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Real Time Pothole Detection in Video Streams Using AI-Driven Deep Learning Techniques

[1]Dr. P. V. S. Sarma, [2]Kurmala Kavya, [3]Mogili RaviRaj, [4]Maraka SadaSivaRao

[1]Associate Professor, COMPUTER SCIENCE AND ENGINEERING, St. Ann's College of Engineering and Technology, Chirala-523187, India.

[2,3,4]B. Tech Student, Dept of Computer Science and Engineering, St. Ann's College of Engineering and Technology, Chirala-523187, India.

ABSTRACT:

Road potholes are a major cause of traffic accidents, vehicle damage, and increased maintenance costs, while traditional manual inspection methods are slow and inefficient. To address this problem, this project proposes a Real-Time Pothole Detection System in Video Streams Using AI-Driven Deep Learning Techniques. The system employs a YOLOv3-Tiny deep learning model, based on convolutional neural networks, for fast and accurate pothole detection. The trained model is integrated into a Flask-based web application using OpenCV's Deep Neural Network (DNN) module. Live video input is captured from a mobile camera stream and processed frame by frame to identify potholes, which are displayed with bounding boxes and confidence scores along with an alert mechanism which produces beep sound when the pothole is detected. This system provides road safety and reduces the need for manual inspection.

***KEY WORDS:** Pothole Detection, YOLO Algorithm, Real-Time Processing, Mobile, Camera Streaming, Computer Vision, Deep Learning, OpenCV, Flask Web Application*

INTRODUCTION:

Road transportation is essential for daily travel and economic activities, but road surface defects such as potholes create serious safety concerns. Potholes can lead to accidents, vehicle damage, and traffic congestion, increasing maintenance costs. Traditional pothole detection methods rely on manual inspections, which are slow, labor-intensive, and inefficient for large road networks. Recent advancements in artificial intelligence have enabled automated road condition monitoring. Deep learning-based object detection techniques can accurately identify potholes from images and video streams. In this project, a real-time pothole detection system is developed using YOLOv3-Tiny deep learning model. The system analyzes live video streams captured from a mobile camera. Detected potholes are highlighted using bounding boxes and confidence scores. An alert mechanism is provided by generating a beep sound when pothole is detected. The system is integrated into a flask-based web applications for easy access and control. This approach reduces human effort and improves the efficiency of road maintenance.

LITERATURE REVIEW:

Pothole detection has been studied using different approaches such as image processing, machine learning, deep learning, and sensor-based methods. Earlier works, including studies by Kiran P., Kishor Jadav B., and B. Vijayalakshmi, used basic image processing and machine learning techniques like thresholding and segmentation to detect potholes from offline road images. Later, deep learning methods improved accuracy, such as the semantic segmentation approach by Jiahe Fan et al., which focused on identifying potholes in still images using multi-scale features. Another study by Varun Sinha et al. enhanced image quality with ESRGAN before applying YOLOv7, showing better results in detecting potholes in low-resolution images, but still based on offline image datasets. Some research also explored non-vision techniques, where potholes were detected using vibration sensors, laser scanning, or 3D reconstruction instead of camera inputs. Overall, previous systems mainly worked on static images or sensor data rather than real-time video, which creates a space for live pothole detection using continuous camera streaming.

RELATED WORK:

Many studies have explored different ways to detect potholes to improve road safety and maintenance. Early work mainly used basic image-processing methods such as edge detection and thresholding, but these techniques often struggled with changes in lighting and road texture. Some projects used vibration or sensor-based systems to identify road bumps, but they could not always separate potholes from other surface defects. With the growth of deep learning, models like YOLO and Faster R-CNN have been used to detect potholes from images and have shown better accuracy than traditional methods. Other research focused on segmenting potholes to outline their exact shape, though these methods were mostly applied on still images. A few works also included GPS to mark pothole locations for maintenance planning. Building on these ideas, this project uses deep learning to detect potholes in real time from live video, aiming to provide faster and more practical detection compared to offline image approaches.

EXISTING METHOD:

In the research work by Vijayalakshmi B et al., pothole detection is carried out using machine learning and basic image processing techniques. The method involves processing road images using grayscale conversion, edge detection, and feature extraction to identify pothole regions. This approach helps in reducing manual inspection to some extent, but its performance depends on predefined features. The system works well only under controlled conditions and faces difficulty when lighting and road surface conditions change. It is mainly tested on offline images rather than live video streams. As a result, continuous real-time monitoring is not supported. The method also does not provide instant alerts to users. Due to these limitations, the existing approach has restricted applicability in real-world road monitoring systems.

PROPOSED METHOD:

The proposed method improves existing pothole detection approaches by using deep learning techniques instead of traditional image processing methods. A YOLOv3-Tiny model is used to detect potholes from road images automatically without manual feature extraction. Live video is captured using a mobile or IP camera and processed frame by frame for continuous detection. This allows the system to work in real time rather than on offline images. Detected potholes are shown with bounding boxes and confidence values for better visibility. An audio alert is generated to inform users when a pothole is detected. The system is implemented using a Flask-based web application, making it easy to access and operate. Overall, the proposed method provides a more practical solution for real-time road monitoring.

ARCHITECTURE

The below block diagram shows how the system works in a detailed way.

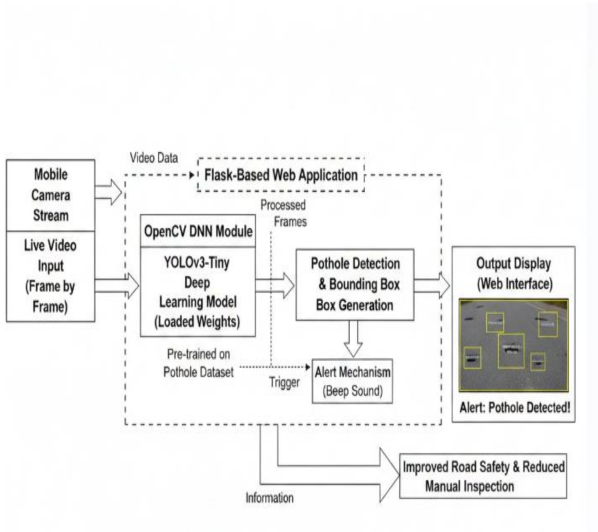

Fig 1: System Architecture

METHODOLOGY DESCRIPTION:

The methodology of the proposed real-time pothole detection system is designed to automate road condition monitoring using deep learning and live video analysis. The process begins with capturing continuous road video using a mobile phone or IP camera mounted on a vehicle. This live video stream is transmitted to the system through a network connection and serves as the primary input. The incoming video is split into individual frames to allow frame-by-frame analysis. Each frame is then pre-processed by resizing and applying noise reduction techniques to enhance image quality and ensure uniform input dimensions for the detection model. The pre-processed frames are passed to the YOLOv3-Tiny deep learning model, which has been trained to identify potholes on road surfaces. The model analyzes spatial and texture features in each frame and predicts pothole locations using bounding boxes along with confidence scores. Non-maximum suppression is applied to remove overlapping detections and improve accuracy. Once potholes are detected, the system overlays bounding boxes and labels on the video frames for clear visualization. Simultaneously, an audio alert mechanism is activated to provide immediate notification when a pothole is identified. The processed frames with detection results are streamed in real time through a Flask-based web application. Users can view the live video, start or stop detection, and monitor road conditions through the web interface. This continuous processing pipeline enables efficient, real-time pothole detection while reducing reliance on manual inspection and improving overall road safety.

RESULTS AND DISCUSSION:

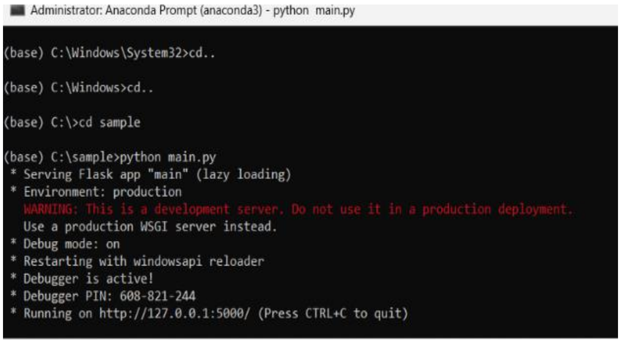

Fig 2: Flask Server Execution

This image shows the successful execution of the project's main Python file, where the Flask development server starts and runs the real-time pothole detection web application on the local host.

Fig 3: Home Page

This image shows the home page of the pothole detection application with basic navigation options to learn about potholes and access the detection feature.

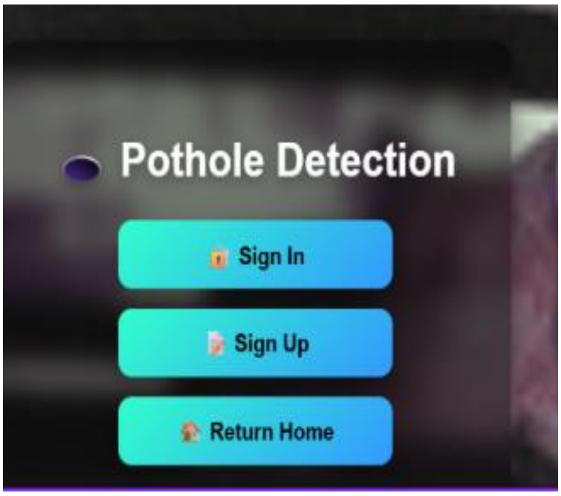

Fig 4: Login Screen

This image shows the login screen of a Pothole Detection app with a simple background and a heading. It has three buttons Sign In, Sign Up, and Return Home for basic navigation.

Fig 5: Sign In Page

This image shows a simple login form with fields for username and password. A blue "Sign In" button is provided to submit the information.

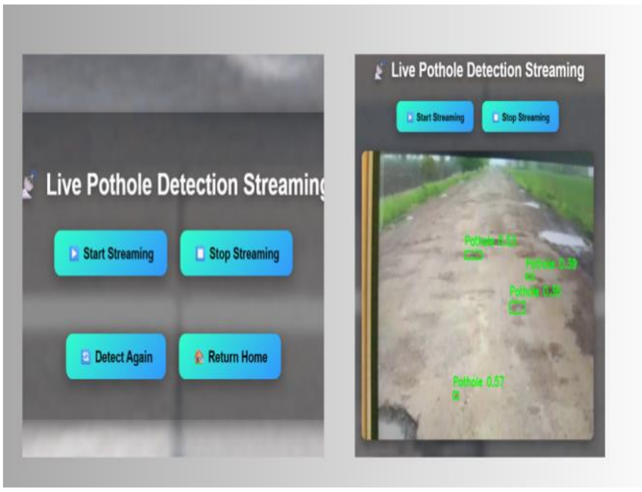

Fig 6: Live Pothole Detection Interface

This image shows the interface of a live pothole detection system. It has control buttons on the left and a live video feed on the right with detected potholes highlighted in real time.

CONCLUSION AND FEATURE ENHANCEMENT:

CONCLUSION:

This project uses images to detect potholes on roads and helps in identifying damaged spots more easily. It aims to make reporting and checking road conditions simpler while reducing manual effort. The results show that the system can detect potholes fairly well and provide useful information for planning maintenance work.

FUTURE ENHANCEMENT:

Future enhancements could include using advanced deep learning models like YOLOv8 or Transformers to improve detection accuracy and reduce false alerts. Integrating GPS mapping and cloud-based dashboards would help track pothole locations in real time and share data with authorities. Adding edge computing support on mobile devices or drones could make the system faster and more adaptable for large-scale monitoring.

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