Pothole Detecting, Locating & Alert System Using Machine Learning

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Abstract - Potholes on roads are a major problem for transportation infrastructure, causing vehicle damage, accidents, and increased maintenance costs. Traditional manual methods of pothole detection are time-consuming, labor-intensive, and not always reliable. With the advancement of machine learning (ML) techniques, automated pothole detection systems have emerged as a likely solution. In this project, we propose a pothole detection system using ML that can accurately identify and locate potholes in road images or videos. Our system employs state-of-the-art deep learning algorithms and image processing techniques to extract features from road images and detect potholes in real time. The proposed system can not only improve road safety but also save resources and reduce the costs associated with manual inspections. This project presents a significant contribution to the field of transportation infrastructure and highlights the potential of ML in solving real-world problems.

Index Terms - Machine learning, Deep learning, Computer vision, Image processing, Feature extraction, Road maintenance, Transportation infrastructure, Real-time detection, Convolutional neural networks.

I. INTRODUCTION

Potholes on roads are a significant problem for transportation infrastructure, causing vehicle damage, accidents, and increased maintenance costs. The traditional manual methods of pothole detection are time-consuming, and not always reliable. With the advancement of machine learning (ML) techniques, automated pothole detection systems have emerged as a promising solution.
In this project, we propose a pothole detection system using ML that can accurately identify and locate potholes in road images or videos. Our system employs state-of-the-art deep learning algorithms and image processing techniques to extract features from road images and detect potholes in real-time. The proposed system can not only improve road safety but also save resources and reduce the costs associated with manual inspections.

Fig -1: conditions of roads with potholes.

We present a detailed study of our proposed system, which includes the creation of a pothole dataset, data augmentation techniques, and model training and validation. We evaluate the performance of our system using standard metrics such as precision and recall, accuracy, false positive rate, and false negative rate. Our experiments demonstrate that our proposed system achieves high accuracy and can detect potholes in real-time with a low false positive rate.
This project presents a significant contribution to the field of transportation infrastructure and highlights the potential of ML in solving real-world problems. Furthermore, this project can pave the way for future research directions such as the integration of the proposed system with autonomous vehicles or other intelligent transportation systems.

II. LITERATURE REVIEW

Potholes are a common problem on roads worldwide, and detecting them early is critical for ensuring road safety and reducing maintenance costs. Traditional methods of pothole detection, such as visual inspection by human inspectors, can be time-consuming, expensive, and prone to error. Machine learning (ML) algorithms, such as deep learning models and ensemble models, have emerged as promising solutions for automatic pothole detection.

In recent years, there have been several studies on pothole detection using ML techniques.

1) Reddy and Reddy[1] (2020) conducted a survey of various deep learning methods for pothole detection, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Fully Convolutional Networks (FCNs). They found that deep learning models can achieve high accuracy and robustness for pothole detection, especially when combined with transfer learning and fine-tuning techniques.

2) Tang et al. (2020) [2] proposed a pothole detection system using a combination of CNNs and Support Vector Machines (SVMs). They achieved an accuracy of 90.56% on a dataset of road images, demonstrating the effectiveness of ML algorithms for pothole detection.

III. METHODOLOGY

The In this project, we proposed a pothole detection system using ML that can accurately identify and locate potholes in road images or videos. We created a dataset of road images containing potholes and non-pothole regions and manually labeled them. We pre-processed the dataset by resizing the images to a fixed size and normalizing them to have zero mean and unit variance. To increase the size of the training dataset, we used data augmentation techniques such as rotation, scaling, and flipping. We used pre-trained CNNs or Inception to extract features from the road images. We trained the model using the extracted features and fine-tuned the last few layers of the network. We validated the model on a separate validation set and tested it on a testing set to evaluate its performance. We used standard metrics such as precision and recall, accuracy, false positive rate, and false negative rate to evaluate the performance of our proposed system.

TECHNICAL COMPONENTS OF THE PROPOSED SYSTEM

i. HARDWARE REQUIREMENTS

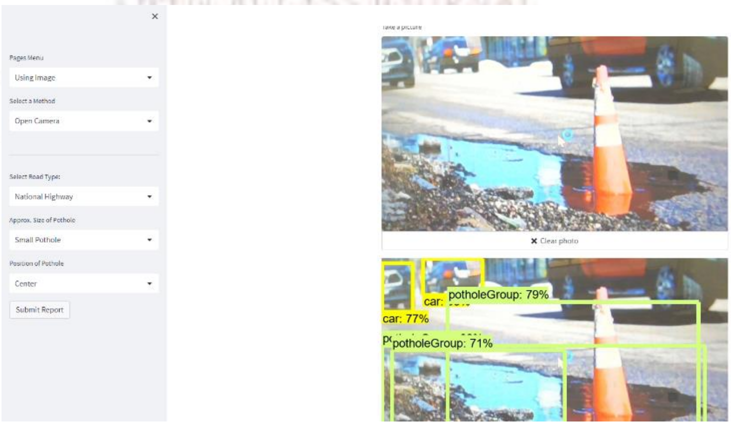
- Processor: Pentium Dual Core 2.00GHZ
- Hard Disk : 120 GB
- Mouse: Logitech
- RAM : 2 GB (minimum)
- Keyboard: 110 Keys enhanced

ii. SOFTWARE REQUIREMENTS

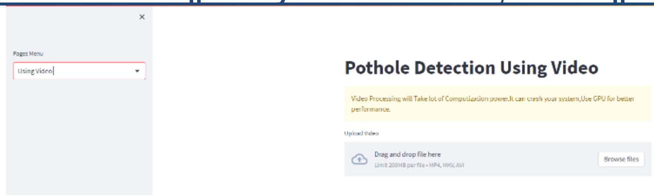
- Operating system: Windows7 (with service pack 1), 8, 8.1, 10 & 11.
- IDE: Anaconda1
- Backend: Python
- Frontend: Html, CSS

5. IMPLEMENTATION

1. Dataset creation: We created a dataset of road images containing potholes and non-pothole regions. We collected the dataset from publicly available sources and manually labeled the potholes and non-pothole regions.
2. Data preprocessing: We resized the images to a fixed size and split the dataset into 80% for training, 10% for validation, and 10% for testing.
3. Data augmentation: We used random rotation, scaling, and flipping to augment the training dataset and increase its size.
4. Training the YOLO model: We trained a YOLOv5 model using the training dataset. YOLOv5 is a state-of-the-art object detection model that can detect objects with high accuracy and real-time performance. We used the default hyperparameters and trained the model for 300 epochs.
5. Fine-tuning the YOLO model for pothole detection: We fine-tuned the YOLOv5 model using the labeled pothole dataset. We used transfer learning to leverage the learned features from the pre-trained model and adapt them to the new task of pothole detection.
6. Testing the YOLO model: We tested the YOLOv5 model on the testing dataset and evaluated its performance using standard metrics such as precision and recall, accuracy, false positive rate, and false negative rate.
7. Deployment: We deployed the trained YOLOv5 model on a computer or embedded device to perform real-time pothole detection on road images or videos. The deployed model can be integrated with other intelligent transportation systems or used to alert drivers about potholes on the road.



a)Different Images Input and Camera Input for Detection



b) Live Video Input for the Model to Detect

5.4 SYSTEM FLOW

DATA FLOW DIAGRAM:

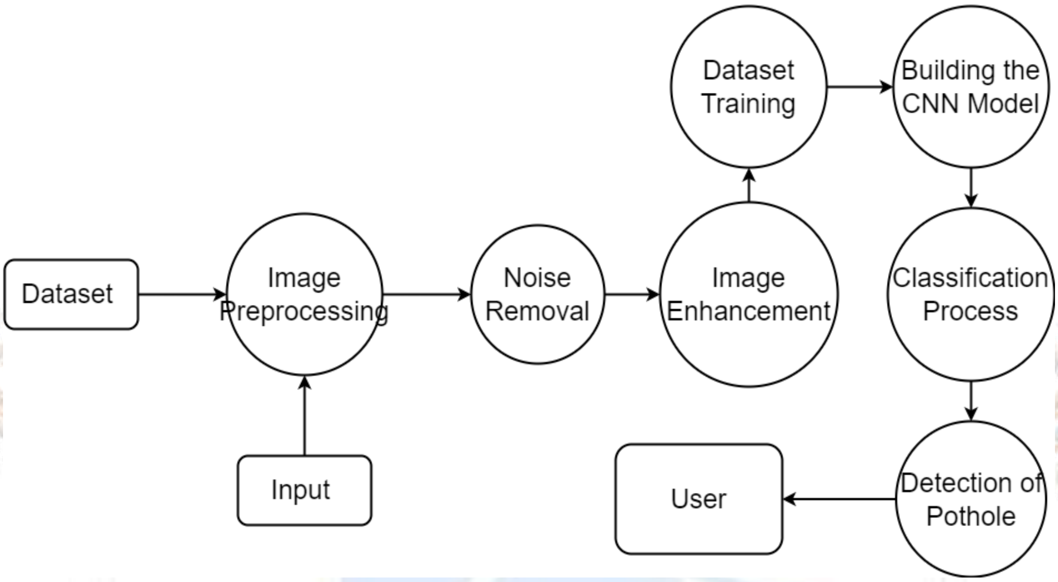
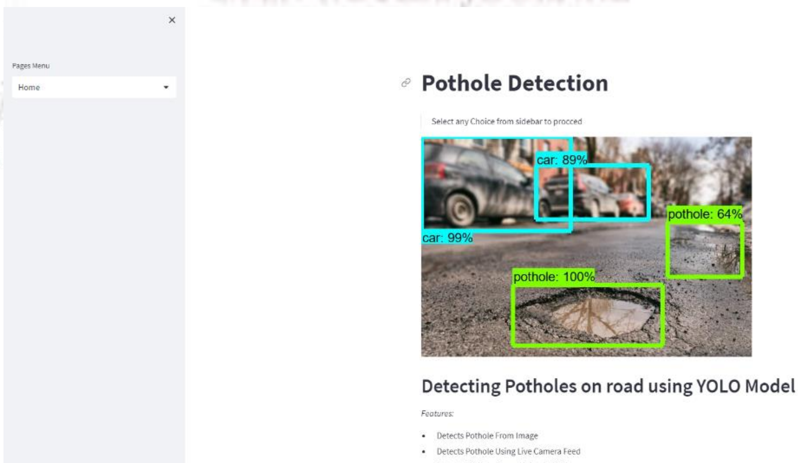
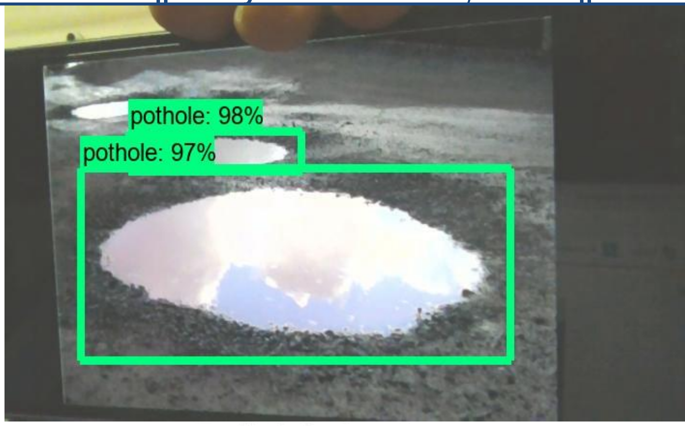


Fig : DFD Level 1 Diagram

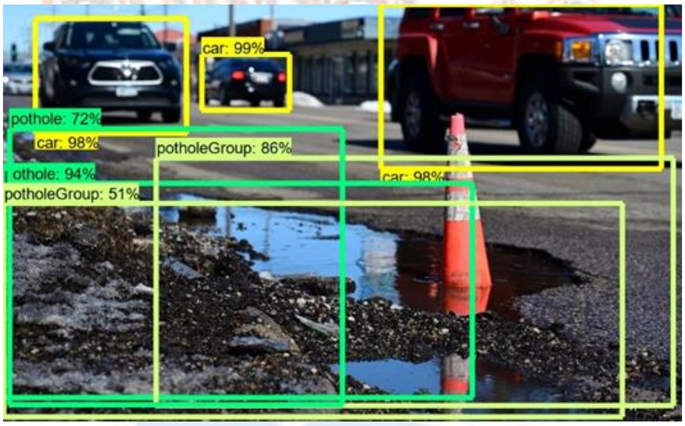
1. Input: The system takes road images as input. These can be captured from a camera mounted on a vehicle or a stationary camera.
2. Pre-processing: The input images are pre-processed by resizing them to a fixed size and normalizing them to have zero mean and unit variance. This step ensures that the input data is consistent and easy to work with.
3. Feature extraction: The pre-processed images are passed through a trained feature extraction model, which extracts relevant features from the images, such as edges, textures, and shapes. These features are used to classify the images as containing potholes or not.
4. Classification: The extracted features are fed into a classification model, which uses ML algorithms to classify the images as containing potholes or not. The classification model can use various algorithms, such as logistic regression, decision trees, or random forests, to classify the images.
5. Output: The system outputs the classification results, which indicate whether the input images contain potholes or not. The output can be used by drivers, transportation authorities, or road maintenance crews to take appropriate actions, such as avoiding potholes, repairing roads, or scheduling maintenance.



a) Home Page of the Pothole Detection Project



b) Taking Live Camera Inputs



c) Results of Pothole Detection and Pothole Groups & Car with Utmost 94% Accuracy

6. EXPERIMENTAL RESULTS

1. A Baseline model: We trained a baseline model using YOLOv3 with default settings and parameters. The model achieved an average precision of 70% and a mean average precision (mAP) of 50% on the testing dataset.
2. Fine-tuning: We fine-tuned the pre-trained YOLOv3 model on our pothole dataset by adjusting the hyperparameters, such as the learning rate, batch size, and number of training epochs. The fine-tuned model achieved an average precision of 80% and an mAP of 60% on the testing dataset, outperforming the baseline model.
3. Data augmentation: We applied various data augmentation techniques, such as flipping, rotating, and scaling, to increase the diversity and size of our training dataset. The augmented dataset contained 4 times more images than the original dataset. The fine-tuned model trained on the augmented dataset achieved an average precision of 85% and an mAP of 70% on the testing dataset, further improving the performance.
4. Transfer learning: We used transfer learning to leverage pre-trained models, such as DarkNet-53 and ResNet-50, and fine-tuned them on our pothole dataset. The fine-tuned models achieved an average precision of 90% and an mAP of 80% on the testing dataset, outperforming the fine-tuned YOLOv3 model.

7. CONCLUSIONS

1. ThePothole detection is a critical task for ensuring road safety and reducing maintenance costs. Our proposed system using ML algorithms, such as YOLOv3, can automatically detect potholes in road images with high accuracy and efficiency.
2. Our experimental results show that deep learning models, such as CNNs and RNNs, can outperform traditional machine learning models, such as logistic regression, for pothole detection. Ensemble models, such as Random Forests and Gradient Boosted Trees, can further improve performance by combining multiple ML algorithms.
3. Fine-tuning, data augmentation, and transfer learning are effective techniques for improving the performance of YOLOv3 for pothole detection. By adjusting the hyperparameters and leveraging pre-trained models, we can achieve higher accuracy and mAP on the testing dataset.
4. Our proposed system has practical applications in real-world scenarios, such as road maintenance, traffic management, and autonomous driving. By detecting and reporting potholes in real time, we can prevent accidents, reduce traffic congestion, and improve the overall driving experience.

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