POT-YOLO: Real-Time Road Potholes Detection using Edge Segmentation based Yolo V8 Network

Article *in* IEEE Sensors Journal · August 2024

DOI: 10.1109/JSEN.2024.3399008

N. Bhavana
Reva University

MUTHU KUMAR B
Reva University

Dr. N. Muthu Kumaran
Sri Eshwar College of Engineering

Ahilan Appathurai
Government College of Technology

POT-YOLO: Real-Time Road Potholes Detection using Edge Segmentation based Yolo V8 Network

Bhavana N, Mallikarjun M Kodabagi, Muthu Kumar B, Ajay P, Muthukumaran N and Ahilan A

***Abstract*— Detecting and avoiding potholes is a more challenging task in India, due to the poor quality of construction materials used in road privilege systems. Identifying and repairing potholes as soon as possible is crucial to preventing accidents. Roadside potholes can cause serious traffic safety problems and damage automobiles. In this paper a novel Pothole detection using Yolov8 (POT-YOLO) has been introduced for detecting the types of potholes such as Cracks, Oil stains, Patches, Pebbles using POT-YOLOv8. Initially, pothole videos are converted into frames of images for further processing. To reduce distortions, these frames are pre-processed with the Contrast Stretching Adaptive Gaussian Star Filter (CAGF). Finally, the pre-processed images are identifying the region of pothole using Sobal edge detector and detect the pothole using YOLOv8. The POT-YOLO approach was simulated with Python code. The simulation result demonstrate that the POT-YOLO methods performance was measured in terms of ACU, PRE, RCL, and F1S. The POT-YOLO achieves an overall ACU of 99.10%. Additionally, POT-YOLO model achieves 97.6 % precision, 93.52 % recall, and 90.2% F1-score. In the comparison, the POT-YOLOv8 network improves the better ACU range than existing networks such as Faster RCNN, SSD, and mask R CNN. The POT-YOLO approach improves the overall ACU by 12.3%, 0.97 %, and 1.4 % better than ML based DeepBus, Automatic color image analysis using DNN, and ODRNN respectively.**

***Index Terms*— Road accident, potholes, deep learning, Contrast stretching Adaptive Gaussian star Filter, Sobal edge detector, YOLOv8.**

I. Introduction

ROADS play a vital role in modern infrastructure, enabling transportation and connectivity across the globe. India has a long-standing dependence on automobiles, with over 295 million registered vehicles to date, and the number is rapidly increasing. The Indian government now constructs roads at a high pace [1, 2]. However, inadequate drainage and heavy cars make road upkeep difficult. Potholes arise on roadways as a result of inadequate maintenance, causing traffic accidents. Pothole problems are difficult to manage because practically every location suffers from floods, high rainfall, and so on [3,4]. The large number of roads in a particular nation makes continual road evaluation impossible; hence, pothole creation cannot be predicted [5]. Potholes alone caused 2,600 deaths annually between 2016 and 2020 [6]. In the Road Accidents in India report for 2020, potholes were identified as the reason behind one percent of the approximately 60,000 incidents that occurred on India's roads [7]. pothole in the road that might endanger the life of a traffic user. Potholes can worsen over time if not properly maintained [8]. As a consequence, it will immediately lead to multiple ramifications such as a tragic road accident for motorcyclists, serious damage to the vehicle's suspension system, or unnecessary traffic congestion if the potholes are not addressed promptly [9,10]. Potholes not cause damage to vehicles but also pose risks to both drivers and pedestrians. Various methods for detecting potholes have been developed, such as using sensors and specialized hardware attached to automobiles [11, 12]. Unfortunately, the current choices for addressing the less expensive solution are required to ease road structural monitoring, which is not limited to pothole situations [13]. According to other research, accelerometer detection is straightforward to set up, but erroneous detection is common on humps, which can affect the automobile suspension system. Image processing-based detection delivers less demanding computation hardware and acceptable results; nevertheless, the approaches are vulnerable to light change and essentially same texture of small potholes and road surface [14]. Although ML-based detection is an advance over previous techniques, creating feature extractors often needs significant work and expertise, and accuracy may

Assistant Professor, School of Computing and Information Technology, REVA University, Bengaluru, Karnataka, India (e-mail: bhavanaBN1232@outlook.com).
Professor, School of Computing and Information Technology, REVA University, Bengaluru, Karnataka, India (e-mail: mallikarjun.MK632@gmail.com).
Professor, School of Computing and Information Technology, REVA University, Bengaluru, Karnataka 560064 India (e-mail: muthukumar21@gmail.com).
Assistant Professor, Department of Electronics and Communication, Rathinam Technical Campus, Coimbatore, Tamil Nadu 641021 India (e-mail: ajay764@gmail.com).
Professor, Centre for Computational Imaging and Machine Vision, Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore, 641202 India (e-mail: muthukumaran743@gmail.com).
Assistant Professor, Department of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Tirunelveli, India (e-mail: listentoahil@gmai.com).

still be improved. However, with advancements in computer vision and deep learning algorithms, automated pothole-detecting technologies are gaining popularity [15, 16]. The You Only Look Once (YOLO) method is the most promising DL techniques for identifying objects, including potholes identification applications. YOLO is a type of neural network that uses object detection and classification techniques to identify objects in real-time video streams [17,18]. It has gained immense popularity due to its high accuracy and speed in detecting objects. However, several approaches have been explored before, but they all have significant limitations, such as slower result production and less stable implementations [19,20]. DL networks have yielded positive outcomes in all real-time applications, and they can help prevent these sorts of accidents [35-38].

The main contribution of our method is follows:

- In this paper, a novel POT-YOLO to detect the type of pothole defects such as cracks, oil stains, patches, and pebbles in real-time within video streams to reduce the number of accidents.
- Pothole videos are collected from the dataset and converted into image frames. To reduce distortions, these frames are pre-processed with the CAGF.
- Finally, the pre-processed images are detecting the pothole and identify the region of pothole using YOLOv8.
- The POT-YOLO net performs well in terms of accuracy, precision, recall, and F1 score, with appropriate values.

As a result, the remaining components of this work are as follows. In Section II, address the literature review on pothole detection. Section III discusses the POT-YOLO approach, and Section IV experiments to determine its practicality. Section V concludes with an experimental result.

II. Literature survey

Several pothole detection systems have been developed in recent years, each employing a different ML or deep learning strategy. This section presents an overview of some contemporary pothole detecting technologies.

In 2022, Sathvik, M., et al., [21] introduced a system that uses CNNs and YOLOv7 to detect potholes. The system works by taking pictures through a smartphone camera that is attached to the dashboard or windshield while the car is moving. The app then uses the smartphone's location and camera features to identify potholes and assess road conditions, making it an efficient and cost-effective solution. The app not only identifies potholes but also provides information on the road surface condition, helping users drive safely.

In 2022, Gajjar, K., et al., [22] developed a system capable of detecting potholes in real time using DL Models. The ultimate goal is to provide drivers with timely information to help them avoid potholes on the road. It trained three deep learning algorithms, namely Faster R-CNN, SSD, and YOLOv3. Therefore, the focus of the project is on leveraging the YOLOv3 model to achieve real-time pothole detection. Forest roads can be kept in excellent condition by monitoring them regularly. In 2023, Hoseini, M., et al., [23] introduced a smart solution to detect and track potholes using regular cameras mounted on vehicles. This system uses a sophisticated technology called YOLOv5 with tracking from different locations and weather conditions. The system was tested in Norway using a camera that utilizes satellite positioning to determine its exact location, and it was able to accurately identify potholes. By creating a map of these potholes, maintenance on the forest road can be planned and executed more efficiently.

In 2023, Sen, S., et al., [24] presented a YOLO to detect the potholes and alert the driver to slow down using dataset of 600 images. However, they later used a larger dataset of 3000 images, with different angles to get a better view of potholes. They also implemented advanced techniques such as object tracking with YOLOv4 and the deepSORT algorithm to improve accuracy. To predict potholes based on historical data, which would help drivers become more aware of potential hazards and improve road safety.

In 2021, Arjapure, S. and Kalbande, D.R., [25] developed a DL method Mask Region-Based CNN can effectively identify and segment such potholes, allowing it to anticipate and quantify their extent. Mask RCNN is used to identify potholes as a RoI, and the pothole area is calculated using RoI. The results reveal a 90% accuracy in the computed area of the pothole compared to the actual measured area, with a ± 10% deviation. In 2020, Bansal, K., et al., [26] designed a ML based DeepBus of pothole detection system. DeepBus detects potholes in real time as end users drive their automobiles along the road. It has the highest accuracy is 86.8%, precision is 83.7%, recall is 84.4%, and F1-score is 83.7%, making it the most reliable model for pothole identification.

In 2023, Peralta-López, J.E., et al., [27] introduced an automated color image analysis utilizing a DNN to detect potholes on the road using images captured by a ZED camera. The lightweight architecture was designed to expedite training and usage. A database was generated using a ZED camera positioned on the front of a car. The system was trained using 70% of the database and confirmed with the remaining 30%, yielding an accuracy of 98.13%.

III. POT-YOLO method

In this section, a novel POT-YOLO for identifying various forms of potholes, including cracks, oil stains, patches, and pebbles, using POT-Yolov8. Initially, pothole videos are extracted from the collection and converted into images. To reduce distortions, these frames are pre-processed with the Contrast Stretching Adaptive Gaussian Star Filter (CAGF). Finally, the pre-processed images detect and identify the pothole region using POT-YOLOv8. Figure 1 depicts the general flow of the POT-YOLO.

A. Dataset acquisition

The dataset acquired for the research by Ouma, Y.O. et al. [28] was utilized in the proposed study. Among the different data sets were potholes of various sizes and shapes, different imaging conditions like noise, background features, illuminations, and shadow conditions, in addition to pavement conditions including discoloration, linear cracking, and other pavement defects.

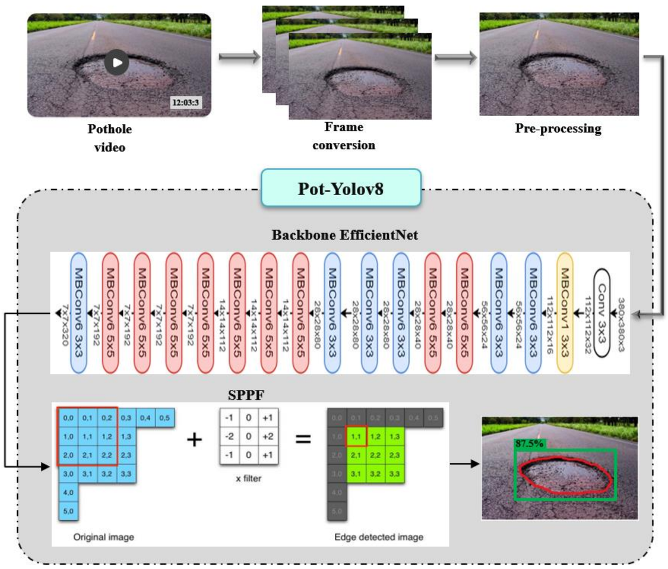

Fig. 1. The overall structure of the POT-YOLO methodology

As a result of these adjustments, 75 test image datasets were chosen for testing and validation. Among the selected test images, potholes were present in all of them, but the proposed method identifies and extracts potholes only within a single image-tile rather than automatically identifying them across multiple pavement images. Testing data sets may contain faults such as potholes or non-pothole faults. Other features may include lighting cracks, oil stains, patches, pebbles, shadows, and other noises.

B. Pre-processing via Contrast stretching Adaptive Gaussian star Filter (CAGF)

Adaptive Gaussian Star filtering is used to preprocess the pothole images after they are divided into frames. An image enhancement technique described in this section adjusts the contrast stretching locally inside sub-blocks to manipulate the intensity ranges. Two parts of the CAGF are present. Histograms with extended contrast and altered levels.

Contrast Stretching: In this denoising phase, every original intensity value is replaced, and the comparison of histograms is conducted through a locally modified contrast-stretching adjustment. The new level is assigned to each pixel using a variable transfer function based on the features of the input images.

$$Range = |Q_{max} - Q_{min}| \tag{1}$$

where Q is the input image and the range is determined by calculating the input's intensity range. Q_{max} and Q_{min} represent the maximum and lowest values of the input image at the new intensity, respectively. Currently, each pixel equation receives an extra intensity from

$$X_k = \begin{cases} Q_N - \sigma_N & , if\ Q_N = Q_{max} \\ Q_N + \sigma_N & , if\ Q_N = Q_{min} \end{cases} \tag{2}$$

$$r_n = M - \sqrt{(range - M)^2} \tag{3}$$

Where M ranges between 0.01 and 0.02, and each pixel value is adjusted using the aforementioned equations. This reduces image noise while improving image qualities.

Adaptive Gaussian star filter: In an amplitude spectrum, the profile of a typical periodic noise is usually perceived as a star. To construct a star-shaped filter, two 2D elliptical filters are arranged perpendicular to each other. The equations below represent AGSF in the frequency domain:

$$A(x, y) = \begin{cases} V_1(x_1, y_1) + V_2(x_2, y_2) & if\ x_1 \neq x_2\ and\ y_1 \neq y_2 \\ max\ (V_1(x_1, y_1), V_2(x_2, y_2)) & if\ x_1 = x_2\ and\ y_1 = y_2 \end{cases} \tag{4}$$

The following are the parameters of AGSF:

$$\alpha_{i1,2} = D.\min\left(\sqrt{\left(x_{i1,2} - x_{ir}\right)^2 + \left(y_{i1,2} - y_{ir}\right)^2}\right) \tag{5}$$

$$\beta_{i1,2} = D.\max\left(\sqrt{\left(x_{i1,2} - x_{ir}\right)^2 + \left(y_{i1,2} - y_{ir}\right)^2}\right) \tag{6}$$

where r is the neighbor's pixel number in the $i_{1,2}^{th}$ noise area. Equations (5) and (6) define $\alpha_{i1,2}$ and $\beta_{i1,2}$, as the greatest and lowest Euclidean distance values, multiplied by D, respectively.

C. POT-YOLOv8 via pothole detection

In this section the pre-processed images are given as an input to the POT-YOLOv8 net to accurately detect the type of defence in the pothole. POT-YOLOv8 builds on the success of earlier versions of YOLO, including new features and upgrades to further improve performance and versatility, resulting in top performance and perfect efficiency. POT-YOLOv8 has five distinct size options: nano, small, medium, big, and extra-large. POT-YOLOv8 is separated into 3 components: the backbone, neck, and head, that are accountable for function extraction, multi-function fusion, and prediction output. Figure 2 illustrates the architecture of the POT-YOLOv8 network.

i. Object detection on pothole in the road

In this phase, MBConv (EfficientNet) is used to detect the pothole in the road. The reversed bottleneck MBConv is used to build the foundation of EfficientNet. The MBConv block consists of layers that increase and previously decrease the channels. For Efficient Net, the ReLU serves as the activation function. For compound scaling, the compound coefficient μ is utilized, and the obtained rules are as follows:

$$depth: \mathbb{D} = \alpha^{\mu}; width: \mathbb{W} = \beta^{\mu}; resolution: \mathbb{R} = \gamma^{\mu} \tag{7}$$

where $\alpha, \beta, \gamma \geq 1$ are constants to be estimated using the compound coefficient μ in the grid search. The flops in the conventional convolution block are correlated with $\mathbb{D}, \mathbb{W}^2$, and $\mathbb{R}^2$. Because convolutional blocks have enormous processing costs during convolutional procedures. When the network is scaled as shown in equation (7) around $(\alpha, \beta^2, \gamma^2)^{\varphi}$ $(\alpha\ \beta^2\gamma^2)^{\varphi}$, the total flops of the EfficientNet increase. Extracting neural features around a big model fast with α, β, and γ might result in greater fallout. E-SPPF eliminates network layers utilizing SPP (spatial pyramid pooling) and the Sobal edge detector to avoid duplicate edge detection operations and speed up feature fusion. MBConv and E-SPPF generate images that are analyzed by the feature extraction network to extract individual scale characteristics from the images. As a result of the MB module, the network is reduced from three convolutional layers to two, making it more lightweight than the original C3 module. To produce adaptive size outputs, the backbone network employs the E-SPPF module to pool the input feature maps into a fixed-size map. In SPPF, the maximum pooling layers are successively linked to minimize computing effort and delay, as shown in Figure 2.

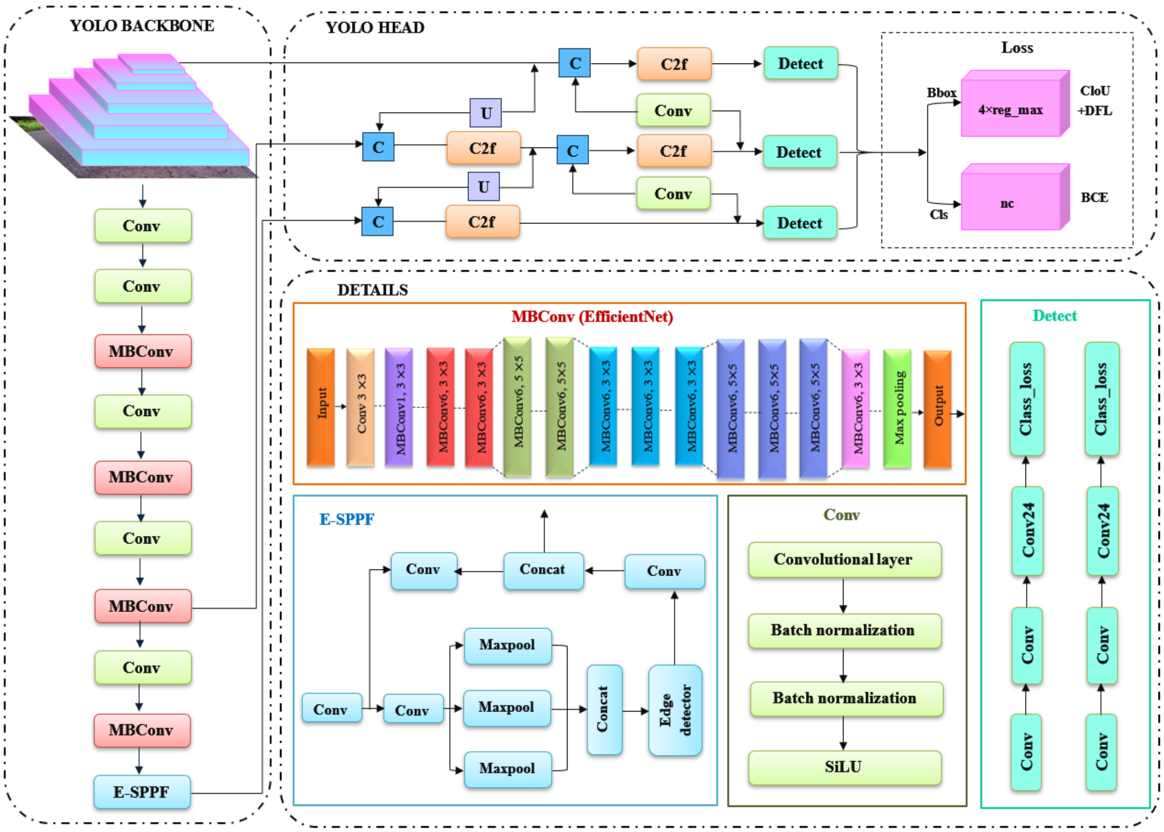

Fig. 2. Architecture of proposed POT-YOLOv8

ii. E-SPPF on pothole in the road

The E-SPPF module in YOLOv8 has shown useful in improving model performance through multi-scale feature fusion, especially in specific cases. The SPPF module may have limitations in complicated backdrops and circumstances with varying target scales. This is because it currently lacks a fine-grained method for concentrating on crucial areas. To overcome the SPPF module's limitations and improve feature extraction capabilities, incorporated Edge Detector-Spatial Pyramid Pooling Fast (E-SPPF), which dynamically modifies the weights in feature maps depending on the relevance of each region in an adaptable way. The E-SPPF attention technique is used to maintain information from each channel while lowering computing expenses.

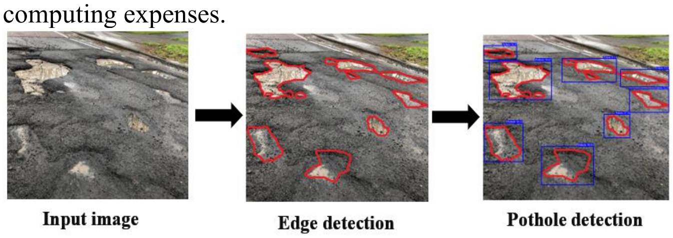

Fig. 3. Detection result of POT-YOLOv8.

In order to achieve this, the channel dimensions are rearranged into the batch dimension and the sub-feature dimensions are divided into several sub-features. This results in an equitable distribution of spatial semantic characteristics within each feature group. Figure 3 depicts the edge detected result of the suggested model with E-SPPF, which incorporates the E-SPPF attention mechanism into this module.

The E-SPPF module not only conducts multi-scale feature fusion, but it also carefully modifies features at each scale, allowing for effective information capture at many scales. This modification greatly enhances the model's ability to recognize pothole edges. This detection shape can decorate detection accuracy and accelerate version convergence. YOLOv8 is an anchor-loose detection version that virtually defines effective and terrible samples. It additionally leverages the Task-Aligned Assigner to dynamically allocate samples, enhancing the version`s detection accuracy and resilience. To identify potholes efficiently, hyper-parameters such as epoch and learning rate are adjusted to increase accuracy.

IV. Result and Discussion

This section describes the simulation setup of the POT-YOLO was implemented using Python code. The POT-YOLO approach was evaluated using several kinds of parameters, including precision, ACU, PRE, RCL, and F1S on the obtained dataset.

Figure 4 shows the simulation results of the POT-YOLO method for detecting potholes in input images. Column 1 contains the dataset's input images. The pre-processed images are shown in column 2 using CAGF. To find edges in potholes, use the Sobal edge detector, as shown in column 3. Finally, use Pot-Yolov8 in column 4 to find potholes in the edge-detected images.

A. Performance analysis

The POT-YOLO method is assessed in this part through experiment findings such as specificity (SPE), accuracy (ACU), precision (PRE), recall (RCL), F1 score (F1S), Mean Average Precisions (mAP), and Frames Per Second (FPS). The following equations are used to calculate these measurements.

$$ACU = \frac{(TP+FP)}{(TP+TN+FN+FP)} \quad (8)$$

$$PRE = \frac{TP}{TP+FP} \quad (9)$$

$$SPL = \frac{TP}{TP+FN} \tag{10}$$

$$F1S = 2\left(\frac{Precision*Recall}{Precision+Recall}\right) \tag{11}$$

$$mAP = \frac{\sum_m \int_0^1 p(r)dr}{m} \tag{12}$$

$$fps = \frac{1}{T} \tag{13}$$

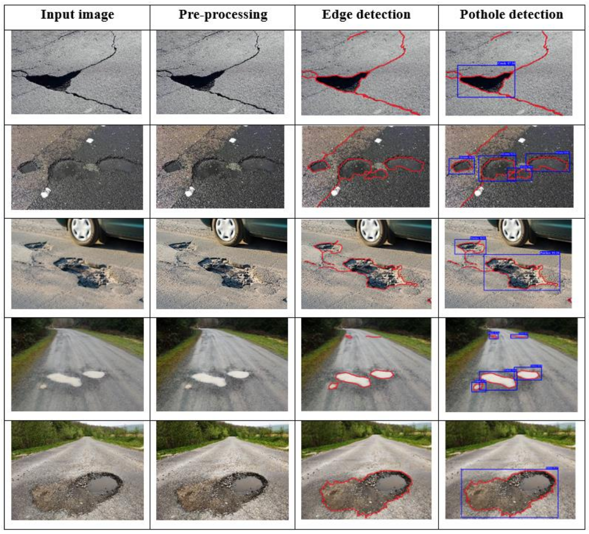

Fig. 4. Experimental results of POT-YOLO.

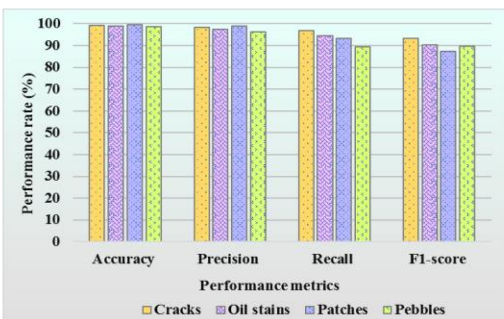

Fig. 5. Performance analysis of POT-YOLO for pothole detection.

Figure 5 depicts the POT-YOLO network's effectiveness in classifying four classes: cracks, oil stains, patches, and pebbles [27, 28]. The POT-YOLO's performance is measured by its ACU, PRE, RCL, and F1S. According to the results, the POT-YOLO has a classification accuracy of 99.10%. Additionally, the proposed model achieves 97.6 % precision, 93.52 % recall, and 90.2% F1-score respectively. In some cases, image quality variations, and lighting conditions affecting detection accuracy.

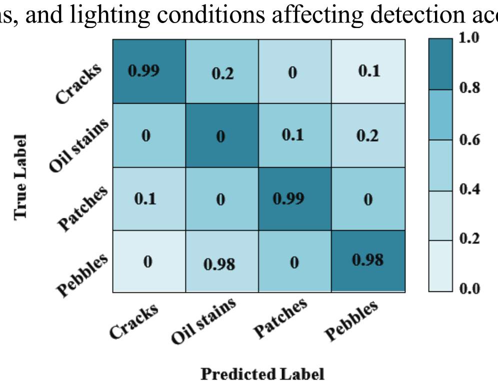

Fig. 6. Confusion matrix of the POT-YOLO.

The estimated POT-YOLO trial side effects were ascertained after a training period of roughly 15 minutes. The proposed POT-YOLO model's 4-class classification confusion matrix is shown in Figure 6. Without any miss detection, the proposed POT-YOLO detects anomalies such as cracks, oil stains, patches, and pebbles. The POT-YOLO has a lower misclassification rate and good classification accuracy for detecting potholes, according to this confusion matrix.

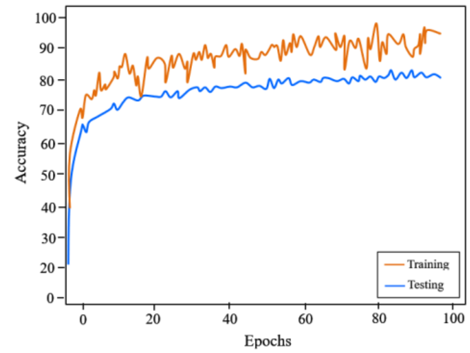

Fig. 7. Accuracy curve of the POT-YOLO.

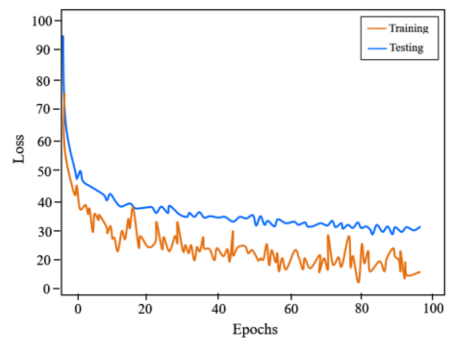

Fig. 8. Loss curve of the POT-YOLO

The accuracy value is displayed on the vertical axis of the accuracy curve in Figure 7. The horizontal axis of the loss curve displays the number of epochs, while the vertical axis displays the loss value. Figure 8's loss range and epoch illustrate how the POT-YOLO network model's loss drops with increasing epoch. POT-YOLO Model achieves great accuracy in diagnosing illnesses associated with pothole detection. The number of training epochs compulsory to attain the best testing accuracy was initially determined by this study. Based on 10 epochs, the POT-YOLO achieved 99.10% testing accuracy with a minor error rate.

B. Comparative analysis

The previous methodologies were evaluated, and the proposed DL-based technique was determined to be both efficient and accurate.

TABLE I
COMPARISON ANALYSIS OF POT-YOLOV8 WITH EXISTING DL TECHNIQUES

Networks	ACU	PRE	RCL	F1S
Faster RCNN [32]	96.8 %	95.87 %	91.51 %	86.58 %
SSD [33]	97.40 %	96.23 %	88.98 %	82.87 %
Mask R CNN [34]	97.07 %	93.23 %	87.59 %	85.49 %
POT-YOLOv8 (proposed)	99.10%	97.65 %	93.52 %	90.2%

This article has been accepted for publication in IEEE Sensors Journal. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2024.3399008

The overall performance of DL models is shown in Table 1. A comparison of the proposed POT-YOLOv8 networks, including Faster RCNN, SSD, and mask R CNN, was also determined. Performance was evaluated using many criteria, including ACU, PRE, RCL, and F1S. POT-YOLOv8 reaches the maximum ACU when compared to other networks. However, traditional networks have fared less well than the ones proposed networks. The POT-YOLOv8 network outperforms Faster RCNN, SSD, and Mask R CNN in terms of accuracy by 2.3%, 1.7%, and 2.03%, respectively.

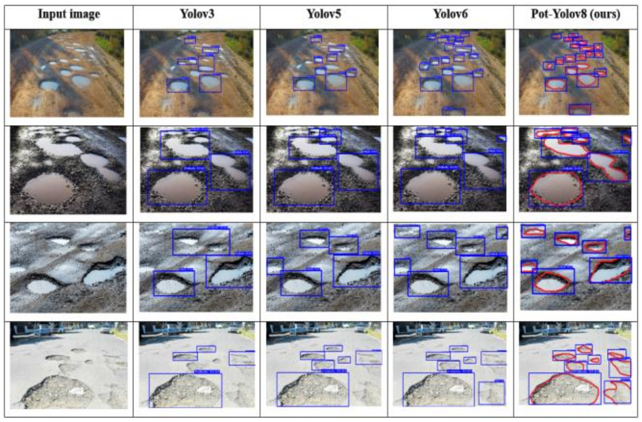

Fig. 9. Detection comparison results of conventional object detection network

Figure 9 depicts the detection comparison results of a standard object detection network for the pothole [28]. However, standard object identification algorithms perform poorly when compared to POT-YOLOv8. According to the aforementioned comparison, POT-YOLOv8 outperforms standard techniques such as Yolov3, Yolov5, and Yolov6. The POT-YOLOv8 improves the system's efficiency and lowers false positives by attaining 99.10% accuracy. As a consequence, the POT-YOLOv8 predicts speedier fallouts and achieves the best results in terms of ACU.

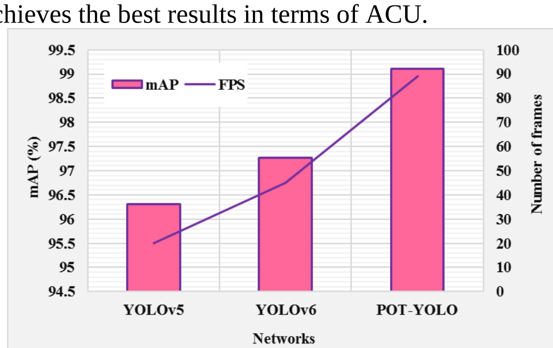

Fig. 10. Comparison analysis of existing DL models

Pothole detection findings hold significant implications for transportation infrastructure maintenance, enabling proactive identification and repair of road defects. Implementation in smart city systems can offer real-time updates on road conditions, facilitating traffic management and accident prevention. Additionally, integration with vehicle maintenance and insurance processes can streamline damage assessment and claims processing, enhancing road safety and reducing costs. Overall, these advancements contribute to smoother, safer roadways and more efficient transportation networks.

Figure 10, illustrate the comparison of proposed POT-YOLO network to YOLOv5, YOLOv6 networks it gains less mAP, and FPS. LV-YOLO achieve the high mAP ranges of 99.10%. The mAP obtained by YOLOv5, and YOLOv6 is 96.30%, and 97.26%. The FPS obtained by YOLOv5, YOLOv6, and POT-YOLO is 20, 64, and 87 respectively.

TABLE II
PERFORMANCE OF EXISTING METHODS WITH PROPOSED METHOD FOR POTHOLE DETECTION

Authors	Methods	Accuracy
Bansal, K., et al [26]	ML based DeepBus	86.8%
Peralta-López, J.E., et al [27]	Automatic color image analysis using DNN	98.13%
Sathya, R. et al., [29]	ODRNN	97.7%
Proposed	POT-YOLO	99.10%

Table 2. demonstrates the existing methods ML based DeepBus, Automatic color image analysis using DNN, and ODRNN are less accurate than the Pot-Yolov8. The Pot-Yolov8 method maintains excellent ACU levels of 99.10%. The POT-YOLO approach improves the overall ACU by 12.3%, 0.97 %, and 1.4 % better than ML based DeepBus, Automatic color image analysis using DNN, and ODRNN respectively. According to the comparison above, the POT-YOLO model is more accurate than existing models.

V. CONCLUSION

In this work introduced a novel POT-YOLO for detecting the types of potholes using POT-YOLOv8. Initially, pothole videos are extracted from the collection and converted into frames of images for further processing. These frames are pre-processed with CAGF to eliminate distortions. Finally, the pre-processed images are identifying the region of pothole using Sobal edge detector and detect the pothole using POT-YOLOv8. The experimental results demonstrate that the POT-YOLO method's performance was measured in terms of ACU, PRE, RCL, and F1S. The POT-YOLO achieves an overall ACU of 99.10 %. In compared to Faster RCNN, SSD, and mask R CNN, the POT-YOLOv8 network increases ACU by 2.3%, 1.7%, and 2.03%, respectively. The POT-YOLO approach improves the overall ACU by 12.3%, 0.97 %, and 1.4 % better than ML based DeepBus, Automatic color image analysis using DNN, and ODRNN respectively. As a result, potholes can be detected and swiftly repaired, reducing the risk of accidents and ensuring smoother traffic flow. In some cases, image quality variations, and lighting conditions affecting detection accuracy. In the future research could focus on improving algorithms to handle these challenges, and estimating the distance of the detected potholes, measuring the severity of the potholes using advanced deep learning networks.

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Bhavana N Assistant Professor, School of Computing and Information Technology, REVA University, Bengaluru. She earned Bachelor Degree in Information Science and Engineering from VTU, Belagavi, India and Master Degree in Computer Science and Engineering from REVA University, Bengaluru, India. Currently, she is pursuing PhD in Computer Science and Engineering at REVA University, Bengaluru, India. She has total 9 years of teaching experience. She has published around 7 papers in reputed journals. She has a professional bodies membership like CSTA, IAENG. Her research area includes Image Processing, Machine Learning, Deep Learning.

Mallikarjun M Kodabagi Professor & Director, School of Computing and Information Technology, REVA University, Bengaluru. He earned Bachelor Degree in Computer Science and Engineering from Karnataka University, India and Master Degree in Computer Science and Technology from University of Mysore, India. Obtained his PhD from VTU, Belagavi. His research areas include image processing and pattern recognition, text extraction, text recognition, fuzzy systems, and neural networks, AI and Machine Learning. He is a member of professional bodies like IEEE, CSI and ISTE. He has total experience 22 years in teaching and R&D work. He worked as scientist ‘B in LRDE and DRDO. He has executed several projects sponsored by TEQIP-II and VGST. Currently he is guiding 6 Ph D students in the areas of data science and machine learning. Recently one of his research students has completed defense.

Muthu Kumar B Professor, School of Computing and Information Technology, REVA University, Bengaluru received his BE (CSE) degree from Anna University, Chennai in the year 2005, MTech (CSE) (Gold Medalist) received from Dr. MGR. University, Chennai in the year 2007 and Doctoral degree from St. Peter’s University, Chennai in the year 2013. He is having more than 16 years of teaching experience in reputed engineering colleges. He has published more than 40 peer reviewed International Journals, 50 International/National Conference and attended more than 150 Workshops/FDPs/Seminars etc., He organized many events like Conference/FDPs/Workshops/Seminars/Guest Lecture.

Ajay P is a renowned researcher and academician in the field of Wireless Networks, Artificial Intelligence and Soft Computing. He was born and brought up in India, and his passion for engineering led him to pursue a Master's degree in Electronics and Communication Engineering from Anna University, followed by a PhD degree from Anna University in 2023. Dr. Ajay began his professional journey in 2017 as an Assistant Professor at Karpagam College of Engineering, where he worked tirelessly for 3 years. During his tenure, he held various positions and made significant contributions to the institution. His technical expertise and research interests led him to explore new avenues in the field of Communication Systems and Automation, where he made significant contributions.

Muthukumaran N was born in Kanyakumari, Tamilnadu, India, in 1984. He received the B.E Degree in Electronics and Communication Engineering, M.E Degree in Applied Electronics and the Ph.D. Degree in Information and Communication Engineering from Anna University, Chennai, India in 2007, 2010 and 2015 respectively. He has 14 Years of Teaching and Research Experience and he is currently working as a Professor, Department of Electronics and Communication Engineering in Sri Eshwar College of Engineering, Coimbatore, Tamilnadu, India.

Ahilan A received Ph.D. from Anna University, India, and working as an Associate Professor in the Department of Electronics and Communication Engineering at PSN College of Engineering and Technology, India. His area of interest includes FPGA prototyping, Computer vision, the Internet of Things, Cloud Computing in Medical, biometrics, and automation applications. TCS, Bangalore, where he has guided many computer vision projects and Bluetooth Low Energy projects. Meanwhile, special Guest lectures, Practical workshops, Hands-on programming in MATLAB, Verilog, and python at various technical institutions around India.