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Real-Time Deep Learning Methodology For Pothole Diagnosis

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ABSTRACT

Identifying potholes on roads is extremely important since they can harm people as well as the suspension and wheels of cars. Potholes must be repaired in order to prevent expensive situations when human discomfort is treated and automobile repairs are necessary. Deep learning methods are employed in this work to detect potholes. Using the cameras on smartphones, the input data are gathered as pictures or videos, which are then pre-processed to provide characteristics that aid in the creation of models and prediction. The training data set has a large number of pothole photos. YOLO and CNN are examples of models that are utilized; they are trained using photos of sample potholes so that they can accurately anticipate potholes. Our system will incentivize public servants to locate and fix roads that are broken and contribute to inconvenience and accidents.

KEYWORDS

CNN; YOLO; Pothole Detection; Deep Learning; Feature Training; Machine Learning; Smartphone Camera

1. INTRODUCTION

Traffic containment performance steadily declines when rainy conditions change, putting commuter safety and efficiency at risk. Heavy traffic is often directed onto asphalt-surfaced roads and walkways. Examples of deformed surfaces that cause problems for cars are potholes and fissures. When self-driving cars are implemented, it will be essential to automate the real-time detection of these road damages for the best possible vehicle performance and passenger safety. Effective research has been done on this issue of repairing road damage by knowledgeable and experienced drivers. Recent advances in technology have led to the condensing and integration of powerful sensors, including accelerometers, GPS, and electronic compass, into mobile devices. The simplest and cost-effective method to locate potholes is to have a smart phone with a pothole detection app loaded on it. Potholes are identified in this study by using real-time data collected from mobile devices. Since most pothole identification techniques rely on specialized and costly hardware equipment, they are either less precise or insufficient to locate potholes in the real world.

The goal of this project is to help drivers identify potential hazards by developing a crack and pothole detecting system for self-driving platforms. Utilizing a convolution neural net architecture and the YOLO technique for separation, pothole identification is implemented. From the background, fissures and potholes appeared. In the garbling layer, the road texture is learned in conjunction with spatial data from the classification basis. The principal contributions are as follows: a complex setup that combines texture and spatial learning. Features are important in determining geographical information about categorization failures when views change. Texture features, which preserve coherence across many

viewpoints, are better suitable for the problem. Instead of using a sliding window to directly apply YOLO/CNN to high-resolution images, which makes them unsuitable for real-time operations, pre-processing techniques offer potential candidates for the network to further deconstruct, ensuring a real-time crack and pothole detection channel. An accurate and consistent classifier that reliably distinguishes between shadows, cracks, background noise, and several more cryptic scripts that are difficult to distinguish using traditional methods. The proposed structure is made to be a plug-and-play module which can be added to different types of self-driving cars and autonomous robotics without altering their basic architecture.

We offer an image processing-based approach for spotting potholes. Based on the YOLO technique and convolution neural network frame, the system employs texture-based information to distinguish between potholes and roads. The YOLO algorithm, which can distinguish between roads with fractures and roads without splits while being quicker and more effective than earlier frameworks, is what makes this technique special. Fig. 1 shows the structure of the construction. It is built up of the YOLO algorithm and convolution neural network that uses the images' spatial information to distinguish between different images according to their textures.

1.1 Motivation

Potholes on poorly maintained roadways may indicate structural problems. The drawback of a pothole is that it makes for an uncomfortable ride and damages the car's wheels, which are costly to fix.

Potholes in the road negatively impact fuel economy, motorist safety, and the condition of the roadways. They are a few of the main causes of car accidents. Deep learning algorithms for pothole recognition are compared in this work. Pothole identification is a critical analytical step in developing workable driving and safety solutions.

2. EXISTING SYSTEM

With the current system, potholes are detected using a variety of sensors and actuators that provide us with particular values based on the diameters of the potholes. These sensors have a tendency to deteriorate with use over time and may eventually show to be ineffective. To identify potholes, the current method also makes use of certain satellite photography techniques. Following that, the discovered potholes are taken for the required filling procedure. Additionally, there are alternative techniques that collect information from an accelerometer and gyroscope to determine the vehicle's speed and angles on the road.

3. PROPOSED SYSTEM

The proposed system starts with data collection modules, which gather the data required for system testing and training. Photos and videos are used to construct the pothole dataset. Filters are inserted after the data has been pre-processed to remove any extraneous or noisy information. The collected dataset is used to train the algorithm to make accurate classifications following pre-processing. Here, we're using the YOLO approach—which is faster and more accurate than other frameworks—to categorize data. The dataset is frequently checked for redundancy using the disassembled video frames that were utilized for training and testing prior to the final system being deployed.

The photos are divided into N grids with equal-dimensional $Q \times Q$ sections in order for the YOLO method to function. Each grid has the responsibility of finding and detecting the object. Along with forecasting the item marker and the probability that the object will be in the cell; these grids also provide the B bounding coordinates associated with the object's cell coordinates. Since cells from the image perform both identification and classification, this technique significantly reduces calculation costs because multiple cells anticipate the same object with different bounding box predictions. Non-Minimal repression is used by YOLO to solve this issue.

The dataset was gathered only after extensive testing and training with the testing dataset. The system is configured for pothole identification in a real-time setting after the data has been tested and trained. The Yolo algorithm is employed to differentiate between cracks and potholes.



Fig. 1 Architecture diagram of a Proposed System

4. LITERATURE SURVEY

[1] Kulkarni, A., Mhalgi, N., Gurnani, S., & Giri, N. “Pothole Detection System using Machine Learning on Android”. *International Journal of Emerging Technology and Advanced Engineering (IJETAE)*, 2014 The limited processing capacity of the embedded CPUs in the black-box cameras was taken into account when designing and implementing the proposed pothole-discovery technique. The studies’ findings clearly show that the suggested algorithm can exclude things like moving cars, patches, manholes, and shade. 71% and 88%, respectively, are the averages for perceptivity and perfection accuracy. Consequently, the algorithm helps in locating related items.

[2] Bhatt, U., Mani, S., Xi, E., & Kolter, J. Z. “Intelligent pothole detection and road condition assessment”. *ArXiv*, 2017 The suggested solution in this case is a mobile application that records motion data about an automobile using the phone's accelerometer and gyroscope sensors. In order to assess roads using this detection data, we trained SVM models to diagnose potholes with 90 delicacies and road conditions with 91 delicacies, outperforming the base rate for both tasks. Using the detection data, the algorithms categorize the state of the road and the existence of potholes for the drivers. The bracket findings are also used to build data-rich visuals that show the traffic conditions in the metropolitan area. This technology will enable government workers to identify and repair hazardous roadways that irritate drivers and result in collisions.

[3] Anand, S., Gupta, S., Darbari, V., & Kohli, S. “Crack-pot: Autonomous Road crack and pothole detection”. *Digital Image Computing: Techniques and Applications (DICTA)*, 2018 As autonomous robots and self-driving cars become more common, it's important to recognize road imperfections and take the appropriate safety precautions to keep passengers safe. An algorithm for spotting potholes and cracks in the road can be installed on an autonomous, trustworthy real-time processing board with a camera. To detect splits and voids, the technique combines a deep neural network architecture with textural and spatial clues.

[4] Madli, R., Hebbar, S., Pattar, P., & Golla, V. “Automatic detection and notification of potholes and humps on roads to aid drivers”. *IEEE Sensors Journal*, 2015 This study analyzes previous methods for identifying

potholes that have been created in order to identify speed bumps and potholes on roads and notify drivers in a timely manner so they can avoid accidents or vehicle damage. It also offers a reasonably priced fix. Ultrasonic detectors can identify potholes and bumps and measure their height and depth independently. The suggested method tracks the positions of speed bumps and potholes using a GPS receiver. The tested data, along with the location, pothole depth, and bump height, are contained in the database. Drivers and government authorities can both benefit greatly from this invaluable source of information. An Android app function warns drivers so that safety measures can be taken to prevent collisions. Alerts come with a loud buzzer and flash indication.

[5] **Fox, A., Kumar, B. V. K. V., Chen, J., & Bai, F. "Crowdsourcing under sampled vehicular sensor data for pothole detection". IEEE International Conference on Sensing, Communication, and Networking (SECON), 2015** The growth of integrated car sensors has made it possible to identify road components like potholes. Though a promising approach, current automotive embedded sensors operate under sample sensor data and at low frequency, which reduces detection accuracy. Crowdsourcing this undersaturated sensor data from numerous automobiles is one potential way to improve the detection accuracy. Asynchronous sensor performance, GPS inaccuracy, sensor noise, and vehicle variability make it difficult to combine sensor data from multiple automobiles. Moreover, car networks may have bandwidth restrictions that limit the amount of data that may be combined. We examine these problems by concentrating on the subject of pothole identification. We build and evaluate multiple crowdsourced pothole detection techniques that leverage the Cloud and moving cars to gauge the impact of real-world restrictions and identification accuracy.

[6] **Chai, X., Deng, L., Yang, Q., & Ling, C. X. "Test-cost sensitive naive bayes classification". IEEE International Conference on Data Mining, 2004** The decision tree algorithms and naive Bayes, for instance, have been improved in the past to handle various costs, primarily by determining various costs of classification errors. However, controlling the test expenses related to locating the missing values in a test case also needs to be taken into account. Depending on how much the value could increase the classification accuracy, it might or might not be worth the effort to find a missing value for an attribute when it arises in a test case. Here, we demonstrate how to create a test-cost sensitive naïve Bayes classifier (csNB) by integrating a test strategy that controls the testing of unknown features.

[7] **Jo, Y., & Ryu, S. "Pothole detection system using a black-box camera". MDPI Sensors (Basel, Switzerland), 2015** The machine literacy models for pothole identification are compared in this research. Several Android devices were used to gather the data, and a 2-alternation-overlapping moving window was used for additional pre-processing to determine which statistical characteristics would be most helpful in training a dual classifier. To ensure complete separation from the confirmation and test datasets, the training dataset underwent a stratified-fold cross-validation technique. Both the Random Forest Tree and the KNN produced excellent results on the Test dataset, with a delicacy of 0.8490

that was comparable.

[8] **Wang, H.-W., Chen, C.-H., Cheng, D.-Y., Lin, C.-H., & Lo, C.-C. "A real-time pothole detection approach for intelligent transportation system". Mathematical Problems in Engineering, 2015** Potholes across vast landscapes can be found more cheaply with this technique. This study suggests a mobile device-based approach for pothole identification. The Euler angle computation is used to regularize the accelerometer data and extract the pothole information. Additionally, positional offenses from GPS data are reduced by using the spatial interpolation method. The results of the trials show that the recommended method can detect potholes with accuracy and without producing false positives, while also performing the advanced delicacy. Therefore, the suggested real-time pothole detecting approach can be employed to increase road safety for IT.

[9] **Divya, K., & Pabitha, P. "Analysing the competency of various decision trees towards community formation in multiple social networks". International Conference on Communication and Signal Processing (ICCSP), 2019** On a social network, every user only has a limited representation of themselves. Mapping these people across multiple online social networks is becoming more and more vital to build communities and identify the key node. Fragmentary data is the biggest issue facing social networks today, but it can be solved by grouping people and comparing their data. This data can then be used for a numerous purpose, such as detecting spammers and prominent nodes. Several user features make it possible to distinguish the influential community from other communities. By altering the class labels, different numbers of trees can be built. To effectively develop communities, the tree's performance metrics (accuracy, recall, precision, and f1-score) should be greater.

[10] **Georganos, S., Grippa, T., Gadiaga, A., Vanhuyse, S., Kalogirou, S., Lennert, M., & Linard, C. "An application of geographical random forests for population estimation in Dakar, Senegal using very-high-resolution satellite imagery". Joint Urban Remote Sensing Event (JURSE), 2019** In this work, we investigate the use of Very-High-Resolution Remote Sensing (VHRS) data to anticipate population density using Geographical Random Forest (GRF), a localized implementation of Random Forest (RF). The explanatory features are the ratios of three different built-up kinds in each area, and we use the neighborhood-level population density from the 2013 Dakar census as an independent variable. The results demonstrated that by taking regional variability into account in the estimations and calibrating GRF at an appropriate geographic scale, we could maximize forecast accuracy. The results can also be visualized, demonstrating the efficacy of the local model and other intriguing spatial differences, as GRF is an ensemble of local sub-models. Thus, it is recommended that remotely detected spatially diverse interactions be modelled using GRF as an intriguing exploratory and explanatory tool.

Table.1 Analyzing and contrasting various methods

Title	Pros	Cons
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“Pothole Detection System using Machine Learning on Android”	Through the use of the charting software library "A Chart Engine," which improves accuracy across the board throughput.	Real-time evaluation of raw sensor data is challenging.
“Intelligent pothole detection and road condition assessment”	The implementation of models to generate road condition maps and a real-time mobile application.	The pothole count in the database needs to be updated and maintained on a regular basis.
“Autonomous road crack and pothole detection. Digital Image Computing: Techniques and Applications”	Roads with and without splits are distinguished from one another using their respective surfaces as a foundation.	Lacks the ability to discern the fixed road cracks because it is unknown how deep they are.
“Automatic detection and notification of potholes and humps on roads to aid drivers”	Even when potholes are full of muddy water during the rainy season, this still functions effectively.	The accuracy of the coordinates makes it challenging to retrieve the pothole locations.
“Crowdsourcing under-sampled vehicular sensor data for pothole detection.”	This aids in gathering information from several cars, enhancing the accuracy of the detection.	The accuracy of the GPS decreases due to asynchronous sensor operation, sensor noise, and vehicle heterogeneity.
“Test-cost sensitive naive bayes classification.”	This algorithm aids in the resolution of misclassification issues and lowers test expenses.	Disregards the missing data if they cause a mistaken classification.
“Pothole detection system using a black box camera”	The device uses black box cameras to find potholes across a larger area and at a reduced cost.	Understanding and executing mathematical procedures can be challenging.
“A real-time pothole detection approach for intelligent transportation system. Mathematical Problems in Engineering.”	GPS data location inaccuracies are removed using the spatial interpolation approach.	The resources and computational power are expensive.
“Analyzing the competency of various decision trees towards community formation in multiple social networks”	Used to divide various social network communities into separate groups.	The model forecasts a sensation of randomness based on information gathered from social communities.
“An application of geographical random forests for population estimation in Dakar, Senegal using very high-resolution satellite imagery.”	RF aids in increasing precision.	Resources & computational power are expensive.

The literature review on the application of the deep learning

YOLO algorithm for pothole detection has brought attention to the potential of deep learning algorithms for precise real-time pothole detection. However, the small and homogeneous dataset, high processing overhead, and restricted use in practical situations are some of the issues that afflict the current systems. To address these issues, the proposed system makes use of an extensive and diverse dataset, an optimized architecture, real-time feedback and updating techniques, and other techniques to improve the precision, reliability, and efficiency of pothole detecting systems. This method could dramatically increase road safety and lower pothole damage expenses with additional study and development.

5. PERFORMANCE ANALYSIS

Performance analysis for pothole detection using deep learning involves evaluating the accuracy, precision, recall, and false positive/negative rates of the system. It can help fine tune the system's parameters and optimize its overall performance, identifying areas for improvement and ensuring its effectiveness and efficiency.

The performance analysis of YOLO algorithm is displayed through various comparisons between different other algorithms. The fig. 2 displays the performance of the YOLO algorithm in pothole detection module.

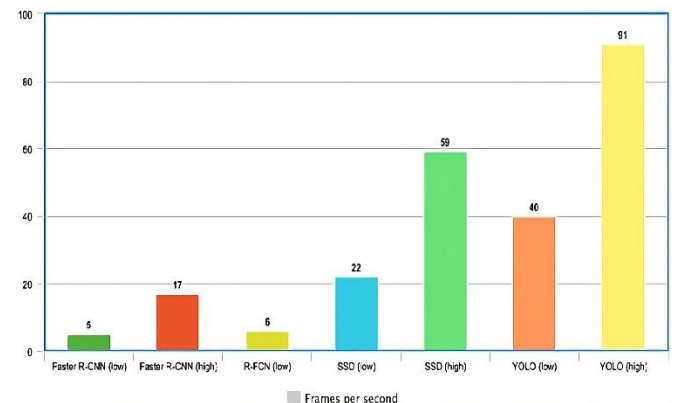


Fig. 2 Accuracy analysis of various Algorithms

The performance analysis of the pothole detection system based on the accuracy of the system is shown in the figure 3. The system put under rigorous testing and is trained according to the real time environment requirements. These analyses were done based on the test cases. The system has been able to perform well under day light condition compared to the low light conditions. The graph shows how accurate is the system in predicting the potholes. YOLO showed the highest mAP@0.5 of 95% with an inference time of 10 ms per image.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (1)$$

Where,

AP_k : the Average Precision of class k

n : the number of classes

The mAP is used as a standard metric to analyze the accuracy of an object detection model.

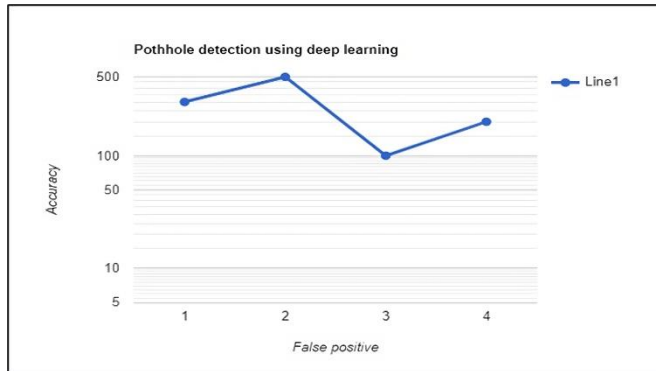


Fig. 3 Accuracy analysis of Pothole detection module

6. CONCLUSION

This study compares and contrasts deep learning algorithms for spotting potholes. The data is initially gathered as photographs from a mobile device, pre-processed to remove the unnecessary statistical information, and processed for developing a classifier. There are enough images of potholes in the training data set. It uses a model like YOLO or CNN that have been extremely accurately trained using sample photographs of potholes to forecast potholes. Our solution will give local officials the ability to locate and fix the damaged roads that inconvenience travellers and result in accidents. This system is straightforward to use and offers accurate information. Pothole detection using deep learning has the potential to revolutionize road maintenance and improve road safety. With the increasing availability of high-resolution images and videos from sources such as drones and dashcams, there is a vast amount of data that can be used to train and fine-tune deep learning algorithms for pothole detection. Through the use of convolutional neural networks (CNNs) and other deep learning techniques, the accuracy and efficiency of pothole detection systems can be greatly improved.

7. FUTURE DIRECTIONS

Increasing the speed and effectiveness of object detection models is one possible area of improvement. Even while a lot of the models used today are very accurate, they can be time-consuming and computationally expensive, particularly for real-time applications. Subsequent studies may concentrate on creating models that are more accurate while remaining lighter and more efficient.

Increasing the object detection models' resilience is another possible area of growth. Present-day models frequently rely heavily on the data and have trouble generalizing to novel and diverse situations. Subsequent investigations may concentrate on creating more flexible and adaptive models that may function effectively even in extremely dynamic and changing settings.

Integrating object detection models with other models and

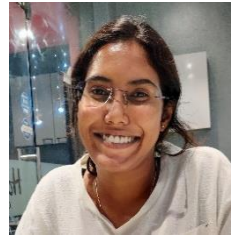
technologies, such augmented reality or natural language processing, is yet another possible field of study. More complex and potent applications to comprehend and engage with the world in novel and interesting ways might be able to be made by fusing object detection with other technologies.

REFERENCES

- Kulkarni, A., Mhalgi, N., Gurmani, S., & Giri, N. (2014). Pothole Detection System using Machine Learning on Android. <https://api.semanticscholar.org/CorpusID:14429117>
- Bhatt, U., Mani, S., Xi, E., & Kolter, J. Z. (2017). Intelligent pothole detection and road condition assessment. ArXiv Preprint ArXiv:1710.02595. <https://doi.org/10.48550/arXiv.1710.02595>
- Anand, S., Gupta, S., Darbari, V., & Kohli, S. (2018). Crack-pot: Autonomous Road crack and pothole detection. Digital Image Computing: Techniques and Applications (DICTA), 1–6. <https://doi.org/10.1109/DICTA.2018.8615819>
- R. Madli, S. Hebbar, P. Pattar and V. Golla. (2015). Automatic Detection and Notification of Potholes and Humps on Roads to Aid Drivers. IEEE Sensors Journal, 15(8), 4313-4318. <https://doi.org/10.1109/JSEN.2015.2417579>
- A. Fox, B. V. K. V. Kumar, J. Chen and F. Bai. (2015). Crowdsourcing undersampled vehicular sensor data for pothole detection. IEEE International Conference on Sensing, Communication, and Networking (SECON), 515-523. <https://doi.org/10.1109/SAHCN.2015.7338353>
- Xiaoyong Chai, Lin Deng, Qiang Yang and C. X. Ling. (2004). Test-cost sensitive naive Bayes classification. IEEE International Conference on Data Mining (ICDM'04), 51-58. <https://doi.org/10.1109/ICDM.2004.10092>
- Jo, Y., & Ryu, S. (2015). Pothole detection system using a black-box camera. Sensors, 15(11), 29316–29331. <https://doi.org/10.3390/s151129316>
- Wang, H.-W., Chen, C.-H., Cheng, D.-Y., Lin, C.-H., & Lo, C.-C. (2015). A real-time pothole detection approach for intelligent transportation system. Mathematical Problems in Engineering. <https://doi.org/10.1155/2015/869627>
- K. Divya, P. M. and P. Pabitha. (2019). Analysing the Competency of Various Decision Trees towards Community Formation in Multiple Social Networks. International Conference on Communication and Signal Processing (ICCCSP), 0099-0103. <https://doi.org/10.1109/ICCCSP.2019.8698110>
- Georganos, S., Grippa, T., Gadiaga, A., Vanhuysse, S., Kalogirou, S., Lennert, M., & Linard, C. (2019). An application of geographical random forests for population estimation in Dakar, Senegal using very-high-resolution satellite imagery. Joint Urban Remote Sensing Event (JURSE), 1–4. <https://doi.org/10.1109/JURSE.2019.8809049>
- Asphalt Industry Alliance. (2019). Annual Local Authority Road Maintenance (ALARM) Survey. Asphalt Industry Alliance. <https://www.asphaltuk.org/wp-content/uploads/alarm-survey-2019-digital.pdf>
- Okfalisa, I. Gazalba, Mustakim and N. G. I. Reza. (2017). Comparative analysis of k-nearest neighbor and modified k-nearest neighbor algorithm for data classification. International conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE), 294-298. <https://doi.org/10.1109/ICITISEE.2017.8285514>
- Jones, S. (2018). Britain's potential cyclists put off cycling due to traffic conditions and potholes [Cycling UK]. Cycling UK. <https://www.cyclinguk.org/article/why-and-how-do-roads-need-be-better-maintained-cyclists>
- Ouma, Y. O., & Hahn, M. (2017). Pothole detection on asphalt pavements from 2D-colour pothole images using fuzzy c-means clustering and morphological reconstruction. <https://doi.org/10.1016/j.autcon.2017.08.017>
- RAC Business. (2016). Potholes and congestion top Brit bosses' business bugbears [Royal Automobile Club]. RAC. <https://media.rac.co.uk/pressreleases/potholes-and-congestion-top-brit-bosses-business-bugbears-1442185>
- Y. Pan, X. Zhang, G. Cervone and L. Yang. (2018). Detection of Asphalt Pavement Potholes and Cracks Based on the Unmanned Aerial Vehicle Multispectral Imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(10), 3701-3712. <https://doi.org/10.1109/JSTARS.2018.2865528>
- D. A. Jordan, S. Paine, A. K. Mishra and J. Pidanic. (2023). Road to

- Repair (R2R): An Afrocentric Sensor-Based Solution to Enhanced Road Maintenance. IEEE Access, 11, 6010-6017.
<https://doi.org/10.1109/ACCESS.2023.3236401>
18. G. Arvanitis, N. Stagakis, E. I. Zacharaki and K. Moustakas. (2023). Cooperative Saliency-Based Pothole Detection and AR Rendering for Increased Situational Awareness. IEEE Transactions on Intelligent Transportation Systems, 25(5), 3588-3604.
<https://doi.org/10.1109/TITS.2023.3327494>
 19. Patwar, Atharv & Mehdi, Mohammed & Kore, Bhaumik & Saval, Pradnya. (2024). A Pothole Can Be Seen with Two Eyes: An Ensemble Approach to Pothole Detection. 10.21203/rs.3.rs-4262204/v1.
<https://doi.org/10.21203/rs.3.rs-4262204/v1>
 20. B. -h. Kang and S. -i. Choi. (2017). Pothole detection system using 2D LiDAR and camera. International Conference on Ubiquitous and Future Networks (ICUFN), 744-746.
<https://doi.org/10.1109/ICUFN.2017.7993890>
 21. M. Sathvik, G. Saranya and S. Karpagaselvi. (2022). An Intelligent Convolutional Neural Network based Potholes Detection using Yolo-V7. International Conference on Automation, Computing and Renewable Systems (ICACRS), 813-819.
<https://doi.org/10.1109/ICACRS55517.2022.10029263>
 22. J. Hong, Y. Jung and K. S. Woo. (2023). Image Data Augmentation and Detection Study for Pothole Detection Algorithm. IEEE International Conference on Big Data (BigData), 6162-6164.
<https://doi.org/10.1109/BigData59044.2023.10386900>
 23. E. S. T. K. Reddy and R. V. (2022). Pothole Detection using CNN and YOLO v7 Algorithm. International Conference on Electronics, Communication and Aerospace Technology, 1255-1260.
<https://doi.org/10.1109/ICECA55336.2022.10009324>
 24. B. K. S B, G. S, M. Kishore, S. R and A. D. J. (2023). Real-time Pothole Detection using YOLOv5 Algorithm: A Feasible Approach for Intelligent Transportation Systems. International Conference on Electronics and Renewable Systems (ICEARS), 1678-1683.
<https://doi.org/10.1109/ICEARS56392.2023.10085336>
 25. Ruchi, S. Indu and R. Kumar. (2022). Detection of Road Potholes Using Deep Learning Based Improved YOLOv4 Network. IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 1-6.
<https://doi.org/10.1109/SOLI57430.2022.10294799>
 26. K. K. Sai, D. D. V. Kumar, A. Sahrudhay and K. Dharavath. (2023). Pothole Detection Using Deep Learning. 2nd International Conference on Futuristic Technologies (INCOFT), 1-6.
<https://doi.org/10.1109/INCOFT60753.2023.10425461>
 27. A. Tithi, F. Ali and S. Azrof. (2012). Speed Bump & Pothole Detection with Single Shot MultiBox Detector Algorithm & Speed Control for Autonomous Vehicle. International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), 1-5.
<https://doi.org/10.1109/ACMI53878.2021.9528185>
 28. T. B. S. V. Pavan, R. H, P. J and V. N. Hegde. (2023). Realtime Detection of Humps and Potholes. International Conference on Smart Systems for applications in Electrical Sciences (ICSSES), 1-6.
<https://doi.org/10.1109/ICSSES58299.2023.10200400>
 29. K. M. Jobayer Al Masud, S. T. Sharin, K. F. T. Shawon and Z. Zaman. (2021). Pothole Detection Using Machine Learning Algorithms. International Conference on Signal Processing and Communication Systems (ICSPCS), 1-5.
<https://doi.org/10.1109/ICSPCS53099.2021.9660216>
 30. K. S B, G. S, M. Kishore, S. R and A. D. J. (2023). Real-time Pothole Detection using YOLOv5 Algorithm: A Feasible Approach for Intelligent Transportation Systems. International Conference on Electronics and Renewable Systems (ICEARS), 1678-1683.
<https://doi.org/10.1109/ICEARS56392.2023.10085336>
 31. V. E. Jesi, J. M. L, S. Saranya, P. C, M. T. A and K. Saranya. (2023). Advancements in Sensor Technology and Computer Vision for Enhanced Road Safety and Anomaly Detection using Machine Learning Approach. International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS), 457-462.
<https://doi.org/10.1109/ICUIS60567.2023.00081>
 32. J. M. C. Manalo, A. S. Alon, Y. D. Austria, N. E. Merencilla, M. A. Misola and R. C. Sandil. (2022). A Transfer Learning-Based System of Pothole Detection in Roads through Deep Convolutional Neural Networks. International Conference on Decision Aid Sciences and Applications (DASA), 1469-1473.
<https://doi.org/10.1109/DASA54658.2022.9765227>
 33. Rasyid et al., (2019). Pothole Visual Detection using Machine Learning Method integrated with Internet of Thing Video Streaming Platform. International Electronics Symposium (IES), 672-675.
<https://doi.org/10.1109/ELECSYM.2019.8901626>
 34. R. Agrawal, Y. Chhadva, S. Addagarla and S. Chaudhari. (2021). Road Surface Classification and Subsequent Pothole Detection Using Deep Learning. International Conference for Emerging Technology (INCET), 1-6.
<https://doi.org/10.1109/INCET51464.2021.9456126>
 35. Saluky, Y. Marine, A. Zaeni, A. Yuliati, O. R. Riyanto and N. Bahiyah. (2023). Pothole Detection on Urban Roads Using YOLOv8. International Conference on ICT for Smart Society (ICISS), 1-6.
<https://doi.org/10.1109/ICISS59129.2023.10291192>
 36. A. Parmar, R. Gaiar and N. Gajjar. (2023). Drone based Potholes detection using Machine Learning on various Edge AI devices in Real-Time. IEEE International Symposium on Smart Electronic Systems (iSES), 22-26.
<https://doi.org/10.1109/iSES58672.2023.00016>

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