STM JOURNALS

Journal of
Control & Instrumentation

https://journals.stmjournals.com/joci

ISSN: 2229-6972 (Online)
ISSN: 2347-7237 (Print)
Volume 16, Issue 1, 2025
January–April
DOI (Journal): 10.37591/JoCI

Review JoCI

Pothole Detection Utilizing Machine Learning: A Review

Aayush Chandorkar[1,*], Swaraj Salvi[1], Purva Mhatre[1], Bhagyalaksmi V.[2]

Abstract

Potholes must be found and fixed quickly to maintain infrastructure, maximize transportation systems, and guarantee road safety. Using the Sequential API and the Keras library, this study presents a neural network model for pothole detection. Convolutional layers with Rectified Linear Unit (ReLU) activation, global average pooling, dense layers with dropout, and SoftMax activation for binary classification make up the model architecture. Image loading, resizing, array conversion, labeling, shuffling, normalization, and one-hot encoding are all examples of preprocessing steps. By precisely identifying potholes, this technology seeks to improve overall road maintenance and traffic flow management while facilitating prompt repairs. Every road, regardless of its engineering features or traffic volume, needs routine maintenance. Most routine maintenance tasks are small-scale, geographically distributed, and frequently involve manual labor. To a considerable extent, the requirement for routine maintenance can be predicted and is planned for at specific times throughout the year. To avoid early road deterioration, routine maintenance should be performed on all roads regularly. The engineers must make sure that funds are allocated in the annual maintenance plan. The activities vary in frequency. Moreover, routine maintenance tasks can be classified as either reactive or cyclic, albeit it's not always easy to tell the difference between the two.

Keywords: Road maintenance, pothole detection, machine learning, Arduino microcontroller, central monitoring system

INTRODUCTION

Pothole detection is very important because it plays a significant role in road safety. Prompt identification and repair of potholes helps prevent accidents and damage to vehicles. Potholes can cause accidents by destabilizing vehicles, particularly two-wheelers, and can lead to serious injuries or fatalities.

Second, efficient pothole detection and repair contribute to the overall maintenance of roads. If not immediately fixed, potholes can develop into more serious infrastructure problems that require more involved and expensive repairs. Timely detection allows authorities to efficiently allocate resources and cost-effectively maintain road infrastructure.

*__Author for Correspondence__
Aayush Chandorkar
E-mail: aayushchandorkar@gmail.com

[1]Student, Department of Electronics and Telecommunications, K. C. (Kishinchand Chellaram) College of Engineering, Thane(W), Maharashtra, India
[2]Assistant Professor, Department of Electronics and Telecommunications, K. C. (Kishinchand Chellaram) College of Engineering, Thane(W), Maharashtra, India

Receiving Date: October 09, 2024
Accepted Date: January 05, 2025
Published Date: January 08, 2025

Citation: Aayush Chandorkar, Swaraj Salvi, Purva Mhatre, Bhagyalaksmi V. Pothole Detection Utilizing Machine Learning: A Review. Journal of Control & Instrumentation. 2025; 16(1): 35–43p.

In addition, pothole detection is essential for optimizing transportation systems. Well-maintained roads ensure smooth traffic flow and reduce congestion and travel time. This is not only beneficial for individual commuters, but also for businesses that rely on the timely transportation of goods.

The Keras library with the Sequential API was used to establish the neural network structure. The architecture of the model, as defined in the kerasModel4 function, comprises several layers.

Convolutional Layers (Conv2D)

The first convolutional layer had 16 filters/kernels of size (8, 8) with a stride of (4, 4).

The function used was a Rectified Linear Unit (ReLU). The second convolutional layer had 32 filters of size (5, 5) with a padding set to "same" to preserve the spatial dimensions of the input.

Activation Layers (Activation)

Activation Layers (Activation): To add nonlinearity, ReLU activation was used following each convolutional layer.

Global Average Pooling (GlobalAveragePooling2D)

Calculate the average quantity for every feature map, and shrink the geographical dimensions of the input. This results in a fixed-size output, regardless of the input size.

Dense Layers (Dense)

The two dense layers follow the global average pooling layer. The first dense layer consists of 512 units, which have ReLU activation and a dropout probability of 0.1. The second dense layer had two units (for binary classification) with SoftMax activation.

Dropout Layers (Dropout)

Dropout was applied to the first dense layer at a dropout rate of 0.1. By randomly changing the portion of input units to zero during training, dropout helps avoid overfitting.

SoftMax Activation (Activation)

SoftMax activation was applied to the final dense layer, producing a probability distribution over the two classes (pothole and non-pothole).

Data Preprocessing

The code performs several steps to preprocess the training and testing data.

Loading Images

Images from specified directories for the pothole and non-pothole classes were loaded using the glob module.

Resizing Images

Each image was resized to a specified size (300 × 300 pixels) using cv2.resize.

Creating NumPy Arrays

The image data were converted to NumPy arrays (temp1, temp2, temp3, temp4). The combined training and testing datasets were created as the X_train and X_test arrays, respectively.

Labeling

Labels were assigned to the training and testing datasets (Y_train and Y_test). Pothole images were labeled 1, and non-pothole images were labeled 0.

Shuffling

Both the input data (X_train, X_test) and labels (Y_train, Y_test) were shuffled using the shuffle from scikit-learn. This helps us to ensure that it randomizes the order of the training samples so that it can help improve machine learning.

Normalization

To scale pixel values to the interval [0, 1], they were normalized by dividing them by 255.

One-Hot Encoding

Categorical labels (y_train, yeast) were encoded one-hot using np_utils.to_categorical. This technique is used to represent categorical variables as numerical values in the model.

LITERATURE REVIEW

Image Processing and Spectral Clustering [1]

This technique uses spectral clustering and image processing to identify and approximate the potholes. Spectral clustering was performed to identify regions using histogram-based data from grayscale images. We located the potholes and calculated their surfaces using these techniques. Images with various pothole shapes were used to test the approach, and the results demonstrated that the potholes can be reasonably estimated.

Arduino Uno and Sensors [2]

To accomplish such detection and depth estimation, a physics-based geometric framework is employed. It considers how the resolution decreases as the camera moves further. Owing to the presence of water in the underlying soil structure and traffic moving over the affected area, asphalt pavements are the primary source of potholes, which are structural failures on road surfaces. By reducing the difficulty of identifying potholes and utilizing less human labor, this project saves time and aids society in increasing road safety.

Computer Vision and Machine Learning [3]

The proposed system employs a convolutional neural network (CNN) trained on a diverse dataset of road images to automatically identify and classify potholes. The use of a CNN enables the model to learn intricate features and patterns associated with potholes, making it adept at detecting these anomalies with high accuracy.

To enhance real-time pothole detection, the system integrates computer vision algorithms to process live video feed from cameras mounted on vehicles or infrastructure. To locate possible potholes, image processing methods such as contour analysis and edge detection are used. The trained CNN was then employed to validate and classify these regions, providing a robust and efficient solution for pothole detection.

Pothole Detection System Using Machine Learning [4]

The proposed system employs a combination of supervised learning and feature engineering to train a machine learning model to discern potholes from road images. The training dataset was carefully curated to encompass diverse road conditions, lighting scenarios, and pothole types, thereby ensuring the adaptability of the model to real-world environments.

To enhance reliability, the system incorporates a multi-model approach that fuses information from various sensors, such as cameras and accelerometers.

Random Forest Tree and KNN [5]

A comparison of machine learning models for pothole identification was presented in this study. To extract pertinent statistical features for training a binary classifier, the data were preprocessed using a 2-second non-overlapping moving window after being gathered from numerous Android smartphones, routes, and automobiles. The training dataset was subjected to stratified K-fold cross-validation, and the test dataset was completely separated from the training and validation datasets. With an accuracy of 0.8889, the Random Forest tree and KNN performed the best on the test dataset.

Applying random search hyperparameter tweaking to optimize the accelerometers and gyroscopes—sensors that measure changes in acceleration and rotation, respectively—improved the model's effectiveness. When a vehicle encounters a pothole, it experiences sudden changes in acceleration and rotation, which can be detected using these sensors.

Deep Learning Approach to Pothole Detection [6]

The proposed system leverages the power of a CNN to analyze road imagery and identify potential road surface anomalies.

The first phase of the system involved training a CNN on a diverse dataset comprising road images captured under various environmental conditions. The network learns the intricate features of road surfaces and can differentiate between normal road conditions and areas with potholes. Transfer learning techniques are employed to boost the model's performance, enabling effective adaptation to different geographic regions and road types.

The deep learning approach not only excels in pothole detection but also offers insights into overall road surface deterioration. This technology contributes to proactive maintenance, reduces infrastructure damage, and ensures safer roadways.

Road Pothole Detection Using Smartphone Sensors [7]

This paper presents an innovative approach to pothole detection by harnessing the sensing capabilities of smartphones such as accelerometers and gyroscopes to detect and report potential potholes.

The system employs signal processing techniques to analyze data from smartphone sensors, focusing on patterns indicative of road irregularities. These patterns are then used to develop machine learning systems that can differentiate between potholes and typical roadway circumstances. This approach allows the creation of a lightweight and efficient pothole detection system that leverages the ubiquity of smartphones.

PROPOSED AND TESTED METHODS

Sensor-Based Systems [8]

Gyroscopes and accelerometers are sensors that measure rotational and acceleration changes, respectively. When a vehicle encounters a pothole, it experiences sudden changes in acceleration and rotation, which can be detected using these sensors.

GPS: Vehicle mobility and location can be tracked using a global positioning system (GPS). Anomalies in vehicle movement, such as sudden deceleration or deviation from the expected path, can indicate the presence of a pothole.

Computer Vision [9]

- *Image Processing:* Cameras capture images or videos of the road surface, which are then processed using computer vision algorithms.
- *Feature Extraction:* Algorithms extract features such as texture, color, and shape from images to identify potential potholes.
- *Pattern Recognition:* Machine learning techniques are often employed to recognize patterns indicative of potholes, such as cracks, depressions, and irregularities on the road surface.

Acoustic Sensor [10]

- *Microphones:* Acoustic sensors, such as microphones, capture the sound waves generated by vehicles passing over potholes.
- *Signal Processing:* Signal processing techniques analyze the captured sound data to identify characteristic signatures associated with potholes, such as the frequency spectrum and amplitude variations.

Machine Learning [11]

- *Data Collection:* Datasets containing labeled examples of potholes (positive samples) and non-pothole road surfaces (negative samples) were collected from various sources, such as sensor data or images.
- *Feature Extraction:* Pertinent features, such as auditory impulses, sensor readings, or image pixels, are extracted from the data.

Journal of Control & Instrumentation
Volume 16, Issue 1
ISSN: 2229-6972 (Online), ISSN: 2347-7237 (Print)

- *Model Training:* To learn to differentiate between potholes and non-potholes, machine learning models, such as recurrent neural networks (RNNs) for sequential data or CNNs for image data, were trained on the labeled dataset.
- *Deployment:* The trained model was deployed to detect potholes in real-time by processing incoming sensor data or images.

LiDAR

- *Laser Scanning:* To produce precise 3D maps of the road surface, LiDAR sensors send out laser pulses and time how long it takes for the light to reflect.
- *Point Cloud Processing:* Algorithms analyze the generated point cloud data to detect anomalies indicative of potholes, such as depressions or irregularities on the road surface.

Sensor Integration [12]

Data from multiple sensors such as cameras, accelerometers, GPS, and LiDAR were integrated and synchronized. The datasets used are shown in Figure 1.

Multi-modal Fusion: Fusion techniques, such as sensor fusion algorithms or deep learning architectures, such as multi-input neural networks, are employed to combine information from different sensor modalities for more robust pothole detection.

EXPERIMENTAL EVALUATION

Convolutional Layer

Output Size (O): $O = \frac{W-K+2P}{S} + 1$

Where
W is the input size
K is the kernel size
P is padding
S is stride

Figure 1. Datasets involved in the experiment.

Pooling Layer

Output Size(O): $O = \frac{W-F}{S} + 1$

Where

F is the pool size

Flatten Layer

Number of neurons: N – H X W X D

Where

H, W, and D are the height, width, and depth of the input

Dense Layer

Output Size (O): O = Activation (Weight X Input + Bias)

WORKFLOW

The model training process involved the use of the defined neural network architecture to learn patterns and relationships within the training data. In the provided code, this is performed using the model fit method, which trains the model on the training dataset [13].

The main points of the model training part are explained as follows:

Model Training

- X_train contains the input images after preprocessing.
- y_train contains the corresponding labels for each input image.

epochs

An entire run through the entire training dataset is called an epoch. It represents the percentage of training data that will be utilized as validation data. In this instance, the performance of the model on unknown data was tracked using 10% of the training data as validation data [14].

Training Process

The fit approach was used to train the model, and the training data were used to update the model’s parameters (weights and biases).

Every epoch involves feeding the network the complete training dataset and comparing the actual labels with the model predictions. The parameters (weights and biases) are presented in Table 1.

The categorical cross-entropy (loss function) was calculated, and the model parameters were adjusted to minimize this loss using the Adam optimizer. To assess the model’s performance on unknown data and avoid overfitting, validation data were utilized [15].

Table 1. Parameters (weights and biases).

Images	Probability	Precision	Recall
Image1	0.9992459	72.6	65.5
Image2	0.9999815	67.9	88.1
Image3	0.9997384	91.3	36.2
Image4	0.9999244	76.4	86.6
Image5	0.9999962	78.2	50.3
Image 6	0.9993789	74.7	81.2

Journal of Control & Instrumentation
Volume 16, Issue 1
ISSN: 2229-6972 (Online), ISSN: 2347-7237 (Print)

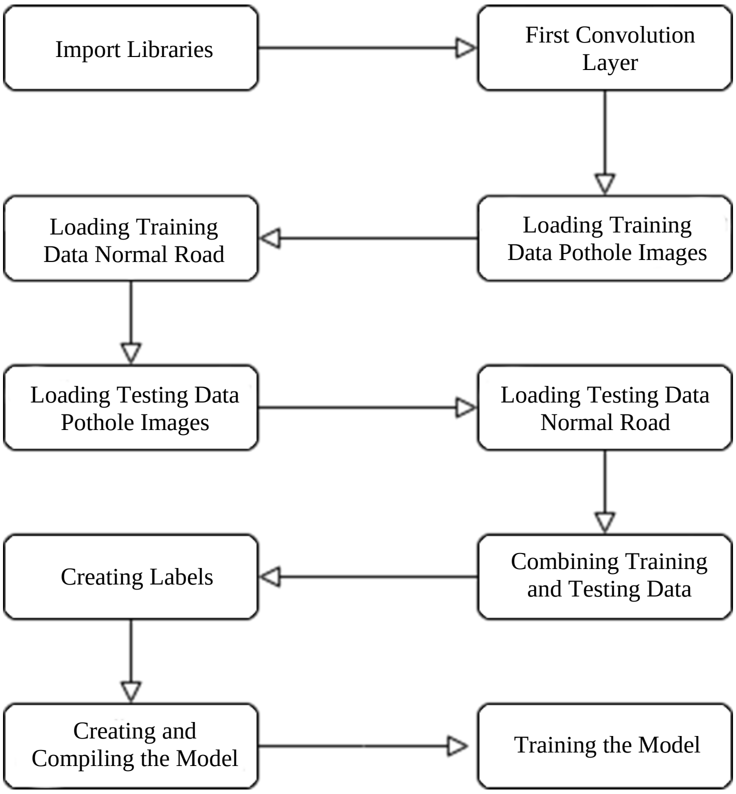

Figure 2. Flow diagram of the working mechanism.

History Object

A historical object with details about the training procedure, including training and validation loss and accuracy across each epoch, was returned by the fit method. This object can be used to visualize the training progress and identify potential issues such as overfitting or underfitting.

Model Evaluation

After training the model, it was important to evaluate its performance on both the training and testing datasets. This was performed using the evaluation method, and the accuracy metrics were printed for both datasets. The effectiveness of the model on a particular dataset was evaluated using the evaluation technique shown in Figure 2 [16–20].

CONCLUSION

The model appeared to have learned effectively from the training data if the training accuracy was high. The testing accuracy shows how well the model applies to data that has not yet been observed. A similar or close testing accuracy to the training accuracy is desired for good generalization. This is the standard procedure for preserving the trained model for later usage or deployment after the model has been evaluated.

Future Scope

Pothole detection using machine learning has a promising future, with several potential applications and advancements.

1. *Smart Transportation:* Implementing pothole detection in vehicles can improve road safety by providing real-time alerts to drivers, allowing them to avoid potholes and reduce vehicle damage.
2. *Infrastructure Maintenance:* Municipalities and transportation authorities can use pothole detection systems to prioritize road repairs more efficiently. Machine learning algorithms can analyze data collected from various sources, such as vehicles equipped with sensors or satellite imagery, to identify areas with high pothole density.

3. *Crowdsourced Data Collection:* Mobile applications allow users to report the potholes they encounter while driving. Machine learning models can then analyze crowdsourced data to create up-to-date maps of pothole locations, aiding maintenance planning.
4. *Autonomous Vehicles:* Autonomous vehicles must detect potholes to navigate effectively. Machine learning algorithms can be trained to recognize and classify road hazards, including potholes, enabling autonomous vehicles to adjust their speeds or routes to avoid them.
5. *Infrastructure Monitoring:* Machine learning models can be deployed alongside existing infrastructure, such as traffic cameras or drones, to continuously monitor road conditions and identify potholes as they form. This proactive strategy enables early maintenance and correction before the potholes worsen.

REFERENCES

1. Buza E, Omanovic S, Huseinovic A. Pothole detection with image processing and spectral clustering. In: Lopes S, editor. Recent Advances in Computer Science and Networking: Proceedings of the 2nd International Conference on Information Technology and Computer Networks (ITCN ‘13); 2013 Oct 8–10; Antalya, Turkey. University of Minho: WSEAS Press; 2013. p. 48–53.
2. Boopathi D, Gagana BP, Girish ST, Kiran M, Gowda CDV. Automatic detection and filling of potholes. Int Res J Mod Eng Technol Sci. 2023 May;5(5):6148–53.
3. Dhiman A, Klette R. Pothole detection using computer vision and learning. IEEE Trans Intell Transp Syst. 2020;21:3536–50. DOI: 10.1109/TITS.2019.2931297.
4. Ren J, Liu D. PADS: A reliable pothole detection system using machine learning. International Conference on Smart Computing and Communication. Springer; 2016. p. 327–38.
5. Egaji OA, Evans G, Griffiths MG, Islas G. Real-time machine learning-based approach for pothole detection. Expert Syst Appl. 2021;184:115562. DOI: 10.1016/j.eswa.2021.115562.
6. Varona B, Monteserin A, Teyseyre A. A deep learning approach to automatic road surface monitoring and pothole detection. Pers Ubiquitous Comput. 2020;24:519–34. DOI: 10.1007/s00779-019-01234-z.
7. Ping P, Yang X, Gao Z. A deep learning approach for street pothole detection. 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService), Oxford, UK. 2020. p. 198–204. DOI: 10.1109/BigDataService49289.2020.00039.
8. Bharat R, Ikotun AM, Ezugwu AE, Abualigah L, Shehab M, Zitar RA. A real-time automatic pothole detection system using convolution neural networks. Appl Comput Eng. 2023;6:750–7. DOI: 10.54254/2755-2721/6/20230948.
9. Kotha M, Chadalavada M, Karuturi SH, Venkataraman H. Potsense: Pothole detection on Indian roads using smartphone sensors. Proc 1st ACM Workshop Auton Intell Mob Syst. ACM; 2020. p. 1–6. DOI: 10.1145/3377283.3377286.
10. Song H, Baek K, Byun Y. Pothole detection using machine learning. Adv Sci Technol Lett. 2018;150:151–5. doi:10.14257/astl.2018.150.35.
11. Kumar A, Chakrapani DJ, Kalita DJ, Singh VP. A modern pothole detection technique using deep learning. 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India. 2020. p. 1–5. DOI: 10.1109/IDEA49133.2020.9170705.
12. Kulkarni A, Mhalgi N, Gurnani S, Giri N. Pothole detection system using machine learning on android. Int J Emerg Technol Adv Eng. 2014;4:360–4.
13. Acharjee C, Singhal S, Deb S. Machine learning approaches for rapid pothole detection from 2D images. In: Kar N, Saha A, Deb S, editors. Trends in Computational Intelligence, Security and Internet of Things. ICCISIoT 2020. Cham: Springer; 2020. (Communications in Computer and Information Science; vol. 1358). https://doi.org/10.1007/978-3-030-66763-4_10.
14. Tahir H, Jung ES. Comparative study on distributed lightweight deep learning models for road pothole detection. Sensors (Basel). 2023;23:4347. DOI: 10.3390/s23094347. PubMed: 37177550.
15. Kharel S, Ahmed KR. Potholes detection using deep learning and area estimation using image processing. In: Arai K, editor. Intelligent Systems and Applications. IntelliSys 2021. Cham: Springer; 2022. (Lecture Notes in Networks and Systems; vol. 296). https://doi.org/10.1007/978-3-030-82199-9_24

ISSN: 2229-6972 (Online), ISSN: 2347-7237 (Print)

16. Kavati I. Deep learning-based pothole detection for intelligent transportation systems. In: Patgiri R, Bandyopadhyay S, Borah MD, Emilia Balas V, editors. Edge Analytics. Singapore: Springer; 2022. (Lecture Notes in Electrical Engineering; vol. 869). https://doi.org/10.1007/978-981-19-0019-8_20.
17. Owusu KA. Building a pothole detection and tracking system. [Capstone Project]. Berekuso (GH): Ashesi University; 2019. Available from: http://hdl.handle.net/20.500.11988/523
18. Yebes JJ, Montero D, Arriola I. Learning to automatically catch potholes in worldwide road scene images. IEEE Intell Transp Syst Mag. 2021;13:192–205. DOI: 10.1109/MITS.2019.2926370.
19. Anik FS, Ahmed A, Maheen A, Alam P. Identification and comparative analysis of potholes using image processing algorithms. [PhD diss.]. BRAC University; 2018.
20. Ryu SK, Kim T, Kim YR. Image-based pothole detection system for ITS service and road management system. Math Probl Eng. 2015;2015:1–10. DOI: 10.1155/2015/968361.