Pothole Detection using a Convolutional Neural Network and Transfer Learning

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Abstract

Potholes on roads pose significant risks to vehicle safety, infrastructure maintenance, and public health, contributing to accidents and expensive repairs. Traditional manual detection methods are labor-intensive and inefficient. This study proposes an efficient pothole detection framework that leverages Convolutional Neural Networks (CNNs) and transfer learning. Using pre-trained models such as VGG-16 and MobileNet, the proposed system achieves high accuracy in identifying potholes from road images while reducing computational costs. The methodology involves preprocessing road images, fine-tuning pretrained CNN models, and evaluating performance using metrics such as accuracy, precision, recall, and F1 score. This approach improves road safety and infrastructure management by providing a scalable and accurate solution for the automated detection of potholes.

1 Introduction and Motivation

Potholes are a pervasive issue in road infrastructure, leading to vehicle damage, accidents, and significant financial loss. According to a 2018 report by the Indian Ministry of Road Transport and Highways, over 9,800 deaths were attributed to pothole-related incidents [11]. Manual road inspection for potholes is time-consuming, costly, and prone to human error, necessitating automated solutions. Advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown promise in image-based object detection tasks, making them suitable for pothole detection.

CNNs excel at capturing spatial hierarchies in image data, enabling the accurate identification of potholes based on visual features. However, training CNNs from scratch requires large datasets and significant computational resources, which may not be feasible for all applications. Transfer learning addresses this challenge by leveraging pretrained models, such as VGG-16, MobileNet, and ResNet, trained on large datasets, such as ImageNet, and fine-tuned for specific tasks, such as pothole detection [12]. This approach reduces the training time and data requirements while maintaining high accuracy.

The motivation for this work stems from two key observations:

- **Road Safety and Efficiency**: Automated pothole detection can enhance road safety by alerting drivers and authorities in real-time, reducing accidents and maintenance costs.

- **Scalability and Accessibility**: Transfer learning enables the deployment of robust models on resource-constrained devices, making the solution accessible for widespread use in intelligent transportation systems.

This project aims to develop a scalable and accurate pothole detection system using CNNs and transfer learning, contributing to safer roads and efficient infrastructure management.

2 Literature Review

Author	**Methods**	**Maximum Accuracy**	**Minimum Accuracy**
Chemikala Saisree, Dr Kumaran U [1]	ResNet50, InceptionResNetV2, VGG19	98%	97%
Rodrigo Moraes, Lucas Gauer, et al. [2]	YOLOv3, YOLOv4, Faster R-CNN, SSD MobileNet	92.5%	74.8%
Md. Akhlas Uddin, Mohammed Forhad Uddin, et al. [3]	CNN, ResNet50, VGG16, MobileNetV2, YOLOv5	96.8%	85%
Muhammad Haroon Asad, Saran Khaliq, et al. [4]	YOLOv1 to YOLOv5, Tiny-YOLOv4, SSD-Mobilenetv2	95%	85%
Jiahe Guang, Xingrui He, et al. [5]	Local Attention ResNet18-CNN-LSTM	99.2188%	93.443%
Rufus Rubin, Chinnu Jacob, et al. [6]	YOLO-Xception with Attention Mechanisms	99%	26%
Oche Alexander Egaji, Gareth Evans, et al. [7]	Naïve Bayes, SVM, Logistic Regression, KNN, RF	88.89%	83.33%
Nachuan Ma, Jiahe Fan, et al. [8]	Classical 2-D, 3-D Point Cloud, CNN, Hybrid Methods	98.95%	80%
Anas Al-Shaghouri, Rami Alkhatib, Samir Berjaoui [9]	SSD-TensorFlow, YOLOv3-Darknet53, YOLOv4-CSPDarknet53	85.39%	32.5%

Author	Methods	Maximum Accuracy	Minimum Accuracy
Tian Guan, Jianyuan Cai, et al. [10]	GASB-ShuffleNetv2, PF-CenterNet, Binocular Vision	98.61%	80.26%

3 Proposed Methodology

The proposed methodology for pothole detection consists of the following key components:

- **Dataset Collection**: Collect a diverse dataset of road images containing potholes and non-pothole regions from publicly available sources, such as Kaggle, with 352 normal images and 329 pothole images [13].
- **Data Preprocessing**: Resize images to 224x224 pixels and apply image processing techniques, such as Otsu's thresholding, to enhance pothole visibility. Data augmentation techniques (e.g., rotation, flipping, brightness adjustment) are used to increase dataset diversity and prevent overfitting.
- **Model Architecture**: Utilize a pre-trained CNN model (VGG-16 or MobileNet) as the base architecture. Add fully connected layers for binary classification (pothole vs. non-pothole), with a softmax output layer.
- **Transfer Learning**: Initialize the model with weights pre-trained on ImageNet and fine-tune the top layers on the pothole dataset to adapt to specific features of road images.
- **Training**: Train the model using a split dataset (80% training, 10% validation, 10% testing) with the Adam optimizer and categorical cross-entropy loss. Apply early stopping to prevent overfitting.
- **Evaluation**: Evaluate performance using accuracy, precision, recall, F1-score, and AUROC. Compare results with baseline CNN models trained from scratch.
- **Deployment**: Optimize the model for real-time deployment on edge devices, ensuring scalability for intelligent transportation systems.

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