



Detection of Potholes Using CNN

P Nithiyasree, T Arundhati, S Soorya, Vatturi Harshitha and
Kavitha Subramani

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

October 8, 2023

DETECTION OF POTHOLE USING CNN

NITHIYASREE P
Department of Computer Science
and Engineering
Panimalar Engineering College
Chennai -123.
nithiyasreetvm2001@gmail.com

ARUNDHATHI T
Department of Computer Science and
Engineering
Panimalar Engineering College
Chennai -123.
arundhathidasan.t@gmail.com

SOORYA S
Department of Computer Science and
Engineering
Panimalar Engineering College
Chennai -123.
sooryasoorya@gmail.com

VATTURI HARSHITHA
Department of Computer Science
and Engineering
Panimalar Engineering College
Chennai -123.
harshithavatturi@gmail.com

KAVITHA SUBRAMANI
Department of Computer Science and
Engineering
Panimalar Engineering College
Chennai -123.
kavitha.pec2022@gmail.com

Abstract- Without a doubt, roads are the ones that connect people from one place to another without any hiccups. India plays a vital role in economic maximization as it serves as the second-largest road network. We have a delay problem that causes road accidents like Tyre bursts and collisions due to improper maintenance, resulting in the occurrence of large cavities as the road becomes worse, even more in rainy conditions, forming a lot of potholes on it. Deep Learning is a technique that learns features and tasks directly from raw data. To create a deep learning model that will aid in pothole detection. Uses a video as an input to build a CNN model that uses OpenCV to spot potholes in real-time. This project can be used to locate potholes and evaluate the condition of the road by both motorists and government representatives. In order to enable real-time vehicle operation (for driver assistance or autonomous driving) or offline data gathering for road repair, methods for spotting potholes on road surfaces are being developed. These factors have led to extensive research into pothole location techniques in studies carried out all around the world.

Keywords- CNN(Convolutional Neural Network), Deep Learning,Potholes.

I. INTRODUCTION

The most visible indicator of a poorly maintained road and a structural problem are potholes. Today, hitting a pothole with a car can cause more than just an unpleasant ride. Additionally, the wheels and suspension system of the vehicle may sustain costly damage. However, poor road conditions are also a major contributing factor. A number of factors, including flooding, rain, damage from heavy cars or inadequate physical upkeep of the road, can make a road's state dangerous. The significance of a road feature to traffic serves to define it at the macroscale. For instance, speed bumps are also elements that affect traffic and must be detected for driver assistance. A particular kind of road fault is a pothole. It may be a randomly shaped structural fault in a road, and it is frequently impossible to pinpoint its exact "border". They can be hazily described, yet it is possible to pinpoint their greatest depth. In contrast to

this, objects like automobiles, people, cyclists, dogs, and cats have clearly defined shapes. We can say with certainty that detecting a pothole is a difficult object-detection task due to its unpredictable shape and complex geometric structure. This analysis makes use of a wider range of data. Potholes create a variety of challenges depending on the weather, lighting, road layout, and traffic. Data was collected from a variety of sources because there isn't an available benchmark dataset for pothole identification. It is recommended that future discussions of pothole detection advancements use the five distinct datasets, which were captured under diverse weather conditions. Two distinct approaches to reconstruction built on cutting-edge deep learning algorithms are the study's contributions. Experiments show that the tactics enable humans to accurately spot potholes from a distance. Experiments that have been evaluated show that modern deep learning-based algorithms perform noticeably better than traditional based on 3D scene reconstruction. By filling in the knowledge gap created by datasets gathered under various lighting situations, this study contributes new knowledge to the field of pothole detection. In this project, we will enhance the system with a deep learning model to help with pothole identification. We'll build a CNN model that uses an image as an input to find potholes. Real-time detection will also be accomplished using OpenCV. This project can be used by motorists to find potholes and by government workers to inspect the state of the road. The method can increase driver safety and self-driving car performance by anticipating potholes. This study also provides a summary of earlier investigations of surface flaws on roads. In order to find solutions that will lessen the consequences of potholes and increase the durability of pothole repairs, the main goal of this study is to examine some of the crucial factors involved in their creation and repair. One of the components covered is performing a stress analysis of pothole repairs to determine whether certain repair shapes are more advantageous than others. Other aspects covered include investigating and documenting the use of conventional and cutting-edge materials and technologies for pothole repairs.

II. LITERATURE SURVEY

M. Ricardo Carlos et al [1], proposed a formulation which keeps the suggested fixes to a minimal level of detail because it does not differentiate between the severity degree or functional status of road artifacts.

Rui Fan et al [2], The experimental results show that across all training data modalities, The most accurate GAL-DeepLabv3+ for detecting potholes is the one we've proposed.

J. Javier Yebe et al [3], The disparity map should be constructed, a surface should be fitted, and a specified height threshold should be utilised to identify any shallow road places that might be used to locate potholes.

Zhen Feng et al [4], In order to achieve the best outcomes, this study recommends a special data fusion network for the segmentation of roads and potholes. Using a channel attention fusion module and a dual attention fusion (DAF) module, respectively, the RGB and disparity data are hierarchically merged.

Rui Fan et al [5], Utilising CUDA on an NVIDIA RTX 2080 Ti GPU, the suggested methodology is put into practise. The results of the trial demonstrate the cutting-edge accuracy and efficiency of our proposed road pothole detecting system.

Uttam Kumar et al [6], An improved YOLOv2 architecture is recommended to remedy the "pothole" and "normal road" class imbalance, and its performance is compared to comparable object recognition systems.

Chao-Yu Siao et al [7], the randomization domain, which offers agents a variety of randomly generated surroundings with variously coloured and textured objects.

Adeel Ahmed et al [8], A simple and novel method for 3D reconstruction of potholes for automated inspection and road surface assessment is described in the suggested study.

Rui Fan et al [9], to segment the depth maps, which has been demonstrated to improve performance when dividing sections of damaged and undamaged roads.

Amita Dhiman et al [10], Experiments show that the suggested methodologies enable precise identification of potholes from a distance.

Shebin Silvester et al [11], The use of YOLOv3 and YOLOv4 is trained using a customised dataset. A splitting-based method for identifying potholes and estimating their dimensions has been suggested.

Hidekazu Fukai et al [12], Kirchoff's theory and the KNN approach put forth the suggestion that officials should be informed of the position and GPS coordinates in order to efficiently identify potholes at all levels, mostly based on surface roughness.

Ganesh Babu R et al [13], The identification of accelerometer and gyroscope data is performed using a specially trained Deep Feed Forward Neural Network. A deep learning-based system was developed and integrated with an Android app to locate potholes and display the locations on a map.

Abhishek Kumar et al [14], They utilise the model on an image in various locations and scales. Parts of the image with a high score are called detections. YOLOv3 uses a variety of approaches to enhance training and performance, including multi-scale predictions, an improved backbone classifier, and others.

Zeyu Gao et al [15], Using image data from actual potholes and typical roads, we concentrated on locating potholes. We initially collected the data, then preprocessed it by scaling and shrunk it.

III. EXSISTING SYSTEM

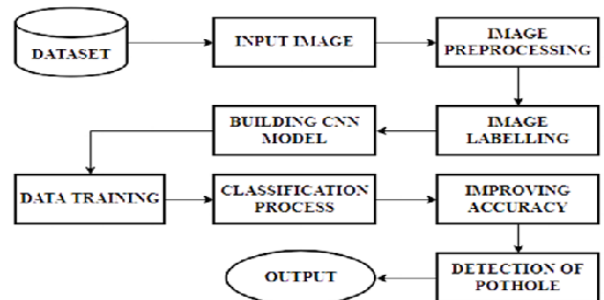
The existing system is based on image detection and also the dataset being used in the existing system contains only inaccurate images thus leading to poor accuracy and efficiency. The existing systems face a serious problem in addressing road maintenance in the lack of communication between civilians and the authorities. The tracking of locations is very poor, especially in areas that require the most repair. Besides, there is limited involvement of civilians. Their involvement is very crucial for the enhancement of societal living and cooperation. The existing systems are not very robust in tracking the progress of the repair. The existing systems also do not inform the complainants about the poor conditions or the repairs going on, thereby increasing fatality in such areas.

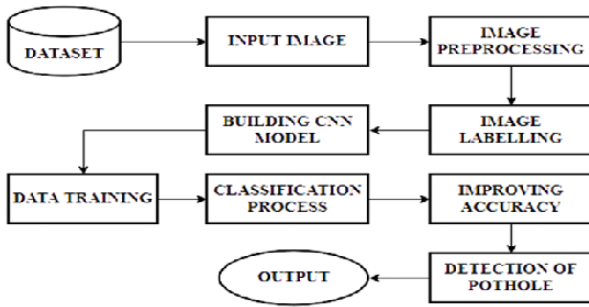
IV. PROPOSED SYSTEM

In real-time using computer vision and is being used with high accuracy. Compared to the existing systems, the system is highly efficient. This system uses the bounding box method. This system proposes a solution that uses a real-time pothole detection system that automatically detects potholes. In this proposed system we are going to use a pothole detection system using CNN. We will start by dataset preprocessing and data augmentation. Then we will build a CNN model using a sequential model and in this phase all the layers and hyper parameters of the CNN model will be decided. We will also create checkpoints to stop the model when we reach higher accuracy. We will save the best model that produces the highest accuracy. All this is done besides reporting the existing conditions of the road network.

V. ARCHITECTURE OVERVIEW

This diagram just gives a brief description of each entity that has been added to the system. The diagram comprises a series of steps and decision-making processes in addition to showing how they are all related to one another. In this figure, every functional connection is outlined.





The system starts by importing a dataset with images of various formats, consisting of an N number of roads. The image is taken to preprocess, that is, cleanse the data. Here, image preprocessing techniques like grayscale conversion, background noise removal, and image enhancement are performed. Minor alterations to the existing dataset to increase diversity without collecting new data are done by data augmentation. This preprocessing has the effect of increasing the image's complexity while also standardizing it. The data is clean to proceed with the training and testing, respectively. Pre-existing data will be coupled with the existing data to train them effectively and provide accurate details with higher efficiency. The training data is the first batch of data that a software utilises to learn how to use techniques like neural networks and provide sophisticated results. The most important step is to create our own CNN model to visualize image details. A process of convolution, pooling (max pooling done here), and flattening are running to get a predicted output. Then, train the CNN on the training set and evaluate it on the validation set. This is how a system reads an image and makes predictions that are so robust. A machine learning algorithm is used to learn how to assign a class label to the data. Imagine that we have a good road and another one with cracks. So, here the classifier learns to tell whether there is a pothole or not in the output layer. The whole system learns with new and existing data by increasing the accuracy and analysis to detect potholes.

VI. MODULE DESIGN SPECIFICATION

DATASET TRAINING

1200 photos of the potholes on the road make up the dataset. These images were collected online using the Google search engine to search for Potholes images. These images are then preprocessed using image augmentation. This is followed by labeling the images. The dataset is used to produce a practise set and a testing set. The education folder receives 80% of the photos, while the test folder receives 20% of the remaining data. Following the labelling and division of all the photos into sets for practise and testing, the next segment is Dataset Training. Pre-existing data will be coupled along with the existing data to train them effectively and provide accurate details with higher efficiency. The training data is the first batch of data that a software utilises to learn how

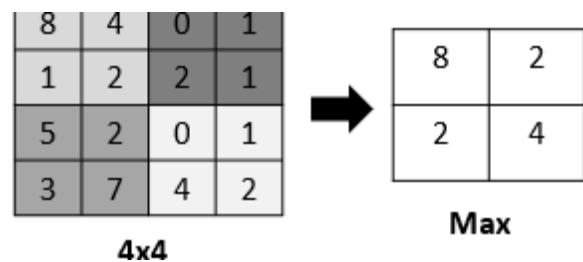
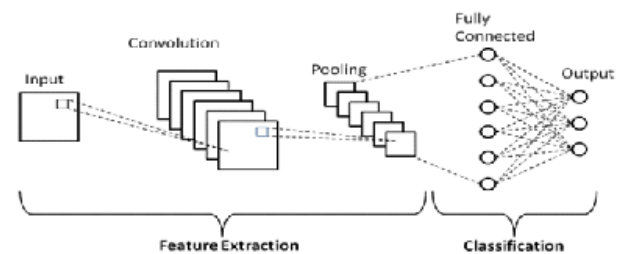
to use techniques like neural networks and provide sophisticated results.

BUILDING THE ALGORITHMS USING COMPUTER VISION

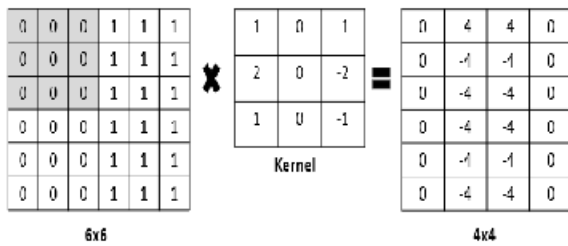
For pothole detection from input photos, we employ computer vision. Because CNN architecture produced outstanding classification results in the practical data set, it was chosen to create the detection system. This object detection model has been chosen over others because it provides reasonable accuracy while operating more quickly. The input photos are processed to produce a feature map using CNN's contribution. Fully connected layers receive the feature vector that was generated. They then split into two output layers that are related to one another. By contrasting another ground truth picture matrix with the CNN classification output matrix, a classification is performed.

CONVOLUTIONAL NEURAL NETWORK

Convolution is the first step, where 0 is represented as white and 1 as black on an image. There are many filters, also known as kernels, from $v_1, v_2, v_3, \dots, v_6$. Here, only one filter is shown to understand the vertical edges. A vertical edge is the one that separates the 0 and 1 shown in the 6x6 image matrix. The process starts by multiplying the shaded part of the image with the kernel values to get the first output 0 in the 4x4 matrix. Since the kernel is 3x3, only the 3x3 grid is taken in the original image. Then it is a stride jump to the next grid.



This process goes on till we have filled all the values and that is our original image. In-Max scalar is applied in the output layer where minimum value changes to 0 and maximum value to 255. We get the colored image. A quick formula to check what matrix will be the output image is calculated by, n is the size of original image and f is the size of kernel.



Next comes the padding and striding happens. You can see the original image is 6x6 but the output layer is 4x4, so clearly a bit of information is missed. In this case we apply padding to get the boundary. Padding is adding a grid around all the sides. Padding can be 0 or 1 and it depends on.

Utilising a 2x2 kernel with a stride of 2 and max-pooling on a 4x4 channel. A 2x2 Kernel is being convolved at this time. The channel has four values of 8, 4, 1, and 2 if we observe the initial 2x2 set on which the kernel is focusing. To extract the image's features, pooling is used. It selects the highest value among the grid's distinct colours. The fully connected layer creates predictions using the final features that the convolutional process has extracted.

COMPUTER VISION

Modern computer vision algorithms are built on neural networks using convolution, which provide a significant performance gain over traditional image processing methods. The term "computer vision," also abbreviated as "CV," refers to a branch of study that aims to create methods for assisting computers in comprehending the information in digital pictures like pictures and movies. A model is developed using a dataset of certain items in object classification, and the model then assigns new objects to one or more of your training categories. Your model will be able to identify a specific instance of an object for object identification.

TENSOR FLOW OBJECT DETECTION

TensorFlow is a computer creative vision technology used in object detection. As the name implies, it enables us to identify, track, and locate an object in a picture or a video. A software tool that uses computer vision can identify, locate, and hint at an object from a given image or video is known as object detection. The distinguishing feature of item detection is that it recognises the object (person, table, chair, etc.) and its precise location inside the provided image. Drawing a bounding field across the object describes the region. The placement of the item may also or incorrectly be determined by the boundary field. The capacity to find the item interior of a photo defines the overall performance of the set of rules used for detection. These item detection algorithms might be pre-skilled or may be skilled from scratch. In maximum use cases, we use pre-skilled weights from pre-skilled

fashions, after which we fine-track them as in step with our necessities and exclusive use cases.

OPEN CV

The task of computer vision is one of the most exciting and difficult in the field of artificial intelligence. Computer software and the visualisations around us are connected by computer vision. It enables computer programmes to recognise and understand the environmental visualisations. For instance: based on how an object's saturation, form, and length feature it out. This task may seem very simple to the human mind, but in the computer vision pipeline, we first gather the data, then perform data processing tasks, and finally we train and instruct the version to understand how to distinguish between the culmination based on length, form, and fruit colour.

Numerous programmes are available right now to do tasks related to computer vision, deep learning, and device learning. A computer's vision is by far the best tool for such difficult activities. An open-source Python library is called OpenCV. Numerous programming languages, including Python and R, support it.

ADVANTAGES OF OPEN CV

- OpenCV is a source library that is free and open, and it performs better on computers with less RAM.

PREDICTION OF OUTPUT

The final module for the system is a prediction of the output. The first step for the system is capturing the image or video of a face through a camera using software to detect the Pothole. The network design receives the input image as input. To make it simpler to spot the important details, noise is removed from the image during image enhancement or pre-processing. The proposed method will be applied to the acquired image in order to recognise the damaged area and ensure proper classification. Then the output will be produced predicting whether a given image identifies the presence of a pothole or not. The functionality of our detection system can be embedded into traffic management systems, desktop software, websites and so on.

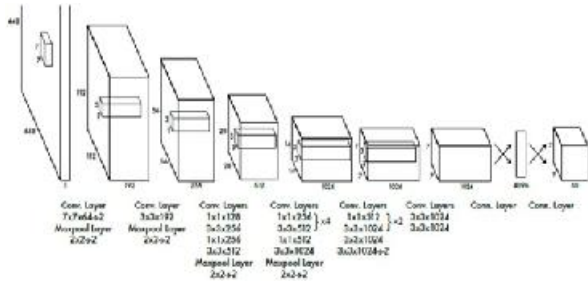
ALGORITHMS

YOLO

A simple technique called YOLO, which stands for "You Only Look Once," converts a picture from its pixels to bounding coordinates and categorises chances in a straight line. It considers an object recognition task as a single regression problem. The central neural network of this system simultaneously predicts multiple bounding boxes and sophistication probability. In a given image, grids of identical squares are created. Each grid creates a number of bounding boxes and rates each one's level of confidence. The self-assurance ratings

show how certain the version is that an item is present in the field. YOLO forecasts each bounding field using data from the full image by combining all the object recognition components into a single neural network. At the same time, all class boundary boxes are predicted.

YOLO has several versions, beginning with YOLOv1–YOLOv5 and ending with PP-YOLOv2, which was released in April 2021. The accuracy of fashion is high.



YOLO V3

The real-time object identification rules in You Only Look Once, Version 3 (YOLOv3) may identify specific devices in moving pictures, live broadcasts, or static images. YOLO uses skills developed by a deep convolutional neural network to find an object. There are three YOLO options available. Years after the app's initial deployment in 2016, YOLO version 3 purportedly debuted in 2018. A more recent variation of YOLO and YOLOv2 is known as YOLOv3. YOLO makes use of the Keras or OpenCV deep analysis libraries.

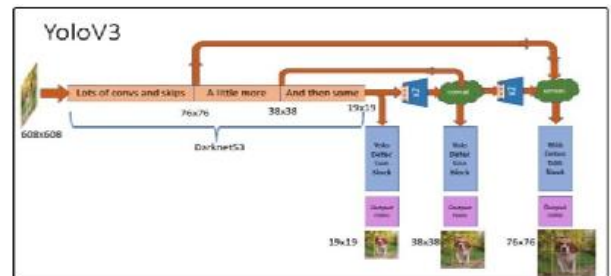
Specific gadgets in a class can be recognised as subjects of interest by artificial intelligence (AI) software. The convolutional layers' skills are passed on to a classifier, as is typical for object detectors, which predicts the detection. In YOLO, a convolutional layer that employs 11 convolutions serves as the foundation for the prediction. A suitable right image is first transformed into a grid by the YOLOv3 set of rules. Each grid forecasts a different set of spherical devices with boundary boxes that perform well in the aforementioned established classifications.

In terms of timing, precision, and specificity, there are variants that are superior to YOLOv3 and earlier versions. In terms of accuracy, tempo, and architecture, YOLOv2 and YOLOv3 are further apart. YOLOv2 changed to using Darknet-19 as its primary feature extractor, while YOLOv3 is currently using Darknet-53. Darknet - fifty three is another foundation created by YOLO. We can see that ResNet101 is outperformed by Darknet-fifty by 1.5 times. The stated accuracy does not necessitate any trade-off between accuracy and speed among Darknet backbones, despite the fact that it is far, if not as accurate as ResNet-152 bus times speedier.

YOLOv3 is swift and precise even when conventional location precision (map) and intersection over union (IOU) values are taken into account. It functions much faster than some detecting systems with comparable performance, therefore the expression "You

only need to look once." Additionally, without having to retrain the model, you can simply balance between speed and accuracy by altering the model's size.

A YOLO-V3 feature extractor called Darknet-53 (52 convolutions) processes images at various spatial compressions using three prediction heads (like FPN), skip connections (like ResNet), and three prediction heads. Like Yolo-V2. A range of input resolutions work nicely with Yolo-V3. Each of the numerous checkpoints in the model zoo of GluonCV is for a different input resolution, but they all store the same network parameters. Yolo-V3 received 37 mAP (mean average precision) on the COCO-2017 validation set when tested with an input resolution of 608 x 608 pixels (mean average precision). This score outperforms the trained Faster-RCNN-ResNet50 version made by GluonCV (a faster-RCNN architecture with ResNet-50 at its core). It does so 17 times more quickly. Only detectors with mobilenet-SSD architectures (speeds comparable to Yolo-V3) achieved mAP scores of 30 or above.



VII. RESULTS & DISCUSSIONS

This method is applicable to both autos and road analysis, as was previously stated. The CNN model, a deep learning-based and affordable method for pothole detection, has been developed to address the issue with the current system, which uses humans to accomplish road pothole screening tasks. This demonstrates how quickly deep learning can solve challenging problems. A simple prototype with test results shows that the system can spot potholes 90% of the time.

VIII. CONCLUSION AND FUTURE ENHANSMENT

Roads are heavily used, the environment is poor, and routine maintenance is neglected, all of which contribute to the production of potholes that cause accidents and unneeded traffic. A technique for automatically detecting potholes is presented in this research. We focused on identifying the potholes using both picture data from potholes and image data from regular roads. This can encourage motorcyclists to be more cautious, which will help to reduce accidents and vehicle maintenance expenses. The findings suggest that this technique might be used to spot potholes and keep the roads in good shape. New models that aid in meeting the demands of the developing world are being developed as a result of increasing trends and the accessibility of sophisticated technologies.

In the future, this system can be enlarged with an inbuilt map system recommending secondary routes to the user driving the vehicle that consists of fewer potholes.

IX. SAMPLE SCREENSHOTS

POTHOLE DETECTION FRAME



POTHOLE GROUP DETECTION FRAME



X. REFERENCES

[1] Adeel Ahmed;Moez Ashfaq;Muhammad Uzair Ulhaq;2022,” Pothole 3D Reconstruction With a Novel Imaging System and Structure From Motion Techniques”,2022 IEEE Transactions on Intelligent Transportations Sytems (Volume :23, Issue : 5)

[2] Zhen Feng; Yanning Guo; Qing Liang; Ming Liu,2022,” MAFNet: Segmentation of Road Potholes With Multimodal Attention Fusion Network for Autonomous Vehicles”, IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, VOL. 71, 2022

[3] Rui Fan; Yuan Wang; Ming Liu; Ioannis Pitas, 2022,” Rethinking Road Surface 3-D Reconstruction and Pothole Detection: From Perspective Transformation to

Disparity Map Segmentation”, EEE TRANSACTIONS ON CYBERNETICS, VOL. 52, NO. 7, JULY 2022

[4] H. Bello-Salau; A. J. Onumanyi; R. F. Adebisi; E. A. Adedokun; G. P. Hancke, 2021, “Performance Analysis of Machine Learning Classifiers for Pothole Road Anomaly Segmentation”, 2021 IEEE 30th International Symposium on Industrial Electronics(ISIE)

[5] RuiFan ,Hengli Wang ,Yuan Wang , Ming Liu and Ioannis Pitas, 2021,”Graph Attention Layer Evolves Semantic Segmentation for Road Pothole Detection: A Benchmark and Algorithms”,”IEEE Transactions on Image Processing (Volume: 30)

[6] David Montero; Ignacio Arriola; J. Javier Yebe,2021,”Learning to Automatically Catch Potholes in Worldwide Road Scene Images”,2021 IEEE Intelligent Transportation Systems Magazine (Volume: 13, Issue: 3)

[7] SurekhaArjapure; D.R. Kalbande, 2021, “Deep Learning Model for Pothole Detection and Area Computation”, 7th International Conference on Smart Structures and Systems(ICSSS)

[8] A.K.M. Jobayer Al Masud; Saraban Tasnim Sharin; Khandokar Farhan Tanvir Shawon; Zakia Zaman, 2020, “Pothole Detection Using Machine Learning Algorithms”, 2021 15th International Conference on Signal Processing and Communication Systems (ICSPCS)

[9] Ashutosh Shah; Gaurav Sharma; Lava Bhargava, 2021, “Smart Implementation of Computer Vision and Machine Learning For Pothole Detection”, 2021 11th International Conference on Cloud Computing, Data Science & Engineering(Confluence)

[10] M. Ricardo Carlos; Luis C. Gonzalez; Raymundo Cornejo;Fernando Martinez,”2021,” Becoming Smarter at Characterizing Potholes and Speed Bumps from Smartphone Data — Introducing a Second-Generation Inference Problem”, IEEE TRANSACTIONS ON MOBILE COMPUTING, VOL. 20, NO. 2, FEBRUARY 2021

[11]Anup Kumar Pandey; RahatIqbal; Saad Amin; Tomasz Maniak; Vasile Palade; CharalamposKaryotis,

- 2021, "Deep Neural Networks Based Approach for Pothole Detection", 2021 4th International Conference on Signal Processing and Information Security(ICSPIS)
- [12]Ping Ping; Xiaohui Yang; ZeyuGao, 2020, "A Deep Learning Approach for Street Pothole Detection", IEEE Sixth International Conference on Big Data Computing Service and Applications(BigDataService)
- [13]Abhishek Kumar; Chakrapani; DhruvaJyotiKalita; VibhavPrakash Singh, 2020, "A Modern Pothole Detection technique using Deep Learning", 2nd International Conference on Data, Engineering and Applications (IDEA),IEEE
- [14]Pranjal A. Chitale; Kaustubh Y. Kekre; Hrishikesh R. Shenai; RuhinaKarani; Jay P. Gala, 2020, "Pothole Detection and Dimension Estimation System using Deep Learning and Image Processing", 2020 35th International Conference on Image and Vision Computing New Zealand (IVCNZ)
- [15]Chi-Wei Kuan; Wen-Hui Chen; Yu-Chen Lin, 2020, "Pothole Detection and Avoidance via Deep Learning on Edge Devices", 2020 International Automatic Control Conference(CACS)
- [16]Ganesh Babu R.; Chellaswamy C.; Surya BhupalRao M.; Saravanan M, 2020, "Deep Learning Based Pothole Detection and Reporting System", 7th International Conference on Smart Structures and Systems(ICSSS)
- [17]RoopakRastogi; Uttam Kumar; ArchitKashyap; Shubham Jindal; SaurabhPahwa, 2020, "A Comparative Evaluation of the Deep Learning Algorithms for Pothole Detection", 2020 IEEE 17th India Council International Conference(INDICON)
- [18] Jung-Cheng Tsai; Kuan-Ting Lai; Tzi-Chun Dai; Jun-Jia Su; Chao-Yu Siao; Yung-Chin Hsu, 2020, "Learning Pothole Detection in Virtual Environment", 2020 International Automatic Control Conference (CACS)
- [19] Mohd Omar; Pradeep Kumar, 2020, "Detection of Roads Potholes using YOLOv4", IEEE Transactions on Intelligent Transportation Systems", 2020 International Conference on Information Science and Communications Technologies(ICISCT)
- [20]Ernin Niswatul Ukhwah; Eko Mulyanto Yuniarno; Yoyon Kusnendar Suprpto, 2019, "Asphalt Pavement Pothole Detection using Deep learning method based on YOLO Neural Network", International Seminar on Intelligent Technology and Its Applications (ISITIA)
- [21]ShebinSilvester; DheerajKomandur; ShubhamKokate; AdityaKhochare; Uday More; VinayakMusale; Avadhoot Joshi, 2019, "Deep Learning Approach to Detect Potholes in Real-Time using Smartphone",2019 IEEE Pune Section International Conference(PuneCon)
- [22] Rui Fan; Umar Ozgunalp; Brett Hosking; Ming Liu; Ioannis Pitas, 2019, "Pothole Detection Based on Disparity Transformation and Road Surface Modeling", IEEE Transactions on Image Processing (Volume:29)
- [23]Vosco Pereira; Satoshi Tamura; Satoru Hayamizu; HidekazuFukai, 2018, "A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste", IEEE International Conference on Service Operations and Logistics, and Informatics(SOLI)
- [24]AmitaDhiman; ReinhardKlette, 2018, "Pothole Detection Using Computer Vision and Learning", IEEE Transactions on Intelligent Transportation Systems (Volume: 21, Issue: 8, Aug.2020)
- [25]ManjushaGhadge;DheerajPandey;DhananjayKalbande, 2018, "Crack- pot: Autonomous Road Crack and Pothole Detection", 2018 Digital Image Computing: Techniques and Applications(DICTA)