SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper
Open Access

Technology Adoption Modeling: Integrating Engineering Constraints And System Dynamics

Purushottam S. Barve[1], Vijayshree Khugshal[2], Akash Kumar Bhagat[3], Swati Singh[4], Dharmesh Dhabliya[5], Monisha J[6], Jeyanthi P[7], Dr. Sachin S. Pund[8]

[1] Assistant Professor, Department of Mechanical Engineering, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India. Email: purubarve5@gmail.com ORCID: 0000-0002-0835-1433
[2] Assistant Professor, Department of Computer Application, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email: socse.vijayshree@dbuu.ac.in ORCID: 0009-0002-0277-2154
[3] Assistant Professor, Department of Computer Science & IT, Arka Jain University, Jamshedpur, Jharkhand, India. Email: akash.b@arkajainuniversity.ac.in ORCID: 0000-0001-8717-764X
[4] Assistant Professor, Department of School of Engineering & Technology, Noida International University, Greater Noida, Uttar Pradesh, India. Email: swati.singh@niu.edu.in
[5] Vishwakarma Institute of Technology, Pune, Maharashtra, India. Email: dharmesh.dhabliya@viit.ac.in
[6] Assistant Professor, Department of Management Studies, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: jmonishamba@maher.ac.in
[7] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: jeyanthicom@maher.ac.in
[8] Assistant Professor, Department of Mechanical Engineering, Shri Ramdeobaba College of Engineering and Management, Nagpur, Maharashtra, India. Email: pundss@rknec.edu ORCID: 0000-0002-5616-2469

Abstract

In this research, an adoption model for anIntelligent Transportation System (ITS) through the integration of engineering parameters and system dynamics for the detection and assessment of potholes can be developed. The suggested methodology involves the use of the Kaggle-based Potholes Detection You Only Look Once version 8(YOLOv8) dataset that includes annotated images of roads in different environmental conditions. At the first stage, Histogram Equalization (HE) is used during data pre-processing to increase the contrast of road images and make the potholes more visible. The Histogram of Oriented Gradients (HOG) approach can be used for feature extraction. Finally, a novel hybrid optimization model, Bonobo Optimizer and Extreme Gradient Boosting (BO-XGBoost), can be used to classify the potholes on the roads.Evaluations of the developed model have been conducted based on Mean Average Precision (mAP), mAP50, mAP75, and mAP50-95 measures, and it performs better by obtaining 0.989, 0.890, and 0.890 values, respectively. Furthermore, the method outperforms other current models, such asYou Only Look Once version 8(YOLOv8), You Only Look Once version 9(YOLOv9), MobileNet, and You Only Look Once version 11(YOLOv11)-based systems in terms of performance. Moreover, the method is assessed based on computational complexity, infrastructure compatibility, and adaptability. The empirical findings show that the proposed model assists in improving pothole detection efficiency and reduces latencies.

Keywords: Intelligent Transportation Systems (ITS), Pothole Detection, Histogram Equalization (HE), Bonobo Optimizer and Extreme Gradient Boosting (BO-XGBoost).

1. Introduction

There are various challenges faced by the Intelligent Transportation Systems (ITS) because of urbanization, which includes congestion, pollution, accidents, and inefficiency. Artificial Intelligence (AI) technology will be highly influential in transportation management by improving traffic prediction, signal control, and traffic safety. AI-based pothole detection system will be adopted for monitoring the roads in real-time in order to prevent accidents. It is important to understand that well-developed roads have great significance for economic growth and social mobility. Presence of potholes and cracks results in increased maintenance cost, accidents, and damage to vehicles, thereby compromising the comfort level of drivers. Traditional methods of inspecting potholes are inefficient and tedious; therefore, it becomes vital to implement systematic road monitoring. Pothole detection techniques are generally subjective in nature as they depend on public reports or human inspection.These approaches depend heavily on human judgment, which can result in inconsistencies, inefficiencies, and limited scalability in large-scale road monitoring applications [3]. The condition of the road surface is a critical factor in road condition assessments, which play a key role in road safety and durability. Potholes, as one of the most dangerous defects, damage the integrity of roads and vehicles. However, traditional methods of detection are time-consuming, subjective, and inefficient, which has led to intelligent pothole detection methods being developed. The goal is to understand how to increase the accuracy, localization and instant identification of the detected object based on a sensor and image processing technique. A range of solutions have been proposed, including vibration-based systems, image-based systems, and systems based on point clouds, but there are difficulties in the deployment of reliable and scalable solutions for real-world applications [4, 5]. An effective pothole detection system that alerts maintenance staff or road users to repair high-risk potholes would be greatly beneficial to roadway safety, and would prioritize maintenance activities. Current detection approaches, based on sensors or manual checking, however, are not scalable and are not precise enough. The manual inspections are costly and labor-intensive, so they are impractical for large-scale monitoring [6, 7]. Although Advanced Driver Assistance Systems (ADAS) have been developed to ease the pothole detection process, most research has focused on the detected pothole market without considering the control of vehicle dynamics after the pothole is detected, which can significantly enhance road safety [8].

Research Aim: The goal of the proposed method is to increase the performance of Intelligent Transportation Systems (ITS) pothole detection through the implementation of a hybrid optimization method involving the Bonobo Optimizer (BO) and Extreme Gradient Boosting (XGBoost). The hybrid model seeks to improve the accuracy, efficiency, and ability to localize potholes on the roads in real time. Through the use of sophisticated feature extraction methods such as histogram equalization and histogram of oriented gradients, the method is able to detect road defects more efficiently even under diverse weather conditions.

Research organization: The research is structured as follows: Section 1 describes the problem statement for ITS-based pothole detection and objectives. Section 2 provides literature review of existing works. Section 3 explains methodology, which includes HE for pre-processing, HOG for feature extraction, and BO-XGBoost for classification. Section 4 analyzes results and evaluation of the research. Section 5 offers conclusions with future scopes.

2. Related work

The research was held to design a model based on a Time-of-Flight (ToF) camera for the automatic detection and 3-D geometric analysis of potholes in an ITS. The method is based on the combination of depth imaging, adaptive segmentation, and surface reconstruction to estimate the geometry of the pothole. A detection reliability rate over 90% was obtained for moderate and severe potholes. For shallow potholes, the low depth contrast, sensor noise, and threshold sensitivity resulted in reduced accuracy [9]. The research [10] proposed a road damage dataset for ITS, which includes annotated potholes, cracks, and maintenance holes recorded under various urban and rural settings. Road-damage detection was performed using Deep Learning (DL) models such as YOLOv11n and YOLOv11s. Experimental results obtained precision greater than 0.65 and good results of generalization. However, lightweight models had lower detection accuracy when facing complex damage patterns, showing the limitations of representation power and sensitivity to optimization of features.This HRP4K pothole database is created for ITS to help improve the road damage detection in the researches carried out as mentioned in [11]. Several DL-based models have been used to detect the damage on roads, including YOLOv11, YOLOv8, YOLOv5, RT-DETR, and D-FINE. They were all experimented using 6,003 annotated images. The findings resulted in high precision scores of up to 0.742, recall of 0.570, and mAP@0.5 of 0.655. However, the detection ability of these models tends to fall for small potholes and concrete road surfaces. Besides, their effectiveness is low for harsh environmental situations. The proposed ITS-based instant pothole detection system by [12], utilizing the Robot Operating System and various AI models such as YOLOv8n, YOLOv11n, and YOLOv12n, along with an ADAS camera and GNSS module, was capable of automatic detection of potholes in different climatic and lighting scenarios and varying roadways, with an 84% precision and recall rate. Nevertheless, the detection rate of the system was highly inconsistent in complex situations and while encountering sudden road surface changes. The approach introduced by [13] named Edge Channel-aware YOLO ECCYOLO was based on a light version of YOLOv11n, which is used to detect potholes via ITS-based systems. In ECCYOLO, C3k2DCY, CDFA, and ELA-HSFPN blocks were used. ECCYOLO attained an 84.5%, 67.9%, and 74.2% accuracy, recall rate, and mAP@0.5 However, performance may vary depending on dataset characteristics and environmental conditions.The automated pothole detection and optimization of repair operations, which was proposed for an ITS. These include multimodal data fusion with the Sequential Spatio-Temporal Model (SSMT), hybrid Graph Attention Network - Extreme Gradient Boosting (GAT-XGBoost) classification, Soft Actor-Critic (SAC) Deep Reinforcement Learning, and transfer learning withDomain-Adversarial Neural Network(DANN)[14]. The results show that it can be performed with 97% detection accuracy, and even 20% cost reductions. However, there are some limitations regarding the system's scalability and dependence on available data. The research proposes a low-cost pothole detection technique with the use of smartphone vibration sensors and Global Positioning System (GPS) without any extra hardware in vehicles. In this technique, images were formed from the vibration sensors' readings through convolutional neural networks (CNN) [15], where an accuracy rate of 93.24% was achieved during validation and about 80-87% when testing different routes. The research [16] developed PointPaveSeg for ITS-based pavement distress inspection using three-dimensional (3D) images captured with a consumer-grade action camera. The approach involved adaptive re-sampling, weighted fusion loss, dual-stream fusion of features, and hierarchical propagation to enhance segmentation efficiency while balancing classes. Results yielded an accuracy rate of 95.43% and mIoU score of 78.45%, showing high concordance with manual assessment of pavements.A low-cost road monitoring approach for ITSthrough the installation of special sensing devices on urban All-Terrain Vehicles (ATVs)was proposed in this research [17]. Techniques utilized include noise reduction via low-complexity signal processing techniques and pothole detection and International Roughness Index (IRI) calculation. This system achieved an accuracy of pothole detection of 90.5%, with an error of IRI value of 8.41% and a reduction in monitoring duration by 65.4%.This research [18] focused on developing an economical detection system for potholes in intelligent transportation through the use of smartphones. CNN-based models are employed for classifying vibrations in image format. The results demonstrate that the validation accuracy of the model is 93.24%, while the accuracy of the model in a real-world scenario lies between 80 and87%.The research [19] introduced a method for detecting road potholes in low-light conditions, which is based on data augmentation and a You Only Look Once Version 11-+ Feature Pyramid Network + Gradient-weighted Class Activation Mapping (YOLOv11+FPN+Grad-CAM)model. The model gave anmAP of 0.72, which is better than other models, YOLOv8 Medium, etc.Though successful, limitations include the model's reliance on night data sets, and future plans are being developed for real-time driver warnings and adapting to different environmental conditions.

3. Methodology

The pothole detection system based on ITS is presented in Figure 1. Initially, pothole pictures are gathered from the Kaggle database and then separated into training, validation, and testing datasets. HE is used for preprocessing the images to improve image contrast irrespective of different lighting. The HOG technique is utilized to extract features from images. Eventually, potholes are detected using the BO-XGBoost algorithm, where the bonobo optimizer optimizes the sensors' settings and the XGBoost method detects potholes.

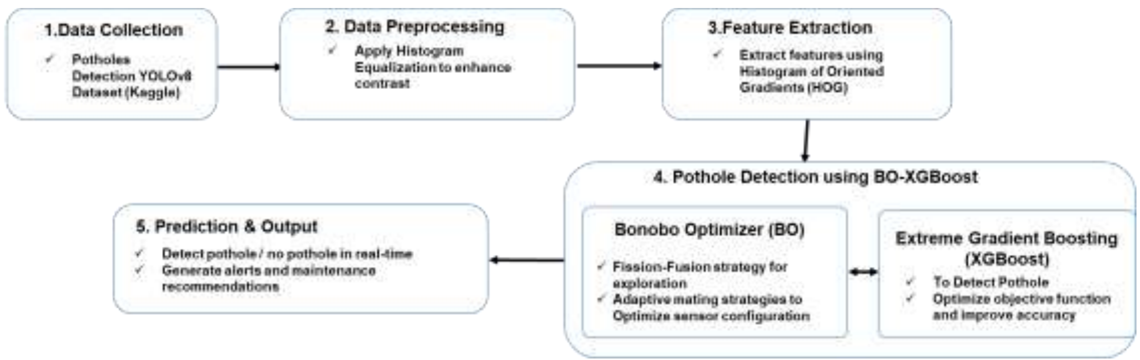

Figure 1: Methodology Architecture

3.1 Data collection

The proposed ITS employs the Potholes Detection YOLOv8 dataset (https://www.kaggle.com/datasets/anggadwisunarto/potholes-detection-yolov8?utm_source=chatgpt.com) from the Kaggle sources to facilitate automatic pothole detection. This is a dataset used in pothole detection and it consists of 1,977 annotated images out of which 1,581 images are used for training while 396 are for validation purposes.The dataset is split into training, validation, and testing datasets in the ratios 70%, 15%, and 15%, respectively.

3.2 Data preprocessing usingHistogram Equalization (HE)

To improve the contrast of an image, thus emphasizing small features in the image, like potholes on the road.It maps pixel values over the entire range (0-255), making any difference between the pothole and the rest of the road surface more pronounced.This method enhances the detection of variations on the surface under different lighting and environmental conditions, including fog.

$$\mathrm{CDF}^{l}(\nu) = \sum_{j=0}^{\nu} G_{q}^{l}\ (j) \quad (1)$$

In Equation (1), ν is the data point used for distribution, q denotes the index of quantization, G refers to vectors associated with the featuresG_q^l (j)is the value of the Histogram at the intensity level j,CDF denotes the cumulative distribution, $\mathrm{CDF}^l(\nu)$refers to the function of the cumulative distribution at the intensity level l, l refers to the intensity level of the pothole images, and j refers to the position of the pothole image grid

$$O_l(\nu) = \left(\frac{\mathrm{CDF}^l(\nu) - \mathrm{CDF}^l_{min}}{M_l - \mathrm{CDF}^l_{min}}\right) \times 255 \quad (2)$$

In Equation (2),$O_l(\nu)$ refers to the intensity of the new pixel after the equalization, CDF^l_{min} represents the non-zero CDF of the value, and Mdenotes the total number of image pixels, $M_l$denotes the total number of image pixels with the intensity level l.

3.3 Feature extraction using Histogram of Oriented Gradients (HOG)

The HOG feature extraction technique works well for pothole detection in road images, as it uses both the amplitude and phase of the gradient to bring out the necessary features in terms of texture and edges for detecting road abnormalities like potholes. Image division occurs into cells and blocks where gradient computation is done for each cell and block. Histograms of gradients are generated and normalization is done to all equally sized blocks. The feature vectors resulting from normalization are then fed into the machine learning system used in pothole recognition.

$$\nabla e(w,z) = \begin{bmatrix} e(w, z+1) - e(w, z-1) \\ e(w+1, z) - e(w-1, z) \end{bmatrix} \quad (3)$$

In Equation (3),where $e(w,z)$ refers to the intensity of the pixel at the position w, z, $\nabla e(w,z)$ represents the vector of the gradient at the position w, z, eis the Intensity of pixel,w is the pixel's horizontal position, and zis the pixel's vertical position in the image grid,and ∇ denotes the gradient.

$$|\nabla e| = \sqrt{h_w^2 + h_z^2} \quad (4)$$

In Equation (4), where$h_w^2 + h_z^2$ represents the values of the gradient in thew andzdirections, respectively, $|\nabla e|$is the magnitude of the gradient, h denotes the difference in height.

$\theta = \tan^{-1}(\frac{h_z}{h_w})$ (5)

In Equation (5), θrefers to the direction of the gradient, $\tan^{-1}$ denotes the inverse Tangential function,h_z denotes the difference in height in the horizontal direction, $h_w$refers to the difference in height in the vertical direction. Figure 2 depicts the original pothole images and processed images depicting noise reduction and feature extraction for more accurate road defect identification.

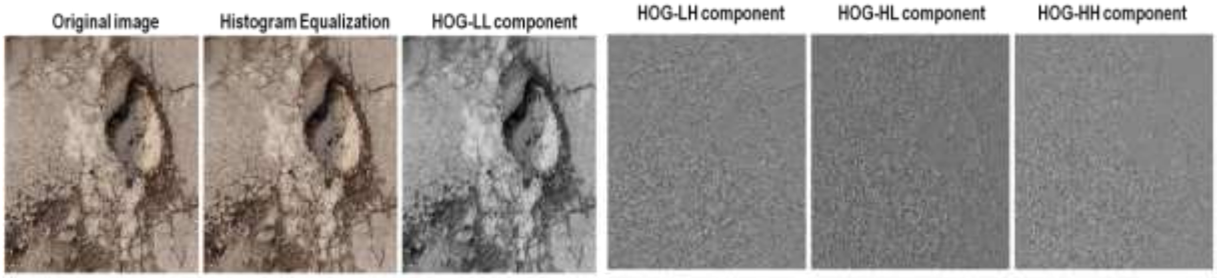

Figure 2: Pothole detection images before and after processing

3.4 Pothole detection using Bonobo Optimizer tuned Extreme Gradient Boosting (BO-XGBoost)

The proposed model uses a hybrid technique, which combines BO and XGBoost for improved pothole detection by adopting adaptive fission-fusion operations and optimizing sensor setup. The Bonobo Optimizer (BO) algorithm divides road segments into groups, conducts local and global fusion of features, and varies the probability of mating between internal and external factors. However, XGBoost utilizes second-order Taylor expansion and ridge regression to minimize errors from imbalance data.

EXtreme Gradient Boosting (XGBoost): An ITS system can also make use of the XGBoost technique for the pothole detection. To detect potholes, the XGBoost technique can add the second-order Taylor expansion of the objective function with the Ridge Regression approach to minimize the loss and the variance of the model, hence enhancing the effectiveness of detecting potholes. The XGBoost models are built by training a series of base models whose outputs are summed up to ascertain whether there is a pothole in that particular section of the road. There is a loss function and a regularization term added to the objective function of the algorithm, thus reducing the chances of overfitting and enhancing generalization to new data.

$Z_j = \sum_{l=1}^{l} e_l\,(w_j)$ (6)

In Equation (6),$Z_j$is the predicted output of thesamplej, w_j is the features of input for the samplej,$e_l$refers to the base modelj, which is the index of the base model, l is the count of base models, j refers to the sample image and $\sum_{l=1}^{l}$ is the summation function which sums the data up to l.

$K = \sum_{j=1}^{m} k\,(z_j\,, Z_j)$ (7)

In Equation (7),z_j refers to the sample of true value,$k\,(z_j, Z_j)$ represents the loss function of the samplej, m is the count of the samples in the dataset, andK is the loss function,Z_j represents the vector of feature, and $\sum_{j=1}^{m}$ refers to the summation of the data from each sample j to the total number of samples m.

$Obj = K + \sum_{l=1}^{l} \Omega\,(e_l)$(8)

In Equation (8),Obj is the objective function,$\Omega(e_l)$ denotes the term of the regularization,Ω denotes the regularization term,e_l denotes the feature of error with the model l and e denotes the error term.

$\Omega(e_l) = \frac{1}{2}\lambda \sum_{i=1}^{S} \omega_i^2 + \gamma S$ (9)

In Equation (9), λ refers to the parameter of regularization,S is the count of leaf, ω_i denotes the weight of the leaf i,ω denotes the weight,γ denotes the penalty term, and γS denotes the penalty on the count of leaf S.

Bonobo Optimizer (BO): BO is one of the methods that could be applied in ITS for the purpose of identifying potholes. This approach involves the partitioning of the road into smaller segments for local detection (fission) and the fusion of the outcomes from different sources to enable global analysis (fusion). Different types of detection models will be studied for evaluating the performance of sensors under different mating strategies (promiscuous/restrictive mating). The balance between local and non-local information will be regulated by parameters such as phase probability and extra-group mating probability. The algorithm will continuously learn from the feedback for efficient detection of potholes.

$$\mathrm{Bo}_{\mathrm{new}_i} = \mathrm{Bo}_i^j + q_1 \times \mathrm{scab} \times \left(\alpha_{\mathrm{Bo}}^i - \mathrm{Bo}_i^j\right) + (1 - q_1) \times \mathrm{scsb} \times h \times \left(\mathrm{Bo}_i^j - \mathrm{Bo}_i^o\right) \quad (10)$$

In Equation (10), $\mathrm{Bo}_{\mathrm{new}_i}$ refers to the updated solution of detecting the pothole with the feature i, Bo_i^j represents the parameter of the current solution in the index j with the feature i, q_1 denotes the factor of randomization, scab is the coefficient of sharing within the bonobo, α_{Bo}^i refers the alpha bonobo which is the best solution, Bo_i^o is the bonobo o with the featurei, h denotes the direction of change, scsb is the coefficient of sharing within the bonobo α, orepresents theselected mating partner bonobo, i refers to which element or feature in the bonobo's solution is being updated, new is the updated value, and the BO denotes the Bonobo Optimizer.

$$\mathrm{Bo}_{\mathrm{new}_i} = \mathrm{Bo}_i^j + q_1\left(\mathrm{Var}_{\mathrm{max}_i} - \mathrm{Bo}_i^j\right) \text{if } \left(\alpha_{\mathrm{Bo}}^i \ge \mathrm{Bo}_i^j \text{and} q_3 \le o_c\right) \quad (11)$$

In Equation (11), $\mathrm{Var}_{\mathrm{max}_i}$ is the parameterjof the maximum value, q_3 represents the random factor, and o_c depicts the probability of the Phase.

$$\mathrm{Bo}_{\mathrm{new}_i} = \begin{cases} \mathrm{Bo}_i^j + h \times f^{-q_3}\left(\mathrm{Bo}_i^j - \mathrm{Bo}_i^o\right) \text{if } \left(q_2 > 0_{xin} \text{and} h = 1 \text{ or} q6 \le o_c\right. \\ \mathrm{Bo}_i^o \text{if } \left(q_2 > o_{xin}\right) \end{cases} \quad (12)$$

In Equation (12), f^{-q_3} is the decay factor of the exponential, q_2 denotes the random factor, and o_{xin} refers to the probability of mating extra-group

Hyperparameter configuration of the proposed model: The optimization for the model parameters has been carried out in such a way that the process of pothole identification can be optimized in ITS. In order to do so, the population size is taken as 30, and the maximum iteration is taken as 100. The learning rate ranges from 0.01 to 0.30, while the range for the number of estimators is 100-500. The maximum tree depth has also been selected to range between 3 and 12, while subsample ratio and column sample by tree are selected to lie between 0.6 and 1.0. Similarly, the gamma and minimum child weights have been selected between 0 and 5, and 1 and 10, respectively.

4. Result

Hardware includes an Intel Core i7 Processor with 16GB RAM an NVIDIA GeForce RTX 3060 GPU, and a 512 GB SSD. The operating system is Windows 11, while programming languages such as Python version 3.11 and Jupyter Notebook have been used along with Scikit-learn and XGBoost packages. The confusion matrix is used to analyze the efficiency of the proposed pothole detection model by assessing the comparison of actual and predicted labels as shown in Figure 3(a). There are 130 correct predictions for the category of non-pothole, while there are 146 correct predictions for potholes. In addition, only 17 instances of false positives and 14 instances of false negatives are found, reflecting minimal classification mistakes and higher prediction efficiency. The graph shown in figure 3(b) illustrates the relationship between the precision and recall for different threshold values. The result attained for PR-AUC, which is 0.8994, demonstrates efficient detection of potholes with fewer false alarms. The ROC-AUC is determined using figure 3(c), which displays the ROC curve. The ROC-AUC value, which is 0.9360, indicates exceptional discrimination ability of the classification model with high sensitivity.

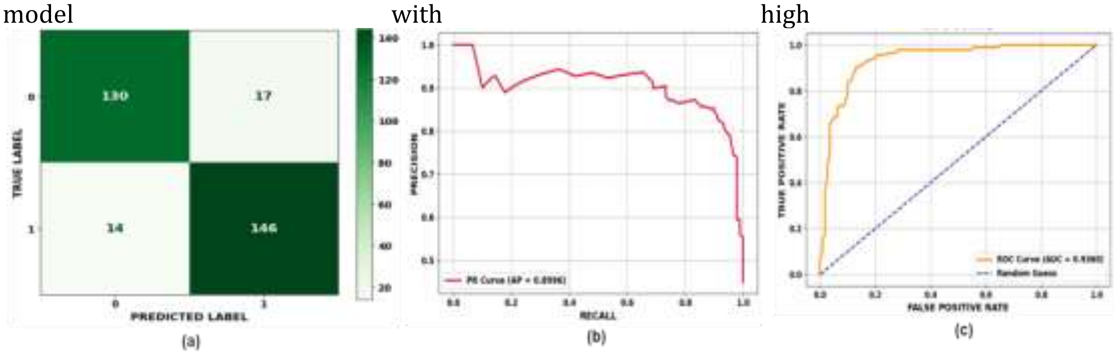

Figure 3: Evaluation of proposed performance (a) confuse matrix, (b) AUC curve, and (c) ROC curve

4.1 Evaluation Metrics

4.1 Evaluation Metrics: The model's performance in detecting potholes is assessed using the metrics mAP50, mAP75, and mAP50-95, which gauge the accuracy at various levels of overlap (IoU).mAP50 is for detecting the overall accuracy, mAP75 is for accurate localization, and mAP50-95 is for overall robustness across multiple IoU thresholds. Such indices demonstrate the effectiveness of the model to detect and accurately locate potholes under different road and environmental conditions, essential for ITS.

4.2 Performance Evaluation: The table below (Table 1) and the figure below Figure 4 (a-c) provide the comparison of all deep learning models for pothole detection through mAP50, mAP75, and mAP50-95. Among YOLOv8, YOLOv9, YOLOv10 and YOLOv11 are high-accuracy models, while RTDERT and MobileNet are low-accuracy models. The enhanced version of the YOLOv11+FPN+Grad-CAM model is capable of feature extraction and localization to obtain the maximum area, hence its higher mAP value. The proposed BO-XGBOOST model performs optimally in terms of mAP50, mAP75 and mAP50–95 scores, which are recorded as 0.989, 0.890 and 0.890, respectively. It was observed that the use of Bayesian optimization is important in optimizing model parameters, while XGBoost enhances classification accuracy and robustness of the process.

Table 1: Comparative Analysis of the Existing Models

Model	mAP50	mAP75	mAP50-95
YOLOv8Nano [19]	0.831	0.732	0.549
YOLOv8Small [19]	0.840	0.724	0.604
YOLOv8Medium [19]	0.867	0.719	0.611
YOLOv9 [19]	0.773	0.754	0.6
RTDERT [19]	0.674	0.569	0.472
MobileNet [19]	0.643	0.584	0.581
YOLOv10 [19]	0.842	0.754	0.641
YOLOv11 [19]	0.853	0.734	0.682
YOLOv11+FPN+Crad-CAM[19]	0.88	0.791	0.72
BO-XGBOOST [Proposed]	0.989	0.890	0.890

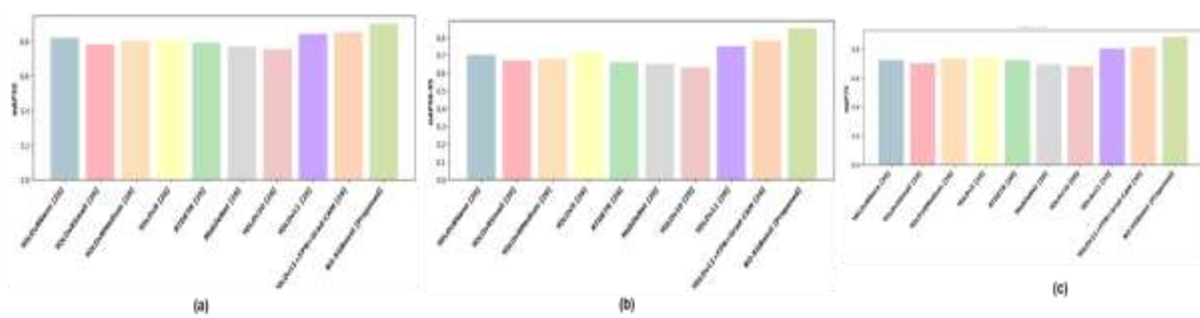

Figure 4: Performance Comparison of Methods across Different Metrics

4.3 Discussion

The comparison brings into focus several methods used for detecting potholes and shows how the suggested approach improves feature detection, reduced computation cost, and increased accuracy in real-time detection and localization. YOLOv8n's [19] lightweight design limits its feature extraction capabilities, thus making it more difficult for it to detect small and complicated objects. YOLOv8Small [19] offers a less effective at handling complex scenes with lots of objects and with changing conditions. YOLOv8Medium [19] is the medium model, which is more accurate but has higher computational complexity, leading to higher memory consumption and inference time. YOLOv9 [19] introduces new features in learning, but demands a lot of training data, and is unstable when objects are partially occluded. RT-DETR [19] is able to achieve high context comprehension, but suffers from high computational and training costs due to its transformer architecture. MobileNet[19] has fewer computational resources, but lower semantic feature representation and precision. YOLOv10 offers more speed at the expense of less robustness in the cluttered environment. YOLOv11 [19] strikes a balance between accuracy and complexity, resulting in more resources being used. YOLOv11 + FPN + Grad-CAM [19] is more interpretable and multi-scale learning with higher latency and implementation complexity. BO-XGBOOST has high prediction accuracy, but the cost of training grows with the number of iterations used for optimization, and the adaptability to instant decreases. In complex environments, the proposed method addresses these limitations by combining efficient feature extraction, optimized learning, and computational complexity reduction to enhance accuracy, and localization capabilities, reduce latency, and ensure robust real-time performance.

5. Conclusion

The research has proposed a technology adoption model that takes into account engineering constraints alongside system dynamics to develop solutions for the problem of pothole detection in an intelligent transportation environment. However, unlike all the previous models, this study focuses on the problem of pothole detection. Nevertheless, a variety of engineering limitations including computational issues, sensor reliability, infrastructural preparedness, as well as environment variance play an essential role in the success of such approaches. To improve the accuracy of pothole detection, a BO-XGBoost based hybrid classification model for feature extraction using HE and HGO was proposed. It was found that this method is superior to any other existing ones and produces both high detection accuracy and localization efficiency. Moreover, the importance of feedback dynamics on the course of technology adoption was considered in the current research. The developed BO-XGBoost based hybrid model turned out to be the best one for the task of pothole detection due to highly accurate and efficient localization with mAP50, mAP75, and mAP50-95 equal to 0.989, 0.890, and 0.890, correspondingly. There are some limitations of the proposed technique, namely the sensitivity to environment changes, lower accuracy of small pothole detection, and high computational complexity.

References

1. Zhang, Z., Jin, C.J., Song, Y. and Li, D., 2026. Ai-related papers in the transportation field: Statistics and evolutionary trends. Transportation Research Interdisciplinary Perspectives, 35, p.101803.https://doi.org/10.1016/j.trip.2025.101803
2. Roman-Garay, M., Rodriguez-Rangel, H., Hernandez-Beltran, C.B., Lepej, P., Arreygue-Rocha, J.E. and Morales-Rosales, L.A., 2025. Architecture for pavement pothole evaluation using deep learning, machine vision, and fuzzy logic. Case Studies in Construction Materials, 22, p.e04440. https://doi.org/10.1016/j.cscm.2025.e04440
3. Faisal, A. and Gargoum, S., 2025. Cost-effective LiDAR for pothole detection and quantification using a low-point-density approach. Automation in Construction, 172, p.106006.https://doi.org/10.1016/j.autcon.2025.106006
4. Zhong, J., Kong, D., Wei, Y. and Pan, B., 2025. YOLOv8 and point cloud fusion for enhanced road pothole detection and quantification. Scientific Reports, 15(1), p.11260. https://doi.org/10.1038/s41598-025-94993-0
5. Patawar, A., Mehdi, M., Kore, B. and Saval, P., 2025. A pothole can be seen with two eyes: an ensemble approach to pothole detection. Machine Vision and Applications, 36(3), p.64.https://doi.org/10.21203/rs.3.rs-4262204/v1
6. Radzi, S.F.M., Abd Rahman, M.A., Yusof, M.K.A.M., Haniff, N.S.M. and Rahmat, R.F., 2025. Computationally Enhanced UAV-Based Real-Time Pothole Detection Using YOLOv7-C3ECA-DSA Algorithm. IEEE Access. https://doi.org/10.1109/ACCESS.2025.3573651
7. Ruseruka, C., Mwakalonge, J., Comert, G., Siuhi, S., Ngeni, F. and Anderson, Q., 2024. Augmenting roadway safety with machine learning and deep learning: Pothole detection and dimension estimation using in-vehicle technologies. Machine Learning with Applications, 16, p.100547.https://doi.org/10.1016/j.mlwa.2024.100547
8. Yuan, C., Hang, S., He, Y., Shen, J., Chen, L., Cai, Y., Weng, S. and Wang, J., 2026. Comfort-Oriented Pothole Traversal Using Multi-Sensor Perception and Fuzzy Control. Sensors, 26(6), p.1925.https://doi.org/10.3390/s26061925
9. Ponnusamy, B., 2026. 3D Vision and Depth Sensing for Intelligent Pothole Detection Using Time-of-Flight Imaging. Measurement: Sensors, p.102002.https://doi.org/10.1016/j.measen.2026.102002
10. Giordani, E., Arcioni, L., Gil-Martín, M., Foresti, G.L. and Marini, M.R., 2026. Real-world road damage dataset with potholes, cracks, and maintenance holes. Scientific Reports. https://doi.org/10.1038/s41598-026-46679-4
11. Chen, H., Tu, Z., Zhao, Y. and Ye, J., 2026. A high-resolution perspective-view road image dataset for pothole detection. Scientific Data.https://doi.org/10.1038/s41597-026-07317-w

12. Almasri, I., Manasreh, D. and Nazzal, M.D., 2025. AI Meets ADAS: Intelligent Pothole Detection for Safer AV Navigation. Vehicles, 7(4), p.109.https://doi.org/10.3390/vehicles7040109
13. Li, H., Zhang, C. and Ye, S., 2026. High-precision pothole detection using the ECC-YOLO network with deformable convolution and attention mechanisms. Scientific Reports.https://doi.org/10.1038/s41598-026-47703-3
14. Meshram, K., Saurabh, A., Kharole, V., Mishra, U., Onyelowe, K.C., Kamchoom, V. and Arunachalam, K.P., 2025. Design of an integrated model for pothole detection and repair optimization using multimodal transformers and hybrid deep learning. Case Studies in Construction Materials, p.e05431.https://doi.org/10.1016/j.cscm.2025.e05431
15. Ozoglu, F. and Gökgöz, T., 2023. Detection of road potholes by applying convolutional neural network method based on road vibration data. Sensors, 23(22), p.9023.https://doi.org/10.3390/s23229023
16. Cheng, P., Yi, J., Pei, Z., Liu, Z., Jiang, D. and Abdukadir, A., 2026. Long-Tail Learning for Three-Dimensional Pavement Distress Segmentation Using Point Clouds Reconstructed from a Consumer Camera. Remote Sensing, 18(7), p.1008.https://doi.org/10.3390/rs18071008
17. Guerra, K., Raymundo, C., Silvera, M., Zapata, G. and Moguerza, J.M., 2024. Pothole detection and International Roughness Index (IRI) calculation using ATVs for road monitoring. Scientific Reports, 14(1), p.19761.https://doi.org/10.1038/s41598-024-70936-z
18. Khan, T.A. and Qin, Y., 2025. Graph-Based Deep Learning and Multi-Source Data to Provide Safety-Actionable Insights for Rural Traffic Management. Vehicles, 7(4), p.151.https://doi.org/10.3390/vehicles7040151
19. Zanevych, Y., Yovbak, V., Basystiuk, O., Shakhovska, N., Fedushko, S. and Argyroudis, S., 2024. Evaluation of pothole detection performance using deep learning models under low-light conditions. Sustainability, 16(24), p.10964.https://doi.org/10.3390/su162410964