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Research Article

Smart Roads Guard: Obstacle Detection and Accident Avoidance System

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Abstract— Road accidents continue to remain a serious issue globally, resulting in injuries and deaths. The Smart Roads Guard system aims to curb the problem with its AI-powered obstacle detection and alerting system. It analyzes footage from roadside cameras to detect dangers and activates the flashlights installed along the road at a sufficient distance and time according to the area where the system is used, which can reach up to one kilometer. This technique enables early real-time detection and allows drivers ample opportunity to alter their speed or change lanes to prevent collisions. To maintain functionality in poor visibility conditions, fog lights are positioned above the cameras on lampposts, which increases detection capabilities during fog conditions and reduces costs. A web-based control platform augments the system by allowing stakeholders such as traffic authorities, universities, private firms, or even residents to monitor and receive real-time alerts to enable a swift countermeasure to road dangers. The system is capable of integration with radar; however, this version is limited to camera-based detection due to budgetary constraints. It utilizes solar energy to improve sustainability, maintaining operation even during bad weather. The Smart Roads Guard is particularly appropriate for developed nations and Gulf regions, where sophisticated infrastructure and weather-related issues necessitate creative and dependable traffic safety solutions. However, it also offers significant value for underserved or uncovered areas lacking traditional traffic monitoring systems. By training the AI model on obstacle images using YOLOv8, we achieved 89% accuracy. The Smart Roads Guard system, which represents a significant advancement in intelligent transportation systems and is easy to implement with low cost, will make road networks safer, smarter, and more sustainable.

Keywords— Object detection; YOLO; Accidents; Road; Obstacle; Sustainability; Artificial intelligence; Safety.

1. Introduction

Accidents that take place on the road are still one of the biggest, troubling factors when it comes to injury or death. As reported by the World Health Organization's Global Status Report on Road Safety, about 1.19 million deaths occurred in 2023, all due to road traffic [1]. Apart from the loss of life, such incidents are painful and costly for people living within a community, especially in areas where traffic is difficult to monitor. Many of these accidents occur due to lack of proper human vision , Weather conditions such as fog. Alongside these unplanned roadblocks.

In relation to these problems and as part of Saudi Arabia's Vision 2030 agenda of reducing road traffic deaths by 50% mid-way through the decade, this paper offers the idea of Smart Road Guard system which works as a multi-functional road safety system designed to help prevent accidents through providing early and real time hazard detection technology [2]. The system uses forms of AI such as computer vision in addition to deep learning technology to spot obstacles using flashlights. These AI signals are sent to the drivers through flashlights mounted on the street lamppost in the road. By notifying road users for one kilometer before obstacles are detected, the system allows drivers crucial time to respond in a safe manner. The system design focuses on new constructions and the adoption of existing structures or innovations. The mounting of cameras on lampposts with the use of solar energy widens the capability range beyond traditional power grid infrastructure for complete solar powered systems and ensures functionality even in remote regions or places prone to adverse weather conditions. A central web-based application facilitates greater operational control to further aid traffic management and emergency responders by providing real-time situational awareness for timely action and coordinated response.

Despite the widespread acceptance of LiDAR and radar as high-precision solutions due to their effectiveness, they often pose a challenge due to their cost, extensive required infrastructure, or limited use in large scale or resource constrained settings [3]. Advanced Driver Assistance Systems (ADAS) and Intelligent Transportation Systems (ITS) are other modern safety technologies that, like many others, tend to emphasize individual vehicles rather than the road surroundings [5][6]. Contrary to this, the Smart Road Guard system provides a developed and emerging economy-friendly solution that is low in cost, infrastructure burden, and easily scalable, making it ideal for use in underdeveloped countries, Gulf regions, and uncovered or underserved areas where traditional solutions do not make sense nor sustain. This research seeks to detect and classify road hazards by adopting the object detection framework of YOLO (You Only Look Once)a cutting-edge deep learning algorithm famed for its rapid pace and reliability in analyzing images in real-time [8].Smart algorithms enable instant reaction protocols because They rely on real-time visual data processing. This function, along with other image-processing technologies, contributes to an intelligent integrated advanced infrastructure system that enables safer and smarter roads. The research adds factors that can be integrated into the implementation of new engineering technologies to improve road safety. Based on the provided explanation, the project systematically tests and verifies all parts of the system from a practical perspective, providing new perspectives on the application of artificial intelligence, design sustainability, and road safety.

2. Related Work

The research relevant to our project is not limited, but we were keen as much as possible to review the most important titles related to the project idea. For example:

2.1 Traffic Accidents in Saudi Arabia

A study conducted by the Hassan M.Al-Ahmadi (Civil Engineering Authority) on traffic safety on 2022 showed that Saudi Arabia has witnessed serious traffic safety issues. The Saher Traffic Management System is one of the proactive traffic safety initiatives and policies that the government has implemented. A comprehensive statistical, descriptive, and spatial analysis was conducted to evaluate the changes in traffic safety conditions before and after the implementation of the Saher system and the results indicated that reckless driving and excessive speed are among the biggest causes of accidents in the Kingdom of Saudi Arabia. The study further showed that the most prevalent types of accidents in Saudi Arabia are collisions with vehicles and fixed objects and swerving accidents. After the measures that the government was keen to consider, the study noted that the rate of accidents, injuries and deaths has tended to decrease [15].

2.2 Road Debris and Traffic Accidents

According to a AAA Foundation for Traffic Safety report, between 2011 and 2014, road debris was responsible for almost 200,000 collisions in the US, resulting in 39,000 injuries and 39,000 deaths. More than 500 deaths. A large percentage of accidents are attributed to drivers swerving off the road while trying to avoid debris, causing them to lose control of their cars. To prevent these accidents, these procedures must be followed, such as securing goods, and it is recommended to practice defensive driving by placing a sufficient distance between other cars to mitigate these risks [16].

2.3 Object Detection

From the latest research, it is certain that the technology used in object detection is an integral part of computer vision, especially in relation to smart transport systems. Tang et al. [9] noted that applying detection systems to the Internet of Things (IoT) has improved real-time supervision as well as maintenance and safety applications. The two main features of object detection are classification, in which the system recognizes an object, and localization, in which the system defines the position of an object in an image or a video. Earlier methods were based on handcrafted features and shallow models which were not suitable for complex situations. The evolution of deep learning has boosted not only accuracy but also the efficiency of object detection.

Novel alterations to the YOLOv5 model presented by Rana et al. [10] are yet others which showed improved performance in the detection of vehicles due to their optimization of network architectures and alterations of feature extraction techniques. These changes lead to higher accuracy of detection and better speed of processing, which is essential for real time performance. In the same way, object detection based on deep learning has greatly aided the development of sustainable transport. Wang [11] points out that AI-powered detection models foster better urban mobility by enhanced traffic control and lower emissions.

Modern object detection techniques, including YOLO-Fusion, SSD, and Faster R-CNN, employ big data sets and advanced training techniques to yield greater precision. The models select appropriate visual features, identify objects, and generate bounding boxes to improve real-time detection. Intelligent transportation AI solutions offer improved pedestrian detection, dynamic obstacle detection, and efficient vehicle monitoring. Comparative studies of various deep learning techniques regularly improve these models to make them more precise and adaptable in different scenarios.

2.4 Object detection in analyzing video-based traffic

Researchers found in [18] that object detection using deep learning technique showed better performance compared with object detection using traditional CNN prior to 2014, and after. Traditional CNN has many disadvantages. It takes a long time to find the object, computationally expensive, not useful in light conditions, requires longer training time, and is limited only to binary classification. This method works in three steps: region selection, feature extraction, and classification. To overcome the problems of traditional CNN, deep learning technologies are used; because deep learning methods focus mainly on video processing to solve many problems such as object detection, and object recognition [18][19]. This includes detecting humans, animals, cars, traffic signs, and other obstacles. It is not limited to detecting objects only, but it can be useful in analyzing traffic distribution, extracting and planning paths, estimating speed, tracking moving objects, and detecting objects on the shoulders of the road. To preserve the driver's privacy from leakage of his information, object detection is used to remove personally identifiable information such as the face and license plate before publishing the video [19].

2.5 Safety and object recognition systems in vehicles

In [14], they studied the potential of advanced driver assistance systems (ADAS) to enhance driving performance and safety. The efficacy of seven on-board sensor-based ADAS functions was evaluated, rather than their collaborative effectiveness. Additionally, they investigated seven ADAS functions in a CV environment within an integrated driving assistance system (iADAS). They found that iADAS reduces accidents and prevents rollovers and skidding, and they found that younger drivers respond faster to collision warnings.

Researchers in “only cite”, worked on a study about motorcycle crash detection and alert system using IoT. The research explored (either use past tense for all paragraphs when representing other works or present tense but be consistent) minimizing the number of fatalities in motorcycle accidents by implementing an alert system that can notify emergency services in the event of an imminent motorcycle crash. It detects when the motorcycle tips over by using the MPU6050 Multi-axes accelerometer. Sending the impact parameters to the Firebase cloud, it notifies the emergency contacts and emergency response services if the values meet the crash criteria [13].

Gaps:

i. Limited Focus on Real-Time Constraints: Although the article discusses object detection algorithms such as YOLO and SSD, it does not provide a thorough analysis of their performance under real-time constraints, such as in high-speed applications (e.g., autonomous vehicles) where detection accuracy and speed are both critical.

ii. Lack of Comprehensive Evaluation measures: While the article mentions evaluation measures, it does not give in-depth comparisons or performance benchmarks for various algorithms across multiple datasets, which might assist readers in understanding the strengths and shortcomings of each technique.

iii. Insufficient data set for traffic analysis: The research stated that the data set did not cover sufficient aspects for studying traffic, such as the lack of data to analyze driver behavior, aerial photos, roadside photos, and camera data installed on the car to synchronize with traffic.

iv. Deep learning methods were not delved into: The research discussed limited methods in deep learning, less than 10 methods, and did not mention in detail the tasks of object detection, path extraction, and video analysis.

v. Response by age group: The elderly may find it difficult to use modern cars and adapt to the technologies they provide, which may cause them to become distracted and have difficulty concentrating on the road.

vi. Lack of internet connectivity: Not all cities can provide strong network connectivity and 5G technologies, which may affect the availability of the system.

vii. Lack of a system that serves all vehicles: There is no system installed in all vehicles to avoid accidents before they happen and warn the driver.

3. Experimental Method

The Smart Roads Guard system is designed to improve road safety by detecting obstacles and alerting drivers. The system includes cameras, flashlights, fog lights, solar panels, and a centralized website. These components work together to quickly detect obstacles and send alerts in real time. The system first identifies obstacles using an AI model based on the YOLO algorithm and a database of known objects. Roboflow was employed to assist in the preparation and labeling of the datasets used for model training. If the obstacle is recognized, the system activates alerts by turning on flashlights to warn drivers and sending alerts to the administrator and the service department through the centralized website. If the system does not recognize the obstacle, or if visibility is low due to fog, it collects details such as the obstacle’s size and location and sends this information to the administrator and service team for review. When an alert is received, administrators can access system alerts, add notes to reports following obstacle removal, and review detailed report records for monitoring purposes. At the same time, the service department is responsible for removing obstacles, updating report statuses (e.g., pending, in progress, or completed), and adding relevant notes. Both user roles can view and manage stored reports, ensuring accountability and streamlined operations. All detected obstacles and corresponding actions are stored within the system for future tracking and analysis. The solar-powered fog lights ensure that the system remains operational even under adverse weather conditions. By continuously monitoring the roads and providing quick alerts, the Smart Roads Guard system helps prevent accidents, manage traffic flow, and maintain road safety.

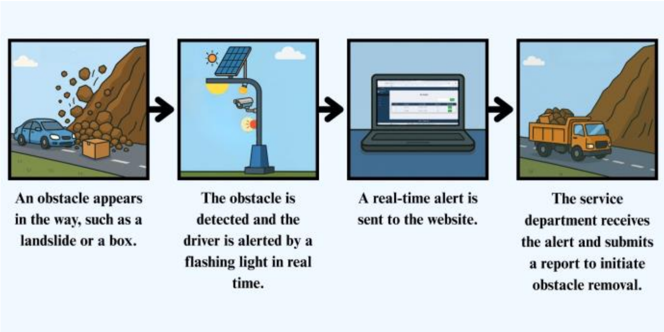

Figure 1. Smart Roads Guard System Workflow.

Turning to the physical setup of the system, DSLR cameras are installed on lampposts at heights ranging from 10 to 15 meters and are positioned at a 60° angle to cover a range of 50 to 60 meters. As shown in Figure 2, when a camera detects an obstacle, it activates solar-powered flashing lights. These alerts warn drivers up to 300 meters ahead, providing sufficient time for deceleration. The cameras are spaced 100 meters apart to ensure continuous coverage across the road. If the system detects traffic congestion, it sends early warnings to improve road safety. Additionally, to address adverse weather conditions, solar-powered fog lights are installed at a 65° angle above the cameras, increasing visibility and extending the alert range up to 500 meters. All obstacle alerts are transmitted to the centralized website, allowing authorized staff to monitor and respond to road conditions in real time.

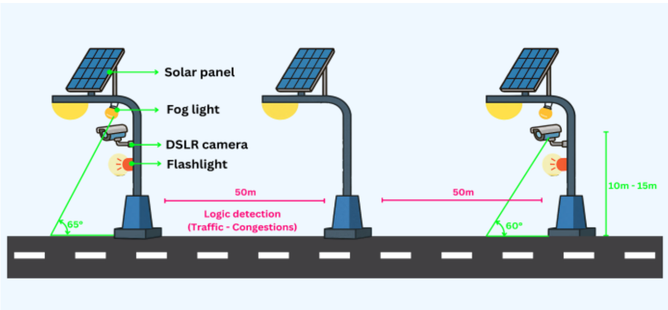

Figure 2. Smart Roads Guard System Physical Setup.

4. Results

In Smart Roads Guard, we developed an advanced AI-based obstacle detection system using YOLOv8, a state of the art real-time object detection algorithm. The model was trained on diverse datasets, including 6,930 accident images, 555 landslide images, 408 fallen tree images, and 5,624 animal images, collected from Roboflow. We used libraries such as ultralytics, torch, opencv-python, pyautogui, and pytesseract, which helped train the AI model. It achieved an impressive 89% accuracy in obstacle detection. As shown in Figure 1, 2, 3 and 4, the AI model detected the obstacles.

Figure 5 showcases the precision-confidence curve of the multi-class classification model, where individual curves are drawn for each class, with the blue bold curve representing the macro-averaged precision across all classes. The x-axis represents the model's prediction confidence, and the y-axis captures the precision. Some classes, like accident_class1 and loup, maintain high precision across multiple confidence levels, while others, such as baffle and guard, have more nuanced shifts. The model appears to attain perfect precision (1.00) at an approximate confidence level of 0.885, which may suggest that estimates made beyond this value would be trustable. This evaluation emphasizes again the class focus approach by precision limits while indicating essential guidance to alter the confidence level to improve accuracy.

Figure 6 and Table 1 demonstrate the model’s performance over four types of obstacles: animals, landslides, falling trees, and accidents. The confusion matrix shown in Figure 6 has a strong diagonal pattern, which validates that most types of obstacles are correctly classified. It is worth mentioning that natural obstacles such as landslides and fallen trees were classified with a precision of 100% and 93%, respectively. Accident-related obstacles also had moderate classification performance, achieving an average accuracy of 71%. For the animal obstacles, including buffalo, cheetah, hippopotamus, lion, and wolf, the model had a mean accuracy of 62.4%. Although animal classification posed a challenge due to the perceived likeness some species share, the outcome is still quite positive. In summary, the model demonstrates reliable performance in the detection of diverse category obstacles, which suggests its usefulness in practical applications.

The system also features a web platform for admins and service departments, providing real-time alerts, report generation, and data storage for easy search and review. The webpage contains many features that help the administrator, and the service department identify the obstacle, its location, and take action. Figure 7 shows the welcome page where the user chooses whether he is an admin or a member of the service department. A notification will be sent at the top of the page when an obstacle is detected. This notification is included in the Alerts page shown in Figure 8, which contains a table showing the basic data for the obstacle alert, such as detection time, classification, alert ID number, and more details. When the user click’s "View" from the "More Details" column, they will be directed to the alert details page. In addition, there is a reports page where reports generated by the service department are displayed on a table displaying the most important information. The user can click "View" in the "More Details" column and be directed to the report details page. Furthermore, the site provides basic pages such as login, account activation, and forgot password.

Figure 3. Fallen tree detection

Figure 4. Landslide detection

Figure 5. Accident detection

Figure 6. animal (buffalo) detection

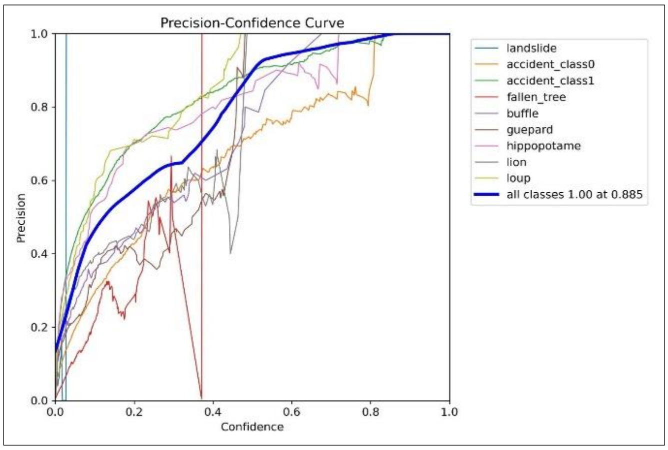

Figure 7. Precision-Confidence Curves for Multi-Class Obstacle Classification

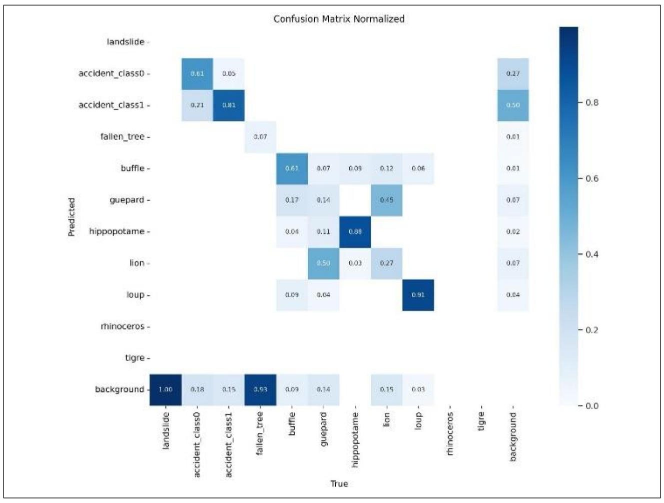

Figure 8. Confusion matrix

Table 1. Average accuracies by category

Obstacle classification	Average Accuracy (%)
Accidents	71%
Falling Tree	93%
Landslide	100%
Animals	62.4%

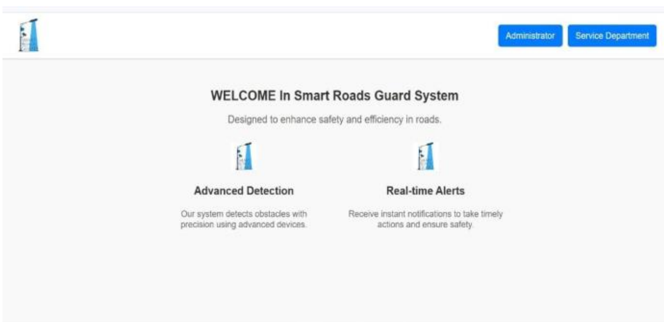

Figure 9. Welcome page

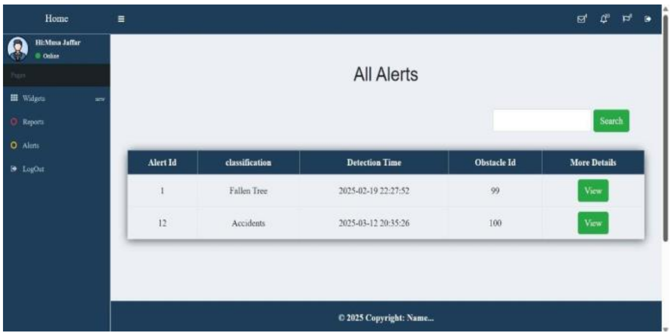

Figure 10. Alerts page

5. Discussion

The 'Smart Roads Guard' system exemplifies the significant potential of integrating advanced technologies to improve traffic safety infrastructure, with artificial intelligence serving as a central component of this innovation. Notably, the implemented AI model achieved an impressive 89% accuracy in the detection of road obstacles, underscoring its practical effectiveness and reliability. The system is also linked to a website to complete the obstacle detection process and take the necessary action.

The core objective of this research lies in enhancing road safety through the development of a smart, integrated system that is seamless and adaptable to both public and individual capabilities. The "Smart Roads Guard" system was designed in alignment with the findings of previous studies, complementing them in the pursuit of the intended goal. While there are functional similarities between the proposed system and the "Saher" system implemented on roads in the Kingdom of Saudi Arabia, both aiming to reduce traffic accidents and road chaos, and the key difference lies in the approach each system adopts. Whereas "Saher" focuses on monitoring vehicle speed, the "Smart Roads Guard" emphasizes early detection of road obstacles that may disrupt traffic flow and pose risks to pedestrians. This distinction highlights the necessity of the proposed system in addressing road safety issues not currently covered by existing solutions.

The system's performance results demonstrate significant impact, as previously noted, due to its flexible design that adapts to both public and individual capabilities. This means it is not limited to specific vehicle types or age groups. However, its benefits may be particularly evident in cases involving inattentive drivers or young individuals who exhibit reckless driving behavior. The success of the system stands as evidence of its role as a modern, technologically advanced solution aimed at enhancing road safety and preserving lives. The system was trained using diverse and high-quality datasets from the Roboflow platform, which included realistic images of various obstacles such as traffic accidents, landslides, fallen trees, and animals. This contributed to improving the model's accuracy and enhancing its ability to make effective predictions.

Although the system offers valuable and modern solutions, there are several limitations in its implementation. The system relies on the quality of cameras and visual sensors under varying weather conditions. Additionally, it may not be able to detect or classify hazards that are not clearly visible on the road. Moreover, even if the system successfully detects an obstacle, the driver's response remains a critical factor in avoiding accidents or disruptions. A reckless driver, for instance, may fail to react appropriately to the system's warnings.

In conclusion, the *Smart Roads Guard* system presents a compelling integration of artificial intelligence and practical interface design, offering a robust solution for enhancing road safety. The successful deployment of the YOLOv8 model, with its high detection accuracy, alongside a well-structured web platform, demonstrates the system's readiness for real-world applications. The results highlight not only the technological feasibility but also the operational effectiveness of such an approach in identifying and managing road obstacles in real-time.

6. Conclusion and Future Scope

The developed system efficiently addresses the issues of road safety by detecting obstacles in the road and areas where official monitoring is not considered, thereby providing timely alerts to prevent collisions and fatalities. The basic objective of creating a proactive system for warning drivers in real time was achieved through artificial intelligence and computer vision techniques. The trained AI model could identify common obstacles with 89% model accuracy, reflecting the algorithm's effectiveness in real-life situations. The utilization of a control website facilitated real-time monitoring, auto-generation of alerts, and the ability to alert concerned authorities for immediate action, contributing to the efficiency of the safety system. The project also addresses sustainability with solar-powered cameras and lights, enabling continuous operation even in hostile weather and isolated areas where conventional power sources are unavailable.

The impact of this work is that it has the potential to significantly reduce accidents on the road and in unmonitored zones by offering a smart and scalable safety solution. The application of AI not only demonstrates technological advancement in traffic management but also follows the mission of making roads safer for all. Although the result is promising, some limitations prevented the full implementation of the system. One of the major limitations was the unavailability of high-quality datasets with diversity, which affected the generalization ability of the model for all kinds of obstacles. Additionally, due to budget constraints, the actual deployment of physical components such as cameras and lighting setups could not be accomplished, and the testing process had to be limited to simulations and theoretical validation.

There is considerable room for improvement and expansion of this project in the future. Future efforts should be directed towards obtaining or creating a much larger dataset to improve model accuracy and diversify the types of obstacles detectable. Also, implementing the project on actual hardware devices will provide hands-on experience and validate the effectiveness of the system under real-world conditions. Incorporating other sensor technologies and increasing the coverage area can be explored as well. All these enhancements will lay the groundwork for a more robust and scalable safety network that can be implemented by traffic authorities and private organizations to minimize road hazards and casualties.

Data Availability

The data sets used to verify the output of this study are publicly accessible on the Roboflow Universe platform and were solely used for research and model training. The data sets include annotated images of road obstacles in the form of landslides, fallen trees, car damage, traffic accidents, and animals—typical obstacles that motorists can encounter on the road. Each dataset was selected based on its relevance to real-world road safety conditions and contributed to training and testing the AI model. The list of datasets, with direct access links, is provided below for the sake of transparency and reproducibility of the study:

- Landslide Detection Dataset 1
- Landslide Detection Dataset 2
- Accident Severity Detection Dataset
- Filtered Obstacles Dataset
- Fallen Trees Detection Dataset 1
- Fallen Tree Dataset 2
- Animal Classification Dataset
- Animal Detection Dataset
- AIVLE5 Test Dataset
- DM Dataset
- Car Damage Location Detection Dataset
- Animal Detection Dataset 3

These open-source datasets remain available in the public domain and can be accessed for possible future research or verification, as per their respective license terms.

Study Limitations

Although the results of this study are encouraging, several limitations were identified that could possibly have influenced the overall usability and applicability of the suggested system. The first significant challenge was the unavailability of access to high-quality, varied datasets, which reflect realistic road conditions in the real world. The limitation influenced the capability of the model to generalize in different types of obstacles and varying environments. Despite the utilization of several publicly accessible datasets, the absence of a combined or overarching dataset resulted in the reality that the system had been trained on disjointed samples, thus potentially restricting its general detection effectiveness.

Furthermore, since the project was under budget restraints, it was not feasible to utilize or test the system with actual physical hardware components like cameras, flashlights, and fog lights. Thus, our tests were found on theoretical analysis and computer simulations instead of field tests, which might not completely capture the difficulties involved in real deployment. These limitations point to the necessity for additional investment in both hardware realization and data collection to achieve the full potential of the system in practical applications.

Conflict of Interest

There was no conflict of interest.

Funding Source

None.

Authors' Contributions

Dr Dalia AlGezawi provided continuous academic guidance, supervised the research process, and reviewed the manuscript to ensure the quality and clarity of the final work. Raghed Aljassim, Batool Alsaffar , Hajer Alsaleh , Zainab Alfandi , Yassmin Alhaji contributed equally to all aspects of the research, including conceptualization, data collection, system development, model training, analysis, and manuscript writing. Each author participated collaboratively in designing the project, solving challenges, and reviewing the final version of the manuscript. All authors approved the final version of the manuscript.

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