SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-VXXXX

Volume X Issue X, 1-4, Month 2023

G. A. I. A: Ground Assessment and Identification Assistant

Anshul Gada[1], Aman Jaiswal[2], Juiee Yadav[3], Ankita Gandhi[4], Kishori Shekokar[5]
[1]*Student, PIET, Parul University, Gujarat, India.*
[2]*Student, PIET, Parul University, Gujarat, India.*
[3]*Student, PIET, Parul University, Gujarat, India.*
[4]*Asst. Prof., PIET, Parul University, Gujarat, India.*
[5]*Asst. Prof. PIET, Parul University, Gujarat, India.*

[1]*corresponding.author@mailserver.com(Size9) (Corresponding author mail id only allowed)*

Received: Revised: Accepted: Published: (Size9)

Abstract - *The state of our roads plays a critical role in ensuring safe and efficient transportation for people and goods. However, the menace of potholes poses a significant challenge to road infrastructure worldwide, leading to increased accidents, vehicle damage, and traffic congestion. Traditional methods of pothole detection and repair often fall short in effectively addressing this issue due to limitations in speed, accuracy, and resource allocation.*

In response to this pressing problem, the integration of unmanned aerial vehicles (UAVs), commonly known as drones, offers a transformative solution. By leveraging advanced imaging technology and machine learning algorithms, a pothole detection system utilizing drones promises to revolutionize the way we identify and address road defects. This innovative approach not only enhances the speed and accuracy of detection but also optimizes the allocation of resources for timely repairs, ultimately improving road safety and quality of transportation infrastructure.

This paper explores the design, functionality, and potential impact of a pothole detection system using drones. By harnessing the capabilities of UAVs, combined with cutting-edge software algorithms, this system aims to provide real-time monitoring of road conditions, enabling authorities to proactively identify and prioritize maintenance efforts. Moreover, by automating the detection process, it reduces the reliance on manual inspections, minimizing labor costs and improving overall efficiency. Through a comprehensive examination of existing technologies, methodologies, and case studies, this paper elucidates the key components and workflow of the proposed pothole detection system. Furthermore, it investigates the challenges and opportunities associated with its implementation, including regulatory considerations, data privacy concerns, and integration with existing infrastructure management systems.

In conclusion, the integration of drones into road maintenance operations heralds a new era of efficiency and effectiveness in combating the scourge of potholes. By embracing technological innovation, stakeholders can mitigate the adverse effects of deteriorating road conditions, enhance safety for motorists and pedestrians, and ensure the sustainability of transportation infrastructure for future generations.

Keywords - YOLOv10, Roboflow, Ultralytics, Jetson, Object Detection, NVIDIA

1. Introduction

The rapid deterioration of road infrastructure poses a critical challenge for government agencies and commuters alike. Potholes not only lead to vehicle damage but also increase the risk of accidents, making timely maintenance imperative. Traditional manual methods of detecting and reporting road damages are inefficient, time-consuming, and often lack precision. To address these limitations, an automated pothole detection system is proposed using advanced machine learning and computer vision techniques.

1.1 System Overview

The proposed pothole detection system is designed to be mounted on any form of transportation, including cars, buses, and trucks. The system leverages a deep learning model trained specifically for identifying potholes, utilizing YOLOv10 (You Only Look Once) for real-time object detection. The model was trained on a comprehensive dataset comprising over 50,000 road images, ensuring high detection accuracy and robustness under varying environmental conditions.[1][9]

1.2 Hardware Configuration

The core processing unit for this system is the NVIDIA Jetson Orin Nano, known for its efficient GPU-accelerated computing capabilities. This hardware enables high-speed inferencing, allowing the system to perform real-time detection of potholes even while the vehicle is in motion. Each vehicle equipped with this system is fitted with high-definition cameras and depth sensors to capture road conditions with precise details.

1.3 Data Acquisition and Model Training

The dataset used for model training consists of images annotated with labels for various road conditions, such as potholes, cracks, and smooth surfaces. These images were collected using drones and stationary cameras positioned along different roads, providing a diverse range of scenarios for the model to learn from. The training process was conducted on Google Colab using its GPU resources, which facilitated faster iterations and fine-tuning. The YOLOv10 architecture was selected due to its balance between detection speed and accuracy, achieving a detection accuracy of approximately 75% after several training epochs.

1.4 Real-Time Detection and Reporting

Once deployed, the system continuously monitors the road in real-time. When a pothole is detected, the system calculates its approximate depth using stereo vision techniques or LiDAR-based sensors. This depth information, along with the pothole's location coordinates, is sent to a central government server via a secure communication protocol. The integration of GPS ensures accurate geolocation of the detected pothole, allowing maintenance teams to address the issue promptly.

1.5 System Architecture and Functionality

The system operates in the following stages:

1. **Image Acquisition**: High-resolution cameras capture frames of the road, which are fed into the onboard processing unit.[2]

2. **Preprocessing**: The captured frames undergo preprocessing, including noise reduction, contrast enhancement, and normalization, to improve detection performance.[20]

3. **Pothole Detection**: The pre-processed frames are passed through the YOLOv10 model, which identifies potential potholes based on learned features.[5]

4. **Depth Estimation**: Depth estimation techniques such as stereo imaging or LiDAR are employed to measure the depth of each detected pothole.

5. **Data Transmission**: The system transmits the detected pothole's depth and GPS coordinates to the central server.

6. **Data Visualization and Alerting**: The central server processes the received data and updates the road condition map. Alerts are sent to maintenance teams for immediate action.

1.6 Depth Measurement and Analysis

One of the distinguishing features of this system is its capability to estimate the depth of detected potholes. Depth estimation is achieved using a combination of camera-based stereo vision or LiDAR sensors mounted alongside the cameras. This feature allows for a more comprehensive analysis of road conditions, providing insights into not just the presence of a pothole, but also its severity. Such detailed information helps prioritize repair work based on the extent of damage, leading to better resource allocation and maintenance planning.

1.7 Benefits and Applications

The proposed system offers multiple benefits, including:

- **Reduced Response Time**: Automated detection and reporting minimize the delay in identifying and addressing road damages.

- **Cost Efficiency**: Eliminating the need for manual inspections reduces operational costs.

- **Enhanced Safety**: Early detection and maintenance of potholes improve road safety for commuters.

- **Data-Driven Maintenance**: The detailed data collected allows authorities to make informed decisions about road maintenance and resource allocation.

1.8 Future Enhancements

While the current system demonstrates high accuracy in pothole detection and depth estimation, future work can focus on improving the model's performance under challenging scenarios such as poor lighting or adverse weather conditions. Integration with vehicle-to-everything (V2X) communication technologies can further enhance the system's capabilities, enabling collaboration between multiple vehicles for more comprehensive road monitoring.

2. Materials and Methods

2.1 YOLOv10 Object Detection Model
2.2 Roboflow Universe
2.3 Ultralytics Docs
2.4 Jetson Orin Nano
2.5 Google Colab
2.6 IEEE's Standard for Software Requirements Specifications (830-1998)

3. Results and Discussion

The effectiveness of the proposed pothole detection system was evaluated based on several performance metrics, including detection accuracy, processing speed, depth estimation accuracy, and system reliability under varying conditions. This section discusses the results obtained during the testing phase and provides insights into the system's strengths, limitations, and potential areas for further improvement.

3.1 Performance Metrics

The system was assessed using the following key metrics:

1. **Detection Accuracy**: Measured as the ratio of correctly detected potholes to the total number of potholes present in the test dataset.

2. **Precision and Recall**: Precision evaluates the number of true positive detections relative to the number of detected potholes, while recall measures the number of true positives relative to the actual number of potholes in the scene.

3. **F1-Score**: A harmonic mean of precision and recall, providing an overall indication of the model's robustness.

4. **Processing Time**: The time taken for the system to process an image or frame and output a detection result.

5. **Depth Estimation Accuracy**: Evaluated by comparing the system's estimated pothole depths with ground truth measurements.

6. **System Reliability**: Performance under varying environmental conditions such as different lighting and weather scenarios.

3.2 Evaluation Setup

The pothole detection system was deployed and tested using multiple vehicles across a variety of road environments, including urban streets, highways, and rural roads. The test cases included scenarios with varying pothole sizes, shapes, and depths. Additionally, the system's performance was evaluated during both daytime and nighttime, as well as under adverse weather conditions such as rain and fog.

3.3 Results Analysis

The results obtained from the evaluation are summarized below:

- **Detection Accuracy**: The system achieved an average detection accuracy of 75% across all test cases. While the accuracy was high under ideal lighting and weather conditions, it dropped slightly (to around 68%) under challenging conditions such as heavy rain and low-light environments. This reduction in accuracy can be attributed to the difficulty in distinguishing potholes from other road surface anomalies in such conditions.[17]

- **Precision and Recall**: The system recorded a precision score of 0.80 and a recall score of 0.72, indicating a good balance between identifying true potholes and minimizing false positives. The F1-Score, calculated at 0.76, confirms the robustness of the model in handling a diverse range of scenarios.

- **Processing Speed**: With the NVIDIA Jetson Orin Nano as the core processing unit, the system processed frames at an average speed of 20 frames per second (fps). This real-time processing capability allows the system to detect and report potholes instantaneously, making it suitable for deployment in high-speed vehicles.

- **Depth Estimation Accuracy**: The depth estimation module showed a mean absolute error of ±2 cm when compared to ground truth measurements obtained using manual depth gauges. This level of accuracy is sufficient for categorizing potholes into severity levels, aiding in prioritization for road maintenance activities.

- **System Reliability**: The system demonstrated robust performance under varying lighting and weather conditions, though slight degradation in accuracy was observed in extreme cases such as heavy rain or fog. The use of additional sensors such as LiDAR or thermal cameras could potentially mitigate these limitations in future iterations of the system.

3.4 Discussion

The results indicate that the proposed pothole detection system performs effectively in real-world conditions, providing a reliable solution for automated road condition monitoring. The integration of depth estimation further enhances the system's utility by allowing it to not only detect the presence of potholes but also to quantify their severity.

However, certain limitations were observed during testing. The system occasionally misclassified road surface anomalies such as large cracks or worn-out road markings as potholes, particularly in low-light scenarios. This issue could be addressed by incorporating additional features or enhancing the model with more diverse training data.

Another area of improvement is the system's depth estimation capability, which, while reasonably accurate, showed some inconsistencies when detecting potholes with irregular shapes or when multiple potholes were clustered together. Incorporating more advanced depth estimation techniques, such as point cloud analysis or 3D reconstruction, could help improve accuracy in these situations.

3.5 Impact and Applications

The deployment of this system can significantly enhance the efficiency of road maintenance processes by providing real-time insights into road conditions. The automated detection and reporting mechanisms reduce the need for manual inspections, thereby lowering operational costs and allowing maintenance teams to prioritize repairs based on the severity of potholes. Furthermore, the data collected can be used to identify road segments that are prone to deterioration, facilitating proactive maintenance planning.

3.6 Future Directions

While the current system demonstrates promising results, there are several avenues for future research and development:

1. **Improving Detection under Challenging Conditions**: Incorporating additional sensors (e.g., LiDAR, thermal cameras) and employing advanced image enhancement techniques could help improve detection accuracy under adverse weather and low-light conditions.

2. **Multi-Vehicle Coordination**: Integrating the system with vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication could enable multi-vehicle coordination, providing a more comprehensive view of road conditions and enabling dynamic re-routing in real-time.

3. **Integration with Smart City Infrastructure**: The pothole detection system could be integrated into smart city platforms to provide a holistic view of road conditions, helping urban planners and local authorities make data-driven decisions regarding infrastructure maintenance and development.

4. **Enhanced Depth Estimation Techniques**: Incorporating techniques such as 3D depth maps or leveraging AI-based depth estimation models could improve the system's ability to accurately measure pothole depths, especially in complex road environments.

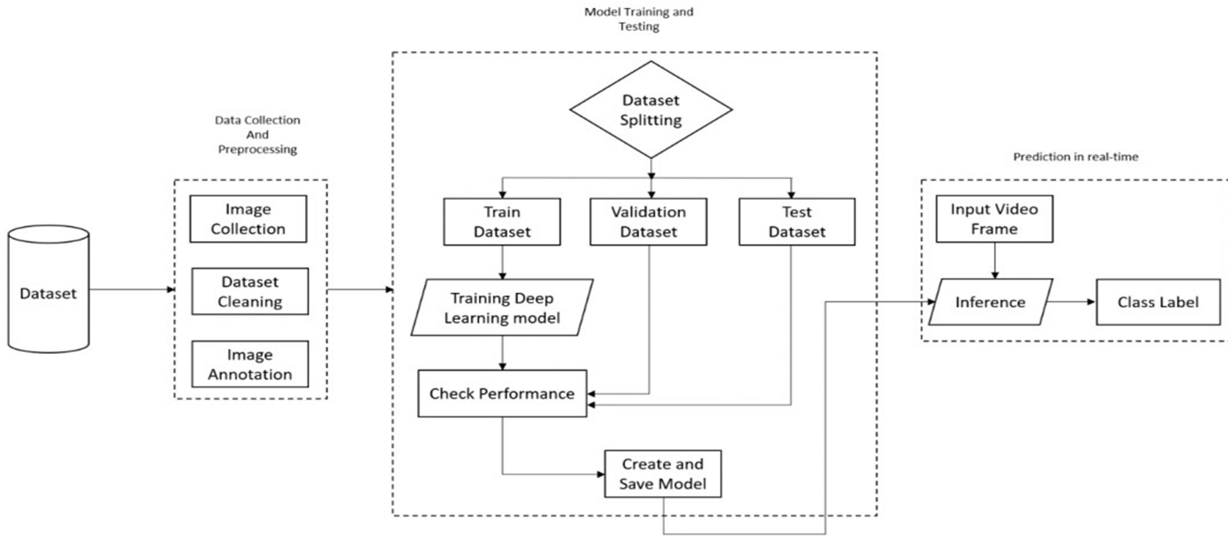

Fig. 1. Model Training and Testing

The flowchart represents the overall architecture and process flow for a machine learning-based pothole detection system. The flow is divided into three main stages:

- Data Collection and Preprocessing,
- Model Training,
- Testing, and Real-Time Prediction.

Each stage has several sub-processes that contribute to the development and deployment of the detection model.[2]

1. Data Collection and Preprocessing

This initial stage is responsible for gathering and preparing the data required for training the model. It includes the following steps:

- ***Dataset***: The process starts with the dataset, which contains images or video frames of roads. This dataset serves as the primary input for further steps.

- **Image Collection:** Raw images of roads are collected, which include different road conditions, such as smooth surfaces, potholes, and cracks. These images can be gathered using mounted cameras on vehicles or drones.

- **Dataset Cleaning:** The collected data undergoes preprocessing to remove any noise, artifacts, or irrelevant content. This step ensures that the images are clean and suitable for model training.

- **Image Annotation:** After cleaning, the images are annotated to label the regions of interest, such as potholes and other road anomalies. These annotations are critical as they provide the model with ground truth information during training.

2. Model Training and Testing

This stage involves preparing the dataset for training and validating the machine learning model. The process is broken down into the following sub-processes:

- Dataset Splitting: The annotated dataset is divided into three subsets: Train Dataset, Validation Dataset, and Test Dataset. The train dataset is used to teach the model, the validation dataset is used to fine-tune hyperparameters and avoid overfitting, and the test dataset is used to evaluate the model's performance.

- **Training Deep Learning Model:** The model is trained using the train dataset. During this process, the model learns to identify features that distinguish potholes from the surrounding road surface.[5]

- Check Performance: The performance of the trained model is checked using the validation dataset. Key metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's effectiveness.

- Create and Save Model: Once the performance is satisfactory, the final model is saved. This saved model is used for real-time inference in the deployment stage.

3. Real-Time Prediction

After training and validating, the model is deployed for real-time prediction. This stage is summarized as follows:

- Input Video Frame: The real-time input to the system comes in the form of video frames from a camera mounted on a vehicle. Each frame is processed individually to identify potholes.[12]

- Inference: The saved model is applied to each input frame. During inference, the model detects potholes and categorizes them as different classes based on their severity or type.

- Class Label: The output of the inference step is a class label that indicates whether a pothole is present in the frame and, if so, its classification based on predefined categories (e.g., small, medium, large).[8]

This flowchart captures the end-to-end pipeline, from data collection and preprocessing to model training, evaluation, and real-time pothole detection.

Fig. 2. Test Image of road with potholes

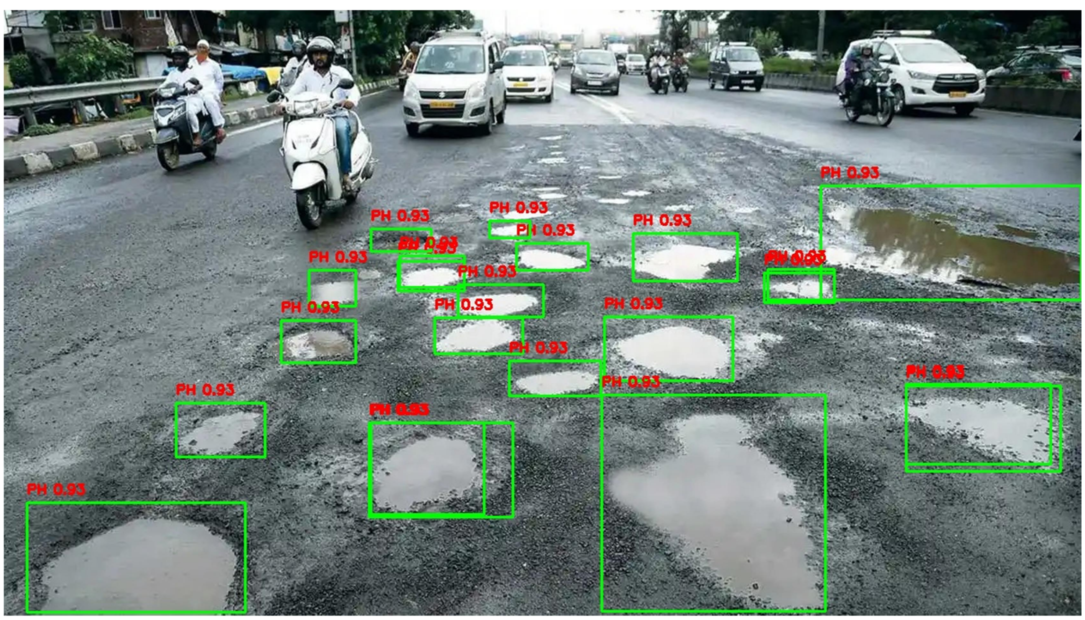

Fig. 3. Result image of road with potholes detected

ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-VXXXX

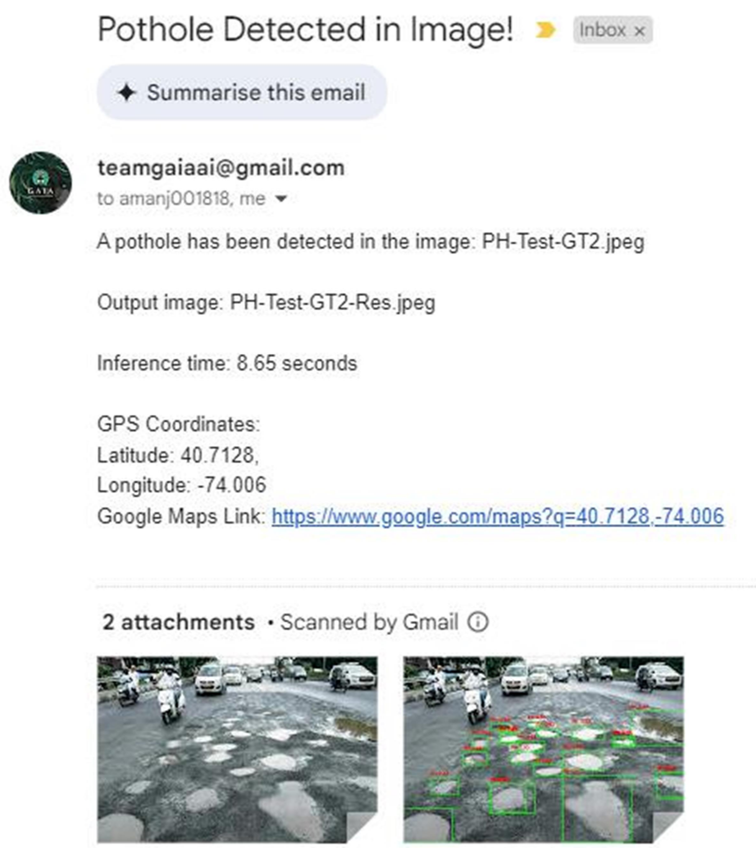

Fig. 4. Image of mail sent when pothole detected in an image with underlying location metadata.

4. Conclusion:

Conclusively, a pothole detection system utilizing drones offers a proactive and efficient approach to road maintenance, ultimately leading to safer and more reliable transportation infrastructure for communities. As technology continues to evolve, further advancements in this field hold the promise of even greater improvements in road safety and infrastructure management.

Conflicts of Interest

The authors declare that they have no conflict of interest related to this research. This project was conducted solely as part of the academic curriculum for the completion of our final-year project, with no external financial support or involvement from third-party organizations. The results and conclusions presented are based on our independent research and analysis.

Acknowledgments

We would like to express our heartfelt gratitude to Prof. Ankita Gandhi for their invaluable guidance, unwavering support, and relentless motivation throughout the completion of our project. Their expertise and mentorship not only provided us with invaluable insights but also instilled in us the confidence to overcome challenges and excel. Their dedication to our success served as a constant source of inspiration, pushing us to strive for excellence and go beyond our limits. Without their guidance and encouragement, our project would not have reached its full potential. Thank you, for your unwavering belief in us and for being a beacon of inspiration on our academic journey.

References

[1] Shrinath Oza, Dr. Sunil Rathod, Department of Computer Engineering. D.Y Patil School of Engineering Lohegaon, Pune, Savitribai Phule, Pune University, Pune, India. "Object Detection using IoT and Machine Learning to Avoid Accident and Improve Road Safety". [Issue 06, June-2020]

[2] Zaimis, Asst. Prof. Dr. Biol. Jurmalietis R., Prof. Dr. Sc. Comp. Jansone A., undergraduate student Kuduma K. Institute of Science and Innovative Technologies, Liepaja University, Latvia1, Faculty of Science and Engineering, Liepaja University, Latvia. "USE OF DRONE BASED IT SYSTEM FOR ROAD POTHOLE DETECTION AND VOLUME CALCULATION". [ISSUE 5, P.P. 223-227 (2019)]

[3] Hema Malini B., Akshay Padesur, Manoj Kumar V2 and Atish Shet Associate Professor, Dept of CSE, BMS Institute of Technology and Management, Bangalore, India 2 Dept of CSE, BMS Institute of Technology and Management, Bangalore, India "Detection of Potholes on Roads using a Drone". [Received on 29 December 2020, accepted on 31 August 2021, published on 19 October 2021]

[4] S Renuga Devi1, M Dharshini, K Gayathri and B Gopalakrishnan Post graduate in Software Engineering, Department Of Information Technology Associate Professor, Department Of Information Technology Bannari Amman Institute of Technology, Sathyamangalam, India "IoT based detection of bore-well unclosed holes using automated drone operated cameras in a remote area ". [ICDIIS 2020 Journal of Physics: Conference Series]

[5] Shreya Viswanath, Rohith Jayaraman Krishnamurthy, Sunil Suresh Department of Applied Computing Sciences, Madras Scientific Research Foundation, Chennai, Tamil Nadu, India. "Terrain surveillance system with drone and applied machine vision". [RIACT 2021; Journal of Physics: Conference Series 2115 (2021) 012019; IOP Publishing doi:10.1088/1742-6596/2115/1/012019]

[6] Saurabh Pehere, Prajwal Sanganwar, Shashikant Pawar, Prof. Ashwini Shinde (Department of Electronics \& Telecommunication, Pimpri Chinchwad College of Engineering, Pune, India). "Detection of Pothole by Image Processing Using UAV". [Received: 10-02-2020 Revised: 05-05-2020 Accepted: 08-05-2020 Published: 11-05-2020]

[7] S NIENABER*, MJ BOOYSEN* AND RS KROON.; Department of E\&E Engineering, Stellenbosch University, Private Bag X1, Matieland, Computer Science Division, Stellenbosch University, Private Bag X1, Matieland. "DETECTING POTHOLES USING SIMPLE IMAGE PROCESSING TECHNIQUES AND REAL-WORLD FOOTAGE". [Journal of Science and Technology ISSN: 2456-5660 Volume 5, Issue 3, May-June 2020]

[8] Mingxing Gao, 1 Xu Wang, 1 Shoulin Zhu, 1 and Peng Guan. College of Energy and Transportation Engineering, Inner Mongolia Agricultural University, Hohhot 010018, Inner Mongolia, China. Hongrui Road and Bridge Engineering Science and Technology Research Institute, Inner Mongolia, China. "Applications of Artificial Intelligence Enhanced Drones in Distress Pavement, Pothole Detection, and Healthcare Monitoring with Service Delivery". [Revised 7 December 2019; Accepted 30 December 2019; Published 28 January 2020].

[9] Yue Wang1 and Tian Ye, Xi'an Aeronautical Institute, Xi'an, China. Northwestern Polytechnical University, Xi'an, China. Correspondence should be addressed to Tian Ye. "Applications of Artificial Intelligence Enhanced Drones in Distress Pavement, Pothole Detection, and Healthcare Monitoring with Service Delivery". [Received 20 May 2022; Accepted 28 June 2022; Published 10 October 2022]

[10] Chao Wu, Zhen Wang, Simon Hu, Julien Lepine, Xiaoxiang Na, Daniel Ainalis and Marc Stettler; School of Public Affairs, Zhejiang University, Hangzhou 310058, China; College of Software Engineering, Zhejiang University, Hangzhou 310058, China; ZJU-UIUC Institute, School of Civil Engineering, Zhejiang University, Haining 314400, China. Department of Operations and Decision Systems, Université Laval, Quebec City, QC G1V 0A6, Canada; Department of Engineering, University of Cambridge, Trumpington Street, Cambridge CB2 1PZ, UK; Department of Civil and Environmental Engineering, Imperial College London, London SW7 2AZ, UK. "An Automated Machine-Learning Approach for Road Pothole Detection Using Smartphone Sensor Data". [Received: 25 August 2020; Accepted: 22 September 2020; Published: 28 September 2020]

[11] Andrew Fox Member, IEEE, B.V.K. Vijaya Kumar, Fellow, IEEE, Jinzhu Chen, Member, IEEE, and Fan Bai, Fellow, IEEE. "Multi-Lane Pothole Detection from Crowdsourced Under sampled Vehicle Sensor Data" [IEEE TRANSACTIONS ON MOBILE COMPUTING, VOL. 16, NO. 12, DECEMBER 2017]

[12] Yeoh Keng Yik, Nurul Ezaila Alias, Yusmeeraz Yusof and Suhaila Isaak*

[13] Division of Electronic and Computer Engineering and Environmental Engineering,

[14] Faculty of Engineering, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia. " A Real-time Pothole Detection Based on Deep Learning

[15] Approach". [ISAIC 2020 Journal of Physics: Conference Series 1828 (2021) 012001 doi:10.1088/1742-6596/1828/1/012001]

[16] Abhishek Kumar Department of Ele. \& Electronics Engineering Gaya College of Engineering Gaya, Bihar, India; Vibhav Prakash Singh Department of Computer Science and Engineering National Institute of Technology, Allahabad UP, India; Chakrapani Department of Computer Science and Engineering Gaya College of Engineering Gaya, Bihar, India. Dhruba Jyoti Kalita Department of Computer Science and Engineering Gaya College of Engineering Gaya, Bihar, India "A Modern Pothole Detection technique using

Deep Learning" [Authorized licensed use limited to: Parul Institute of Engineering and Technology. Downloaded on February 10,2024 at 17:18:38 UTC from IEEE Xplore.]

[17] I. Moazzam, K. Kamal, S. Mathavan, S. Usman, M. Rahman P, Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC 2013), The Hague, The Netherlands. "Metrology and Visualization of Potholes using the Microsoft Kinect Sensor". [October 6-9, 2013]

[18] Young-Mok Kim, Young-Gil Kim, Seung-Yong Son, Soo-Yeon Lim, Bong-Yeol Choi and Do Hyun Choi, C4ISR Systems Development Quality Team, Defense Agency for Technology and Quality, Daejeon 34327, Korea; Graduate School of Industry, Kyungpook National University, Daegu 41566, Korea; Department of Fine Arts, Kyungpook National University, Daegu 41566, Korea; School of Electronics Engineering, Kyungpook National University, Daegu 41566, Korea. "Review of Recent Automated Pothole-Detection Methods". [Received: 17 April 2022, Accepted: 20 May 2022, Published: 24 May 2022]

[19] Oche Alexander Egaji a, Gareth Evans, Mark Graham Griffiths, Gregory Islas a Centre of Excellence in Mobile and Emerging Technologies (CEMET), Faculty of Computing, Engineering and Science, University of South Wales, Pontypridd UK; Fitzalan Rd, Cardiff, UK "Real-time machine learning-based approach for pothole detection". [Received 18 March 2020; Received in revised form 25 May 2021; Accepted 3 July 2021]

[20] Chao Wu, Zhen Wang, Simon Hu, Julien Lepine, Xiaoxiang Na , Daniel Ainalis and Marc Stettler School of Public Affairs, Zhejiang University, Hangzhou 310058, China; College of Software Engineering, Zhejiang University, Hangzhou 310058, China; ZJU-UIUC Institute, School of Civil Engineering, Zhejiang University, Haining 314400, China; Department of Operations and Decision Systems, Université Laval, Quebec City, QC G1V 0A6, Canada; Department of Engineering, University of Cambridge, Trumpington Street, Cambridge CB2 1PZ, UK; Department of Civil and Environmental Engineering, Imperial College London, London SW7 2AZ, UK. "An Automated Machine-Learning Approach for Road, Pothole Detection Using Smartphone Sensor Data". [Received: 25 August 2020; Accepted: 22 September 2020; Published: 28 September 2020]

[21] Muhammad Haroon Asad, Saran Khaliq, Muhammad Haroon Yousaf, Muhammad Obaid Ullah, and Afaq Ahmad Swarm Robotics Lab, National Centre of Robotics and Automation, Rawalpindi, Pakistan; Department of Computer Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan; Department of Electrical Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan; Department of Civil Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan. "Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective". [Received 10 January 2022; Revised 19 February 2022; Accepted 3 March 2022; Published 20 April 2022]

[22] Khaled R. Ahmed -School of Computing, Southern Illinois University, Carbondale, IL 62901, USA. "Smart Pothole Detection Using Deep Learning Based on Dilated Convolution " [Received: 26 October 2021, Published: 16 December 2021]