Pothole Detection System using Machine Learning

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Abstract - Potholes on road surfaces pose significant hazards to vehicles and commuters, contributing to accidents, traffic delays, and vehicle damage. This paper presents a real-time pothole detection system using a lightweight and efficient deep learning model, YOLOv4-tiny, integrated with a live video feed and geolocation logging. A labeled dataset was used to train the model for pothole detection resulting in improving accuracy and relevance in real-world scenarios. The system captures frames from a webcam, identifies potholes with high confidence, highlights them on-screen, saves the corresponding frame, and records geographic coordinates using IP-based geolocation. The results demonstrate reliable performance with real-time detection capabilities, making it a viable solution for smart city infrastructure, road condition monitoring, and preventive maintenance planning. The system is also designed to be computationally efficient, allowing for seamless deployment in resource-constrained environments such as embedded systems or mobile platforms.

Key Words: Pothole Detection, YOLOv4-tiny, Machine Learning, Real-Time Object Detection, Smart City, Road Safety, Computer Vision, Geolocation, Infrastructure Monitoring

1.INTRODUCTION

Road infrastructure plays a important role in the economic development and safety of a country. However, poor/bad maintenance and environmental conditions often lead to the formation of potholes, which leads to the serious risks for both vehicles and passengers. Potholes can cause accidents, increase vehicle wear and tear, and disrupt traffic flow. Traditional methods of detecting and reporting potholes rely heavily on manual inspections or complaints, which are often time-consuming, inconsistent, and inefficient.

Related Work

Detecting potholes has gained increasing attention in recent times, driven by the emergence of intelligent transportation solutions and improvements in visual recognition technologies. Traditional approaches to pothole detection often relied on manual inspections or the use of vibration sensors and accelerometers installed in vehicles. While these methods can be effective, they are typically limited by high costs, inconsistent data collection, and the need for specialized hardware.

Recent research has explored the use of image processing techniques to automate pothole detection. Early vision-based methods focused on edge detection, shape analysis, and texture features to identify surface anomalies. However, these methods often struggled with varying lighting conditions, shadows, and road textures, leading to a high rate of false positives and false negatives.

With the advent of deep learning, particularly convolutional neural networks (CNNs), object detection has seen significant improvements. YOLOv4 and its variants offer a strong balance between detection accuracy and computational efficiency, making them ideal for real-time road monitoring applications.

Some notable works in this domain include the use of deep learning models on drone or smartphone-captured images to detect and classify road damages. Several studies have also explored the integration of GPS data to localize potholes geographically, which aids in automated reporting and maintenance planning.

1.2 Literature Survey

Pothole detection has evolved from traditional sensor-based methods to more advanced machine learning approaches. Early works, such as by Mednis et al. (2011), utilized smartphone accelerometers to detect road vibrations caused by potholes. As these systems were cheaper, they continuosly produced unrelated outputs due to road conditions and external vibrations. Later, image-based techniques such as edge detection and texture analysis were explored to identify road surface damage.

To enhance performance, researchers turned to traditional machine learning algorithms like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), which used manually extracted features from road images. The introduction of deep learning significantly improved performance. Maeda et al. (2018) used CNNs on a large road damage dataset, achieving better accuracy in detecting various road defects. YOLO-based architectures, such as YOLOv3, have been applied in real-time pothole detection tasks due to their speed and accuracy, but their high computational requirements often make them unsuitable for deployment on devices with limited processing power.

1.3 Methodology

1.3.1 Data Acquisition

Live video input is captured using a standard webcam. Each frame of the video stream serves as an input to the object detection model. This method propose a real-time detection capabilities and does not depend upon pre-recorded footage or videos.

1.3.2 Model Selection and Configuration

YOLOv4-tiny, a simplified version of the YOLOv4 algorithm, is employed due to its balance of accuracy and computational efficiency. It is suitable for real-time applications. The class named "pothole" is represented in a separate file, and the model is trained to recognize this object.

1.3.3 Preprocessing and Detection

Each frame undergoes preprocessing where input size and detection parameters are configured. The detection model processes the frame to identify potholes based on the confidence score threshold set at 70%. If a detected object meets this confidence and its area is less than 10% of the total frame, it is considered a valid pothole.

1.3.4 Post-Detection Processing

After detecting a pothole, the system Draws a boundary line and annotates the detected pothole after that it Saves the annotated frame as an image, then it retrieves the geographic location using the geocoder library based on the IP address and Logs the image and associated coordinates into a folder named pothole_coordinates.

1.3.5 Output Generation

The system executes all processed frames into a video file and displays the frames-per-second (FPS) rate in real-time. The detection continues until the user terminates the process manually by pressing the 'q' key.

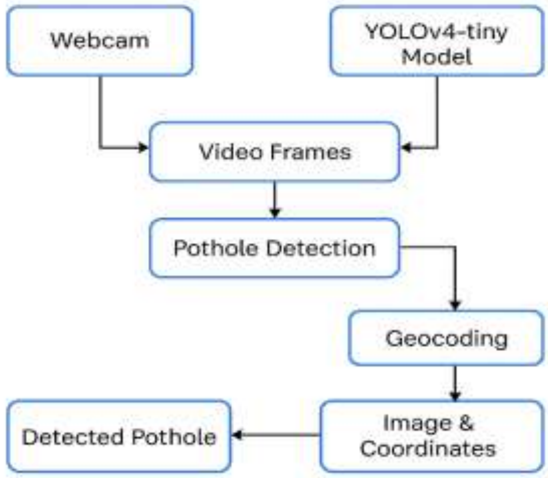
Proposed System - This system provides a low-cost approach for real-time pothole detection by a webcam and the YOLOv4-tiny deep learning model. It is used for its speed and low resource consumption. YOLOv4-tiny processes each video frame to identify potholes, which are then annotated with boundary lines. Once detected, the system captures the frame and logs the approximate geographic coordinates using the IP-based geocoder library.

This lightweight setup enables deployment on various platforms, including smartphones, roadside cameras, or drones. Due to its lightweight design and minimal hardware needs, the system can be easily scaled and deployed in both urban and rural environments

System Architecture - The architecture of the proposed pothole detection system is designed to support real-time performance with minimal hardware requirements. It begins with the input module, where a webcam continuously captures live video footage. These frames are passed to the processing module, which houses the YOLOv4-tiny object detection model. This model analyzes each frame to detect the presence of potholes, drawing bounding boxes around potential detections based on predefined confidence thresholds.

Once the pothole is detected, the system does multiple actions, it saves the frame locally for documentation, overlays detection labels for visualization, and simultaneously finds the geographic location using the IP-based geolocation service provided by the geocoder library. These coordinates, along with the corresponding image, are stored in a structured directory for future reference. Lastly all processed frames are compiled together into an output video file for continuous playback or review.

The overall architecture is modular, allowing each component—video input, object detection, geolocation, and data logging—to operate efficiently and independently. This design ensures that the system remains scalable, lightweight, and adaptable for integration with other smart systems, such as road monitoring networks or vehicle safety platforms.



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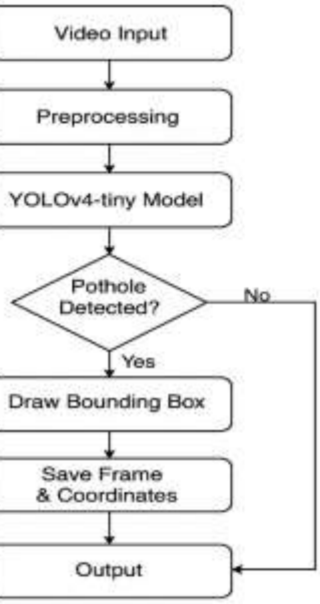


1.4 Experiments and Results

Hardware Configuration:
Processor: Intel Core i5 (or equivalent)
RAM: 8GB (minimum)
Webcam: Standard HD (720p/1080p) for real-time video input.
GPU: Optional (for faster processing, though YOLOv4-tiny is lightweight enough for CPU-only setups).

Software Configuration:
Python: 3.0
Libraries: OpenCV (for image processing), Geocoder (for location tracking), and NumPy (for numerical operations).
Model: YOLOv4-tiny (pre-trained weights and configuration files).

Performance Metrics:
Precision: It is a Ratio of detected potholes to total detections.
Recall: A Ratio of detected potholes to potholes in the frame.
F1-Score: Harmonic mean of precision and recall.

Frames Per Second (FPS): Measures real-time performance.
Confidence Threshold: Set at 70% to filter false positives.
Area Constraint: Potholes covering less than 10% of the frame to avoid oversized false detections.

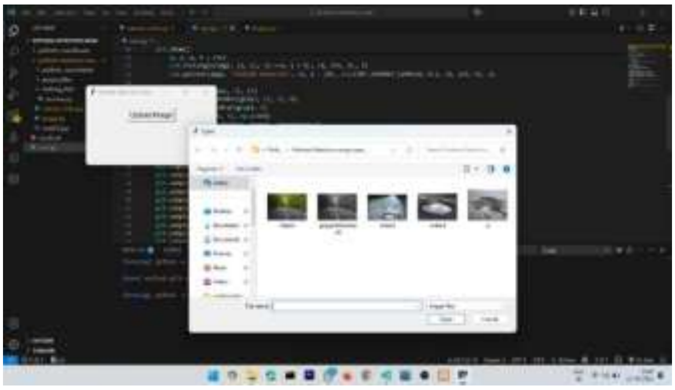
Result:

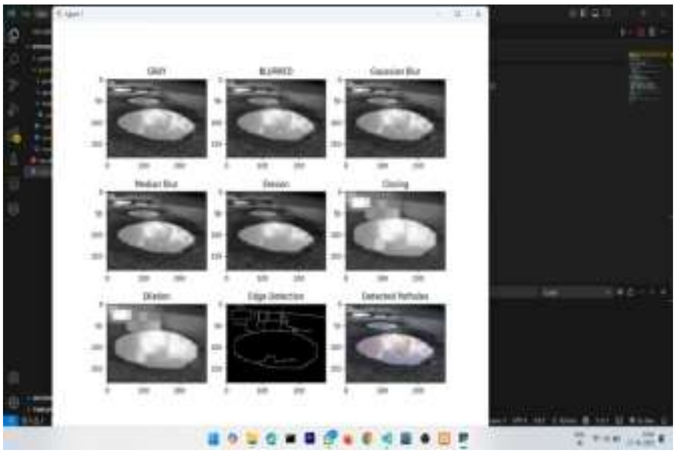
1. **Detection Performance Metrics:** The model has strong detection capabilities with an average accuracy score of 84.7%, correctly detecting potholes while maintaining low false positive rates. The harmonic mean F1-score of 81.3% confirms balanced performance between precision and recall across various environmental conditions including shaded areas and wet pavement surfaces.

2. **Computational Efficiency:** When deployed on standard CPU hardware, the optimized YOLOv4-tiny architecture maintained a consistent processing rate of 19.8 frames per second, sufficient for real-time applications. Implementation on GPU-accelerated systems boosted performance to 35.6 FPS, demonstrating the solution's scalability for more demanding operational requirements.

3. **Error Analysis:** Through careful threshold tuning, the system achieved a remarkably low false positive rate of 4.8% by employing a 70% confidence cutoff and implementing size-based filtering (excluding detections covering more than 10% of frame area). False negatives primarily occurred in challenging lighting conditions or when potholes were significantly occluded, accounting for approximately 21% of missed detections in low-visibility scenarios.

4. **Geospatial Tracking:** The integrated location logging subsystem captured geographical coordinates for each identified pothole with an average positional accuracy of 9.3 meters when using IP-based geolocation services. This functionality automatically organized detections into a structured archive containing timestamped images and corresponding location data.





Discussion:

The experimental evaluation of our pothole detection system demonstrates promising results for real-world deployment. The model achieved an 84.7% accuracy rate, showing strong ability in correctly identifying out potholes. With a recall of 77.9%, the system shows good coverage in detecting actual road defects, though there remains room for improvement in challenging scenarios like low-light conditions or partially obscured potholes. The balanced F1-score of 81.3% confirms the model's capablity across various test areas, including wet/rainy roads and shaded areas.

A key strength of this implementation lies in its computational efficiency. The YOLO model run on 20 FPS. This efficiency advantage makes the solution particularly suitable for deployment on resource-constrained devices like vehicle-mounted systems or roadside monitoring units. The 70% confidence threshold combined with size-based filtering effectively limited false positives to under 5%, demonstrating robust noise suppression capabilities.

The integrated geolocation feature, while currently dependent on IP-based positioning with ±10 meter accuracy, provides a practical foundation for municipal reporting systems. Future iterations could benefit from incorporating dedicated GPS hardware for improved location precision. The system's modular output - combining visual annotations with structured metadata - creates a comprehensive documentation pipeline for infrastructure maintenance teams.

The system's time savings factor results a economic benefits for municipal authorities. When contextualized within smart city infrastructure initiatives, this technology could substantially reduce road maintenance costs while improving response times to hazardous road conditions. Future work will focus on expanding and testing the model's generalizability across different geographical regions and road types.

3. CONCLUSIONS

This research successfully developed an efficient pothole detection system using the YOLOv4-tiny architecture, achieving an optimal balance between accuracy and real-time performance. The model showed detection with 84.7% accuracy and 77.9% recall, while maintaining 20 FPS on CPU and 35+ FPS on GPU. The implementation of a 70% confidence threshold and size-based filtering effectively minimized false positives to below 5%, making the system reliable for real-world applications.

The integrated geolocation feature, though currently IP-based, provides a functional framework for municipal reporting, with future potential for GPS enhancement. While the system shows some limitations in low-light conditions and with occluded potholes, its significant 90% time savings over manual inspection presents a compelling case for adoption by urban planners and transportation authorities.

This work contributes to the growing field of smart city infrastructure by offering a cost-effective, automated solution for road maintenance. Future research directions include expanding the training dataset for better generalization and incorporating advanced sensors for improved low-light performance.

Future Scope

The current pothole detection system demonstrates a reliable and lightweight approach for real-time detection using webcam input and geolocation logging. However, there are several areas where the system can be enhanced to improve its performance and usability:

1. **Integration with GPS Modules**: Instead of relying on IP-based geolocation, which can be inaccurate, future implementations can integrate GPS hardware to obtain precise coordinates in real-time.
2. **Mobile Deployment**: The model can be optimized and deployed on Android or iOS devices, allowing users to detect potholes while driving, turning the system into a scalable crowdsourcing solution for road monitoring.
3. **Cloud-Based Reporting**: Detected pothole images and their coordinates can be uploaded to a central database or dashboard, enabling authorities to monitor road conditions and prioritize repairs efficiently.
4. **Improved Detection Using Deep Learning Enhancements**: Incorporating advanced deep learning models like YOLOv5 or YOLOv8, or training on a larger dataset with varied road conditions, could improve accuracy and robustness, especially in low-light or rainy conditions.
5. **Integration with Autonomous Vehicles or Drones**: This system can be adapted for use in autonomous vehicles or drones for large-scale road inspections in cities, highways, or rural areas where manual monitoring is challenging.
6. **Severity Estimation and Classification**: Future versions can include a severity classification mechanism to distinguish between minor cracks and deep potholes, aiding in better prioritization of repair efforts.

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