Bangladesh University of Business & Technology

Group ID	14
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Title of the project	Pothole Detection Using CNN, Transfer learning

Author	Dataset	Methods	Proposed Architecture	Maximum Accuracy	Minimum Accuracy	Remarks / Gaps
Chemikala Saisree, Dr Kumaran U	a mix of images of muddy roads (sourced from the internet) and highway roads (from Kaggle)	ResNet 50, InceptionResNetV2, VGG19	Pothole Detection Using Deep Learning Classification Method.	98%	97%	Future work includes expanding the training data and utilizing advanced CNNs, such as Xception and MobileNet, to enhance accuracy. It also highlights challenges like overfitting and the lack of muddy road datasets.
MohanPrakash B1*, Sriharipriya K.C1	Roboflow Pothole Dataset	YOLOX , GLCM , SVM	Enhanced pothole detection system using YOLOX algorithm	85.6%		The study highlights the lack of evaluation on detection and inference time in models like YOLOv3, YOLOv4, YOLOv5, and YOLOX-nano—crucial factors for real-time pothole detection applications.
Chandra S1*, K Dubey K2, Agarwal G3, Chakraborty N4	India-road-specific drivable-area segmentat	YOLOv5, Local Binary Pattern	Pothole Detection in Drivable Area using Deep Learning	84.5%		There's a clear research gap in Indian highway-specific road sign identification and in building robust

	ion dataset	(LBP) + SVM				models that perform well under diverse environmental conditions. Future work should also explore advanced augmentation techniques and better sensor data integration for autonomous systems.
Rodrigo Moraes, Lucas Gauer, Diego R. Lucio, Guilherme Z. Bueno, Paulo R. S. Mendonça, Ana Carolina L. Oliveira, Thiago R. R. Marques, Adriano M. C. Vieira	Own dataset of 9,000 images (collected with low-cost cameras on vehicles)	YOLOv3, YOLOv4, Faster R-CNN, SSD MobileNet	Pothole detection system using YOLOv4-Tiny for real-time deployment on embedded systems	92.5% (YOLOv4)	74.8% (SSD MobileNet)	Evaluated only on Brazilian road conditions generalization to other regions not tested. Real-time performance on extremely low-power devices still limited
Md. Akhlas Uddin, Mohammed Forhad Uddin, Abdullah Al Mahmud, Md. Golam Rabiul Alam, et al	Kaggle pothole dataset + self-collected images (various road conditions)	CNN, ResNet50, VGG16, MobileNetV2, YOLOv5	Deep learning framework combining YOLOv5 for detection and transfer learning models for classification	96.8% (YOLOv5-based detection)	85% (basic CNN)	Focused mainly on image-based detection; does not integrate with IoT/real-time road monitoring systems.
Muhammad Haroon Asad , Saran Khaliq , Muhammad Haroon Yousaf , Muhammad Obaid Ullah , and Afaq Ahmad	Pothole image dataset consisting of 665 images with shadows, vehicles, and illumination variations.	YOLOv1, YOLOv2, YOLOv3, YOLOv4, Tiny-YOLOv4, YOLOv5, SSD-mobilenetv2.	Real-time pothole detection using deep learning models deployed on OAK-D camera with Raspberry Pi for AI-on-the-edge.	95%	85%	Dataset is relatively small (665 images) and may lack sufficient diversity for broader real-world generalizability across different road types or regions.

Jiahe Guang1,3,*, Xingrui He1,4, Zeng Li [2, 5], Shiyu He [2, 6]	U.S. database of 501 road images	local attention ResNet 18-CNN-LSTM	Road Pothole Detection Model Based on Local Attention ResNet18-CNN-LSTM	99.2188%	93.443%	Not addressed in the paper.
Rufus Rubin,[1] Chinnu Jacob,[1] Sumod Sundar,[1] Gabriel Stoian,[2] Daniela Danciulescu,2, and Jude Hemanth[3]	A merged collection comprising the MakeML pothole dataset, a custom dataset, and a Kaggle dataset	YOLO-Xception with Attention Mechanisms	Pothole Detection and Assessment on Highways Using an Enhanced YOLO Algorithm With Attention Mechanism	99%	26%	Not addressed in the paper.
Oche Alexander Egaji a a , 1 , * , Gareth Evans a , Mark Graham Griffiths a , Gregory Islas b	O. A. Egaji et al. (2021)	Naïve Bayes, SVM, Logistic Regression, KNN, RF	Real-time machine learning-based approach for pothole detection	88.89%	83.33%	Simulation-based models lack real-world validation, which limits their generalizability. Small datasets and train-test overlap raise concerns about model reliability and accuracy.
Nachuan Ma 1, Jiahe Fan 1, Wenshuo Wang 2, Jin Wu 3, Yu Jiang 4, Lihua Xie 5 and Rui Fan 1, *	Multiple open-access datasets including Pothole-600 (multi-modal with 55 groups of color images and transformed disparity images), CCSAD (500 GB	Classical 2-D image processing (e.g., thresholding, morphological operations), 3-D point cloud modelling and segme	Taxonomy of road imaging systems (cameras, laser scanners, Microsoft Kinect) and pothole detection algorithms categorized into classical 2-D, 3-D point cloud, machine/deep learning, and hybrid.	98.95%	80%	Classical 2-D and 3-D approaches are outdated and sensitive to environmental factors like illumination; future focus on hybrid methods combining 3-D reconstruction with semantic segmentation

	of high-resolution stereo images with IMU and GPS data), Maeda's dataset (9,053 color road images with 15,435 damages), and others for classification and segmentation tasks.	ntation (e.g., surface fitting, RANSAC), machine/deep learning (e.g., SVM, CNNs for classification, object detection like YOLO/SSD/Faster R-CNN, semantic segmentation like U-Net/DeepLabv3+), and hybrid approaches.				
Anas Al-Shaghouri, Rami Alkhatib, Samir Berjaoui	1087 images (Lebanese roads + internet sources) with more than 2000 potholes	SSD-TensorFlow, YOLOv3-Darknet53, YOLOv4-CSP Darknet53	Real-time pothole detection using deep learning (YOLO-based)	85.39% mAP (YOLOv4)	32.5% mAP (SSD-TensorFlow)	Dataset size relatively small; needs larger and more diverse images for robustness. Limited testing under varied weather/lighting conditions.
Tian Guana , Jianyuan Caia , Yu Wanga , Wei Yanga,* , Xiaobo Changb , Yi Hana	6,848 road surface pothole condition recognition datasets constructe	Improved ShuffleNetv2 with group attention	Pavement pothole detection system integrating GASB-ShuffleNetv2 for pothole state	98.61%	80.26%	Ranging accuracy decreases significantly with increasing distance (e.g., error up to 13.73% at 20 m), limiting effectiveness for long-range

	d using a vehicle-mounted binocular camera, supplemented with open datasets for pavement pothole detection.	shuffle block (GASB), pyramid convolution with feature fusion in CenterNet (PF-CenterNet), binocular vision with semi-global block matching and weighted least squares filter for disparity and distance estimation.	recognition (non-distressed, severe, completely broken), PF-CenterNet for pothole area detection, and a binocular vision-based model for distance estimation.			perception in high-speed scenarios.	