Smart Road Condition Monitoring and Optimal Routing System Using Yolo V11

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Abstract—This project tackles the urgent problem of potholes on roads through the creation of areal-time pothole detection and map-ping system. Making use of the YOLO V11 deep learning algorithm, our system analyzes video feeds to detect potholes on the road surface accurately and efficiently. This allows for real-time alerts to drivers, enabling them to respond quickly and evade accidents. In addition, the system produces a dynamic map of identified potholes, constantly refreshed with new information. This map not only gives a visual display of road condition but also feeds into an optimal routing module. The routing system takes advantage of this real-time information to recommend safer and more efficient routes, leading drivers away from roads with high densities of potholes.Aimed for flexibility and integration into diverse vehicle platforms, the system maximizes real-time performance for efficient operation in dynamic driving conditions. Future work will target increased detection accuracy under varied conditions to further optimize the reliability and efficiency of the system. This project is a major breakthrough in road safety technology, providing an end-to-end solution for pothole detection and avoidance.

Keywords — YOLOv11, Deep Learning, Routing System, Pothole detection.

I. INTRODUCTION

A *Background:*

Poor road conditions like potholes and cracks endanger road users, resulting in accidents, congestion, and damage to vehicles. Manual, time-consuming, and ineffective traditional inspection techniques and conventional navigation systems usually ignore road conditions. To compensate for this, the system proposed here utilizes YOLOv11, a deep object detection model, to detect potholes from road images or video input. The coordinates of the potholes are saved in a database and plotted on a map interface to assist users in avoiding damaged roads. This system improves road safety, minimizes vehicle damage, and optimizes routes by combining road condition information with route planning.[3][16]

B *Problem Statement:*

Road damage, especially potholes, is dangerous for drivers and causes accidents, vehicle loss, and delay in travel. Con- ventional methods of monitoring roads are laborious, time- consuming, and less efficient, while current navigation systems do not take into consideration the road quality. The goal of this project is to create a Smart Road Condition Monitoring and Optimal Routing System based on

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the YOLOv11 model for real-time pothole detection. Pothole coordinates detected are stored in a database and combined into a map interface to facilitate user to recognize and steer clear of damaged roads, making travel safer and more efficient[1][5].

C *Objectives:*

The primary aim of this project is to create and establish an Optimal Routing and Smart Road Condition Monitoring System to achieve road safety and optimized travel by bringing together road condition analysis in real time with navigation[13]. The project aims are as follows:

1) *Pothole Detection with YOLOv11:* Establish a robust detection system on the basis of the YOLOv11 model to accurately detect potholes from road images or video streams. YOLOv11's strong object detection capability will offer good accuracy, even in challenging environments with cross lighting and road textures[2][6].
2) *Data Storage and Management:* Keep the pothole co- ordinates detected in a structured database for efficient data retrieval, update, and management. This database will be the central repository for pothole information on various road networks.
3) Map Integration for Visualization: Offer a user-friendly map interface with highlighted location of the stored data of potholes. The visual output will allow users to identify dangerous roads and make the appropriate travel choices[14].
4) Optimal Route Suggestion: Develop a routing algorithm which computes the shortest and safest path based on road conditions along with conventional navigation param-eters such as traffic density and travel time. This will put users on safer and smoother routes[3].
5) Real-Time Updates and Notifications: Permit the system to update pothole information dynamically and provide real- time notifica- tions to the users when reaching damaged roads or suggest alternate routes[3].
6) Improved Road Maintenance Planning: Offer beneficial information to the local authorities with detailed reports of pothole locations, which may assist in better planning for road maintenance and rehabilitation[7].

II. RELATED WORKS

A *Pothole Detection and Road Condition Monitoring*

- Fan et al.[1] mention their previous work where they proposed PT-SRP, an efficient subpixel dense stereo algorithm for 3D road geometry reconstruction. They also refer to another previous work where they proposed PT-FBS, a GPU-friendly disparity estimation algorithm for energy minimisation in fully connected MRF models.
- The ”Pothole Detection Using Computer Vision and Learning” explicitly states that the authors have already published about three developed methods for pothole detection in conference papers. This current paper builds upon those reported materials by providing a review, presenting the previously published methods with additional material, adding a new method, and offering a comparative evaluation using a more diverse dataset. The paper also includes a literature review section that covers:
    - Manual techniques for road anomaly detection.
    - Techniques using accelerometers or gyroscopes as vibration detection systems.
    - Basic strategies of implying image or video processing techniques.
    - Techniques based on 3-dimensional (3D) scene reconstruction.
    - Current work using learning strategies.
- The literature review[9] cites various prior works on pothole and pavement distress detection, including:
    - Public reporting systems that use citizens as sensors.
    - Mobile phone-based systems for real-time pothole detection.
    - Wavelet transform-based methods on multi-GPUs.
    - Stereoscopic cameras for pothole detection and volume estimation.
    - ITS and road management image-based systems.
    - Automated detection of road distress.
    - 3D pavement image stabilisation with the Kalman filter.
    - Semi-global matching stereo processing.
    - Real-time 3D scanning systems for pavement distortion inspection.
    - Laser imaging-based pothole detection and severity measurement.
    - 3D projection transformation-based pothole detection.
    - UAV-based imaging for 3D measurement of unpaved road surface distresses.
    - Multisensor-integrated intelligent road detection systems.
    - Visual surveying platforms for autonomous road surface dis- tress detection.
    - Road hazard detection and sharing with multimodal sensor analysis on smartphones.
    - Autonomous robot strategies to inspect pavement dis- tresses.
    - Real-time road detection using shadow-free feature extrac- tors.
    - Deep convolutional neural networks (CNNs) for pothole detection.
    - Pothole detection using thermal imaging and

  - CNNs.
  - Application of neural networks in stereo vision for road pavement condition evaluation.
  - Pothole detection using machine learning.
  - Road damage detection using deep neural networks with smartphone images.
  - Road marking feature extraction evaluation.
  - Real-time pothole detection on DSPs.
- The ”Pothole detection in adverse weather: leveraging synthetic images and attention-based object detection methods”[14] has an ”Existing research on pothole detection and image-to-image translation” section where the authors summarize key approaches and techniques adopted in the areas.
- The ”Real-time detection of road manhole covers with a deep learning model”[15] has a ”Related work” section where prior studies on road manhole cover detection, referring to the constraints of YOLO when it comes to small and densely grouped objects. It cites Redmon et al.'s initial YOLO and other object detection algorithms such as Faster R-CNN, SSD, YOLOv5s, YOLOv7, and YOLOv8s, against which their proposed algorithm is compared.

B Routing Systems and Technologies

- ”Implementation of dynamic cost based routing for navigation under real road”[8] refers to ”An Introduction to pgRouting with OpenLayers”, suggesting the usage and accessibility of these tools for routing purposes.
- ”Bakillah et al.[10] addresses available routing services and issues in being real-time, inspiring their suggested event processing service with Big VGI. It is referring to the research on the quality of geo-data.
- Emam et al.[16] states utilizing open-source services, i.e., OSM and GraphHopper, for path routing in their suggested autonomous driving architecture.
- Saki et al.[11] proposes future research to utilize other open-source alternatives such as OSRM and compare its performance with Valhalla. It also refers to some works on map-matching algorithms and their reviews.
- Jastrzab et al.[12] discusses applicable work in reference to their artic- le, presenting routing models that maximize learned preference probabilities and transition matrix learning algorithms from his- torical observations. They also compare their work with a very recent inverse optimisation approach. The article also gives a brief summary of prominent works solving combinatorial optimisation problems through neural networks such as Pointer Networks and Graph Attention Networks.
- Jastrzab et al.[12] refers to surveys of vehicle routing problems across years and elaborates on related work in personalized and context-aware routing and driving route prediction based on Hidden Markov Models.
- Canoy et al.[13] further refers to their already published first-order Markov model methodology in a conference proceeding, which is extended in this paper.

C Pothole Detection and Road Condition Monitoring

- Jha et al.[6] refers to different researches conducted in road safety with the assistance of IoT and Machine Learning, pointing out their potential in developing smart and effective road safety systems.

This collection is a substantial part of the related work discussed throughout the given sources, addressing different aspects of road condition monitoring, object detection, and optimal routing systems.

III. METHODOLOGY

A Problem Formulation

Road deterioration, especially potholes, is a major threat to transport systems, causing accidents, vehicle loss, and high maintenance costs. Current road monitoring techniques are manual and ineffective, and navigation systems currently in use do not take into account road condition when recommending routes[6-7].

The aim of this project is to create an automated pothole detection and routing system that:

1) Identifies potholes in real-time utilizing the YOLOv11 deep learning model.
2) Saves the coordinates of detected potholes in a database for reference.
3) Consolidates the pothole data into a mapping interface to enable real-time updates of road conditions.
4) Recommends best routes that take into consideration road condition, enhancing travel security and efficiency

B Data Acquisition

To train the YOLOv11 model for pothole detection, a high- quality dataset of road images is required. The data acquisition process includes:

1) *Data Collection:* Dashcams from different locations are used to gather road images.

The dataset contains images of roads in various states (smooth roads, pothole roads, and crack roads)[7][15].

Images are captured under different lighting, weather, and traffic conditions to enhance model robustness[4][14].

2) *Data Preprocessing:* The preprocessing step include:

Image annotation: Manually annotate the potholes in the images gathered using tools like LabelImg to draw bounding boxes for model training.

Data augmentation: Rotation, brightness change, and contrast changes are some of the techniques used to enrich the dataset and enhance model performance.

Dataset splitting: The dataset is split into 80% training and 20% testing sets for proper model evaluation[9].

Fig. 1: Image Segmentation

The image shows roads with potholes, these are overlaid in green as part of a segmentation done in Roboflow. These green regions indicate labeled regions of damage that have been used to train a YOLO v11 model to detect potholes. These images depict varied sizes and shapes of potholes on aged asphalt surfaces.

C Training and Working

This phase involves training the YOLOv11 model for pothole detection and implementing a system for processing and storing detected pothole locations.

The fig. 2 illustrates a top-level workflow for a pothole detection system. On the left are ”Sensors” that provide data to a ”Processing” component. There are three steps of the processing phase:

- Image Recognition
- Severity Analysis
- storing the outcome in ”Data Storage

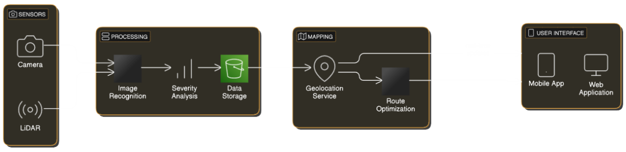

Fig. 2: System Architecture

Subsequently, data moves to the ”Mapping” part, featuring a ”Geolocation Service” and ”Route Optimization”. Eventually, real-time information is updated to the ”User Interface,” which is made up of a mobile application as well as a web application[11].

1) *Training the YOLOv11 Model:*

- The annotated dataset is utilized to train the YOLOv11 model for pothole detection in road images and videos.
- Transfer learning is utilized with a pre-trained YOLO model to accelerate training and enhance accuracy
- Hyperparameter tuning, such as batch size, learning rate, and number of epochs, is tuned to improve detection performance.

2) *Pothole Detection and Data Storage:*

- The YOLOv11 model that has been trained analyzes real- time video feeds from vehicles to identify potholes.
- Upon identification, the GPS coordinates of where the potholes are located are retrieved and saved in a database.
- The database keeps real-time data to keep the pothole record current.

D User Interface Development

The system’s user interface is designed to display pothole locations on a map and provide an optimal route for safe travel.

1) Map Integration:

- – The coordinates of potholes saved in the database are plotted on a map interface via the Ola Maps API.
- – Users are able to see real-time updates of road condi- tions and detect damaged roads prior to traveling[11].
- – The optimal route is dynamically recalculated based on newly discovered potholes, so users always use the safest and most efficient route[3].

2) Optimal Route Calculation:

- – The system incorporates navigation algorithms that take into account both traffic conditions and road quality.

3) User Alerts and Notifications:
   - Real-time alerts are sent to users when reaching roads with potholes detected.
   - Alternate routes are suggested to avoid the affected roads for safer and smoother rides[9].

TABLE I: Severity Condition

Range	**Value**
less than 100	LOW
100-400	MODERATE
greater than 400	HIGH

IV. RESULT AND ANALYSIS

The performance of the Smart Road Condition Monitoring and Optimal Routing System Using YOLOv11 is evaluated based on multiple factors, including loss reduction, precision, recall, and overall model accuracy. Below is an analysis of the provided graphs.

A *Training and Validation Loss Analysis*

The graph in fig.3 indicate the training and validation loss curves for box loss, segmentation loss, classification loss, and distribution focal loss (DFL loss).

- Loss values are observed to decrease consistently across epochs, which means that the model is learning well.
- Validation loss remains low compared to the training loss, indicating no overfitting.

1) *Key Observations*

- ○ The downward trend in box loss, classification loss, and segmentation loss confirms enhanced accuracy, better model performance, and improved pothole detection. This shows that the YOLOv11 model is learning well to identify and classify potholes with higher precision and reliability.
- ○ Validation loss is fairly consistent, verifying good generalization.
- ○ The model is optimally optimizing pothole detection through bounding box localization, segmentation, and classification to ensure pothole detection accuracy. The improvement increases the reliability of the model, making it possible to precisely identify and differentiate potholes while preserving robustness with different road conditions and unseen data.

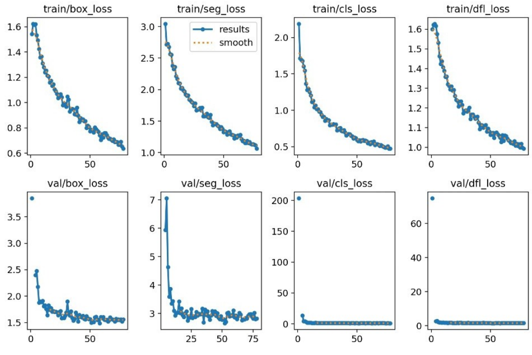

Fig. 3: Loss Analysis

B *Precision and Recall Performance*

- The statistics in fig.4 show the precision, recall, and mean average precision (mAP) across various thresholds.
- Precision and recall consistently improve with training.
- mAP@50 (mean average precision at 50% IoU) enhances remarkably, which indicates excellent object detection accuracy.

1) *Key Observations*

- ▪ The precision and recall values are well-balanced, indicating that the model maintains an optimal trade-off between detecting potholes accurately and minimizing false positives. This balance ensures the model is neither too conservative nor too lenient in its detections, improving reliability.
- ▪ mAP50 and mAP50-95 have growing trends, ensuring better accuracy in pothole detection.
- ▪ The model works well consistently on various test cases.

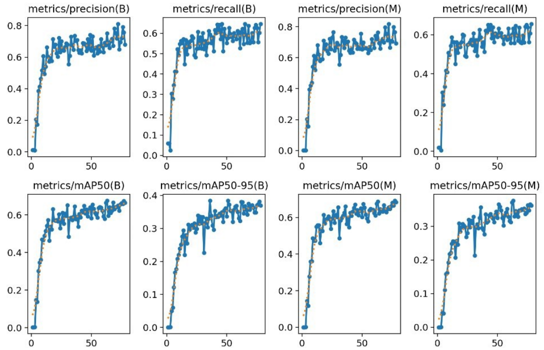

Fig. 4: Precision and Recall Graph

C *F1-Confidence Curve Analysis*

- The F1-Confidence curve in fig.5 illustrates the F1-score vs. confidence threshold for pothole detection.

- The best F1-score is 0.69 at a confidence threshold of 0.4.

1) Key Observations:

- At a confidence level of 0.4, the model achieves an optimal balance between precision and recall, ensuring accurate pothole detection. This trade-off minimizes false positives and false negatives, enhancing the model's reliability and effectiveness in real-world road condition monitoring.
- This indicates that the right threshold for confidence would be 0.4 for maximizing detection precision.

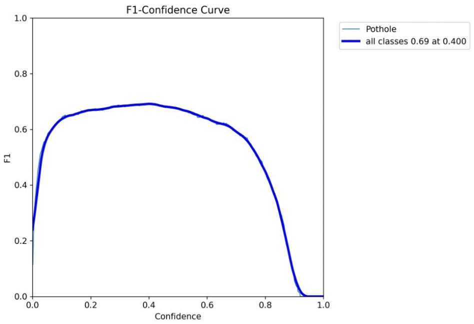

Fig. 5: F1-Confidence Curve

D Precision-Confidence Curve Analysis

- The Precision-Confidence curve in fig.6 shows how precision changes as the confidence threshold is varied.
- Precision is 100% when the confidence threshold is set at 0.897, indicating high confidence at this value.

1) Key Observations:

- Greater confidence values guarantee fewer false positives.
- At a confidence threshold of 0.9, the model is able to identify potholes with practically perfect precision.
- Practical deployment requires a balance between confidence and recall.

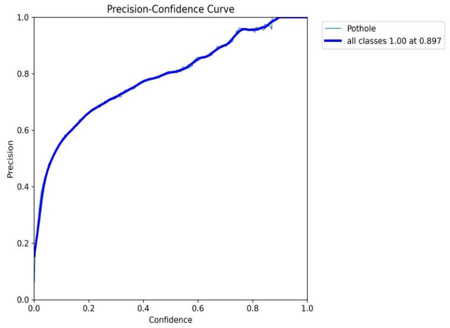

Fig. 6: Precision-Confidence Curve

V. CONCLUSION AND FUTURE WORKS

A. Conclusion

The Smart Road Condition Monitoring and Optimal Routing System Using YOLOv11 effectively identifies potholes and plots their locations to offer optimal routing solutions. The system exploits deep learning-based object detection with YOLOv11 to detect potholes in real-time, record their coordinates in a database, and incorporate them into a mapping interface[1-3][11]. The findings il- lustrate that the model has high recall and precision, with consistent loss curves and the best confidence threshold guaranteeing proper detections. Integrating this system into navigation applications allows users to steer clear of damaged roads, reducing vehicle damage and improving road safety.

B. Future Works

To further enhance the project, the following improvements can be considered:

- Integration with Real-Time Traffic Data: Adding real-time traffic data to give alternative routes based on road conditions as well as congestion[16].
- Multi-Class Damage Detection: Extending the model to identify other road damages, including cracks, speed bumps, and waterlogging, for a more complete road condition monitoring system[5][7].
- Edge AI Deployment: Implementing the model on edge devices such as dashcams, smartphones, or IoT sensors to perform processing on the device and cut down on cloud computing usage[6].
- Enhanced Mapping System: Better mapping inter- face with functionalities such as voice notifications, severity markers, and user feedback mechanisms[11].
- Municipality and Government Coordination: Local government cooperation for provision of pothole data to help facilitate road maintenance and repair planning[4-6][15].

Through the adoption of these innovations, the system can become an end-to-end, real-time road safety system that is mutually beneficial for day-to-day users and city planners.

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