Journal of Advanced Zoology
ISSN: 0253-7214
Volume 45 Issue S2 Year 2024 Page 116-122

Advancing Road Safety: Pothole Detection Using Yolov8 And Wandb Deep Learning

Smt. A. Koteswaramma[1*], M. Divya Sri[2], M. Manohar[3], K. Srihari[4], M. Yabbeju[5]

[1*]*Assistant professor, Department of IT, Seshadri Rao Gudlavalleru Engineering College (SRGEC), AP, koteswari.1201@gmail.com*
[2,3,4,5] *Department of IT, Seshadri Rao Gudlavalleru Engineering College (SRGEC), AP, sridivya.g02@gmail.com[2], majjimanohar7989@gmail.com[3], kamisettisrihari@gmail.com[4], yabbejumadduluri@gmail.com [5]*

***Corresponding Author:** *Smt. A. Koteswaramma*
[*]*Assistant professor, Department of IT, Seshadri Rao Gudlavalleru Engineering College (SRGEC), AP, koteswari.1201@gmail.com*

Abstract

Self-driving vehicles have emerged as a revolutionary breakthrough in modern transportation, promising unparalleled safety, efficiency, and convenience. However, navigating through unpredictable road conditions, especially in the presence of potholes, remains a significant challenge that poses potential safety risks. This study introduces an innovative cloud-powered next-generation self-driving safety system that harnesses the power of AI, specifically YOLOv8 (You Only Look Once version 8), in conjunction with the wandb (Weights & Biases) deep learning platform. This integration enables pothole detection and advanced navigation, elevating the safety standards of autonomous driving. The selection of YOLOv8, a cutting-edge object detection model, is by its exceptional accuracy and speed. YOLOv8 employs a singular neural network to predict object bounding boxes and class probabilities directly, allowing for rapid and precise object detection. This cloud-based architecture also supports continuous model updates and refinements, ensuring the system's adaptability to evolving road conditions and pothole variations. With potential applications extending beyond potholes, this system paves the way for safer and more reliable autonomous transportation, revolutionizing the landscape of self-driving technology.

Keywords—Self-driving vehicles, Pothole detection, YOLOv8 (You Only Look Once version 8), AI(Artificial Intelligence), Cloud-powered safety system, Advanced navigation.

I. INTRODUCTION

Roads are an essential means of transportation. It carries a major percentage of passenger traffic of any country. It is known that most of the roads in developing countries would be congested and narrow resulting

in poor surface quality and the maintenance of the roads is not satisfactory. Due to poor maintenance, poor surface quality or due to a variety of other reasons a pothole could be formed on roads. A pothole is a kind of disruption in the surface of a road in which a portion of the road material is damaged. In rainy seasons, if these potholes are covered by water, it might lead to accidents which might be fatal too. It gets difficult to track all the potholes by the concerned authorities.
Potholes took a deadly toll in 2020, claiming almost 10 lives daily with annual fatalities in the country adding up to 3597—a more than 50% rise over the toll for 2021. This is a major problem in many developed countries also. Detecting potholes manually is a labour-intensive and time-consuming task. Many techniques have been implemented to detect potholes like vibration-based methods, 3D reconstruction-based methods, and vision-based methods. But each of these techniques has some limitations. . Detecting potholes is crucial not only for the safety of human drivers but also for the advancement of autonomous or self-driving vehicles. Safety and Comfort for Passengers: For human-driven vehicles, hitting a pothole can lead to accidents, vehicle damage, and discomfort for passengers. In the case of self-driving cars, these issues could impact passenger safety and overall user experience. Machine Learning and Automation: Self-driving cars utilize advanced machine learning algorithms for perception and decision-making. Training these algorithms to recognize and respond to potholes can improve their ability to navigate complex road conditions safely.
The aim of this paper is to develop a Pothole Detection System, which assists the concerned authorities to find and fix the potholes. In this work, an effort is being made to identify the potholes and report them to the relevant authorities which can help them take action.. Images and videos are captured in real-time and the YOLOv8 image processing algorithm is used. This can help to take caution while traveling on roads with potholes, this helps in enhancing the public safety and enables the concerned authorities to fix the potholes faster. while speaking about road safety, potholes play a crucial role. when driving for prolonged hours or under stress or tension, the driver tends to miss out concentration. One of the primary reasons behind such accidents is the driver’s inability to pay attention to every single detail on the road and that’s when the ADAS comes into the picture. the data can either be directly reported to the driver by giving an alert symbol in the cabin of the vehicle or the data can be used by the autonomous driverless system where the system decides on what action it needs to mete out in order to prevent a collision and ensure a safe and comfortable riding experience for the passengers.

II. LITERATURE REVIEW

In paper, "A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste," Pereira et al. (2018) present a compelling solution for road pothole detection using a convolutional neural network (CNN). Focusing on a low-cost approach, the researchers trained their model exclusively on a diverse dataset of images collected from various locations, encompassing different environmental conditions such as wet, dry, and shady conditions. The experiment, conducted with 500 testing images, demonstrated impressive results, showcasing the model's capability to achieve remarkable metrics simultaneously. With an accuracy of 99.80%, precision of 100%, recall of 99.60%, and F-Measure of 99.60%, the proposed CNN-based approach proves to be highly effective in road pothole detection, suggesting its potential for practical implementation in real-world scenarios.
In their work titled "A Deep Learning Approach for Street Pothole Detection," Ping et al. (2020) address the critical issue of potholes as a structural threat to road safety and efficiency. They compare four models—YOLO V3, SSD, HOG with SVM, and Faster R-CNN—trained and tested with a preprocessed dataset. Results show YOLO V3 outperforms others with faster and more reliable detection. This research contributes to the field of pothole detection, emphasizing the effectiveness of deep learning, particularly YOLO V3, in addressing road safety and efficiency concerns.
In "Deep Learning Based Pothole Detection," Rajan et al. (2023) address the global issue of potholes impacting road safety. They propose a solution using the Yolo algorithm for real-time pothole detection with cameras installed on moving vehicles. The project aims to reduce accidents by alerting drivers through a beep sound, emphasizing the importance of leveraging deep learning to enhance road safety worldwide.
In "Pothole Detection Using Machine Learning Algorithms," Al Masud et al. (2021) address the significant issue of potholes on Bangladeshi roads, emphasizing the need for a system that alerts both drivers and authorities. The study employs image data of potholes and normal road conditions, utilizing MobileNetV2 for feature extraction and applying dimensionality reduction techniques. Among five machine learning algorithms tested, Support Vector Machine (SVM), Logistic Regression, and Elastic Net exhibit superior performance, with SVM achieving the highest accuracy of 99%. This research demonstrates the efficacy of machine learning in pothole detection, particularly highlighting SVM as a promising approach for enhancing road safety.

Srikanth et al. (2023) address the significant issue of road crashes caused by potholes in India, reporting 4,775 and 3,564 incidents in 2019 and 2020, respectively. The study focuses on improving pothole detection for safe autonomous vehicle operation. Using Faster Region-based Convolutional Neural Network (FRCNN) and You Only Look Once (YOLOv5) algorithms, the research demonstrates promising results through real-time testing on an autonomous vehicle. This work contributes to advancing pothole detection in the context of autonomous transportation, crucial for enhancing road safety in Indian scenarios.
"Intelligent Deep Learning based Pothole Detection and Reporting System," R. R, Shreya S, and A. R (2021) address the critical need for efficient road maintenance to prevent accidents caused by potholes. Manual assessment of road conditions is labor-intensive, leading to an increasing demand for automatic pothole identification systems. The proposed solution employs three deep learning algorithms—Convolutional Neural Network (CNN), Mask Region-based Convolutional Neural Network (Mask RCNN), and You Only Look Once (YOLOv3)—trained and tested with a dataset. The study also incorporates hardware components for reporting detected potholes, facilitating prompt repair and maintenance actions.

III. METHODOLOGY

The pothole detection system undergoes several key steps to ensure its effectiveness. The initial phase involves the collection of a diverse dataset comprising road images and videos that capture a range of road conditions and pothole scenarios. To prepare this data for training, a meticulous annotation process is employed, utilizing tools like Roboflow to label pothole presence and locations within each image or video frame.

The heart of the system lies in the training of the YOLOv8 model, a cutting-edge object detection architecture. Configured with specific parameters and class labels, including "pothole," the model undergoes iterative training processes. This training phase is crucial as it enables the model to learn to identify and precisely locate potholes within the visual data. Throughout this training, the wandb platform serves as a valuable tool for monitoring and visualizing key metrics, such as loss, accuracy, and precision, providing insights into the model's learning progress.

Once training is complete, the model's performance is rigorously evaluated using a separate dataset it has never encountered. This evaluation phase assesses the model's accuracy and effectiveness in real-world scenarios. Among the various trained models, the system selects the best-performing one based on evaluation results, optimizing it for pothole detection. This selected model is then saved for future use or deployment.

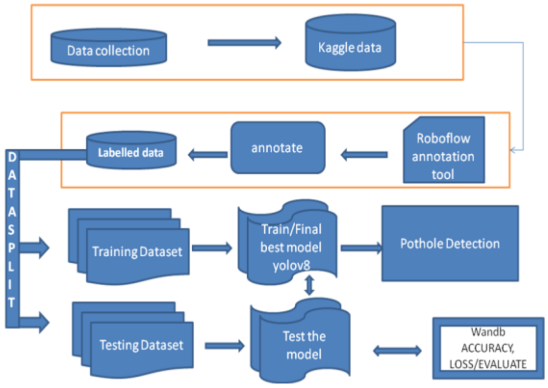

Fig:1 *Proposed block Diagram*

To enhance user interaction and accessibility, a graphical user interface (GUI) is developed using the Tkinter library. This GUI empowers users to effortlessly upload road images or videos, initiate the pothole detection process, and visualize the results. The selected YOLOv8 model analyzes the provided media for potholes, and the GUI presents the results to users, typically with bounding boxes or visual indicators highlighting detected potholes. This streamlined process ensures a user-friendly experience in identifying and addressing potholes through the developed system.

A. Data Collection

Collect a diverse dataset of images or videos that represent different road conditions and contain potholes. Consider factors like weather, lighting, road types, and traffic conditions. Ensure there is sufficient data for training, validation, and testing.

B. Data AnnotationEquations

- Import Data into an Annotation Tool:
 Utilize a data annotation tool like Roboflow to import the dataset. These tools facilitate the annotation of pothole presence and location in each image.
- Open an Image:
 Within the annotation tool, access individual images from the dataset for annotation.
- Label Data with Bounding Boxes or Polygons:
 Annotate the images by creating bounding boxes or polygons around each pothole in the image. Ensure precision in marking the location and extent of each pothole, and include a label indicating that it is a pothole.
- Download Annotated Data:
 Following the annotation process, export the annotated data in a format suitable for training the pothole detection model.

C. Model Training

Define training parameters, including the batch size, learning rate, number of epochs, and optimizer settings. The first step is to load your prepared dataset, which includes images of roads with annotated potholes. This dataset is typically split into training, validation, and test sets. The training set is used to teach the model, the validation set is used to fine-tune hyperparameters and monitor performance, and the test set is used for final evaluation. YOLOv8 uses a custom architecture designed for object detection. You need to initialize the model with the appropriate configuration, including the chosen YOLOv8 variant (e.g., YOLOv5s, YOLOv5m, etc.), backbone network (e.g., CSPDarknet53, CSPDarknet53-PANet, etc.), and the number of classes (in this case, the class for "pothole"). YOLO models use a specific loss function that combines classification loss (how well the model identifies objects) and localization loss (how accurately the model predicts object locations). This loss function guides the model to improve its predictions during training. Then select an optimization algorithm (e.g., Adam) and set the learning rate, which determines how quickly the model updates its parameters based on the loss. Learning rate schedules are often used to adjust the learning rate during training to improve convergence. The training loop involves iterating over batches of images from the training set. For each batch, the following steps occur:

- Forward Pass: The model takes the batch of images as input and makes predictions for the presence and location of potholes. These predictions are compared to the ground truth annotations.
- Loss Computation: The loss function calculates how far off the model's predictions are from the ground truth annotations. This computed loss is used to update the model's parameters in the next step.
- Backpropagation and Parameter Update: The gradient of the loss with respect to the model's parameters is computed via backpropagation. The optimization algorithm then updates the model's parameters in a direction that minimizes this loss.

D. Model Testing

Evaluate your trained model on a separate validation dataset and, if available, a test dataset. Calculate relevant metrics to assess its performance. During the model evaluation process, log relevant metrics that provide insights into its performance. Common metrics for object detection tasks like pothole detection include precision, recall, F1-score, and mean average precision (mAP).

E. GUI Development

Create a user-friendly graphical user interface (GUI) using a framework like Tkinter in Python. Design the GUI to allow users to upload images or videos and initiate the pothole detection process. Implement functionality to display the detection results, including bounding boxes around potholes.

IV. RESULT AND DISCUSSION

The F1 score, confidence curve, precision-recall curve, and confusion matrix collectively offer a comprehensive understanding of the model's strengths, weaknesses, and areas for improvement in pothole detection.

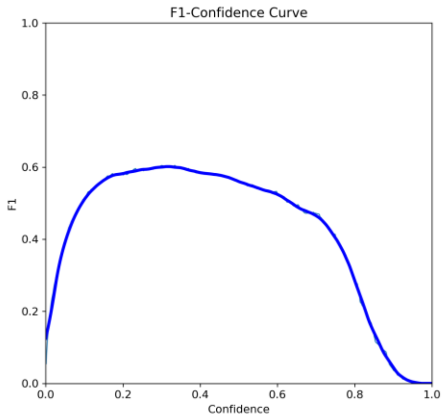

Fig:2 *F1 Confidence Curve*

The F1 Confidence Curve is a visualization that shows how the F1 score varies across different confidence thresholds in a binary classification problem. It is particularly useful when dealing with models that provide a confidence or probability score along with their predictions. In this case, the calculated F1 score is around 0.5996, suggesting a reasonable balance between precision and recall.

Precision is the ratio of correctly predicted positive observations to the total predicted positives. Recall is the ratio of correctly predicted positive observations to the total actual positives. The Precision-Recall Curve is created by plotting precision on the y-axis and recall on the x-axis, with each point on the curve corresponding to a different decision threshold.

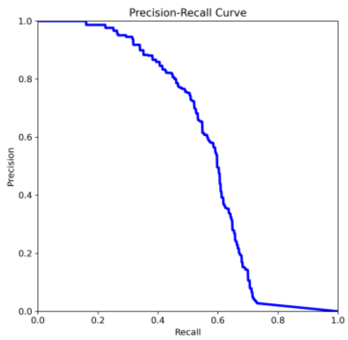

Fig:3 *F1 Precision – Recall Curve*

The model correctly identified 180 instances as negative (True Negatives), showcasing its ability to accurately classify negative cases. However, it incorrectly labeled 68 instances as positive when they were actually negative (False Positives), indicating a propensity for Type I errors. Additionally, the model failed to recognize 150 positive instances, marking them as negative (False Negatives), pointing to a susceptibility to Type II errors.

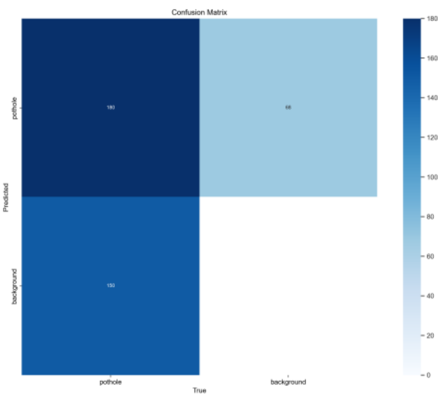

Fig:4 *Confusion Matrix*

Integrate the pothole detection algorithm's results into the GUI. Highlight detected potholes on the displayed images and provide relevant information, such as the number or size of potholes.

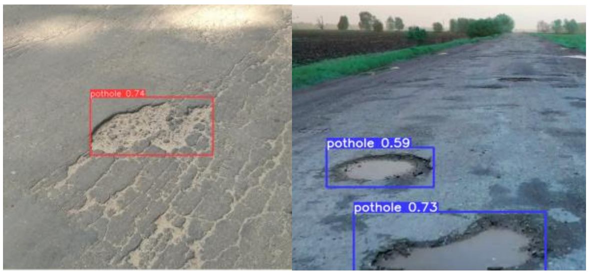

Fig:5 *Output of images and video showing pothole*

V. CONCLUSION

The integration of a cloud-powered next-generation self-driving safety system utilizing YOLOv8 and the wandb deep learning platform represents a significant stride towards addressing the challenges posed by unpredictable road conditions, particularly the presence of potholes. The choice of YOLOv8, known for its exceptional accuracy and speed in object detection, enhances the system's capability to rapidly and precisely identify potholes, thereby elevating safety standards in autonomous driving. The cloud-based architecture of this system offers several advantages, including continuous model updates and refinements. This adaptability ensures that the system remains effective in navigating through evolving road conditions and coping with various pothole variations. The use of cloud resources also enables real-time communication and coordination, enhancing the overall efficiency of the self-driving safety system.

REFERENCES

1. V. Pereira, S. Tamura, S. Hayamizu and H. Fukai, "A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste," 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 2018, pp. 279-284, doi: 10.1109/SOLI.2018.8476795.
2. P. Ping, X. Yang and Z. Gao, "A Deep Learning Approach for Street Pothole Detection," 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService), Oxford, UK, 2020, pp. 198-204, doi: 10.1109/BigDataService49289.2020.00039.
3. D. R. Rajan, M. K. Faizan, R. Kundelu, N. Nandal and V. S. Gunda, "Deep Learning Based Pothole Detection," 2023 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2023, pp. 1-5, doi: 10.1109/ESCI56872.2023.10100020.
4. A. K. M. Jobayer Al Masud, S. T. Sharin, K. F. T. Shawon and Z. Zaman, "Pothole Detection Using Machine Learning Algorithms," 2021 15th International Conference on Signal Processing and Communication Systems (ICSPCS), Sydney, Australia, 2021, pp. 1-5, doi: 10.1109/ICSPCS53099.2021.9660216.
5. H. N. Srikanth, D. S. Reddy, D. K. Sonkar, R. Kumar and P. Rajalakshmi, "Pothole Detection for Autonomous Vehicles in Indian Scenarios using Deep Learning," 2023 IEEE 26th International Symposium on Real-Time Distributed Computing (ISORC), Nashville, TN, USA, 2023, pp. 184-189, doi: 10.1109/ISORC58943.2023.00033.
6. R. R, S. Shreya and A. R, "Intelligent Deep Learning based Pothole Detection and Reporting System," 2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT), Erode, India, 2021, pp. 1-5, doi: 10.1109/ICECCT52121.2021.9616703.
7. S. Silvister *et al*., "Deep Learning Approach to Detect Potholes in Real-Time using Smartphone," *2019 IEEE Pune Section International Conference (PuneCon)*, Pune, India, 2019, pp. 1-4, doi: 10.1109/PuneCon46936.2019.9105737.
8. J. M. C. Manalo, A. S. Alon, Y. D. Austria, N. E. Merencilla, M. A. Misola and R. C. Sandil, "A Transfer Learning-Based System of Pothole Detection in Roads through Deep Convolutional Neural Networks," 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 2022, pp. 1469-1473, doi: 10.1109/DASA54658.2022.9765227.
9. Y. Bhatia Aparna, R. Rai, V. Gupta, N. Aggarwal and A. Akula, "Convolutional neural networks based potholes detection using thermal imaging", *Journal of King Saud University - Computer and Information Sciences*, 2019.

10. K. Wang, M. Liu and Z. Ye, "An advanced YOLOv3 method for small-scale road object detection", *Applied Soft Computing*, vol. 112, pp. 107846, 2021.
11. "Pothole and Object Detection for an Autonomous Vehicle Using YOLO", 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 2021.
12. Y. Bhatia Aparna, R. Rai, V. Gupta, N. Aggarwal and A. Akula, "Convolutional neural networks-based potholes detection using thermal imaging", *Journal of King Saud University - Computer and Information Sciences*, 2019.
13. V. Pereira, S. Tamura, S. Hayamizu and H. Fukai, "A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste", *2018 IEEE International Conference on Service Operations and Logistics and Informatics (SOLI)*, 2018.
14. R. R. S. Shreya and A. R, "Intelligent Deep Learning based Pothole Detection and Reporting System", *2021 Fourth International Conference on Electrical Computer and Communication Technologies (ICECCT)*, 2021.
15. X. Xi, Z. Huang, L. Ning and Y. Zhang, "Real-time Pedestrian Detection Algorithm Based on Improved YOLOv3", *Journal of Physics: Conference Series*, vol. 2002, no. 1, pp. 012075, 2021.
16. O. Moses, "Official English Documentation for ImageAI! — ImageAI 2.1.6 documentation", *Imageai.readthedocs.io*, 2021, [online] Available: https://imageai.readthedocs.io/en/latest/.
17. J. Macalisang, A. Alon, M. Jardiniano, D. Evangelista, J. Castro and M. Tria, "Drive-Awake: A YOLOv3 Machine Vision Inference Approach of Eyes Closure for Drowsy Driving Detection", *2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 2021.
18. R. Sevilla, A. Alon, M. Melegrito, R. Reyes, B. Bastes and R. Cimagala, "Mask-Vision: A Machine Vision-Based Inference System of Face Mask Detection for Monitoring Health Protocol Safety", *2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 2021.
19. M. Melegrito, A. Alon, S. Militante, Y. Austria, M. Polinar and M. Mirabueno, "Abandoned-Cart-Vision: Abandoned Cart Detection Using a Deep Object Detection Approach in a Shopping Parking Space", *2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 2021.
20. P. Ping, X. Yang and Z. Gao, "A Deep Learning Approach for Street Pothole Detection", 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService), 2020.