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Pothole and Road Hump Detection Using YOLO model

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Abstract:

Every single one of the cars on the road, whether they're fully autonomous or not, relies on the state of the roads to return safely. Tire wear and deadly traffic accidents are both caused by surface abnormalities like speed bumps and potholes. Thus, it is helpful to detect and characterize these abnormalities in order to lessen the likelihood of accidents and vehicle damage. It is more difficult to discover street anomalies in street photographs because of their inherent multivariate nature, which includes redundant and extensive information in addition to much tainted measurement noise. In this study, we offer a YOLO-based automatic color picture analysis system for road pothole detection using mobile camera snaps. A lightweight architecture was created to expedite both the training and usage processes. Each of the seven layers is appropriately aligned and responsive to one another. A pixel-for-pixel reproduction of the original image is achieved. In an effort to gather as much data as possible, the conventional stride and pooling operations were administered. That makes the model we made better at spotting potholes and warning drivers to be extra careful.

Keywords: Street anomalies, deep neural network, synchronized layers, Pothole detection, YOLO Neural network.

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I. INTRODUCTION

In Mexico, road surface irregularities are a leading cause of accidents and vehicle breakdowns. More than 12,000 traffic incidents took place across the nation in 2018, with road conditions being the second most common cause, at 13.9%, behind drivers themselves. A hospital worker in Mexico City's La Conchita area slipped into an unmarked, deep trench in April 2023. So, both autonomous and manual vehicles would benefit from early anomaly identification because it would make driving easier and less dangerous, leading to fewer accidents and less financial and human losses. The scientific and technical community throughout the world has come up with a plethora of approaches to identify suspicious activity on roads. These include systems that employ image processing, systems that use accelerometers and GPS sensors found in smartphones (e.g., in), and many more. Some of these systems also incorporate corporate AI approaches into detection, including deep learning and supervised machine learning. We are currently focusing on improving our ability to recognize road abnormalities like speedbumps and potholes for use in autonomous passenger cars.

With accelerometers, you can be very sure that a bump or pothole has been detected even after the vehicle has driven over it. It is more challenging to utilize this sensor to anticipate the presence of a speed bump or pothole without access to an online database that is regularly updated.

[1] In their description of the state-of-the-art deep learning models for real-time pothole detection, Muhammad Haroon Asad et al. detail the YOLO family and SSD-mobilenetv2, two models that are geared towards deployment on edge devices.

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Despite outperforming other models, YOLOv5 shows signs of misclassification and fails to detect potholes at long distances, even though its mAP@0.5 is 95%. Based on the results, the author has determined that YOLOv4 is the most accurate pothole detection model, and that Tiny-YOLOv4 is the most effective real-time pothole detection model, achieving a 90% detection accuracy and 31.76 FPS. Future adjustments and extensions to the real-time deployment can potentially address the accuracy restrictions as well.

[2] In their analysis and description of the three kinds of automated pothole detection, Young-Mok Kim et al. outlined the most recent research methodologies for each. Also included are summaries of the procedures and findings from recent automated pothole-detection studies that utilized each approach. Methods based on visual perception rely heavily on feature extraction, as well as training and assessment. In order to extract features, those methods employ image processing technologies like SIFT and edge detection. Both the training and testing phases of those approaches make use of deep-learning technologies including SVM, CNN, and YOLO. There are typically three stages to vibration-based methods: data preparation, feature extraction, and classification. In order to prepare the data for feature extraction, signal-processing methods like filtering, Fourier transform, and correlation are utilized. Classification makes use of machine learning methods like k-nearest neighbor, linear regression, and random forest. The approaches offered in this study are based on 3D reconstruction and cover topics including data processing, training, and testing. Those approaches use deep learning and signal processing tools like filtering, principal component analysis, and a tweaked U-Net. Research trends in the future are expected to revolve around the development and application of these common indicators. The author has future plans to include a public pothole dataset into an edge device that can identify potholes in real-time. The author intends to conduct an accuracy evaluation using standard indicators for the established system in order to ensure the research is objective.

[3] A road surface 3-D reconstruction and pothole detection system that is efficient is described by Rui Fan et al. using stereo vision. The author initially made the PT technique more broad by factoring in the stereo rig roll angle while estimating PT parameters. The potholes are now easily identifiable from the smooth road thanks to DT. SLIC assembled a set of super pixels from which the modified discrepancies were extracted. Finding the super pixels—pixels with values lower than an adaptive threshold set using k-means clustering—finally allowed us to discover the potholes' author. On a GeForce RTX 2080 Ti GPU, the suggested pothole detecting algorithm was executed using CUDA. The trial findings showed that the author's system can achieve a 98.7 percent success rate and an F-score of 89.4 percent. This is because it can correctly identify objects that are not moving as they should. Consequently, the author intends to develop an algorithm in subsequent works to partition the rebuilt road surface into distinct planar patches, which can thereafter be treated independently utilizing the said algorithm.

Section 2 In this study provides a literature review of pertinent works; Section 3 Detail the methodology used in the study; Section 4 Analyzes the results of the experiments; and Section 5 ends by outlining potential areas for future research.

II. LITERATURE SURVEY

[4] As Sneh Kurhade et al. describe, routine The author encounters significant difficulty on highways due to humps and potholes. Since roads are a primary means of mobility for the majority of people, the author cannot afford to gloss over this crucial issue. Furthermore, the author is still utilizing tar-roads, which are prone to damage from either heavy rainfall or the screeching of tires, or both. The author's day could be ruined, major injuries or even death could result from accidents and roller coasters caused by screwed up roadways. With this in mind, the author suggests a method to construct a gadget that, when installed in a vehicle, might identify any obstruction, undulating surface, pothole, or broken section of road.

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[5] Amel ali alhussan et al. detail their innovative method for differentiating between smooth roads and those with potholes. In order to extract high-level characteristics from the input image, the suggested method relies on using the deep network ResNet-50. Binarized dip-throat optimization is also used to pick the important features. Conversely, an efficient SMOTE technique is suggested for balancing the dataset. In addition, the characteristics that were chosen for classification are processed by the random forest classifier. In order to get the most performance out of this classifier, the continuous dip-throated optimization approach is used. The suggested method is further evaluated for stability and efficiency using statistical analysis. It became clear from the outcomes that the suggested method was the best and most efficient.

[6] Acceleration sensors, according to Dong Chen et al., could be mounted on the vehicle's wheel steering lever and would record structural vibrations produced by the wheels' impact with the road. Through the Internet of Things (IoT), a suite of fast reflectometry methods for road quality is formed by fusing real-time analysis with Spatio-temporal data, and amplitude intensity analysis at 60-90 Hz frequency is utilized to determine the road roughness. A collection of road defect information maps with a real-time resolution are produced by the cumulative analysis of aberrant trajectory data on the server-side, using author web-GIS. You can discretize and multiscale the geospatial with the help of this class of GeoSOT-based algorithms, which stand for GEOgraphical coordinates Subdividing grid with one-dimensional integral coding on 2n-tree. Beidou Grid Code will also reach maturity in the future, joining Google Plus Code. It will be able to express all observation data obtained from sensor author web and remote sensing methods. This will provide great room for improvement in the system of geospatial observation in terms of cost, power consumption, and computational pressure.

[7] This article proposes a pothole detecting system that has been trained for 5000 epochs using the YOLOX model, as explained by Mohan Prakash B et al. In addition to visualizing all parameters, we compute the model's mean precision, average precision, and average recall. Images of potholes of varying shapes and sizes, as well as multiple potholes, are included in the dataset utilized to train the model. The YOLOX-nano model was trained using this pothole dataset, and it was then compared to other YOLO models. We employ the author's trained model in comparison to four other models: two for YOLOv3 (YOLOv3-tiny) and two for YOLOv4 (YOLOv4-tiny), two for YOLOv5 (YOLOv5s and YOLOv5m), and two for YOLOR (YOLOR-W6 and YOLOR-P6). The results demonstrate that out of all the models tested, the YOLOX-nano model provides the most accurate predictions. With an Average Precision of 85.6%, the model outperformed the YOLOv5m model by 24.06%. A real-time dashboard camera might potentially incorporate the technology down the road. When a pothole is identified by the dashboard module, the system can be triggered with a GPS module that will indicate the coordinates. When repair crews arrive at the scene of the accident, they can utilize the coordinates to pinpoint exactly where the potholes are. Training the algorithm on a specialized dataset using photos from the vehicle's dashboard view can also increase accuracy.

[8] The variety of studies included in this review, which Smita Prajapati et al. presented overall, shows how the Internet of Things (IoT) has the potential to revolutionize road maintenance, traffic safety, and pothole identification. Each research looked at a different angle, with the overarching goal of pushing technologies that use the Internet of Things to detect road anomalies like potholes. There has been a sea change in the approach to monitoring and maintaining road infrastructure with the advent of technologies that are enabled by the Internet of Things. Using cooperative information sharing, real-time data processing, sensor integration, and machine learning algorithms, new approaches to fixing road hazards like speed bumps and potholes have emerged. The model can detect potholes and logs their positions and depths in an internal database. In order to identify areas prone to

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accident occurrence, it additionally analyzes road imperfections. A higher-resolution camera is required for live detection, however it is possible to accomplish it via image processing. More improvements are on the way, including an API for government access, improved bump and pothole detection, and machine learning for adaptive classification.

[9] What A. Lincy et al. states is Road safety is greatly compromised by potholes. In wet and cloudy weather, it becomes difficult to see and identify potholes. The YOLO V7 algorithm was used to construct the pothole detection system in this paper. Since YOLO's 45 FPS processing speed is its most appealing feature, opting to employ YOLO V7 was a brilliant move. The concept of generalized object representation is also known to YOLO. Among the top object detection algorithms, it achieves real-time processing speeds and complexities on par with convolutional neural network (CNN) techniques. A 94.5% success rate with less computing time was achieved using YOLOv7-based pothole detection, which supports its use in real-time.

[10] A pothole monitoring and mapping system, developed by Sanskar Jindal et al., is considered essential for reducing traffic accidents and improving road quality in the author's country, both of which contribute to faster growth. The most effective algorithm for pothole identification is the YOLO family approach, which has been tested in versions 4, 5, and 7 and is available to the public. Versions 5 and 7 were nearly identical in this system; however, version 5 was selected for pothole detection since it featured the Tflite module, making it the best fit for both the system and the user. For this system, Version 4 was rejected due to its relatively low accuracy score. Because of its great accuracy, performance, and author's ability to export into Android applications using Tflite, YOLOv5 is the optimal algorithm for pothole identification. The YOLOv5 project model was trained on 70% of the dataset photos and then created. With an accuracy of 0.73 and a recall of 0.62, the model managed to attain a mAP of 0.73.

[11] The method developed by Gerasimos Arvanitis et al. uses LiDAR data in conjunction with driving patterns to detect obstructions on the route. With the author's method, linked vehicles may exchange data, so drivers can be warned of impending potholes even when they can't see them coming. Thanks to this cooperative driving strategy, drivers are more aware of their surroundings and less likely to be involved in accidents caused by unforeseen impediments. The author's method has difficulties due to the absence of benchmark datasets derived from LiDAR sensors, as it relies on analyzing point clouds. As a workaround, the author supplemented the CARLA simulator's maps with the author's own synthetic dataset, making for more lifelike driving experiences. When tested against other cutting-edge methods for accurate pothole recognition in real datasets, the author's method performed well and produced encouraging results. It is possible to broaden the scope of the author's proposed method to include road debris, uneven surfaces, and potholes. The author is able to identify these dangers and give drivers comparable augmented reality graphics by employing the same LiDAR sensor technologies.

[12] In their description of the possibilities of YOLOv8 models for pothole identification, Siddharth Sasane et al. offer a system design that integrates YOLOv8 models with a GUI to simplify the process and give a user-friendly interface for effective pothole detection and reporting. One approach that shows great promise for traffic hazard detection is the YOLOv8 model, and more specifically, the Nano form. It achieves a remarkable balancing act between precision, speed, and resource efficiency, making significant advancements in road safety and infrastructure maintenance. In addition to advancing our understanding of road hazards, this study paves the way for more efficient and secure maintenance of road infrastructure. Possible future projects could involve working with local governments to put the YOLOv8-based system into action. In order to determine its viability, scalability, and compatibility with current urban infrastructure management

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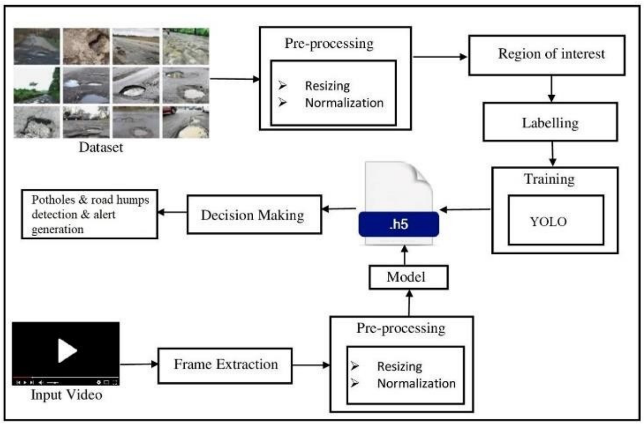
systems, pilot projects may be necessary. In doing so, the study does double duty: it further establishes the YOLOv8 model as a technical marvel and helps smart city efforts progress, which in turn promises a more secure and resilient urban environment.

[13] According to Shafi Ullah Adid et al., potholes pose a significant threat to the infrastructure and economy of Bangladesh. The enormous national road network cannot be adequately managed using conventional pothole detection systems, which frequently rely on human inspection. Using deep learning techniques, this work mainly aims to detect potholes on roadways in Bangladesh. Following our curation of the pothole dataset, which includes photographs taken by us, two other datasets were created: one for pothole detection, which has 1300 images, and another for pothole classification, which contains 6000 images. Motion blur reduction and optical distortion correction are part of the preprocessing technique that aims to improve the datasets' diversity. Various cutting-edge deep learning models are utilized in the author's methodology. These models include: EfficientNetB0, InceptionResNetV2, ResNet101, ResNet50, VGG16, DenseNet201, DenseNet169, MobileNetV2, InceptionResNetV2, and a combination of CNN and ResNet101. A remarkable 97.89% accuracy is displayed by the CNN and ResNet101 combination. YoloV7 achieved an impressive 0.709 accuracy while YoloV8 achieved 0.959 accuracy in pothole detecting assignments.

[14] Abeer Aljohani et al. suggested a CNN-RF-PSO combo. At its foundation, the suggested approach employs a four-layer convolutional neural network (CNN) for feature extraction and feature maps. Optimal RF with PSO is deployed for pothole detection at the end. The experimental results show that the suggested hybrid technique for pothole identification achieves an accuracy, precision, sensitivity, and F1-score of 99.37%. When compared to standalone DL models like DenseNet and ML models like XGB, the suggested approach achieved superior performance. The suggested solution outperformed competing alternatives in terms of sensitivity and accuracy when it came to detecting potholes. For an image with a resolution of 1080 x 720 pixels and an NVIDIA® T4 GPU, the estimated time required to evaluate the model is 0.02 seconds. The author plans to look into using a mix of more varied metaheuristics algorithms as optimizers for pothole detection, as well as testing various types of convolutional layers for feature extraction.

[15] According to Rahul Dhingra et al., CNNs, YOLO, SSD, and HOG are the best object detection algorithms currently available, hence they recommend using these to train your models. The author used HOG and CNNs to build two models, one for each of the pre-existing models (YOLO and SSD). After considering all of the models, YOLO achieved the highest accuracy rate of 82% in solving this specific problem. The author noted that the accuracy improved in direct correlation with the amount of data used to train the model, suggesting that the author was severely lacking in data for all of the models. Further improvement in accuracy is possible. The author was able to reach an accuracy of 82% despite the little dataset.

METHODOLOGY



Step 1: YOLO V8 Pothole Image Training — Using the image, the system is able to successfully identify the pothole. Locating the image's pothole is the first step in the process of warning generation. The pothole recognition module uses the Yolov8

approach to successfully identify potholes. This model needs to be trained before it can be used to detect potholes. The initial stages of training include downloading the roboflow dataset and installing the ultralytics for the Yolov8 model. To obtain the pothole recognition dataset, visit https://public.roboflow.com/object-detection/pothole and then connect Roboflow to your API key. Efficiently retrieves the directory's file list by scanning the downloaded dataset. The next step is to use the file list to get the directory's file count. There will be a total of 465 files utilized for training. The 46 files are moved to the new location in a jumbled state after being sorted alphabetically. A new count of the directory's files shows 419 in the training directory and 179 in the other.

Once you have incorporated the roboflow data and effectively shuffled the potholes dataset, we can begin training the yolov8 model for the yolo item detection task. The training set for the detection model consists of 200 epochs with a batch size of 32 and a picture size of 640. Once the yolov8 model has been trained, the project runs are saved in the specified location as a zip file.

The YOLOv8 is a variation of Convolutional Neural Networks (CNNs). Utilizing the components of the CNN technique in a novel and efficient way, it accomplishes object recognition with enhanced accuracy. Yolo employs a max pooling layer, many batch and dropout normalizations, 24 parameter convolutional layers, and other techniques to regularize the model and avoid overfitting. The model is completed by two fully connected layers. After the initial convolutional layers decompose and decrease the channels, they are max-pooled with a 2x2 kernel and a stride of 2. Max pooling is applied uniformly across all levels of the model. The increasing data load is managed by increasing the kernel sizes of subsequent convolutional layers. The ReLU activation function is utilized in this layer architecture. Every layer's activation function is identical except for the fully linked layers. These layers create Yolo8's trained data file, the.pt file, using a linear activation function. Next, we'll use this.pt file to let you know if there's a pothole. The road humps dataset, which can be found at https://universe.roboflow.com/detection-system/humps-bumps-potholes-detection/dataset/8, is likewise processed using the identical method. You can find information regarding the Yolov8 model in Table 2.

S. no	Layer Type	Parameters
1	Convolutional Layer	7x7x64 Stride-2
2	Maxpool Layer	2x2 Stride 2
3	Convolutional Layer	3x3x192
4	Maxpool Layer	2x2 Stride 2
5	Convolutional Layer	1x1x128
6	Convolutional Layer	3x3x256
7	Convolutional Layer	1x1x256
8	Convolutional Layer	3x3x512
9	Maxpool Layer	2x2 Stride 2
10	Convolutional Layer	1x1x256
11	Convolutional Layer	3x3x512
12	Convolutional Layer	1x1x256
13	Convolutional Layer	3x3x512
14	Convolutional Layer	1x1x256
15	Convolutional Layer	3x3x512
16	Convolutional Layer	1x1x256
17	Convolutional Layer	3x3x512
18	Convolutional Layer	1x1x512
19	Convolutional Layer	3x3x1024
20	Maxpool Layer	2x2 Stride 2
21	Convolutional Layer	1x1x512
22	Convolutional Layer	3x3x1024
23	Convolutional Layer	1x1x512
24	Convolutional Layer	3x3x1024
25	Convolutional Layer	3x3x1024
26	Convolutional Layer	3x3x1024 Stride 2
27	Convolutional Layer	3x3x1024
28	Convolutional Layer	3x3x1024
29	Fully Connected Layer	
30	Fully Connected Layer	

Table 2: Model Summary for YOLOv8

Step 2: Testing the model for pothole: In this case, we're feeding the pothole with video input and extracting frames to feed in real-time. We apply the trained model file.pt to the live streaming frames in order to locate the pothole. This file provides us with the rectangular coordinates of their top left corners. From here, we can observe the stability of the frames being checked, as well as the red and white markings of road humps and potholes. It may be inferred from the confidence values that red potholes are more extensive and white potholes are shallower.

The frame extraction and processing process can be improved by using the queue and the sequence through H net model as stated in [16] by shubham gade et al. In [16] Hungarian net model is being used to sequence the EV charging process, This model can be efficiently used to manage the frames to detect road humps and pot holes efficiently.

III. RESULTS AND DISCUSSION

The proposed method for Pothole and Road hump detection using YOLO model.was developed using the Anaconda framework, Python, and the Spyder IDE. The development computer has 1 terabyte of secondary memory and 8

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gigabytes of main RAM. A number of factors have been considered in order to determine how feasible the proposed plan is. In this part, we detail the results of the experimental study.

Figure 3 shows the results of the human dataset training in terms of accuracy and loss.

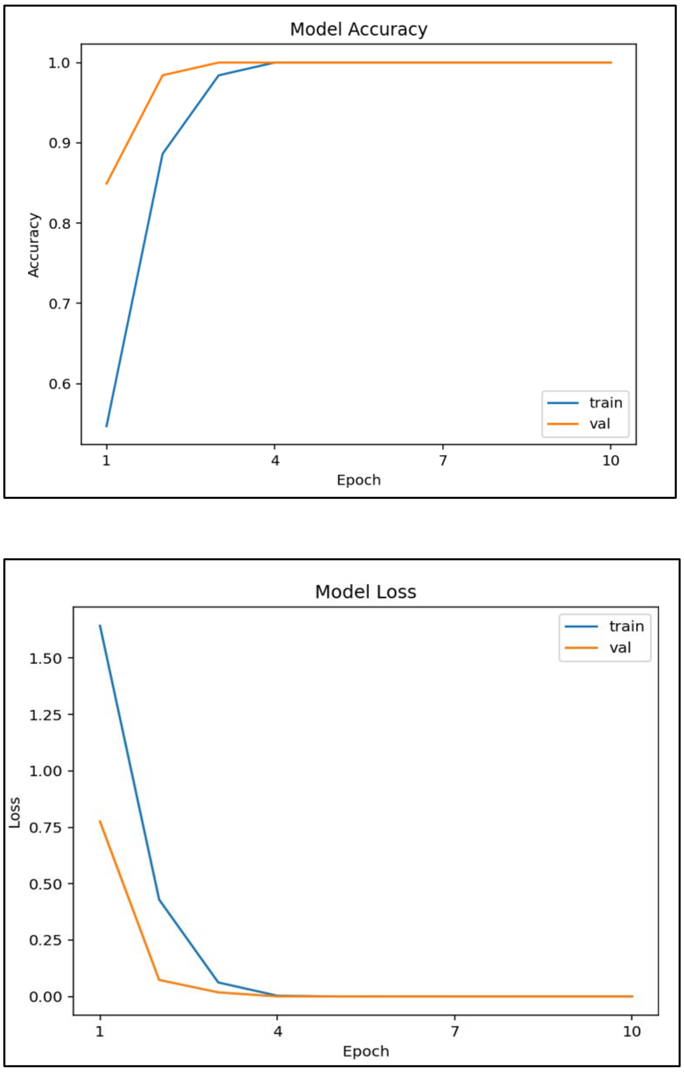

Figure 3: Accuracy and loss for X-CNN

Figure 4: Obtained results for pothole detection

Figure 5: Obtained results for Road humps detection

Figures 3 and 4 show the graphs that were produced, which show that the system is getting a recall of 93% and a precision of almost 100%. This means that the model is being used in the best way possible to detect road humps and potholes.

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IV. CONCLUSION AND FUTURE SCOPE

The realization of the input dataset is the initial step in training the YOLO model. The dataset will be subject to a shuffling procedure after its construction. The YOLO module applies resizing and normalization to the input photos in order to speed up the neural network model training process. It is possible to extract potholes from preprocessed photos by using them to identify possible regions of interest that can be labeled. We will efficiently tag the images with the regions of interest before giving them to the model for training. To effectively identify road humps and potholes, training is conducted on the YOLO network and testing is carried out using real-time input footage. Road humps and less dense potholes are shown in red, while less dense potholes and road humps are shown in white. This helps to distinguish between the two.

Surveillance cars will be a part of the system's future extension, enabling accurate autonomous road condition monitoring. On top of that, these surveillance cars would be outfitted with GPS modules that would allow them to locate the exact locations of the roadhumps and potholes. The quantity of raw materials required to fix the potholes and the extent of road damage can be estimated by evaluating their sizes. This means that most planning and inspections can be done from a distance.

REFERENCES

[1] Muhammad Haroon Asad, Saran Khaliq, Muhammad Haroon Yousaf, Muhammad Obaid Ullah, and Afaq Ahmad, "Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective", Hindawi Advances in Civil Engineering Volume 2022, Article ID 9221211, 13 pages https://doi.org/10.1155/2022/9221211

[2] Y.-M.; Kim, Y.-G.; Son, S.-Y.; Lim, S.-Y.; Choi, B.-Y.; Choi, D.-H. Review of Recent Automated Pothole-Detection Methods. Appl. Sci. 2022, 12, 5320. https://doi.org/ 10.3390/app12115320

[3] Rui Fan ,Umar Ozgunalp , Yuan Wang ,Ming Liu," Rethinking Road Surface 3-D Reconstruction and Pothole Detection: From Perspective Transformation to Disparity Map Segmentation", 2168-2267 _c 2021 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.

[4] Prof. Chandrakant Bhange, Sneh Kurhade, Laukik Arewar and Ashish Kumar,"Automatic Detection and Notification of Humps and Potholes", © 2022 JETIR July 2022, Volume 9, Issue 7 www.jetir.org (ISSN-2349-5162).

[5] amel ali alhussan 1, doaa sami khafaga 1, el-sayed m. el-kenawy 2, abdelhameed ibrahim 3, marwa metwally eid 4, and abdelaziz a. abdelhamid 5,6, "Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self Driving Cars", Received 18 June 2022, accepted 1 August 2022, date of publication 5 August 2022, date of current version 15 August 2022.

[6] Dong Chen, Nengcheng Chen , Xiang Zhang , and Yuhang Guan ," Real-Time Road Pothole Mapping Based on Vibration Analysis in Smart City", ieee journal of selected topics in applied earth observations and remote sensing, vol. 15, 2022.

[7] Mohan Prakash B and Sriharipriya K.C, "Enhanced pothole detection system using YOLOX algorithm", B and K.C Autonomous Intelligent Systems (2022) 2:22 https://doi.org/10.1007/s43684-022-00037-z.

[8] Prof. Vidya Sagvekar, Om Sohani, Smita Prajapati, Sakshi Zanjad, "Elevating Transportation Efficiency: An Inclusive Review On Iot- Enabled Pothole And Hump Detection System For Road

 ©IJSRED: All Rights are Reserved

Safety", www.ijcrt.org © 2023 IJCRT | Volume 11, Issue 10 October 2023 | ISSN: 2320-2882.

[9] A.Lincy, Dhanarajan G, Sanjay Kumar S1 and Gobinath B, "Road Pothole Detection System", ITM Web of Conferences 53, 01008 (2023),ICDSIA-2023, https://doi.org/10.1051/itmconf/20235301008.

[10] Sushila Palwe, Anita Gunjal, Sanskar Jindal, Akshat Shrivastava, Atharva Deshmukh, School of SCET, MIT WPU, Pune 411038, Mehul Navalakha, School of SCET, MIT WPU, Pune 411038, India.

[11] Gerasimos Arvanitis , Nikolaos Stagakis , Evangelia I. Zacharaki ,and Konstantinos Moustakas,"Cooperative Saliency-Based Pothole Detection and AR Rendering for Increased Situational Awareness", ieee transactions on intelligent transportation systems, vol. 25, no. 5, may 2024.

[12] Siddharth Sasane, Akshat Tickoo, Kevin Xavier, Prof. Manish Parmar," pothole detection system using yolo v8 algorithm", www.ijcrt.org © 2024 IJCRT | Volume 12, Issue 6 June 2024 | ISSN: 2320-2882.

[13] Shafi Ullah Adid , Md. Emon and Taofica Amrine," A hybrid approach to detect and classify pothole on Bangladeshi roads using deep learning", International Journal of Science and Research Archive, 2024, 12(01), 1045–1053 Publication history: Received on 18 April 2024 revised on 24 May 2024; accepted on 27 May 2024.

[14] Abeer Aljohani." Optimized Convolutional Forest by Particle Swarm Optimizer for Pothole Detection", International Journal of Computational Intelligence Systems (2024) 17:7 https://doi.org/10.1007/s44196-023-00390-8.

[15] Rahul Dhingra, Mayank Dhingra, Meghna Sharma,"Pothole Detection Using Machine Learning Models", Accepted : 10 March 2024, Published:28 March 2024 Available Online at : www.ijsrset.com doi https://doi.org/10.32628/IJSRSET241126

[16] Shubham Gade, Amita Singh, Shubham Sarote, " Efficient H-net model-based slot assignment solution to accelerate the EV charging station searching process ",ISSN: 2349-6002,Volume:11 ,Issue: 6,PageNo: 2590-2597

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