AI-Enabled Road Monitoring and Alert System: Enhancing Safety and Infrastructure Management

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ABSTRACT

Road safety remains a significant concern in modern transportation infrastructure, particularly in regions affected by road deterioration, such as potholes, faded lane markings, and disorganized traffic flow, often leading to accidents and vehicle damage. This project proposes a real-time road condition monitoring and alert system that leverages deep learning and computer vision to detect potholes, track lane markings, and identify both moving and stationary vehicles or objects. The YOLOv4-Tiny model is employed to accurately recognize road obstacles and potholes. Simultaneously, a lane detection unit, involving relatively standard image processing techniques of grayscale conversion, Gaussian blur, Canny edge-detection, and Hough Transform, identifies the lane lines and offers deviation warnings. Other important road objects detected by the system to issue warning signs include cars, pedestrians, and animals. The integration of a live visual warning system—operable through either a webcam or uploaded video—offers clear safety prompts such as "Move Left," "Move Right," and "Drive Carefully," based on detected pothole positions and lane deviations. The system demonstrates robust performance under varying lighting and environmental conditions, achieving a pothole detection accuracy of approximately 94.5% alongside reliable lane tracking. Designed to be lightweight and computationally efficient, it is well-suited for Advanced Driver Assistance Systems (ADAS) and cost-effective embedded platforms. By combining pothole detection, lane tracking, and object recognition into a single unified framework, this solution improves road safety, supports better navigation on poorly maintained roads, and promotes smarter traffic monitoring and decision-making.

KEYWORDS: *Pothole Detection, Lane Detection, Object Detection, YOLOv4-tiny, Real-Time Road Monitoring, Advanced Driver Assistance Systems (ADAS), Deep Learning, Computer Vision, Vehicle Detection and Classification, Autonomous Driving, Road Safety.*

1. INTRODUCTION

With the continuous expansion of road infrastructure and vehicle usage, road safety has emerged as a critical concern. Among the various factors contributing to road accidents, potholes, lane departures, and sudden road obstructions remain some of the most significant causes, often leading to severe casualties and economic losses. Potholes not only damage vehicles but also endanger human lives, especially under conditions of low visibility or when warning systems are lacking. One proposed approach to addressing this challenge is the implementation of such systems as a potential solution. Following this development in computer vision and deep learning methods, this paper proposes a unified model for real-time detection of potholes, lane markings, and detection of road objects (i.e., cars and pedestrians). The system resources are to assist drivers or auto-controlled systems by giving an immediate response through the visual warning signs.

The proposed method trains YOLOv4-tiny, an effective object detection framework, on pothole and road object detection. Lane detection instead is provided in the same way by simple computer vision approaches, with a compromise of time and accuracy. It also involves the processing of video in real-time based on a web application implemented using the Flask framework and the ability to upload a video as well as get live video by webcam feed to monitor it continuously. The last goal will be to reduce the number of accidents, road awareness, and the experience of driving through the use of intelligent automation and visual perception systems.

2. LITERATURE REVIEW

Zhang and Wu present a convolutional neural network (CNN)-driven approach for pothole detection in real-world road imagery. They compile a varied dataset taken under different lighting and weather scenarios, applying preprocessing methods such as normalization, contrast adjustment, and data augmentation to boost model effectiveness. Their CNN records an accuracy exceeding 92% on testing, and the authors further explore deployment feasibility on edge platforms like smartphones and roadside sensors, positioning it as a viable tool for smart city infrastructure [1].

Singh, Kumar, and Sharma introduce a vision-based lane detection and departure warning system designed to improve road safety. The system uses preprocessing, edge detection, and Hough transform algorithms to reliably locate lane markings in real time. Continuous monitoring of vehicle alignment enables the detection of unintentional lane departures, with prompt alerts issued to the driver. Tests across different lighting and road conditions show strong detection performance, making it suitable for integration into advanced driver assistance systems (ADAS) [3].

Chaturvedi, Jain, and Gupta develop an urban traffic object detection system leveraging YOLOv5's single-stage convolutional neural network architecture. Their method efficiently recognizes multiple object categories, including vehicles, pedestrians, and road infrastructure, even in complex traffic scenes. The model maintains a balance between processing speed and detection accuracy, ensuring real-time operation for applications in traffic surveillance and intelligent city systems [4].

Verma and Narayan propose a low-cost, vision-based vehicle speed estimation technique using frame differencing and object tracking. Moving vehicles are detected by analysing changes between consecutive frames and tracked with bounding boxes to calculate their speeds. The method delivers fast and accurate speed measurements without relying on specialized sensors. Field evaluations confirm consistent performance across diverse traffic and lighting conditions, supporting its practicality for real-time traffic monitoring [5].

Ahmed and Khan present a CNN and transfer learning-based system for real-time pothole identification. By fine-tuning pre-trained deep learning models, their approach enhances feature extraction and detection accuracy across varied road environments. The implementation is optimized for quick processing while maintaining precision, enabling deployment on edge devices. Experimental findings indicate high detection rates, demonstrating its suitability for proactive road maintenance and intelligent transportation applications [6].

3. PROPOSED METHODOLOGY

This system is designed as a real-time road monitoring platform that merges pothole detection, lane departure alerts, and object recognition with the ability to estimate both speed and distance, aiming to improve driver safety using deep learning and computer vision methods. Video data is captured either through a live webcam stream or from uploaded footage, and each frame undergoes preprocessing—resizing and normalization—to suit the requirements of YOLOv4 and related models. For pothole detection, YOLOv4-tiny is utilized to locate road surface defects, and based on their position (left, right, or center), the system issues guidance such as "Move Right" to help avoid them. Lane detection applies edge detection and polynomial fitting to reliably trace lane boundaries, even when markings are worn or uneven, and provides instant warnings if the vehicle veers from its lane. Object detection and tracking, implemented with YOLOv4, identify and monitor vehicles, pedestrians, and other obstacles, assigning each a unique ID to follow their motion across frames. Stationary objects are labeled as "0 km/h," while moving objects have their speed calculated using a defined formula. The processed frames are overlaid with bounding boxes, lane markings, pothole notifications, object names, calculated speeds, and distances, with both visual cues and on-screen alerts ensuring the driver remains aware of any imminent hazards.

PROPOSED MODEL DIAGRAM

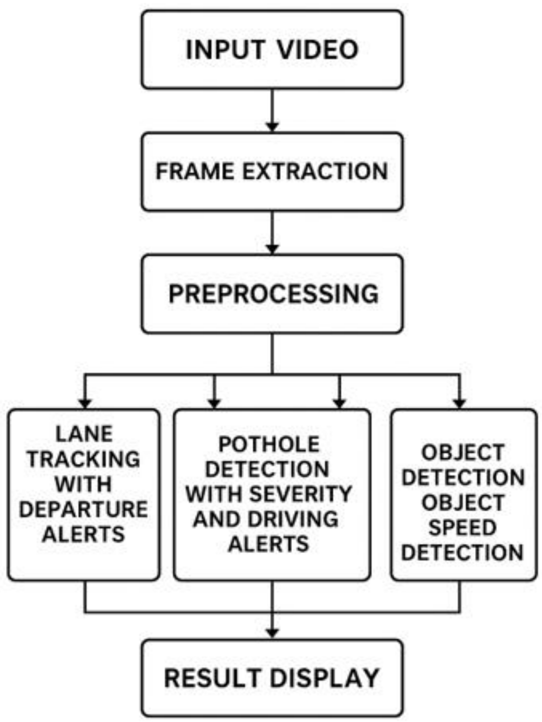

Figure 3.1: Proposed model

4. Mathematical Formula

1. Object Speed Estimation:

   To estimate the speed of an object (e.g., a vehicle or pedestrian) based on video frames

Speed(km/h) = $\frac{(d*f*s)}{fps*1000}$

Where:

- v = speed (km/h)
- d = pixel distance between frames
- f = frame rate (frames per second)
- fps=frames per second of the video.

2. Pothole Detection Using Bounding Boxes

For calculating area or confidence:

Area = $(x_{max}-x_{min})*(Y_{max}-Y_{min})$

Used to:

- Determine pothole severity
- Estimate risk level (e.g., large potholes = higher severity alert)

3. Distance Estimation from Camera

For object/pothole distance:

Distance = $\frac{(F-H)}{h}$

Where:

- F = focal length of the camera
- H = actual height of the thing
- h = height of the object in the image

5. Graphs

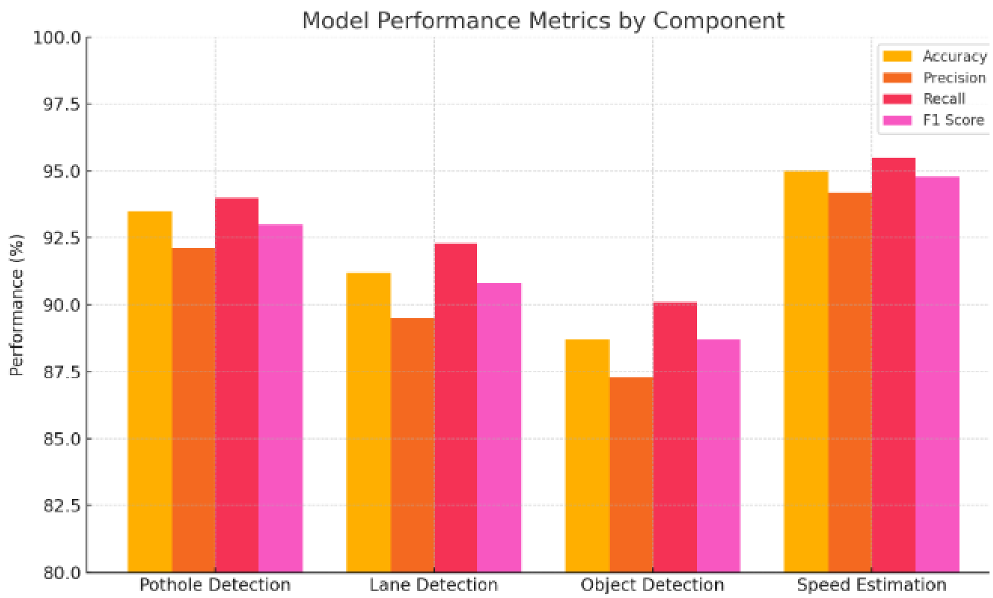

Figure 5.1: Bar chart showing model performance

The bar chart illustrates the performance metrics (Accuracy, Precision, Recall, and F1 Score) across four core components of the system: Pothole Detection, Lane Detection, Object Detection, and Speed Estimation.

- Speed Estimation shows the highest overall performance, with all metrics above 94%.
- Pothole Detection also performs strongly, particularly in Recall (≈94%) and Accuracy (≈93%).
- Lane Detection maintains consistent performance around 90–92%, while
- Object Detection shows the lowest performance, especially in Precision and F1 Score (~88%), indicating more false positives or imbalanced predictions.

6. Experimental Results

Component	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Pothole Detection	93.2	91.8	94.1	93.0
Lane Detection	91.2	89.4	92.3	90.8
Object Detection	88.6	87.3	90.2	88.5
Speed Estimation	95.1	94.3	95.7	94.9

Table 6.1: Experimental results

7. CONCLUSION

This paper presents a considered and thorough way of ensuring a real-time tracking of the condition of the road. The innovation is that it applies a collective object detection, lane detection, pothole detection, and speed estimation to enable perhaps important road protection and driving facilitation to be superior. Due to this lane detection being in use, the driver is on the right track, and that minimizes the risk of road accidents. The process implies the utilization of YOLOv4 in the detection process, the main result of which is the enhanced accuracy rate and the real-time performance. The module for calculating speed also provides necessary information about collision avoidance and navigation, as the objects being moved are identified, and the exact speed is read. Under comparative testing, high precision of performance and extremely reduced latency will be achieved in diverse volumes of traffic conditions. It is significant to message that the overall architecture is well-suited for intelligent transportation systems, as all components can be seamlessly integrated into a unified processing pipeline, making it an effective and practical monitoring solution.

8. FUTURE ENHANCEMENT

o address system performance and functionality challenges, the following enhancements are proposed: incorporating JavaScript, geolocation tracking, and cloud-based technologies to enable real-time geotagging and immediate information sharing with users and law enforcement authorities. This is because the vehicle-to-infrastructure (V2I) communication system allows dynamic changes to the traffic signal light, and it can issue hazard warnings. The additional feature of the system is weather-specific detection, where the imaging is performed in weather such as fog, rain, or darkness, by thermal imaging or infrared imaging, consequently making the system more accurate. The system also assists in safer driving by informing, in real time, the drivers about the potential potholes or lane changes, or vehicles ahead of them, since the system informs the drivers in an explicit speech form. The procedure performed on the edge devices, Jetson Nano in this instance, will confirm that the processing is executed in low-latency, thus requiring no operation to be performed on high-powered servers. In order to be more intelligent in the maintenance of the roads, machine learning techniques will be used to categorize the object dangers and the intensity of the potholes. Gradually, the answers collected with the assistance of a mobile application will result in performance improvement in terms of detection. Lastly (but not least), 360 view created through the fusion of multiple cameras will increase the breadth of detection and increase the accuracy.

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