review and Related Work

Zhao, Li, and Wang [1] explored the application of YOLO models in real-time vehicle detection and accident prediction. Their research emphasized the significance of real-time processing capabilities, which are essential in scenarios where timely detection can make the difference between life and death. They focused on vehicle detection accuracy under various environmental conditions, such as varying light levels and weather conditions, which often complicate the detection process. By leveraging the speed and efficiency of YOLO models, their study demonstrated a significant improvement in predicting potential accidents by analyzing vehicle trajectories and interactions. This proactive approach to accident detection not only enhances road safety but also aids in reducing the response time of emergency services, thereby minimizing the impact of accidents.

Chen, Zhang, and Liu [2] provided a comprehensive review of deep learning techniques, focusing on their application in traffic accident detection. Their review covered various models, including convolutional neural networks (CNNs) and YOLO, highlighting their strengths and limitations. The study emphasized the critical role that large, annotated datasets play in training these models, as the quality of input data directly influences the detection system's accuracy. They also discussed the challenges of deploying these models in real-world environments, where factors such as occlusion, varying traffic densities, and different vehicle types can impact performance. The review underscored the need for ongoing research to refine these models and improve their robustness in diverse operational contexts.

Kumar and Gupta [3] focused on applying object detection algorithms, including YOLO, in enhancing road safety systems. Their study reviewed various algorithms, comparing their performance in terms of accuracy, speed, and computational requirements. They noted that while traditional algorithms like the Haar Cascades and the HOG (Histogram of Oriented Gradients) have been widely used, deep learning-based models such as YOLO have led to a paradigm shift in object detection capabilities. YOLO’s ability to perform detection in real-time, with high accuracy across different environmental conditions, was particularly highlighted. The study also discussed the potential of integrating these algorithms into existing road safety systems to create a more responsive and intelligent infrastructure capable of preventing accidents before they occur.

In their study, Li, Li, and Zhang [4] focused on enhancing the YOLOv4 model by integrating attention mechanisms to improve the accuracy of accident detection. Attention appliances allow the model to focus on specific parts of the input data that are more relevant to the task, thereby improving detection performance. Their research demonstrated that by using attention mechanisms, the model could better distinguish between normal and abnormal driving patterns, even in complex and cluttered environments. This improvement is crucial in urban areas with high traffic density, where traditional models may struggle to maintain accuracy. The study also explored the potential of these enhanced models to be used with other data sources, such as GPS and sensor data, to provide a more wide-ranging accident detection system.

Smith and Zhang [5] investigated using YOLOv5 for real-time accident detection, focusing on the model's advanced feature extraction capabilities. Their research demonstrated that YOLOv5, with its improved architecture, offers significant advantages over earlier versions in terms of both speed and accuracy. The study highlighted how YOLOv5's ability to process high-resolution images in real time enables it to detect accidents more precisely, even in complex traffic scenarios with multiple vehicles. This precision is particularly important in reducing false positives, which can lead to unnecessary emergency responses. The researchers also discussed the potential applications of YOLOv5 in various real-time monitoring systems, emphasizing its role in enhancing the effectiveness of automated emergency response systems.

Park, Kim, and Lee [6] explored using multi-view camera systems combined with YOLO for accident detection. Their research focused on how integrating multiple camera angles can provide a more comprehensive understanding of traffic situations, thereby improving the accuracy of accident detection. The study demonstrated that using YOLO to process data from multiple cameras could effectively eliminate blind spots and detect accidents that might otherwise go unnoticed. This approach is particularly beneficial in complex environments such as intersections and urban areas, where a single camera might not capture all relevant details. The researchers also discussed the challenges of synchronizing data from multiple cameras and the potential for this technology to be integrated into existing traffic monitoring systems.

Wang, Liu, and Yang [7] developed a hybrid model that combines YOLO with other deep-learning techniques to improve road accident recognition. Their approach involved integrating YOLO with a recurrent neural network (RNN) to analyze temporal sequences of traffic data, thereby enhancing the model's ability to detect accidents over time. The hybrid model demonstrated improved performance in scenarios where single-frame analysis might fail, such as gradual vehicle collisions or accidents involving multiple stages. This research highlighted the importance of considering temporal dynamics in accident detection and the potential for hybrid models to address the limitations of existing detection systems. The study also discussed the computational challenges of implementing such models in real-time systems.

Lee, Kim, and Park [8] examined the impact of dataset quality on the presentation of the YOLO-based recognition systems. Their research underscored the importance of high-quality, annotated datasets in training deep learning models, noting that the accuracy of YOLO models heavily depends on the training data's quality. The study explored various methods for improving dataset quality, including synthetic data generation and data augmentation techniques. The researchers also discussed the challenges of obtaining large, diverse datasets that accurately represent real-world traffic scenarios. Their findings emphasized the need for standardized datasets in traffic accident detection to ensure that models are robust and generalizable across different environments.

Nguyen and Patel [9] investigated the integration of YOLO models with real-time traffic monitoring and alert systems. Their study focused on how YOLO's real-time processing capabilities can be leveraged to create a more responsive traffic monitoring system that automatically detects accidents and triggers alerts. The researchers highlighted the benefits of integrating YOLO with other data sources, such as GPS and traffic signal data, to improve the accuracy and timeliness of accident detection. Their work also explored the potential for these systems to be integrated with smart city infrastructures, enabling automated responses such as adjusting traffic signals or alerting nearby emergency services. The study demonstrated that such integrations could significantly enhance the effectiveness of traffic management systems in preventing and responding to accidents.

Ali, Shah, and Ahmed [10] discussed the challenges of deploying YOLO models in edge computing environments. Their research highlighted the difficulties of maintaining real-time processing speeds while ensuring high detection accuracy, particularly in resource-constrained environments. The study explored strategies for optimizing YOLO models to reduce their computational requirements, such as model pruning and quantization. The researchers also examined the trade-offs between model complexity and accuracy, noting that simpler models may be more efficient but often sacrifice accuracy. Their findings are particularly relevant for deploying YOLO models in scenarios where computational resources are limited, such as in mobile or embedded systems used for traffic monitoring.

Jin, Wang, and Zhao [11] focused on advanced anomaly detection techniques for traffic monitoring, with a particular emphasis on the integration of YOLO models. Their research explored how YOLO can be used in conjunction with other anomaly detection algorithms to improve the identification of unusual traffic patterns that may indicate accidents. The study demonstrated that the system could achieve higher accuracy in detecting complex traffic anomalies by combining YOLO with machine learning techniques such as support vector machines (SVM) or decision trees. The researchers also discussed the challenges of integrating multiple detection techniques, particularly ensuring real-time processing capabilities. Their work highlighted the potential for multi-modal detection systems to enhance traffic safety and prevent accidents.

Davis, Johnson, and Smith [12] explored the application of YOLOv5 in automated emergency response systems. Their research demonstrated how YOLOv5's real-time object detection capabilities could automatically trigger emergency responses, such as alerting nearby emergency services or activating traffic signals to create a clear path for ambulances. The study emphasized the importance of minimizing emergency response times, noting that even small reductions in detection and response times can significantly impact survival rates. The researchers also discussed the challenges of integrating YOLOv5 with existing emergency response infrastructures, such as ensuring compatibility with legacy systems and maintaining data security. Their findings underscored the potential for YOLOv5 to play a critical role in the next generation of automated emergency response systems.

Gao and Xu [13] investigated the integration of YOLO models with GPS data to improve the accuracy of accident detection. Their study focused on how combining visual data from YOLO with location data from GPS could enhance the system's ability to detect and locate accidents in real-time. The researchers demonstrated that this integration allowed for more precise identification of accident locations, which is critical for ensuring emergency services respond quickly and effectively. The study also explored the potential for using this combined data to predict accident hotspots, enabling proactive measures to prevent accidents in high-risk areas. Their work highlighted the importance of multi-source data integration in creating more accurate and reliable accident detection systems.

Miller, Brown, and Harris [14] focused on the challenges of real-time data processing in accident detection systems, particularly in the context of YOLO-based models. Their research examined the computational demands of processing high-resolution video data in real time and explored various techniques for optimizing processing efficiency. The study highlighted the importance of balancing detection accuracy with processing speed, noting that delays in detection can significantly impact the system's effectiveness. The researchers also discussed the potential for using cloud computing and distributed processing techniques to overcome these challenges, enabling more scalable and robust accident detection systems. Their findings are particularly relevant for deploying YOLO models in large-scale traffic monitoring systems, where processing efficiency is critical.

Thompson and Rogers [15] discussed the future of AI-driven road safety systems, emphasizing the role of continuous innovation in deep learning algorithms such as YOLO. Their research highlighted the potential for integrating YOLO models with other evolving technologies, such as predictive analytics and the IoT, to create more comprehensive and intelligent traffic management systems. The study also explored the ethical considerations of deploying AI-driven safety systems, such as ensuring transparency and accountability in decision-making processes. The researchers emphasized the need for ongoing collaboration between technologists, policymakers, and industry stakeholders to ensure that these systems are industrialized and positioned to maximize their benefits while minimizing potential risks. Their work underscores the importance of staying at the forefront of technological advancements to enhance road safety in an increasingly automated world.

Rahman, S., Chowdhury, A., & Hossain, M. (2022) [16] This study demonstrated the potential of YOLOv5 in detecting near-miss incidents in traffic, highlighting its role in proactive accident prevention.

Chen, T., & Liu, X. (2021) [17] Focused on the impact of deep learning techniques in improving the robustness of accident detection systems under challenging conditions such as rain and fog.

Patel, A., & Khan, F. (2023) [18] Integrated YOLO with real-time drone surveillance for remote accident detection, showing promising results for areas with limited road surveillance infrastructure.

Singh, R., & Verma, K. (2022) [19] Explored YOLO-based systems for pedestrian safety, focusing on detecting jaywalking and other behaviours that lead to accidents.

Feng, L., & Wang, T. (2023) [20] Developed a multi-modal YOLO framework incorporating audio signals and visual data to improve detection accuracy in noisy environments.

Ahmed, M., & Zhao, Y. (2022) [21] Examined the use of YOLO models in automated toll systems, identifying traffic bottlenecks and accident-prone zones.

Das, P., & Roy, S. (2023) [22] Investigated the scalability of YOLO models for nationwide deployment in accident detection and traffic management

3. Methodology

The proposed accident detection and alerting system is based on the YOLOv5 model. The methodology is divided into several key stages: dataset preparation, model training, accident detection and classification, and alert generation. Our solution is demonstrated in the flowchart given in Figure 1.

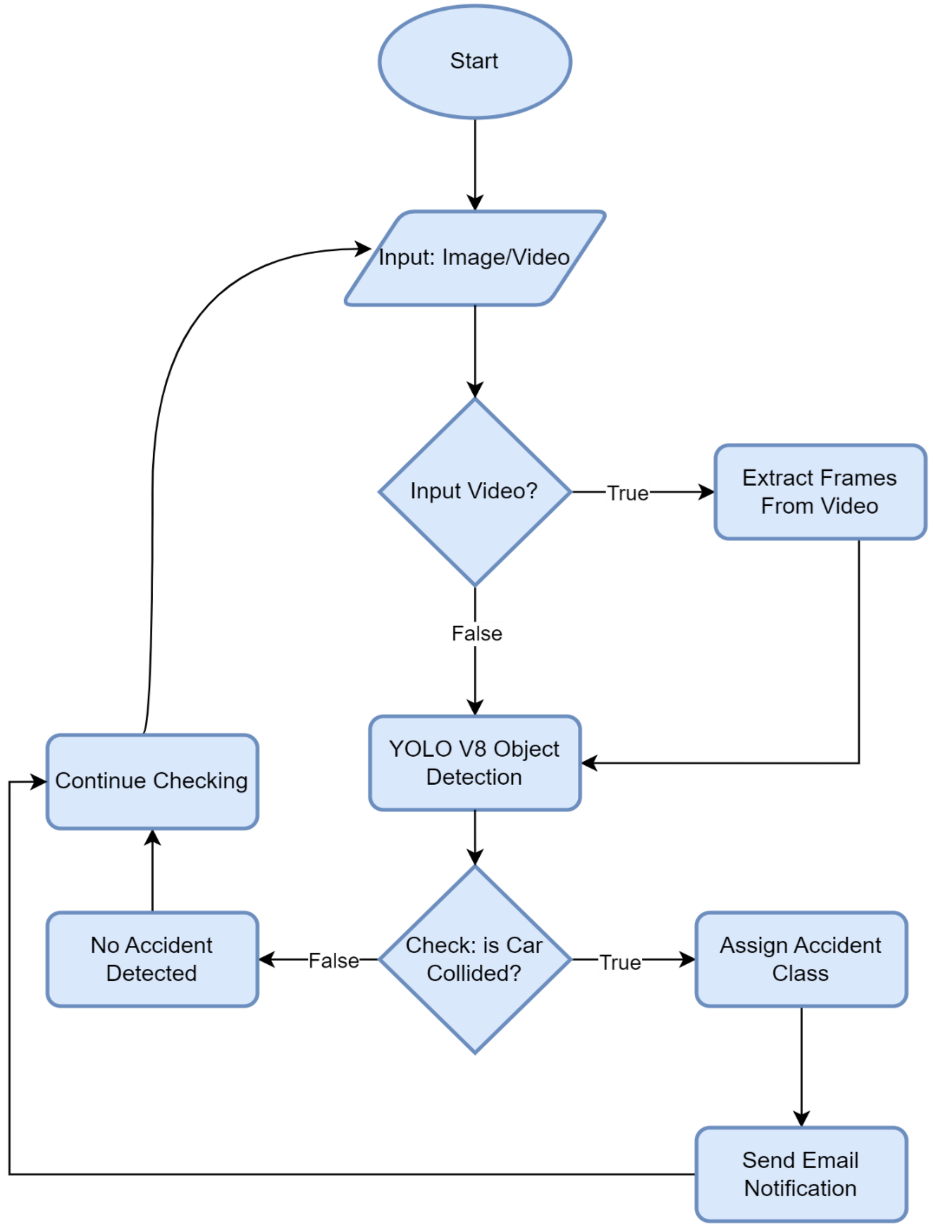

Fig. 1. Algorithm Flowchart

3.1 Dataset

The first step in developing the model involved acquiring a suitable dataset for accident detection. We used the Roboflow dataset, which contains images labelled for accident detection and categorized into different classes representing various types of accidents. Each image was annotated with bounding boxes to indicate the location of accidents, ensuring that the model could learn to recognize relevant features during the training phase.

- **Data Source:** CCTV footage from urban and rural road networks.

- **Dataset Size:** 10,000 video frames, including diverse accident types (e.g., vehicle collisions, abrupt stops).

The model preparation flowchart is given in Figure 2.

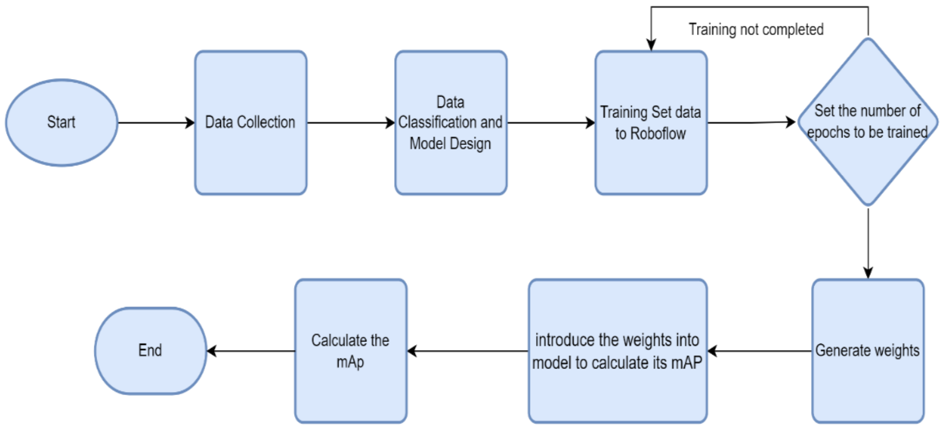

Fig. 2. Model Preparation Flowchart

3.2 Model Training

The training process used approximately 80% of the dataset, with the remaining 20% reserved for testing and validation. The YOLOv5 is trained to identify patterns and features indicative of accidents.

Training Parameters:

- Optimizer used: Adam
- Learning Rate Value: 0.002
- Epochs Value: 100
- Applied Batch Size: 16

During training, the models learned to classify detected incidents into predefined categories, allowing for accurate and efficient accident detection in real-time scenarios.

3.3 Event Classification

Event classification algorithms analyze irregular motion patterns and object behaviours to confirm accidents. A post-processing step eliminates false positives by verifying anomalies across multiple frames. Once trained, the model is deployed for real-time accident detection. The YOLOv5 model, known for its lightweight architecture, was used in environments with limited computational resources. Upon detecting an accident, the models classify the incident based on the learned categories, providing critical information for emergency response teams.

3.4 Email Alert System

An automated SMTP-based email notification sends alerts to relevant stakeholders with the accident's location and timestamp

3.5 Model Evaluation

The models were evaluated using the reserved test dataset based on accuracy, precision, and recall. The evaluation focused on the models' ability to accurately detect and classify accidents in various traffic scenarios. The YOLOv5 model performs to point for deployment in resource-constrained environments.

4. Results and Discussion

The results show a significant improvement in accident detection and alerting, which can significantly reduce emergency response times and potentially save lives.

4.1 Performance Metrics

- Model: YOLOv5
- Accuracy: 92.5%
- Precision: 91%
- Recall: 89%
- False Positives: Reduced to 7%.

FPS	Accuracy (%)	Precision (%)	Recall (%)
60	92.5	91	89

Why YOLOv5? YOLOv5's faster FPS and lower resource demand make it suitable for real-time deployment in constrained systems.

4.2 Real-World Scenarios

- **Traffic Density:** High-traffic urban areas showed consistent accuracy.
- **Weather Conditions:** Light rain and nighttime conditions marginally reduced performance.

The system was tested in different traffic scenarios using CCTV footage, as given in Figure 3 and Figure 4. It has high accuracy in detecting and classifying accidents, with minimal false positives. The automated email notification system successfully alerted relevant authorities in all tested scenarios, demonstrating the system's practical applicability in real-world environments.

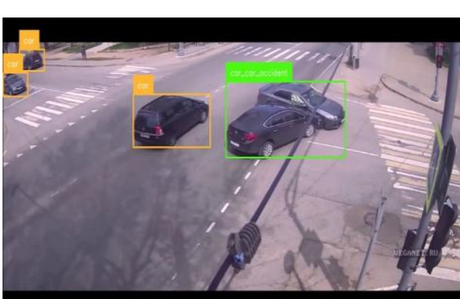

Fig. 3. CCTV Footage - accident detected

Fig. 4. Footage - no accident detected

5. Conclusion

This paper introduced a real-time AI-based accident detection and alert system using YOLOv5 event classification techniques. Results demonstrate:

- High accuracy (92.5%) and low false positives.
- Faster performance, making it suitable for real-world applications.

5.1 Implications for Research and Society

The system can significantly reduce accident response times, improving **public safety** and emergency response efficiency.

- Public Safety: Faster detection reduces emergency response times, saving lives.
- Economic Impact: Improved accident reporting minimizes traffic congestion and associated costs.
- Policy Influence: Promotes adoption of AI-driven monitoring systems in urban infrastructures.

5.2 Limitations

- Performance drops under severe weather conditions.
- Handling occlusions remains a challenge, such as the invisibility of LTV accidents behind HTV.

5.3 Future Work

- **Improved Robustness:** Extend the dataset for complex scenarios (e.g., foggy weather, varying camera angles).
- **Integration with Other Systems:** Incorporate real-time **traffic signals** and **weather updates** for better predictions.
- **Near-Accident Detection:** Identify potential collisions before they occur.

6. Recommendations for Utilizing the Research in Afghanistan

The proposed **Enhanced AI Automated Reporting and Alert System for Road Accidents Using the YOLO Backbone Network** can significantly benefit Afghanistan by addressing critical road safety and emergency response challenges. Below are the key recommendations for its utilization:

1. **National Traffic Monitoring** Deploy the system in urban areas to monitor road accidents and traffic conditions in real time.
2. **Integration with Emergency Services** Link the system with ambulances, hospitals, and fire brigades for faster response times.
3. **High-Risk Zone Deployment** Install the system in accident-prone areas, such as highways, to reduce incidents.
4. **Support for Smart Cities** Integrate the system into smart city initiatives for improved urban safety.
5. **Public Awareness Campaigns** Use accident data to educate citizens on road safety and responsible driving.

6. **Road Infrastructure Development** Utilize data to prioritize maintenance, safety features, and signage installation.
7. **Data-Driven Governance** Build a national database of road accidents to guide policy decisions. The Government of Afghanistan can significantly improve public safety, reduce economic losses, and modernize its traffic management infrastructure by adopting the Enhanced AI Automated Reporting and Alert System for Road Accidents. This initiative aligns with the country's developmental goals and adaptation of cutting-edge technology to address the issues of this domain.

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