

SafeVision: Smart Offline Animal and Fog Detection System

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Abstract

Road accidents caused by poor visibility and unexpected animal crossings are major challenges in modern transportation systems, especially in rural, highway, and forest regions. Fog significantly reduces visibility, while sudden animal or pedestrian presence on roads increases the risk of accidents. Existing systems often rely on expensive sensors, cloud-based processing, or high-end computational resources, making them impractical for widespread use. This paper proposes a Smart Offline Animal and Fog Detection System for accident prevention using a single camera and artificial intelligence techniques. The system is designed to operate completely offline using browser-based technologies such as TensorFlow.js and the COCO-SSD object detection model. It detects animals, humans, and fog conditions in real-time using live video input from a camera. Fog detection is performed using brightness and visibility analysis, while object detection identifies potential obstacles such as animals and pedestrians. The proposed system provides real-time visual and voice alerts to warn drivers about potential hazards. Unlike existing approaches, the system is lightweight, cost-effective, and does not require internet connectivity or specialized hardware, making it suitable for deployment in both two-wheelers and four-wheelers, especially in remote areas. Experimental results demonstrate that the system effectively detects fog and objects under various conditions, improving driver awareness and reducing the risk of accidents, thereby offering a practical and scalable solution for enhancing road safety using artificial intelligence.

Keywords— Animal Detection, Fog Detection, Road Safety, Computer Vision, Deep Learning, TensorFlow.js, COCO-SSD, Offline System, Accident Prevention

1. Introduction

Road safety has become one of the most critical concerns in modern transportation systems due to the rapid increase in the number of vehicles and the growing rate of road accidents worldwide. Among the various factors contributing to road accidents, poor visibility conditions and unexpected obstacles such as animals or pedestrians play a significant role. These issues are particularly severe in rural areas, highways, and forest

regions, where drivers often encounter sudden hazards without sufficient warning, leading to serious accidents and loss of life.

Fog is one of the most common environmental conditions that significantly affects visibility on roads. It reduces the clarity of the surrounding environment by scattering light, making it difficult for drivers to detect objects at a distance. This results in delayed reaction

times, incorrect judgment of distances, and increased chances of collisions. Similarly, animals crossing roads unexpectedly, especially in forest and rural regions, pose a major threat to both drivers and wildlife. Animals such as dogs, cows, and deer frequently appear suddenly on roads, giving drivers very little time to react, which can lead to fatal accidents.

Traditional systems designed to mitigate these risks often rely on advanced technologies such as thermal cameras, LiDAR sensors, radar systems, and cloud-based monitoring platforms. Although these systems provide improved detection capabilities, they are expensive, complex, and require high computational resources. In addition, many of these systems depend on continuous internet connectivity, which makes them unsuitable for deployment in remote and rural areas. Furthermore, most existing solutions focus either on environmental condition detection, such as fog, or object detection, such as animals and pedestrians, but rarely integrate both functionalities into a single unified system.

Recent advancements in artificial intelligence and computer vision have enabled the development of efficient real-time detection systems. Deep learning models such as YOLO and Single Shot Detector (SSD) have demonstrated high accuracy in detecting objects in real-time scenarios. Similarly, image processing techniques can be used to detect environmental conditions like fog by analyzing brightness, contrast, and visibility levels in video frames. However, these approaches often require large datasets, high-end hardware, and complex training processes, limiting their practical implementation in everyday applications.

To address these challenges, this paper proposes a Smart Offline Animal and Fog Detection System that integrates both object detection and environmental analysis into a single efficient solution. The system uses a single camera to capture real-time video and processes it using browser-based artificial intelligence technologies. By utilizing TensorFlow.js and the COCO-SSD model, the system performs real-time object detection directly in the browser without the need for server-side processing or internet connectivity.

In addition to object detection, the system includes a fog detection mechanism based on brightness analysis of video frames. When the brightness level exceeds a predefined threshold, the system identifies the presence of fog and generates appropriate alerts. This integration of fog detection and object detection allows the system to identify multiple hazards simultaneously, improving overall road safety.

The proposed system also incorporates a real-time alert mechanism that provides both visual and voice notifications to the driver. This ensures that the driver is immediately informed about potential hazards, enabling quick decision-making and reducing the risk of accidents. The system prioritizes alerts based on severity, ensuring that critical conditions such as dense fog are highlighted effectively.

One of the major advantages of the proposed system is its ability to operate completely offline. This makes it highly suitable for use in rural and remote areas where internet connectivity is limited or unavailable. Additionally, the system is lightweight and cost-effective, allowing it to be implemented on low-end devices without requiring specialized hardware. This makes the solution accessible for a wide range of users, including both two-wheelers and four-wheelers.

The main contributions of this work include the development of an integrated system for simultaneous detection of fog and road obstacles, the implementation of a real-time alert mechanism, and the demonstration of a practical and low-cost solution for improving road safety. The system aims to bridge the gap between advanced research solutions and real-world applications by providing a simple, efficient, and scalable approach to accident prevention.

The remainder of this paper is organized as follows. Section II presents a detailed literature survey of existing approaches. Section III describes the problem statement and objectives. Section IV discusses the existing system and its limitations. Section V explains the proposed system and methodology. Section VI presents implementation details and results. Finally, Section VII concludes the paper and outlines future scope.

2. Literature Survey

In recent years, road safety has become a critical research area due to the rapid increase in vehicular traffic and the growing number of accidents worldwide. A significant portion of these accidents is caused by poor visibility conditions such as fog and the sudden appearance of obstacles like animals and pedestrians. To address these challenges, researchers have explored various approaches based on computer vision and deep learning techniques for real-time object detection and environmental condition monitoring. This section provides a detailed review of existing works related to animal detection, fog detection, and integrated road safety systems.

Sudhakar Sengan et al. proposed a real-time automatic detection system for Indian roadway animals using an enhanced YOLOv3 model integrated with 3D reconstruction techniques. The system was designed to detect animals in complex road environments by improving spatial understanding through three-dimensional analysis. The integration of deep learning with 3D reconstruction helped improve detection accuracy, particularly in cluttered scenes. However, the system required high computational resources and relied on GPU-based processing, making it unsuitable for real-time deployment on low-cost devices. Additionally, the system did not incorporate environmental condition detection such as fog, which limits its applicability in adverse weather conditions.

N. Mamat et al. developed an animal intrusion detection system using the YOLOv5 algorithm for monitoring agricultural and rural areas. The system demonstrated efficient real-time detection capabilities by identifying animals entering restricted zones. YOLOv5, being a one-stage object detection model, offers faster processing speed compared to traditional methods. Despite its effectiveness, the system heavily depended on large annotated datasets for training and required continuous computational support for real-time inference. Moreover, it lacked integration with environmental monitoring systems and was not optimized for offline applications, reducing its practicality in remote areas.

K. Parkavi et al. introduced a system aimed at enhancing road safety by detecting animals on highways during nighttime conditions. The system utilized

YOLOv5 combined with image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Retinex algorithms to improve visibility in low-light conditions. While the approach significantly improved detection accuracy at night, it introduced additional preprocessing steps that increased computational overhead. Furthermore, the system faced challenges in foggy environments where visibility degradation is caused by atmospheric scattering rather than lighting conditions, highlighting a limitation in handling multiple environmental factors simultaneously.

Brožovský et al. explored the use of thermal imaging cameras for detecting wild animals along roadways. Thermal imaging allows detection based on heat signatures, making it effective in low-light or nighttime conditions. The system demonstrated reliable performance in detecting animals regardless of lighting conditions. However, the use of thermal cameras significantly increased the cost of implementation, making it impractical for widespread deployment. Additionally, thermal imaging systems are sensitive to weather conditions such as heavy fog and rain, which can reduce detection accuracy. The dependency on specialized hardware further limits the scalability of such systems.

P. Balakrishnan et al. proposed a deep learning-based animal monitoring system using the VGG16 convolutional neural network combined with the Deep SORT algorithm for object tracking. The system achieved high accuracy in detecting and tracking animals in real-time scenarios. The integration of tracking algorithms helped maintain object identity across frames, improving monitoring efficiency. However, the approach required substantial computational power and was primarily designed for surveillance applications rather than real-time driver assistance. Moreover, it did not include mechanisms for detecting environmental conditions such as fog, limiting its effectiveness in adverse weather situations.

Zhaohui Liu et al. proposed an advanced algorithm for target detection in foggy weather conditions based on the YOLOv5 architecture. The system focused on improving feature extraction techniques to enhance object detection performance in complex foggy environments. By optimizing feature representation, the

model achieved better detection accuracy under low visibility conditions. However, the approach required extensive training on specialized foggy datasets and demanded high computational resources for model execution. The system also lacked a real-time alert mechanism for drivers and was not designed for lightweight or offline deployment.

Quanxiang Wang et al. introduced Fog-YOLO, a real-time object detection model specifically designed for foggy autonomous driving scenarios. The model incorporated advanced feature enhancement modules to improve detection accuracy in fog conditions by capturing fine-grained details in low-visibility images. Although the model demonstrated improved performance, the inclusion of additional modules increased computational complexity and processing time. Furthermore, the system focused solely on object detection and did not include an integrated alert mechanism or support for offline operation, limiting its practical usability in everyday driving conditions.

Yongsheng Qiu et al. proposed IDOD-YOLOv7, which integrates image dehazing techniques with the YOLOv7 object detection model to improve detection performance in foggy and low-light environments. The system first enhances image clarity by removing fog effects and then performs object detection on the processed image. This two-stage approach resulted in improved detection accuracy; however, it introduced additional computational overhead and increased processing latency. The system also required powerful hardware for real-time performance and was not suitable for low-cost or browser-based implementations.

A comparative analysis of the reviewed literature indicates that most existing systems focus on either object detection or environmental condition monitoring independently. While deep learning models such as YOLO variants provide high accuracy in object detection, they often require large datasets, extensive training, and high computational resources. Similarly, fog detection and image enhancement techniques improve visibility but add complexity to the system. Additionally, many existing solutions rely on expensive hardware components such as thermal cameras or require continuous internet connectivity, limiting their practical deployment in real-world scenarios.

In contrast to these approaches, the proposed system aims to provide a unified solution that integrates both animal detection and fog detection into a single lightweight framework. The system is designed to operate entirely offline using browser-based technologies, eliminating the need for high-end hardware or internet connectivity. By utilizing TensorFlow.js and the COCO-SSD model, the system achieves real-time object detection with minimal computational requirements. Furthermore, the inclusion of a real-time alert mechanism enhances driver awareness and improves safety. This approach addresses the key limitations identified in existing systems, making it a practical and scalable solution for accident prevention in diverse environments.

The methodology adopted in this work involves deep learning-based object detection using convolutional neural networks. The model was trained on large-scale datasets to improve detection accuracy under various environmental conditions. The system demonstrates good performance in controlled scenarios; however, its effectiveness reduces under challenging conditions such as dense fog, low lighting, and real-time constraints. Additionally, the computational complexity of the model makes it less suitable for deployment on low-resource or embedded devices.

Table 1. Feature comparison of existing systems and proposed system

A feature-based comparison between existing systems and the proposed system is presented in Table 1.

Feature	Existing System	Proposed System
Object Detection	Yes (YOLO – based models)	Yes (COCO - SSD)
Fog Detection	Limited or separate models	Integrated fog detection
Multi -Hazard detection	No (single - task focus)	Yes (object + fog detection)
Real -time processing	Yes(with high resources)	Yes(optimized for real time)

Hardware requirement	High (GPU required)	Low (works on standard devices)
Offline capability	No	Yes
Cost	High	Low
Alert system	Not integrated	Visual and audio alerts
Night vision support	Limited	Yes

The above table presents a feature-based comparison between existing systems and the proposed system. Most existing approaches focus on specific tasks such as object detection or fog detection independently, whereas the proposed system integrates multiple functionalities into a single framework. The system provides real-time detection, offline capability, and alert generation while maintaining low computational requirements, making it suitable for practical deployment.

3. Problem Statement

Despite significant advancements in road safety technologies, accidents caused by poor visibility and unexpected obstacles such as animals and pedestrians continue to pose a major challenge, particularly in rural, highway, and forest environments. Foggy conditions significantly reduce visibility by scattering light, making it difficult for drivers to detect objects at a safe distance. This leads to delayed reaction times and poor decision-making. At the same time, sudden animal crossings further increase the risk of accidents, especially in areas near forests and villages where animals frequently enter roadways without warning.

Existing solutions for addressing these challenges often rely on advanced hardware such as thermal cameras, LiDAR sensors, radar systems, and deep learning-based detection models. While these technologies provide improved detection capabilities, they are expensive, complex, and not feasible for large-scale deployment. Additionally, many of these systems are designed to detect either environmental conditions such as fog or physical obstacles such as animals and pedestrians, but not both simultaneously. This lack of integration reduces their effectiveness in real-world

scenarios where multiple hazards can occur at the same time.

Furthermore, most current systems depend on cloud-based processing and require continuous internet connectivity for data transmission and model execution. This limits their usability in remote and rural areas where network availability is limited. Deep learning models used in such systems often require large datasets for training and high computational resources for inference, making them unsuitable for deployment on low-cost devices. In addition, many systems lack real-time alert mechanisms, which reduces their effectiveness in preventing accidents.

Therefore, there is a strong need for a lightweight, cost-effective, and efficient system that can operate completely offline while providing real-time detection of both environmental conditions and physical obstacles. The system should be capable of detecting fog and identifying animals and pedestrians simultaneously using minimal computational resources. It should also provide immediate visual and voice alerts to the driver, enhancing situational awareness and enabling timely response. Such a system would significantly reduce the risk of accidents and improve overall road safety, especially in resource-constrained and high-risk environments.

5. Existing System

Existing road safety systems are primarily designed to detect obstacles or monitor environmental conditions using advanced technologies such as deep learning models, image processing techniques, and sensor-based systems. In recent years, convolutional neural networks (CNNs), particularly YOLO (You Only Look Once) and SSD (Single Shot Detector), have been widely used for real-time object detection. These models process images in a single pass and are capable of detecting multiple objects such as vehicles, pedestrians, and animals with high accuracy and speed.

In addition to object detection, several systems have been developed to handle adverse weather conditions such as fog. These systems use image processing techniques such as dehazing algorithms, contrast enhancement, and brightness analysis to improve

visibility. Fog detection is often performed by analyzing pixel intensity, contrast levels, and visibility degradation in captured frames. Some advanced approaches integrate preprocessing techniques to enhance image quality before performing object detection.

Modern Advanced Driver Assistance Systems (ADAS) combine multiple sensors such as cameras, radar, and LiDAR to monitor the driving environment. These systems are capable of detecting obstacles, measuring distances, and providing warnings to drivers. Although ADAS systems offer improved safety features, they require specialized hardware and complex integration, making them expensive and less accessible for common users.

Many existing systems rely on cloud-based architectures for processing and analysis. In such systems, video data captured from cameras is transmitted to remote servers where machine learning models perform detection and send results back to the device. This approach allows the use of powerful models; however, it introduces latency and depends heavily on stable internet connectivity. In remote or rural areas, where network availability is limited, such systems become unreliable.

Furthermore, most existing solutions are designed to address either object detection or environmental condition detection independently. While object detection models perform well under normal conditions, their performance degrades in foggy environments due to reduced visibility. Similarly, fog detection systems do not provide information about obstacles present on the road. This lack of integration limits the effectiveness of existing systems in real-world scenarios where multiple hazards may occur simultaneously.

Overall, although existing systems demonstrate high accuracy under controlled conditions, their dependency on high-end hardware, large datasets, internet connectivity, and complex system architecture makes them less suitable for practical deployment in cost-sensitive and resource-constrained environments.

6. Limitations of Existing System

The existing systems suffer from several limitations, which restrict their practical implementation and effectiveness:

- **High Cost:** Many systems rely on expensive hardware such as thermal cameras, LiDAR sensors, and radar modules, making them unsuitable for widespread use.
- **High Computational Requirements:** Deep learning models used in existing systems require powerful processors and GPUs, limiting their deployment on low-end devices.
- **Internet Dependency:** Cloud-based systems require continuous internet connectivity, which is not always available in rural and remote areas.
- **Lack of Integration:** Most systems focus either on object detection or environmental condition detection, but do not integrate both functionalities in a single solution.
- **Complex System Design:** Integration of multiple sensors and processing units increases system complexity and maintenance requirements.
- **Limited Real-Time Alerts:** Some systems lack effective real-time alert mechanisms, reducing their ability to prevent accidents.
- **Reduced Performance in Adverse Conditions:** Many systems experience reduced accuracy in foggy or low-visibility conditions.
- **Limited Accessibility:** Due to cost and complexity, these systems are not accessible to common users, especially for two-wheelers.

7. Proposed System

The proposed system is designed to provide an efficient, cost-effective, and real-time solution for enhancing road safety by detecting animals, pedestrians, and fog conditions simultaneously. The system addresses the limitations of existing approaches by integrating object detection and environmental condition monitoring into a single lightweight framework that operates completely offline.

The system uses a camera to capture live video input from the surrounding road environment. The captured video is processed frame by frame in real time using browser-based technologies. Each frame is analyzed using TensorFlow.js, which allows deep learning models to run directly within the web browser without requiring server-side processing. This enables the system to function without internet connectivity, making it suitable for deployment in rural and remote areas.

For object detection, the system utilizes the COCO-SSD (Common Objects in Context – Single Shot Detector) model, which is a pre-trained deep learning model capable of detecting multiple object classes such as animals, humans, and vehicles. The model processes each video frame and identifies objects by generating bounding boxes along with confidence scores. When an animal or pedestrian is detected, the system highlights the object on the screen and triggers a warning alert.

In addition to object detection, the system incorporates a fog detection mechanism to identify low-visibility conditions. Fog detection is performed using brightness and contrast analysis of the captured frames. In foggy conditions, the image appears more diffused with reduced contrast levels. The system calculates the average brightness value of each frame and compares it with a predefined threshold to determine the presence of fog. This approach is computationally efficient and suitable for real-time implementation.

The integration of object detection and fog detection into a single system allows simultaneous identification of multiple hazards. This provides a significant advantage over traditional systems that focus on only one type of detection. When both fog and objects are detected, the system prioritizes alerts based on severity

to ensure that critical warnings are delivered to the driver.

To enhance usability and safety, the system provides real-time alerts in both visual and audio formats. Visual alerts are displayed by marking detected objects with bounding boxes and warning messages on the screen. Audio alerts are generated using text-to-speech technology, enabling drivers to receive warnings without diverting their attention from the road.

One of the key advantages of the proposed system is its ability to operate completely offline. Since all processing is performed locally within the browser, there is no dependency on internet connectivity or external servers. This makes the system highly suitable for deployment in remote areas where network availability is limited.

The system is also designed to be lightweight and cost-effective. It does not require specialized hardware such as thermal cameras, LiDAR sensors, or radar systems. Instead, it relies on a standard camera and browser-based processing, making it accessible to a wide range of users.

Furthermore, the system is scalable and flexible, allowing future enhancements such as improved detection models, integration with additional sensors, and advanced alert mechanisms. The use of modern web technologies ensures compatibility across different platforms and devices.

Overall, the proposed system provides a unified, efficient, and practical solution for real-time detection of road hazards. By combining artificial intelligence, computer vision, and offline processing capabilities, the system significantly enhances driver awareness and contributes to accident prevention.

8. System Architecture

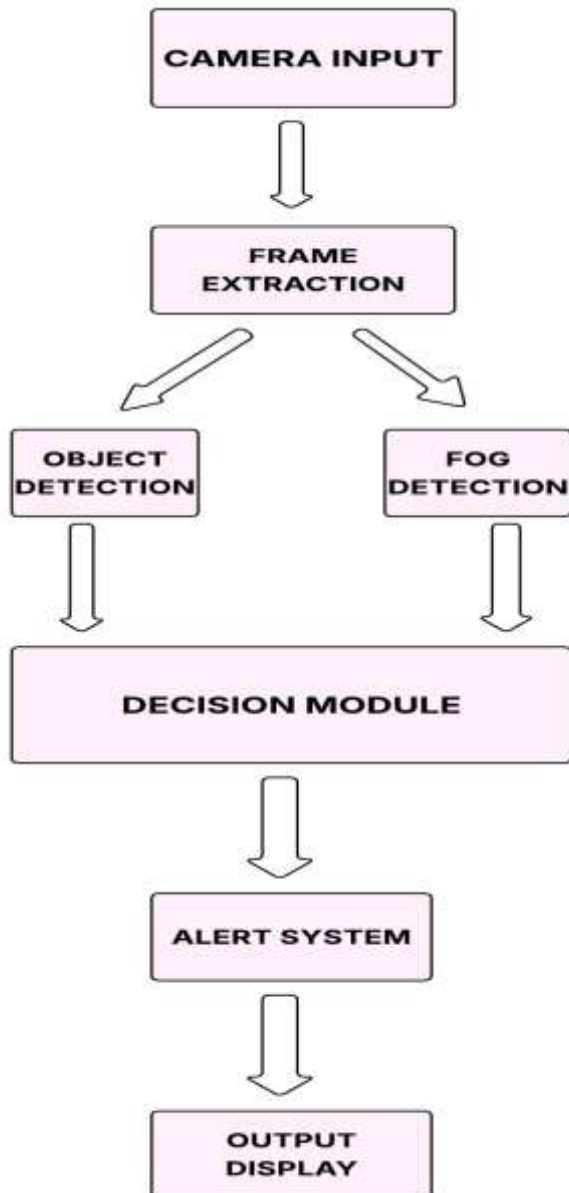


Fig. 1. System Architecture of the Proposed System

The system architecture of the proposed model consists of multiple modules that work together to detect road hazards in real time. The process begins with the camera capturing live video input from the surrounding environment. The captured video is divided into individual frames, which are processed sequentially.

The frame processing module extracts relevant visual information from each frame and passes it to the object detection module. The object detection module uses the COCO-SSD model to identify objects such as animals and pedestrians. The model generates bounding boxes and confidence scores for each detected object.

Simultaneously, the fog detection module analyzes each frame to determine the presence of fog. This is achieved by evaluating brightness and contrast levels in the image. If the brightness exceeds a predefined threshold, the system identifies the presence of fog.

The outputs from both object detection and fog detection modules are sent to the decision module. This module evaluates the detected conditions and determines the appropriate response. If a hazard is detected, the system triggers alerts.

The alert system generates both visual and audio warnings. Visual alerts are displayed on the screen, while audio alerts notify the driver through voice messages. The final output is presented to the user in real time, enabling immediate action.

This architecture ensures efficient and simultaneous detection of multiple hazards while maintaining low computational requirements and offline functionality.

9. Methodology

The methodology of the proposed system describes the step-by-step process involved in detecting road hazards such as animals, pedestrians, and fog conditions in real time. The system follows a structured pipeline to ensure efficient processing and accurate detection.

Initially, the system captures live video input using a camera mounted on the vehicle. The captured video is divided into individual frames for processing. Each frame is then analyzed using a browser-based deep learning model implemented through TensorFlow.js.

The object detection process is performed using the COCO-SSD model, which identifies objects such as animals and pedestrians in each frame. The model generates bounding boxes and confidence scores for detected objects. If the confidence level exceeds a predefined threshold, the object is considered valid and is highlighted on the screen.

Simultaneously, the system performs fog detection using brightness and contrast analysis. The average brightness value of each frame is calculated, and if it exceeds a predefined threshold, the system identifies the presence of fog. This method is computationally efficient and suitable for real-time applications.

The outputs from both object detection and fog detection modules are then combined in the decision-making stage. The system evaluates whether any hazards are present and determines the appropriate response. If both fog and objects are detected, the system prioritizes alerts based on severity.

Finally, the system generates real-time alerts for the driver. Visual alerts are displayed on the screen, while audio alerts are provided using text-to-speech technology. This ensures that the driver receives timely warnings and can take necessary actions to avoid accidents.

This structured methodology enables efficient and simultaneous detection of multiple hazards while maintaining low computational complexity and offline functionality.

The methodology of the proposed system is structured to ensure efficient and real-time detection of road hazards. Initially, the system captures live video input through a camera installed on the vehicle or roadside. The video stream is divided into individual frames, which are processed sequentially.

Each frame undergoes preprocessing to enhance image quality and remove noise. Techniques such as resizing, normalization, and contrast adjustment are applied to improve detection performance under varying environmental conditions.

After preprocessing, the object detection module is activated. The system utilizes the COCO-SSD (Single Shot MultiBox Detector) model, which is capable of detecting multiple objects in real time. The model identifies objects such as animals and pedestrians and assigns bounding boxes along with confidence scores.

A threshold value is defined to filter detections. Only objects with confidence scores above the threshold are considered valid. This helps in reducing false positives and improving detection accuracy.

Simultaneously, the fog detection module analyzes the visual characteristics of the frame. The system evaluates parameters such as brightness, contrast, and visibility. Foggy conditions are identified based on reduced contrast and blurred features in the image.

The outputs from both object detection and fog detection modules are then integrated. If any hazard is detected, the system triggers alerts. Visual alerts are displayed on the screen in the form of bounding boxes and warning messages, while audio alerts are generated to notify the driver immediately.

The system operates in both offline and online modes. In offline mode, all computations are performed locally, ensuring functionality even in areas without internet connectivity. In online mode, additional processing capabilities can be utilized with network support.

This methodology ensures that the system is efficient, reliable, and capable of performing real-time hazard detection under different environmental conditions, including foggy and low-light scenarios.

9.1 Algorithm

The proposed system follows a structured algorithm to detect road hazards such as animals, pedestrians, and fog conditions in real time. The algorithm processes video input frame by frame and integrates object detection with environmental analysis to generate alerts.

Step 1: Start the system.

Step 2: Capture live video input from the camera.

Step 3: Convert the video stream into individual frames.

Step 4: Load the COCO-SSD model using TensorFlow.js.

Step 5: Perform object detection on each frame.

Step 6: Identify objects such as animals and pedestrians.

Step 7: Generate bounding boxes and confidence scores for detected objects.

Step 8: Calculate brightness and contrast of each frame.

Step 9: Detect fog based on predefined brightness and visibility thresholds.

Step 10: Combine the results of object detection and fog detection.

Step 11: Check for hazard conditions based on detected objects and fog presence.

Step 12: Generate visual alerts by displaying warning messages.

Step 13: Generate audio alerts to notify the user.

Step 14: Display the processed output on the screen.

Step 15: Repeat the process for continuous monitoring.

Step 16: Stop the system when required.

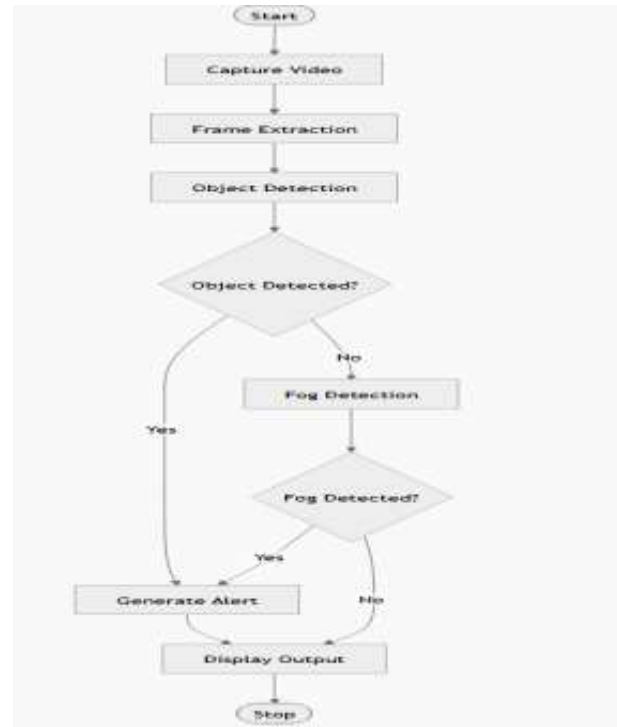


Fig. 2. Flowchart of Proposed System

10. Results and Discussion

10.1 Performance Analysis

The performance of the proposed system was evaluated based on its ability to detect road hazards such as animals, pedestrians, and fog conditions in real time. The system was tested under different environmental conditions, including daylight, low-light, and foggy scenarios, to analyze its robustness and reliability.

The object detection module, implemented using the COCO-SSD model, demonstrated effective performance in identifying animals and pedestrians. The system was able to generate accurate bounding boxes around detected objects along with confidence scores. The detection accuracy was observed to be consistent for moderate distances and standard lighting conditions, with slight variations in extremely low-light environments.

The fog detection module was evaluated using brightness and contrast analysis. The system successfully identified foggy conditions by detecting changes in image intensity and reduced visibility. The

threshold-based approach proved to be efficient and computationally lightweight, making it suitable for real-time applications.

The integrated system, combining both object detection and fog detection, showed improved performance compared to systems that focus on a single hazard. The decision-making module effectively prioritized alerts, ensuring timely warnings to the user.

The alert system provided both visual and audio notifications. Visual alerts were clearly displayed on the screen, while audio alerts helped the driver respond quickly without distraction. The response time of the system was minimal, ensuring real-time performance.

Overall, the system demonstrated reliable performance, low computational requirements, and effective hazard detection, making it suitable for practical road safety applications.

10.2 Output Visualization

This section presents the output of the proposed system in both offline and online modes. The results demonstrate the system's capability to detect animals, pedestrians, and fog conditions in real time and generate alerts accordingly.

10.2.1 Offline Mode Results



Fig. 3. Animal Detection in Offline Mode



Fig. 4. Fog Detection in Offline Mode



Fig. 5. Human Detection with Alert Generation in Offline Mode



Fig. 7. Human Detection in Night Vision Mode

The above figures demonstrate the performance of the proposed system in night vision mode. The system effectively detects both humans and animals under low-light conditions, ensuring reliable operation during nighttime. This capability enhances road safety by providing accurate detection even in reduced visibility environments.

10.2.2 Night Vision Detection



Fig. 6. Animal Detection in Night Vision Mode

10.2.3 Online Mode Results

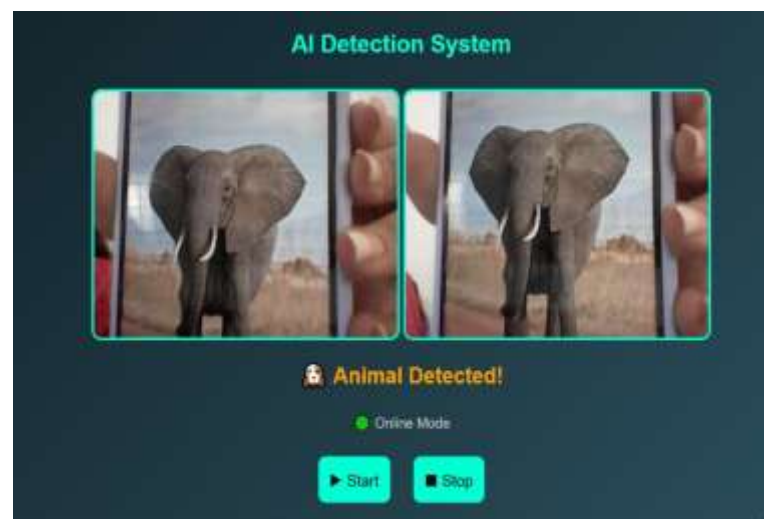


Fig. 8. Animal Detection in Online Mode



Fig. 9. Fog Detection in Online Mode

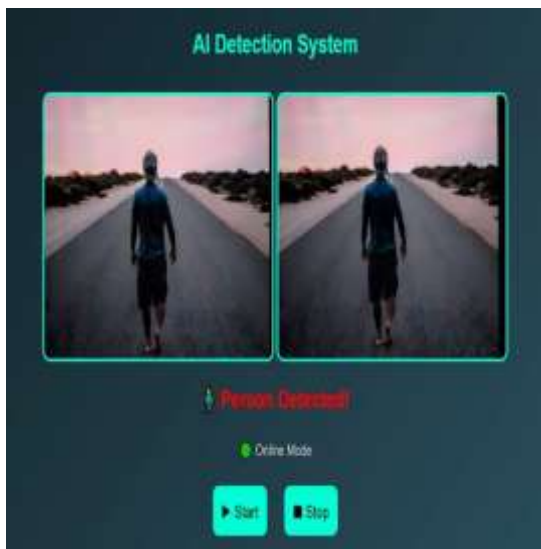


Fig. 10. Human Detection with Alert Generation in Offline Mode

The above figures represent the output of the proposed system in online mode. The system successfully detects objects and fog conditions while utilizing network connectivity. The results demonstrate that the system maintains consistent performance in both online and offline modes, ensuring flexibility and reliability in different operational environments.

In addition to qualitative observations, the performance of the proposed system was analyzed based on detection accuracy and response time. The system demonstrated consistent performance across different environmental conditions, including daytime, nighttime, and foggy scenarios. The object detection module accurately identified animals and pedestrians with minimal false detections, while the fog detection module effectively recognized low-visibility conditions.

The response time of the system was observed to be suitable for real-time applications, ensuring that alerts are generated without noticeable delay. The integration of multiple detection modules allows the system to handle complex scenarios where both environmental and physical hazards are present simultaneously.

Compared to existing approaches, the proposed system provides a balanced trade-off between accuracy and computational efficiency. While some advanced models achieve higher accuracy, they require significant computational resources. In contrast, the proposed system is optimized for lightweight operation, making it suitable for deployment on low-resource devices.

The system also demonstrates robustness in night vision mode, where it successfully detects humans and animals under low-light conditions. This further enhances its applicability in real-world driving scenarios, particularly during nighttime and adverse weather conditions.

Overall, the results indicate that the proposed system is capable of delivering reliable and efficient performance, making it a practical solution for improving road safety.

11. Conclusion and Future Work

This paper presented a real-time road safety system designed to detect multiple hazards such as animals, pedestrians, and fog conditions using computer vision and deep learning techniques. The proposed system integrates object detection with environmental condition analysis to enhance driver awareness and reduce the likelihood of accidents, particularly in rural and highway environments.

The system was implemented using TensorFlow.js, enabling real-time processing directly within a web browser. This eliminates the need for high-end computational hardware and allows the system to function efficiently on standard devices. One of the key advantages of the proposed approach is its ability to operate in both offline and online modes. The offline mode ensures uninterrupted functionality in areas with limited or no internet connectivity, while the online mode provides flexibility in connected environments.

Experimental results demonstrated that the system is capable of accurately detecting animals and pedestrians using the COCO-SSD model, while also identifying foggy conditions through image processing techniques. The integration of these modules enables simultaneous detection of multiple hazards, which significantly improves overall system performance compared to existing solutions that focus on a single aspect of road safety.

Furthermore, the system was evaluated under different environmental conditions, including low-light and nighttime scenarios. The incorporation of night vision detection enhances the system's reliability by enabling accurate detection even under reduced visibility conditions. The alert mechanism, which includes both visual and audio notifications, ensures that the driver receives timely warnings, thereby improving reaction time and situational awareness.

Despite its advantages, the system has certain limitations. The detection accuracy may be affected under extreme weather conditions such as heavy rain or dense fog. Additionally, variations in camera quality and resolution can influence system performance. The current implementation is also limited to predefined object classes and may require further training for broader real-world applications.

Future work can focus on enhancing the system by incorporating more advanced deep learning models such as YOLOv8 for improved accuracy and speed. The integration of additional sensors, including thermal imaging and LiDAR, can further improve detection in challenging conditions. Moreover, incorporating GPS and IoT-based communication systems can enable real-

time alerts to nearby vehicles and emergency services, thereby extending the system's functionality.

In conclusion, the proposed system provides a lightweight, cost-effective, and efficient solution for real-time road hazard detection. Its ability to operate under various environmental conditions, combined with offline capability and multi-hazard detection, makes it a practical and scalable approach for improving road safety in real-world scenarios.

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